“Converging Redundant Sensor Network Information for Improved Building Control”

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Date Report was Issued: March 2008

Period of Performance: December 1st 2003 – September 30th 2007

DOE Award Number:

DE-FC26-04NT41971

Name and Address of Submitting Organization:

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Abstract

This project investigated the development and application of sensor networks to enhance building energy management and security. Commercial, industrial and residential buildings often incorporate systems used to determine occupancy, but current sensor technology and control algorithms limit the effectiveness of these systems. For example, most of these systems rely on single monitoring points to detect occupancy, when more than one monitoring point could improve system performance.

Phase I of the project focused on instrumentation and data collection. During the initial project phase, a new occupancy detection system was developed, commissioned and installed in a sample of private offices and open-plan office workstations. Data acquisition systems were developed and deployed to collect data on space occupancy profiles. Phase II of the project demonstrated that a network of several sensors provides a more accurate measure of occupancy than is possible using systems based on single monitoring points. This phase also established that analysis algorithms could be applied to the sensor network data stream to improve the accuracy of system performance in energy management and security applications. In Phase III of the project, the sensor network from Phase I was complemented by a control strategy developed based on the results from the first two project phases: this controller was implemented in a small sample of work areas, and applied to lighting control.

Two additional technologies were developed in the course of completing the project. A prototype web-based display that portrays the current status of each detector in a sensor network monitoring building occupancy was designed and implemented. A new capability that enables occupancy sensors in a sensor network to dynamically set the “time delay” interval based on ongoing occupant behavior in the space was also designed and implemented.

Executive Summary

Knowing how many people occupy a building, and where they are located, is a key component of building energy management and security. Commercial, industrial and residential buildings often incorporate systems used to determine occupancy, however, current sensor technology and control algorithms limit the effectiveness of both energy management and security systems. Most current building occupancy detection systems use passive infrared (PIR) and/or ultrasonic technologies, signaling space occupancy based on changes in the temperature or sound profile of a space at a single monitoring point. Yet, commercially available occupancy detection systems and products do not always perform according to specification.

There is a growing literature that addresses the effectiveness of occupancy sensors for controlling office ambient lighting systems, and other studies have evaluated the effectiveness of occupancy-based switching for power management of office equipment. This work shows that occupancy sensors reliably deliver significant energy and demand savings in infrequently or unpredictably occupied spaces, such as washrooms, stairwells, corridors, storage areas, and mail carrier sorting. Comparable savings have eluded general office applications, and occupancy sensors have not achieved as wide use as other energy-saving lighting technologies. There are often significant differences between actual observed savings and industry estimates of savings that can be realized through the application of current occupancy sensing control systems.

Two simple premises motivate the work described in this report. First, that more energy savings might be achieved if building occupancy could be determined more accurately. Second, that more detailed and accurate occupancy information can be obtained by more extensive sensing, specifically through the use of a sensor network to measure occupancy.

Highlights of the report are as follows:

Previous research on occupancy detector performance has always assumed that any arbitrarily selected mounting position will accurately characterize occupancy, and thus the selection of mounting position depends only on ensuring that the controlled space was within the detection zone of the sensor. However, work described in this report shows that several individual sensors of the same brand and manufacturer respond differently to occupancy, even in small enclosed private offices. Single detectors mounted arbitrarily in a space will not reliably measure occupancy. Thus, there can be considerable uncertainty associated with the measurement of occupancy using current systems.

Current systems resolve this uncertainty by incorporating a “time delay" setting, manually activated at installation. The time delay is the interval that must elapse before lights are switched off in an empty space. Long time delay settings are used by current systems to compensate for uncertainty associated with occupancy measurement: a long time delay ensures lights are not inadvertently switched off in occupied spaces.

All previous studies of occupancy sensor performance describe data resolved at intervals of greater than five minutes, or only report total occupied time. The occupancy data collected, analyzed, and reported here were resolved to one second or one-minute intervals. It is only with such finer temporal resolution that the argument can be made that benefits will be realized by applying shorter time delay settings.

All previous studies of occupancy sensor performance assume that the measurements collected by the sensor itself are accurate measures of occupancy. Data reported here show that this assumption is incorrect. A comparison of occupancy measured by motion sensor versus human observers shows that measurements from single sensors underpredict occupancy, sometimes by as much as 80% (even for properly functioning sensors). The accurate determination of true occupancy is required to evaluate the performance of both single detectors and sensor networks. Statements comparing the performance of a sensor network against more traditional control methods are more persuasive when true occupancy data are available.

Criteria to evaluate the performance of sensor networks against converging "truth" measures as determined by human observers were also described. Sensor network outputs (stating whether or not a space was actually occupied) were compared against the total occupied time, accuracy (in terms of correlation with occupancy measured by human observers), and the number of times the lights were switched off in occupied spaces. Previous investigators have recognized that while shorter time delay settings would lead to greater energy savings, they did not describe the increased number of times that lights would be switched off in an occupied space (and concomitant user dissatisfaction) that would result from these shorter time delay settings. Results reported here show that it is possible to set a shorter time delay setting with a sensor network, and achieve the same user satisfaction, as with a traditional control system using a longer time delay setting. This leads to greater savings, especially in spaces with frequent occupancy changes.

Having established the benefits of using more than one sensor for occupancy measurement and control, it is important to recognize that a data stream from a sensor network is only useful if an analysis framework is available that can be applied for the purposes of energy management. Eight data fusion methods were applied to sensor network data collected and described here. These algorithms characterized occupancy more reliably and more accurately than was possible using output from a single sensor. The most sophisticated of these methods incorporate knowledge of detector performance and typical occupancy patterns, and this research shows that these more sophisticated methods can also self-diagnose, and identify faulty sensor(s), which will improve the reliability and robustness of the whole control system.

A network of inexpensive occupancy sensors is more accurate, reliable and robust at measuring occupancy, and is potentially more economical in terms of initial investment and operating costs than a single-point detection system. Based on the collected data, we show that it may be possible with a sensor network to reduce the operating time of occupancy-based building systems by an extra 20% (compared to current systems) without sacrificing user satisfaction: the simple payback periods associated with various control options in generic small and large commercial buildings estimated that wireless sensor networks may have payback periods less than 2 years.

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List of Abbreviations

ANN:	Artificial Neural Network
ASHRAE:	American Society of Heating, Refrigerating, and Air-Conditioning Engineers
BN:	Belief Network
BTU:	British Thermal Unit
CLF:	100 linear feet
DAS:	Data Acquisition System
EPRI:	Electric Power Research Institute
hr:	hour
LEED:	Leadership in Energy and Environmental Design
LSE:	Least Squares Estimation
min:	minute
NLPIP:	National Lighting Product Information Program
NN:	Neural Network
PIR:	Passive Infrared
sec:	second
SPOT:	Sensor Placement and Optimization Tool
WPAN:	Wireless Personal Area Networks

1 Introduction

Nearly 100 quadrillion BTU of energy is consumed annually in the United States, with about 18% being consumed by commercial buildings[1-5]. About 76.7% of the energy consumed by commercial buildings is electrical, and most is derived from fossil fuels, which are nonrenewable[1]. New technologies will therefore be crucial to ongoing initiatives related to the energy aspects of building operation and maintenance.

Lighting and HVAC systems have been attractive targets for energy management in the buildings sector, since together they are responsible for about 61% of a building's energy budget (lighting accounting for about 23%, with heating, ventilation and cooling accounting for about 38%)[6-15]. One now near-ubiquitous strategy involves the application of occupancy sensing systems to manage lighting use: occupancy sensing control systems switch lights on in a space when motion is detected, then switch lights off if no motion is detected within a preset interval.

The Energy Policy Act of 2005 (EPAct 2005) includes a tax deduction for energy efficient building systems[11]. Qualified buildings must first satisfy the ASHRAE 90.1-2001 *Energy Standard for Buildings Except Low-Rise Residential Buildings*, in which occupancy sensors are required for lighting control in most commercial and educational spaces[12].

Past studies show that occupancy sensing control systems do not function as well as manufacturers claim. For example, the National Lighting Product Information Program (NLPIP)[14], has published work showing that more than half of a small sample of motion sensing detectors did not respond to a movement occurring within the coverage area claimed for the device. Other studies (described in the literature review) confirm the discrepancy between observed savings and manufacturer claims. Several authorities have concluded that higher savings might be possible, but only after professional tuning and commissioning, which rarely occurs.

Currently available occupancy sensing control systems are based on single-point detection, and measurements collected by a single unit are usually not shared with other building management systems, nor saved for further analysis or use. Each space or zone is always controlled by a single stand-alone detector, which has no additional information available concerning occupancy, as it alone monitors and controls services to a specific assigned space. There can be significant uncertainty associated with the measurement of occupancy using a single detector. Long time delay and high detector sensitivity settings are used to compensate for this uncertainty (the time delay is the interval that must pass before the lights are switched off by the controller, after the last motion has been detected). Time delay settings of 20 to 30 minutes are typical, and as a result more energy is wasted than if occupancy were more accurately measured, and light usage corresponded more closely to actual occupancy. Even despite long time delay settings, lights are often switched off in occupied spaces (because the occupant is located outside the field of view of the single detector), resulting in complaints, which sometimes provokes users to disable sensors and control systems.

The discrepancy between actual sensor performance and manufacturer claims suggests that the design of current sensor and control systems that use occupancy sensors can be improved. The basic premise of this project is that more effective indoor environmental control requires more extensive sensing, and more extensive analysis of sensor data. The work described in this report shows that sensor networks, consisting of several independent detectors monitoring the same space, provide more accurate determination of space occupancy than is possible with a single point of detection. More accurate occupancy measurements lead to more effective control.

The second focus of the research described in this report relates to the analysis of sensor network data. A rigorous analysis framework is required that takes into account additional information that can be applied to improve confidence that the system has made the correct determination about occupancy.

Although the immediate goal of this research has been to enhance the energy management capabilities of occupancy-based control systems for indoor environment services like lighting and ventilation, there are other commercial and residential building applications that can be enabled by the availability of better sensing, and access to the sensor network data stream. These are briefly discussed in the concluding chapter.

2 Occupancy Sensing Technology

2.1 Introduction

The most commonly used devices for detecting occupancy use PIR and/or ultrasonic technologies. Other devices that have been used for occupancy sensing use microwave and audible technologies: these have been applied in relatively few buildings, and there are few studies evaluating the effectiveness of these systems. Still other devices, such as light barriers, pressure sensors, video cameras and biometric systems have also been used to detect occupancy, but these are applied mostly for safety or security and almost never used for building systems control. Each will be reviewed in turn.

2.2 Current Occupancy Sensing Technology

2.2.1 Passive infrared occupancy sensors

One of the most popular technologies applied in commercially available occupancy sensors uses a pyroelectric detector as the main component in a system that is often referred to as a PIR occupancy or motion detector. PIR sensors respond to the change in the temperature pattern across the field of view of the sensor. The sensor is passive, because it does not emit any energy itself, but sends a signal based on the pattern of infrared radiation in the environment.

The main components of PIR sensors are the pyroelectric detector and a Fresnel lens [16]. In an occupancy detecting application, when the sensor detects the heat generated by a human body, the pyroelectric material undergoes a change in polarization. This change in polarization induces a voltage signal. The pyroelectric detector is most sensitive to moving objects that emit heat energy at around 10 μm, the peak wavelength of radiation coming from the human body[16,17].

The Fresnel lens is a thin plastic lens, which is flat on one side and ridged on the other. As shown in Figure 2-1, the construction of a Fresnel lens can be simply imagined as slicing a plano-convex lens in rings, then reforming the surface of the plano-convex lens to the planar side, so that each part of the ring has the same thickness. The Fresnel lens is much thinner than the original convex lens and it has lower absorption losses, but it has the same ability as the convex lens to collect and redirect electromagnetic radiation. In a PIR sensor, the infrared radiation from the human body is collected at the lens from a relatively large field of view, and then converged on the pyroelectric detector.

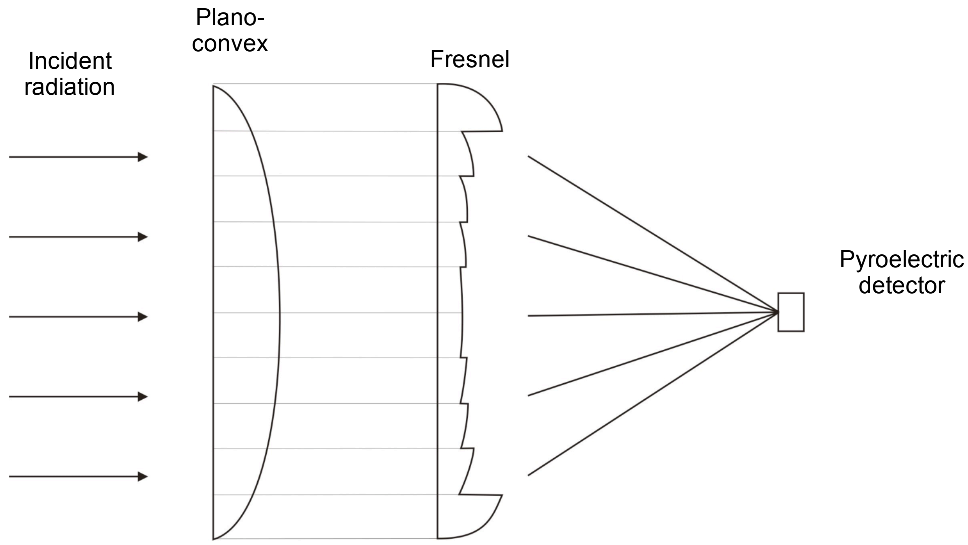


Figure 2-1. Fresnel and plano-convex lenses with the same optical properties

The lens is further etched into fine patterns so that it divides the field of view of the detector into discrete cuneate zones. The sensor responds when it detects a heat change moving from one zone to another. The sensitivity of the sensor decreases as the distance between the sensor and a moving warm body increases, since the gaps between zones widen with distance, although the solid angle remains the same size. Consequently, sensitivity decreases with distance, and it becomes more difficult for the sensor to detect small movements as the target moves further from the sensor.

The orientation of the detector and the lens determine the coverage area and pattern of a PIR sensor. When a PIR sensor senses movement and converts it to a voltage signal, a transducer magnifies this signal, so that the voltage is strong enough to trigger a switch, or to be measured by an external data acquisition system (DAS), as in the work described here.

Most PIR sensors are sensitive to hand movements up to a distance of about 15 ft, arm and upper torso movements up to 20 ft, and full body movements up to about 40 ft[17]. Figure 2-2 shows the typical coverage pattern of PIR sensors[17]. The discrete fan-shaped coverage pattern illustrates that the gaps between sensing zones widen as distance increases. At a distance of 40 ft, these gaps can be as wide as 8 ft. In most small office applications, the distance between the detector and the target is within 15 ft, so the detector *should* be able to detect small movements, however many commercially available sensors cannot detect small motion under these circumstances[14].

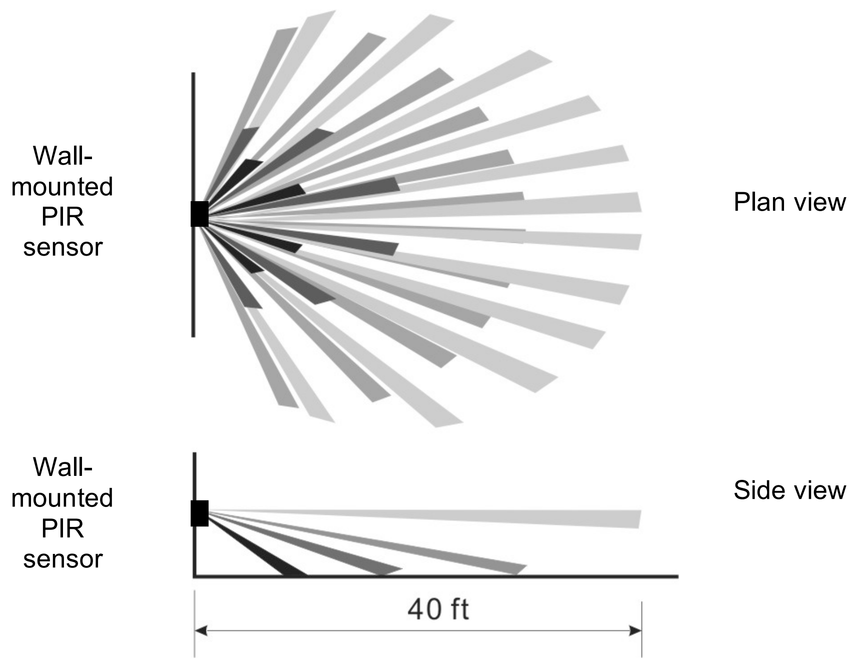


Figure 2-2. Typical coverage of wall-mounted passive infrared sensor[17]

PIR sensors require "line of sight" in order to function properly, that is, the sensor must "see" the movement directly. For example, if a movement is hidden behind a partition it will not be detected. Consequently, PIR sensors often switch off services in occupied spaces, which result in user complaints[17].

2.2.2 Ultrasonic occupancy sensors

Ultrasonic detectors are another popular occupancy sensing technology used in commercial buildings. Unlike their PIR counterparts, ultrasonic sensors are active devices: they emit ultrasonic sound waves, and receive the sound energy reflected back to the sensor from the environment. Sound waves reflected from a moving object will have a different wavelength when reflected back to the detector. This phenomenon is more commonly known as the Doppler effect, which involves a measurable shift in the wavelength of a traveling wave, caused by the motion of a source relative to an observer[18].

The two main components of an ultrasonic motion sensor are an ultrasonic wave emitter and a receiver. The sound source emits waves at frequencies between 25 to 40 kHz, and these waves are reflected when they meet an object. If the object is moving, the reflected waves will have a different wavelength, and thus movement (and presumed occupancy) is detected.

Figure 2-3 depicts the field of view of a typical ultrasonic sensor[17]. Unlike a PIR sensor, ultrasonic sensors do not require "line of sight", since the ultrasonic waves can theoretically be reflected by room surfaces and partitions, and reach every corner of a space. Thus the detection pattern of this type of sensor is continuous, and movements behind partitions may be detected. Ultrasonic sensors are believed to be more effective than PIR detectors in partitioned and irregularly shaped spaces.

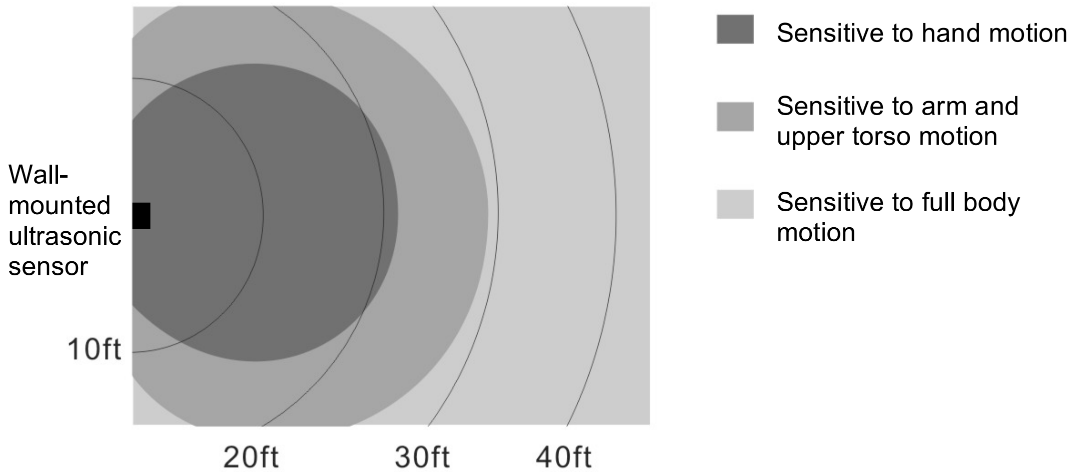


Figure 2-3. Typical sensitivity pattern of wall-mounted ultrasonic sensor[17]

However, the increased sensitivity can mean that ultrasonic sensors are more susceptible to false triggering due to non-occupant movements, or movements in adjacent areas. For example, ultrasonic sensors can be triggered by the air turbulence from HVAC systems, waving leaves outside an open window, or even moving paper coming from a printer[19].

Besides the basic differences between the underlying technologies used to sense motion, PIR and ultrasonic sensors exhibit different detection patterns, effective ranges and sensitivities. PIR sensors have wedged-shaped detection zones, and motions are defined as a target moves between the zones, so the detection pattern of PIR sensors is discrete. In contrast, the detection pattern of ultrasonic sensors is continuous. Like PIR sensors, the sensitivity of the ultrasonic sensor also decreases as the distance between the detector and the target increases, but this is because waves reflected from a longer distance are weaker, not because gaps between zones are larger (as with a PIR sensor). PIR sensors are prone to false-offs (lights switched off in occupied spaces), while ultrasonic sensors are more susceptible to false-ons (lights switched on in unoccupied spaces).

Several other technologies have been deployed to detect occupancy in buildings, and these will be discussed in the following sections, but they are not as commonly used in building applications as PIR and ultrasonic detectors.

2.2.3 Audible sound / Passive acoustic sensors

Audible sound sensors listen for noise (from any source) using a microphone or other audio detector to determine occupancy[20]. Like PIR sensors, they are passive devices, since they do not emit any signals, but instead await changes in received energy. Audible sensors are best applied in an industrial facility or warehouse. They respond to non-human environmental noises, and noises from adjacent spaces, and thus are prone to false-ons.

This technology is relatively old, and is seldom applied alone because of the high false-on rate. Audible sensors have been included in dual-technology units to complement PIR sensors.

2.2.4 Microwave sensors

Microwave sensors are similar to ultrasonic sensors, in that they emit a signal and measure a change in the frequency of a reflected signal. The frequency of signal emitted by a microwave sensor is around 10GHz[20,21].

Microwave sensors are usually designed to be used in larger public areas where typical movements are large-sized, such as corridors, sports halls and school halls. Microwave sensors usually have elongated coverage patterns, and the coverage distance can be as long as 200 ft. The long detection range also enables microwave sensors to be used in non-building applications such as vehicle detection[22].

Microwave sensors are also used in automatic door openers. An emitter located above a door sends out a short burst of microwave radio energy and waits for the reflected wave. If a motion is detected near a door due to the Doppler effect, the door will open automatically.

Microwave sensors are able to see through non-metallic materials, such as plastics, fiberglass and even brick walls. This broadens their application to military or transportation uses, but has limited application in building occupancy detection, since they will be very sensitive to false-ons (occurring in response to occupancy of adjacent spaces).

2.2.5 Light barriers

A light barrier is a device that is installed at an entrance or a safety boundary. These devices use an infrared beam, sent between a transmitter and receiver, usually installed at both sides of an entrance. Passing objects or people interrupt the beam, thereby signaling occupancy.

Safety light barriers are often used in industrial applications to protect machine operators from injury. Sometimes they are installed for security reasons, to detect a burglar and trigger an alarm, for example.

Installation of two horizontally separated pairs of light barriers at an entrance could provide information about movement direction and the number of occupants. However, application of light barriers for the purpose of building system control is very rare.

2.2.6 Video cameras

Video cameras are another commonly used method to detect occupancy, most frequently used in building security systems. Video images are either observed by human operators, or analyzed by computer software. Video cameras are a reliable and accurate way to determine not only if a space is occupied, but also the number of occupants and their identities. However, the cost of human observers to monitor and review video images is too high to be applied continuously, and the resolution of commercially available software-based image analysis is low, and still under development. Most problematic, occupants will likely object to the use of video monitoring as a violation of their privacy. As a result, these systems are rarely used for building energy management.

2.2.7 Biometric systems

A biometric system makes measurements of human physiognomy for identification[23,24]. These are often installed at entrances to restricted areas to identify authorized personnel, sometimes as a replacement or complement to other access methods that use passwords. Biometric systems are usually used to provide secure access control, and the costs of these systems are very high.

2.2.8 Pressure sensors

A pressure sensor utilizes a piezoelectric element that produces an electrical signal when exposed to a vibration or high acceleration[25,26]. It responds to the pressure generated at a footpad, or sends a signal to an alarm when movement occurs at a door or window.

Pressure sensors are usually mounted directly at the location they are intended to monitor; for example, sensors that measure the vibration of breaking glass are designed for mounting at the corner of the protected glass or the window frame. Unlike passive infrared, ultrasonic, microwave and audible sensors that respond to airborne signals, pressure sensors sense the vibrations transmitted through solids.

Pressure sensors are usually installed in residential buildings to detect break-ins and trigger alarms.

2.2.9 Dual technology

A dual-technology sensor, also called hybrid sensor, combines two basic occupancy-sensing technologies in one unit to enhance performance. For example, PIR sensors are less susceptible to false-ons, but sometimes switch off services when the space is still occupied; and so incorporating another technology with a PIR sensor may help reduce false-offs. The most popular combination of technologies is PIR and ultrasonic sensors; the combinations of PIR and microwave, PIR and audible sound are also commercially available. These sensors switch services on when both technologies or the PIR sensor alone detect a motion, and switch services off if both sensors detect no activity.

Dual-technology sensors are common in classrooms and private offices. They are subject to fewer false-ons and false-offs, which increases energy saving and user satisfaction, but prices are considerably higher than single-technology sensors. For example, a simple PIR or ultrasonic sensor typically costs \$60 or \$125, respectively, while a dual-technology sensor costs about \$150. Ultrasonic sensors cost more than PIR sensors because they are usually designed to cover larger areas, similar in size to those covered by dual-technology sensors (typical designed coverage area for ultrasonic and dual-technology sensors is more than 1000 ft^2, versus 300 ft^2 for simple PIR sensors).

2.3 Summary

In commercial buildings, PIR and ultrasonic sensors are typically used for lighting control applications. Sensors that use microwave and passive acoustic technologies are also available, but they are not used as often. Other systems that use video cameras or biometric identification may provide higher resolution for occupant identification and localization; however, at the present time, these are primarily used in security and alarm applications. Hybrid occupancy sensors employ both infrared and ultrasonic capabilities in the same unit, offering improved operation with reduced false triggering.

Table 2-1 provides a comparison of the different systems described in this chapter in terms of "resolution" and initial cost. "Resolution" is defined as whether or not the system can measure the number of occupants in a space, identify, and localize individuals in a space. The resolution of the sensors currently used in building energy management is low: they can only roughly tell if a space is occupied, but cannot provide information about the number and identification of occupants, or where they are located in a space. Video camera and biometric systems have high resolution, but they are also expensive. In building energy control, identification of individuals is usually not required, so video and biometric systems that provide too much detail might be considered an intrusion of privacy. Spatial localization of individuals is important in security; for example, a rescue action would be more effective if occupant location was known. Initial cost is also an important factor in sensor selection, and selection will be a compromise between function and price.

Table 2-1. Comparison of current occupancy sensing technologies

Type of sensors	Resolution	Number of occupants	Person identification	Person localization	Initial cost
PIR	Low	No	No	No	Low
Ultrasonic	Low	No	No	No	Low
Microwave sensors	Low	No	No	No	Low
Audible sound sensors	Low	No	No	No	Low
Light barriers	Low	Yes	No	No	Low
Video camera	Very high	Yes	Yes	Yes	High
Biometric systems	High	Yes	Yes	No	High
Pressure sensors	Low	No	No	No	Medium
Sensor networks	Medium	Maybe	No	Maybe	Medium

Having reviewed the basic technologies currently used in building energy management and security applications to detect occupancy, the next chapter summarizes past research investigating the performance of PIR, ultrasonic and hybrid PIR/ultrasonic systems in lighting control systems.

3 Performance of Occupancy-Based Lighting Control

3.1 Lighting Control Strategies

Occupancy sensing systems are currently used in commercial buildings primarily for lighting control, and so in this chapter, the popular lighting control strategies related to energy conservation are reviewed. While occupancy-based controls are the subject of this report, it is useful to first briefly review other lighting control strategies, although a detailed discussion of all these various methods is beyond the scope of this document. From a simple on/off switch, to programmable intelligent systems, lighting controls are undergoing continuous development that makes them more flexible, reliable, and allows them to be integrated with other building management functions[27-30]. For example, the industry standard protocol BACnet makes it possible to link all aspects of building controls such as heating, ventilating, air conditioning, lighting and security together into a network, using a common control system[31].

In addition to occupancy-based controls, other popular lighting control strategies for the purpose of energy savings include manual switching, scheduling, daylight-based controls, load shedding (or demand limiting) and task tuning[32-62]. Each will be briefly discussed, and then a more detailed review of occupancy-based lighting control systems will be presented.

The simplest form of lighting control is a manual switch, turning lights on or off, usually using a wall switch. The effectiveness of this method depends greatly on occupant behavior and awareness about energy conservation. Research shows that a reminder sticker attached to a wall switch reminding occupants to switch off the lights when they leave the room initially reduces lighting energy use by 15%, but these savings are not maintained, as occupants eventually ignore the reminder sticker with the passage of time. Savings strategies that rely on occupant behavior are not persistent[32,52].

Scheduling controls lights based on predetermined time schedules. Energy savings depend on the occupancy pattern, but are typically 10-50% compared to manual switching[20]. This control strategy is useful when the occupancy pattern is relatively fixed, and is often applied to open-plan offices. Overrides to the schedule via manual wall switches allow occupants to turn lights on again, after the scheduled switch off.

Some lighting controls take advantage of the availability of daylight, dimming or switching off lights when sufficient daylight is available to meet task requirements. Research shows that 50% of subjects will remain unaware of 15-20% lighting level reduction achieved by dimming[36-38], and 80% subjects will accept a reduction in lighting level of up to 50%[36,39]. The effectiveness of this strategy depends on building orientation, window size and other architectural features of the space, as well as local weather conditions. Research shows that savings of 30% to 50% relative to manual switching can be achieved[20,33,34]. In the case of a daylight-linked dimming system, a controller is equipped with a photosensor, which measures the illuminance level (at the wall or ceiling) and attempts to adjust light output to meet task illuminance requirements. Proper placement of the photosensor is important, since the photosensor measures the light level at one point (usually on the ceiling), but regulates the workplane illuminance throughout whole space. If the availability of daylight is overestimated, for example, the space might be insufficiently illuminated, and vice versa. Recently, computerized tools have become available to help with photosensor placement (e.g., SPOT: Sensor Placement and Optimization Tool), which takes the building location, orientation and geometry into consideration to determine the optimum photosensor placement relative to existing or proposed daylighting and electric lighting systems[35].

With load shedding, lights are automatically dimmed or turned off during peak demand periods to save energy and demand cost. Electric utilities often charge higher rates for electricity at peak demand times, so load shedding may only save small amount of energy, but may save considerable demand. The energy savings achieved by load shedding are usually not reported separately, because the implementation of load shedding depends greatly on local power management plans, and is usually accompanied with daylight-based controls or scheduling.

Task tuning is a local control strategy that allows occupants to switch or dim lights based on their preference. It is usually implemented by manual adjustment of a local switch, and possible savings range from 10 to 50%, depending on users' preference[20].

Table 3-1 summarizes important features of the different lighting control strategies discussed in this section. It includes typical energy savings that can be achieved by each control method, whether the method offers possibility for zonal control (i.e., controlling a subset of the lights in a space), and whether the method relies on manual versus automatic control. The savings that can be achieved in a real installation will vary greatly with site condition, space function and occupancy pattern. Daylighting and task tuning are usually local control strategies, controlling one private office or workstation, while scheduling and load shedding usually apply to an entire floor or building. All these control strategies are automatic, except task tuning, which aims to satisfy individual preference and is implemented locally.

Table 3-1. Comparison of lighting control strategies

Control Strategy	Typical Energy Savings	Control Zone		Automation	
		Local	Centralized	Manual	Automatic
Scheduling	10-50%		√		√
Daylight-based controls	30-50%	√			√
Load Shedding (or Demand Limiting)	Small		√		√
Task Tuning	10-50%	√		√	

All these control strategies attempt to save energy by restricting light usage to the needed time or area, in addition to providing adequate illuminance. Scheduling is appropriate only when the occupancy pattern is predictable, and it usually cannot be used alone, but must be accompanied by manual or automatic override switching. The effectiveness of daylighting-related control schemes depends on local weather conditions and building architecture. The successful application of load shedding for building-level lighting control requires that the majority of the lighting systems are dimmable and controllable, and incorporate appropriate software tools to process the demand and utility pricing data. Task tuning control systems are more focused on providing lighting according to user preference, but there is some evidence that the application of these systems may also save energy because some occupants dim the light to a considerably lower than recommended, but apparently still acceptable level[36,39,40].

3.2 Performance of Current Occupancy-Based Control Systems

Occupancy-based lighting control systems detect human movements, and switch lights off and on accordingly. For all but the most diligent users, these systems save energy compared to manual switching, but the savings depend on proper installation and post-installation commissioning. Commissioning a control system usually involves changes to sensor mounting position, adjustment of sensor aiming angle, tuning of sensor sensitivity[34,61], and sometimes even replacement of sensors[45]. In this section, we present a detailed review of the performance of occupancy-based lighting control systems.

Manufacturers usually claim 15-75% energy savings are possible from replacing the manual switches with occupancy sensors[20,41]. Others estimate average energy savings of about 30%[42]. There is a growing literature that addresses the effectiveness of occupancy sensors for controlling office ambient lighting systems, and other studies have evaluated the effectiveness of occupancy-based switching for power management of office equipment[43-53]. There are often significant differences between observed savings and industry estimated savings that result from the application of these systems.

Richman et al. studied the factors affecting energy savings in 141 sample spaces in Hanford, WA, which included 13 space types for a total test time of more than 50,400 hrs[44]. They used lighting loggers to record the duration that lighting systems were switched on in the monitored spaces: each logger was also connected to a single ultrasonic occupancy sensor that was simultaneously recording space occupancy.

They calculated the savings that could result from the application of occupancy sensors by adding time-delay settings of 5, 10, 15, and 20 minutes to the raw occupancy data: this simulates different control scenarios. Savings were calculated by comparing the length of time the lighting systems were in use, relative to the occupied time plus the appropriate time delay. For example, if the lighting in a space remained on for 21 minutes after the occupant departed, the savings for a 15 minute time delay would be 6 minutes. The authors reported potential energy savings of between 50% and 3% for time delay settings of 5, 10, 15, and 20 minutes for private offices, and between 86% and 73% for restrooms. The study concluded that daylight availability, space function, occupancy patterns, and occupant density all affect the energy savings. It is important to note that this paper assumes a single detector provides an accurate measure of occupancy.

Floyd et al. studied the energy savings achieved by retrofitting occupancy sensors in one office building and two educational buildings in Florida, including a total of 56 offices and 72 classrooms[45]. They monitored energy consumption in the different buildings studied for six months before installing occupancy-based lighting controllers, then monitored energy consumption for a similar period after the devices were installed. Savings were calculated as the difference in energy use between the pre- and post-installation periods.

The office building was occupied by the researchers themselves, at the Florida Solar Energy Center (Cape Canaveral, FL), and this facility incorporated a separate metering system for the building lighting system, making it easy to measure pre- and post-installation lighting system use. A total of 23 PIR and ultrasonic sensors were used in this building to control the lighting use.

Monitoring the educational facilities was more difficult, as these buildings had not been constructed with energy studies in mind. In one school, 46 PIR sensors were installed in 33 classrooms, 7 offices and a cafeteria (two sensors were installed in each of the five larger areas); in the second school, 59 PIR sensors were installed in 39 classrooms and 20 offices. Electric power transducers monitored electrical energy and demand, and output from the transducers were converted to digital format and stored in a Campbell Scientific model CR10 data logger every 15 minutes.

The study found that occupancy sensors contributed to a maximum of 19% energy saving in the office building and 11% in one of the schools, and in the other school building, unexpectedly, higher energy consumption was measured after the retrofit. The energy saving in the office building was initially 10%. All sensors were then carefully tuned and relocated for optimal performance. Three out of the 23 sensors were replaced during this process due to malfunction. The time delay settings were changed from 15 minutes to 7 minutes. After these adjustments, the maximum saving of 19% was achieved.

In one school building, 11% energy saving was achieved after professional commissioning and tuning, however, in the other school, energy consumption increased even after careful commissioning. The authors speculated that this increase in lighting power consumption might have resulted from false triggering during the night, or momentary individual visits to spaces during which lights would not have been switched on at all if a manual switch was used to control lights.

Maniccia et al. monitored energy use for four months in 60 perimeter and 21 interior private offices in an office building in Colorado and concluded that 43% energy savings could be achieved by the application of PIR occupancy sensors with a 30-minute time delay setting[46]. The offices were equipped with manual dimmers and switches, occupancy sensors and photosensors, and these controls were integrated with a building automation system (BAS), which monitored the lighting and HVAC systems through a data acquisition system (DAS). The DAS logged the current to each luminaire, the status of each occupancy sensor, and the status of all the other switches and controls. An imaginary 10-hr scenario with lights on-full from 08:00 to 18:00 was adopted as the baseline for energy saving calculations. Monitoring showed that, on average, only 31% of this 10-hr interval was actually occupied (as measured by the single occupancy sensor located in each space). Since each occupancy sensor incorporated a 30-minute time delay setting, a further 8% was added to the total energy consumption, thus 39% of the 10-hr interval was logged energy consumption.

The remaining 61% of the 10-hr period showed no energy consumption, and was considered by the authors to represent savings achieved by the different lighting control strategies used in this building. Since they were able to monitor occupancy sensor and manual switch status, they concluded that 43% of these savings were due to the occupancy sensors, and other 18% were saved by dimming or manual override.

In two subsequent papers, Maniccia et al. and von Neida et al. described a study conducted by the Environmental Protection Agency and the Lighting Research Center of Rensselaer Polytechnic Institute concerning the energy savings potential for occupancy sensors in commercial buildings. The study involved a cross-section of building types including companies, education, healthcare organizations and government entities in 24 states[47,48]. The occupancy and lighting operating time were recorded for two weeks in 158 rooms, including 37 private offices, 42 restrooms, 35 classrooms, 33 conference rooms and 11 break rooms where no automatic controls were implemented. The lighting and occupancy status were monitored using Watt Stopper's Intellitimer Pro IT110 light logger. This device consists of a PIR occupancy sensor and a photosensor with an adjustable light pipe that can be aimed towards a luminaire to log the actual electrical lighting usage. The PIR sensor is used to record occupancy. Every time there is a change in the occupancy or lighting status, the data logger writes an entry, which is retrievable by a computer. The measured lighting operating times served as "baseline" data in energy saving calculations. Different lighting control scenarios were simulated by applying 5, 10, 15, and 20-minute time delay to the logged occupancy data, and energy savings and demand reduction potentials were calculated by comparing these simulated data with the baseline lighting usage data.

For the private offices, 28% energy savings could be achieved if the time delay setting was 20 minutes, and this saving increased to 38% if a short time delay of 5 minutes was applied. In the irregularly occupied spaces, savings ranged from 17% to 60% for time delay settings of 20 and 5 minutes respectively.

Jennings et al. studied the energy savings from various lighting control options, including occupancy sensing, light level adjustment, manual dimming, and daylighting, and concluded 20-26% of energy savings could be achieved by occupancy sensing with a 15 to 20-minute time delay[49]. Energy use was monitored for seven months in 99 private offices in a 21-story office building in California, and particularly, energy savings by occupancy sensing was calculated in 35 offices equipped with a manual switch and occupancy sensor. The building included a distributed control system that also acted as a data acquisition system to collect data about energy use in each of the monitored zones.

Events were logged each time the manual switch changed state, or the sensor detected a change of occupancy. The savings achieved by occupancy sensing was calculated by:

$$\text{Energy savings (\%)} = \frac{\text{Time when office is vacant with switch ON}}{\text{Time when switch is ON}} \tag{3. 1}$$

Where the numerator is the total time the space is vacant, but the manual switch was in the "ON" position: the denominator is the total time the manual switch was in the "ON" position. The calculated daily energy savings ranged from 3% to 50%, with an overall average savings of 20% to 26%.

Chung et al. developed a model to predict energy savings based on occupancy probabilities at different times throughout the day[50]. The model was tested by comparing measured lighting energy consumption in an office building in Hong Kong against simulated energy consumption based on this model. Sixty-eight "smart" sensors, which consisted of an occupancy sensor, a photosensor for illuminance measurement, and an infrared remote control, were installed on the open office area of one floor, each controlling about $10m^2$ of space. Lighting loads under the control of these 68 sensors were connected to a switchboard, and an energy meter was installed at the switchboard to log the energy consumption of the whole area. The monitoring period lasted for 21 days, and the measured and simulated energy consumptions showed good agreement with each other.

Energy consumption after the application of 5, 10 and 20-minute time delay settings to the simulated occupancy profiles were calculated, and the savings achieved by occupancy sensing were calculated based on two baselines. The first baseline was a 14-hr continuous occupancy scenario; the second was a predefined lighting profile as shown in Figure 3-1, which simulated lighting use assuming control by manual switches.

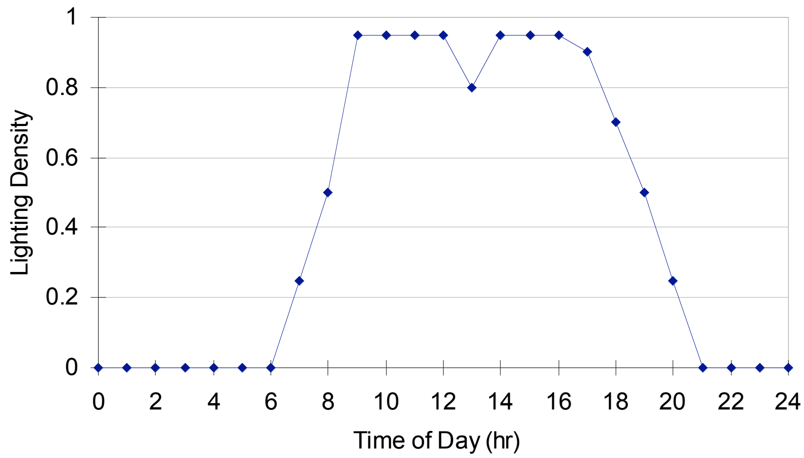


Figure 3-1. Lighting profile for base line 2, by Chung et al.

Predicted energy savings relative to continuous occupancy were 26.1% with a 20-minute time delay and 33.3% for 5-minute time delay. Savings relative to the occupancy profile depicted in Figure 3-1 were calculated as 6% and 15.2% for 20 and 5-minute time delays.

Table 3-2 summarizes the energy savings reported in the studies described above. For comparison, the energy savings estimated by the Pacific Gas and Electric Company, based on manufacturer's claims is also provided at the end of the table[41].

Table 3-2. Summary of energy savings achieved by application of occupancy sensors to lighting control

Source	Energy Savings		Time delay (min)	Baseline for energy saving calculation
	Regularly occupied spaces	Irregularly occupied spaces		
Richman et al. 1996 [44]	3-50%	46-86%	5-20	Total lighted unoccupied time (Savings equal to 100% if no time delay applied)
Floyd et al. 1996 [45]	10-19%(1)	-	7-15	Pre-retrofit lighting energy consumption
Maniccia et al. 1999 [46]	43%	-	30	10-hr lights continuously on scenario
Maniccia et al. 2001 [47]	28-38%	17-60%	5-20	Lighting usage measured by photosensor
Jennings et al. 2000 [49]	20-26%	-	15-20	Lighting usage if lights were controlled by manual switch
Chung et al. 2001 [50]	26.1-33.3%	-	5-20	All lights on from 7AM to 9PM
	6.9-15.2%	-	5-20	Simulated occupancy pattern (Figure 3-1)
PG & E 1997 [41]	25-50%	30-75%	NA	NA

(1) Floyd et al. studied both commercial and school buildings, and found 10-19% energy savings in the commercial building and 11% in one school. However, energy use was increased in the other school building.

The large differences observed in actual measured energy savings are not surprising, since these studies were carried out in different building types, applied different time delay settings to switching operations, and used different baselines against which to calculate energy savings. Some studies compared pre- and post-retrofit energy consumption, some compared energy consumption based on occupancy sensor versus manual switching, while others used simulated occupancy profiles as the baseline for energy savings calculations. Many studies defined "true" occupancy based on the measurement from an occupancy sensor, and often included the sensor time delay setting in measuring occupancy (e.g., Richman). Although these researchers attempted to eliminate extraneous factors that would adversely affect the sensor measurements, they offered no reassurances that many of the factors that are known to affect sensor performance did not compound in their own studies. For example, it is well known that ultrasonic sensors are prone to false-ons (moving paper from a printer[45] or the air flow from a fan can trigger ultrasonic sensors) but these factors were not discussed by Richman et al[44]. Consequently, occupancy determination based on measures from a single sensor is questionable.

Similarly, in the study conducted by Maniccia et al.[47], "true occupancy" was measured by an occupancy sensor, and energy savings were calculated by applying different time delay settings to this measured occupancy profile. "Detection errors" (conditions in which no occupancy was measured by the occupancy sensors, but the lights were turned on and off), were manually modified in the raw data by changing the occupancy status from unoccupied to occupied. All the different space types studied had such errors, and different spaces within a specific type were subject to varying error rates: for example, error rates of as much as 28% were observed in the private offices, up to 13% for classrooms, and up to 1% for restrooms. Clearly, the requirement to extensively modify the raw data demonstrates that measurements of space occupancy that use single occupancy detectors may be less accurate than initially assumed.

Studies using simulated occupancy profiles (e.g., lights on continuously for 10-hr) as the baseline for savings calculations showed higher percentage energy savings[46,50], but (as other research shows), the actual savings that can be achieved in a specific building depends on the occupancy profile in that building.

Some studies calculated savings based on short time delays, (e.g., 5 minutes), and declared good energy savings potential[44,47,50]. Richman et al. noted that savings could be doubled if the time delay setting recommended by the manufacturer was reduced from the recommended 10-20 minutes, to 5 minutes. While this strategy will no doubt increase energy savings, it will also increase the number of times lights are switched off in occupied spaces, which is unacceptable. The short time delay settings advocated by these investigators were not actually applied in the field, but simulated by a mathematical model. It is doubtful this short time delay could be actually applied in a real application and still maintain occupant satisfaction.

In spite of these caveats, all the previous studies showed consistent energy savings but also recommended professional installation and tuning, and adequate instructions to occupants were also noted as key to energy savings. Also interesting is the fact that 3 out of 23 sensors failed in the study conducted by Floyd et al.[45]. If this study is representative, almost 13% of the occupancy sensors installed may not be functioning properly. These were only identified as non-functional as they were included in a research project. It is difficult, if not impossible, to diagnose sensor performance when only a single sensor is used, and in these situations one malfunction means the failure of control in that space.

3.3 Summary and Prospect

Past research investigating the effectiveness of occupancy sensors for controlling office ambient lighting systems shows that occupancy sensors reliably deliver significant energy and demand savings in infrequently or unpredictably occupied spaces, such as washrooms, stairwells, corridors and storage areas, while the savings achieved in regularly occupied spaces, such as private offices and classrooms, are much lower.

Different studies used different baselines to calculate energy savings. Savings calculations based on actual pre-retrofit energy consumption, or energy consumption based on manual switching are more appropriate[45,47,49] than calculations based on an assumed schedule (for example, all lights are on for 10 hours per day). According to studies comparing energy use after installation of occupancy sensors with manual switching as the baseline, energy savings of about 25% can be achieved in private offices with a sensor time delay setting of 20 minutes, which is the lower bound for manufacturer claims.

Although some investigators calculated higher energy savings that would be realized with shorter time delay settings (e.g. 5 minutes, based on a mathematical model), a 5-minute time delay is unlikely to meet with occupant acceptance, as lights will be switched off in occupied spaces. The shortest time delay applied in a case study was 7 minutes[45], and this was only possible after careful and professional commissioning, including changes to sensor mounting position, adjustment of sensor aiming angle, tuning of sensor sensitivity: this much care is rarely applied in real applications, and would greatly increase installed costs if widely implemented.

Given the detection errors in previous research, and the variation in reported energy savings, there appears to be considerable uncertainty associated with the determination of occupancy using a single point of measurement (i.e., a single detector). Uncertainty can arise from many factors, including occupancy pattern, sensor measurement noise, and/or the limited coverage area associated with a single sensor. To compensate for this uncertainty, current systems usually set long time delays (at least 20 minutes) and high sensitivities, which saves energy relative to baseline conditions, but still may result in wasted energy relative to the maximum savings that might be possible.

Collecting more data (as with a sensor network) is only advantageous if a rational analysis framework can be identified to treat the data stream from the sensor network. The next chapter describes several data processing methods that can be applied to a data stream from an occupancy sensor network.

4 Data Processing Techniques

4.1 Introduction

There can be uncertainty associated with the determination of occupancy using a single-point of detection, and measured energy savings due to the application of occupancy sensors vary with field conditions, and depend greatly on control commissioning. Control system performance, energy savings and user satisfaction might be enhanced using a sensor network to detect occupancy that consists of multiple, inexpensive distributed detectors that together function as a system.

The challenge in applying a sensor network to any application area relates to the data processing methods that are applied to the stream of data from the sensor network[63-106]. Information provided by the sensor network needs to be integrated, or "fused" based on an appropriate algorithm that can relate output from the network to the domain of interest (in this case space occupancy). When properly processed and integrated, the outputs from multiple sensors should provide more reliable and accurate estimation and prediction than is possible using any single sensor: for example, with multiple sensors monitoring the same process, it should be possible to distinguish properly functioning from non-functioning sensors. On the other hand, without proper integration and processing, it is possible that worse control performance might be obtained from a sensor network, compared to the operation of a single sensor.

The sensor network proposed for occupancy detection represents a binary hypothesis testing problem[76], because the status of any monitored space can only be either 1 (occupied) or 0 (vacant). In this scenario, the decision made by each sensor is:

$$x_i = \begin{cases} 0, \text{ if sensor } i \text{ decides } H_0 \\ 1, \text{ if sensor } i \text{ decides } H_1 \end{cases} \tag{4. 1}$$

where $i=1, \ldots, N$, and N is the number of sensors in the network; H_0 corresponds to the condition in which the space is vacant; H_1 represents the condition in which the space is occupied. The goal of multisensor data fusion is to make a global decision Y, which combines the outputs from several x_i, and which best describes the truth.

Algorithms applied to multisensor data fusion for different structured sensor networks have been studied in a variety of applications[74-85]. Data fusion is defined as "the process of combining data to refine state estimates and predictions"[75]. Data fusion was initially applied to military applications, as a means to detect and identify potential ground targets using electromagnetic and acoustical measurements. In recent years, sensor data fusion has been more widely used in such diverse areas as ocean surveillance, remote sensing, medical diagnosis, and engineering, since these techniques are well-suited to fault detection and reliability of complex systems[79,80].

Valet, Mauri, and Bolon[73] reviewed numerous articles published in refereed journals concerned with data fusion, published between 1997 to 1999, and found that data fusion techniques were widely investigated and applied in military, geoscience, robotic and medical applications: engineering applications only accounted for 6% of the reviewed papers. Consequently, the application of data fusion technologies in engineering, especially in building control, may advance the development and implementation of building automation systems, achieve energy savings, and more effective control system performance.

Joshi and Sanderson[74], Iyengar and Brooks[76], Luo, Yih and Su[77], Kokar and Kim[78], Hall and Llinas[80], Crowley and Demazeau[81], have provided comprehensive reviews of multisensor data fusion technologies. Data fusion techniques include estimation theory, statistical inference methods, information theory methods and artificial intelligence methods. In a data fusion application, variables are *commensurate* if they can be measured in the same units. As applied to lighting control, we combine data from several PIR sensors to find the best prediction of occupancy, and then make a control decision; all sensors are measuring the same physical phenomena in the same binary format, thus the sensor data are commensurate[80]. Consequently, we only review the data fusion techniques that apply to commensurate data. Eight methods are reviewed: logical function OR, logical function AND, logical function MAJORITY, moving average filtering, rule-based reasoning, Bayesian belief network, least squares estimation, and artificial intelligence methods. Each will be discussed in turn.

4.2 Logical Functions (OR, AND, & MAJORITY)

The simplest approach to combining data from multiple sources would be to select a fusion rule from the set of commonly used logical functions, such as OR, AND, and MAJORITY functions. For example, in the OR rule, the global decision y=1 (the space is occupied) is taken if the output from at least one of the sensors is 1. For a three-sensor network:

$$y = \begin{cases} 1, \text{if } x_1 = 1 \text{ or } x_2 = 1 \text{ or } x_3 = 1 \\ 0, \text{otherwise} \end{cases} \tag{4. 2}$$

The AND rule is that y=1 only when all of the local decisions are 1, i.e.,

$$y = \begin{cases} 1, \text{if } x_1 = 1 \text{ and } x_2 = 1 \text{ and } x_3 = 1 \\ 0, \text{otherwise} \end{cases} \tag{4. 3}$$

The MAJORITY rule is that y =1 if more than half of the local decisions are 1, and in the case of three inputs, MAJORITY rule means at least two of the local decision must be 1, i.e.,

$$y = \begin{cases} 1, \text{if } (x_1 = 1 \text{ and } x_2 = 1) \text{ or } (x_2 = 1 \text{ and } x_3 = 1) \text{ or } (x_1 = 1 \text{ and } x_3 = 1) \\ 0, \text{otherwise} \end{cases} \tag{4. 4}$$

A sample input and output of these logical functions is shown in Table 4-1.

Table 4-1. Sample results of logical functions for three binary inputs

Input			Output y		
X_1	x_2	x_3	OR	MAJORITY	AND
0	0	0	0	0	0
0	1	0	1	0	0
0	1	1	1	1	0
0	0	1	1	0	0
1	1	0	1	1	0
1	0	0	1	0	0
1	1	1	1	1	1

The selection of logical functions is arbitrary, and a correct decision is not guaranteed. For example, if sensors exhibit high sensitivity, the output from the most sensitive sensor will have priority in determining occupancy, and will result in false triggering (e.g., lights switching on in an unoccupied space): in this case, the MAJORITY or AND rules will be more suitable than the OR rule. On the other hand, if the sensors are not sensitive enough, the OR rule is more appropriate, because it takes full advantage of the data from each sensor. In the most extreme case, if a sensor is malfunctioning and pulses continuously, applying the OR rule will generate continuous positive output and the result, obviously, will be worse than the output from any of the single properly functioning sensors.

4.3 Moving Average

Discrete measurements within the sensor network data stream will be subject to imprecision and errors. Noise from external sources, random hardware noise, imperfect technology and the quality of the (usually inexpensive) sensors used in lighting control applications, all act to degrade the performance of individual sensors, and hence the sensor network. Therefore it is often necessary to apply some form of preprocessing to sensor data, before making any control decision based on sensor output. Preprocessing may occur at the same time as data fusion: for example, by comparing the behavior of several sensors to one another, a short fluctuation observed from one sensor may be discounted or even omitted. Alternatively, the data from each sensor can be preprocessed before combining with others. Data preprocessing may reduce the effect of random errors, detection of outliers, malfunctioning sensors, and the recovery of missing values[76].

A moving average is one type of digital signal filtering, and is also a common preprocessing technique. Digital filters can be designed to modify the frequency of an input signal. The frequency response of a digital filter can be characterized as all pass, band-pass, band-stop, high-pass and low-pass. Each describes which frequency band of the input sequence is allowed to pass through the filter. For example, a low-pass filter is used to remove high-frequency noise. Occupancy persists over time, which means the occupancy status during the present time slot is likely to remain the same into the next time slot. High frequency activities are not likely to happen in an office application, so a low-pass filter, which filters out the short-term fluctuations, should be applied to the data before further processing. A common form of low pass filter applied to time-series data is a moving average filter. The formula for a simple M-term moving average is:

$$Z_{ti} = \frac{x_{ti} + x_{(t-1)i} + \ldots + x_{(t-M)i}}{M} \tag{4. 5}$$

where x_{ti} is the measured value of i_{th} sensor at time slot t, and Z_{ti} is the average i_{th} sensor output, which is in fact the unweighted mean of the previous M data inputs.

4.4 Rule-Based Reasoning

Rule-based reasoning captures the reasoning capability of a human expert by specifying the rules that relate task inputs to specific outputs.

In a sensor network, the inputs are: sensor pulses at different times, sensor mounting position, and the concurrent performance of other sensors (peers). These can all be used to help define an accurate algorithm that relates sensor network performance to occupancy.

The following simple rules were defined to examine the sensor status at any time slot. If a majority of the sensors pulse (at least 2 out of 3), then the output will be 1 (and the space is deemed occupied). However, if only one of the sensors pulses, the output from the sensor network in the previous time slot is examined, because small movements are likely to be missed by one or more sensors: if the sensor output in the previous time slot is determined to be 1, the output of current time slot will also be set to 1. Finally, even if none of the sensors pulse, the output is not immediately set to 0 (in which case the space would be assumed empty), but a time delay is set before the system concludes that no occupants are present. Pseudocode describing this relationship is as follows:

```
if majority sensors pulsed (2 or 3 sensors pulsed)

    output(n)=1;

if only one sensor pulsed

    if output(n-1)=1, output(n)=1

    else, output(n)=0;

if none of the sensors pulsed,

    if output(n-1)=1, apply a time delay

    else, output(n)=0
```

4.5 Bayesian Belief Network

Bayesian inference is a popular statistical method in which evidence or observations are used to infer the probability that a hypothesis may be true[106]. In multisensor data fusion, Bayesian inference allows data to be combined based on the *a priori* probabilities of sensor behaviors, in other words, it updates the *a posteriori* probability of a hypothesis based on observational evidence, which includes the true reading from all sensors[77].

Bayesian inference can be implemented by a form of probabilistic graphical model, known as Bayesian belief network, or simply belief network. A belief network comprises of a set of variables, and a graphical structure with attached probabilities connecting the variables. It is commonly represented as a graph with a set of nodes and edges[89]. The nodes represent the variables, and the edges represent the conditional dependencies. If an edge $e(i, j)$ is directed from node i to another node j, then variable j depends directly on variable i, and i is a parent of its child j.

Suppose X_i ($i = 1$ to n) is the set of variables in a belief network, and *parents* (X_i) denotes the set of parent variables of X_i, then the joint distribution of the variables is product of the local distributions:

$$\mathrm{P}(X_1,\ldots,X_n) = \prod_{i=1}^{n} \mathrm{P}(X_i \mid parents(X_i)) \tag{4. 6}$$

For example, Figure 4-1 shows that a decision u is conditional on two factors: f_1 and f_2, and f_1 is conditional on f_0. f_0 is the parent of f_1, f_1 and f_2 are the parents of u, and f_0 and f_2 have no parents[90].

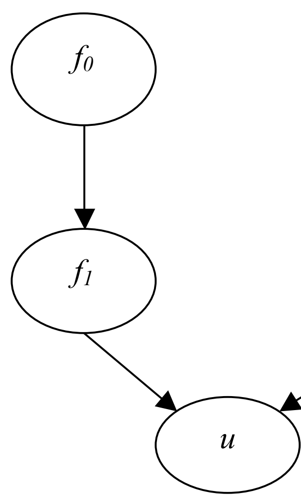


Figure 4-1. A sample Bayesian belief network describing influences among four variables

The joint probability function depicted by the graph is

$$\mathrm{P}(f_0, f_1, f_2, u) = \mathrm{P}(u|f_1, f_2)\ \mathrm{P}(f_1| f_0)\ \mathrm{P}(f_0)\ \mathrm{P}(f_2) \tag{4. 7}$$

The model can answer questions like "What is the likelihood that u is true, given that f_1 is true?" by applying the conditional theory and summing over all the variables that are not of immediate interest to the joint probability (nuisance variables):

$$\mathrm{P}(u=\mathrm{T} \mid f_1=\mathrm{T}) = \frac{\mathrm{P}(f_1=\mathrm{T}, u=\mathrm{T})}{\mathrm{P}(f_1=\mathrm{T})} = \frac{\sum_{f_0, f_2 \in \{\mathrm{T,F}\}} \mathrm{P}(f_0, f_1=\mathrm{T}, f_2, u=\mathrm{T})}{\sum_{f_0, f_2, u \in \{\mathrm{T,F}\}} \mathrm{P}(f_0, f_1=\mathrm{T}, f_2, u)} \tag{4. 8}$$

The key feature of belief networks of use in this particular application is their ability to model and reason about uncertainty, in other words, to use probability as a measure of uncertainty. In the previous example, if we define u as the response of a single occupancy sensor and f_1 as the occupancy status, the fact that the space is occupied does not imply that the sensor will definitely pulse (because the sensor might be defective, or the occupant might not move at that moment). However, we can define an objective probability that the sensor will pulse. In the belief network, we model this by filling in a conditional probability table for each node. For the node u the probability table might look like that presented in Table 4-2.

Table 4-2. A sample conditional probability table, showing the conditional probabilities of variable *u* given f_1 and f_2

f_1	f_2	P(u=False)	P(u=True)
False	False	0.5	0.5
True	False	0.5	0.5
False	True	0.99	0.01
True	True	0.4	0.6

The table presents that, for example, when f_1 is True (space occupied) and f_2 is True (say, a sensor functions correctly, if f_2 denotes sensor status), the probability of u=True (sensor pulses) is 0.6; whereas if the space is not occupied and the sensor functions correctly, the probability of sensor pulsing is only 0.01. When the sensor is defective (f_2 = False), the probability of sensor pulsing might be 0.5, regardless of occupancy status.

The conditional probabilities of the variables may be determined using the probabilities of previously observed values; for example, the probability of sensor pulsing may be determined as previously measured pulse frequencies when a space is occupied or unoccupied.

After defining the relationship between variables and the corresponding probabilities, we can input previously collected evidence to calculate the probabilities associated with a certain variable. For example, we input u=True (sensor pulses) to calculate the probability of occupancy status (f_1). A detailed description of the methods used to determine the probabilities used in this research is described in 11Appendix A.

Generally, Bayesian inference can reduce the uncertainty associated with noisy data by taking into account the conditional probabilities associated with the response of all sensors that prevail during occupied and unoccupied states.

The application of belief networks to sensor network occupancy detection was first studied by Dodier et al.[88,107, 108]; the work described in this document improves the initial model described by Dodier et al.[108] and expands the model to more general office applications.

4.6 Least Squares Estimation

Least squares estimation fuses data by searching for a solution that minimizes the squared error between the observed data and the target data[94]. Suppose our model is of the form:

$$y_t = \sum_{i=1}^{N} x_{it} w_i \tag{4. 9}$$

Where y_t is the estimated value from sensor network at time t; x_{it} is the measured value of i_{th} sensor at time t. N is the number of sensors.

A mechanism is required to determine w_i such that the error of the estimated value would be minimized, i.e., we need to minimize the function:

$$\sum_{t=1}^{T} (o_t - y_t)^2 \tag{4. 10}$$

where o_t is the true occupancy at time t; T is the total number of time slots.

In other words, we present our model as a matrix equation:

$$XW = O \tag{4. 11}$$

where X is the measured data from each sensor at each time slot ($T \times N$ matrix); O is the true occupancy at each time slot ($T \times 1$ array). W is an unknown $N \times 1$ array.

A least square estimate of W, W^* is sought to minimize the squared error $|XW - O|^2$. The W^* can be solved as following:

$$W^* = (X'X)^{-1} X'O \tag{4. 12}$$

where X' is the transpose of X and $(X'X)^{-1} X'$ is the pseudo-inverse of X if $X'X$ is non-singular.

Once W^* is determined using a set of training data (previously collected data set with a known occupancy profile), we can apply W^* to a new data set with unknown occupancy, and calculate the predicted value as:

$$Y = XW^* \tag{4. 13}$$

The $N \times 1$ array W^* can be considered as a series of weights applied to the original data and the calculated sensor network output $y_t = \sum_{i=1}^{N} x_{it} w_i$, is closest to the truth o_i.

4.7 Artificial Neural Networks

An Artificial Neural Network (ANN) is an information processing model that is designed to mimic the way biological nervous systems process information. It is a system of interconnecting processing elements (neurons) working together to solve specific problems[91,97]. Figure 4-2 illustrates an example of a two-layer artificial neural network with nodes interconnected in a feed-forward way. The networks receive three inputs and integrate them to produce an output.

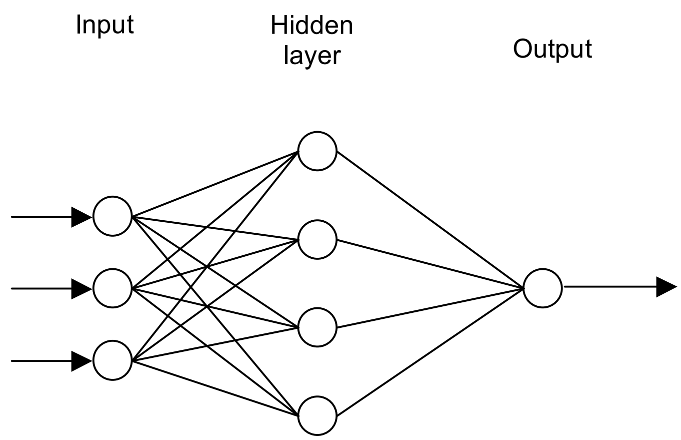


Figure 4-2. A simple example of artificial neural networks

In more practical terms neural networks are non-linear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data.

The most attractive feature of a neural network is that it includes the possibility of learning. Neural networks learn by example, like humans, which involves adjustments to the strength of the synaptic connection between neurons. Generally, learning means using a set of previously collected observations to find an optimal solution f^* from a class of functions F to solve a specific task. For the optimal solution f^*, $C(f^*) \le C(f) \forall f \in F$ (no solution has a cost less than the cost of the optimal solution).

There are three major learning paradigms: supervised learning, unsupervised learning and reinforcement learning. In supervised learning, a set of example pairs is given, and the aim is to find a function that matches the examples in an optimal sense. A commonly used cost function in supervised learning is the mean-squared error, which tries to minimize the average error between the network's output, $f(x)$, and the target value y over all the example pairs, or, to minimize the cost function:

$$\widehat{C} = \frac{1}{N} \sum_{i=1}^{N} \left| f(x_i) - y_i \right|^2 \tag{4. 14}$$

In multi-layer neural networks, the cost function is usually minimized with a back-propagation algorithm. The general process of back-propagation is: 1) A training sample is presented to the neural network. 2) The network's output is compared to the desired output from that sample, and the error in each output neuron is calculated. 3) Weights of each neuron are then adjusted to lower the local error. 4) The neurons at the previous level will be “responsible” for the local error, with greater responsibility to neurons connected by stronger weights. 5) Repeat the steps above on the neurons at the previous level until error is minimized.

In unsupervised learning, a target is not specified, and the cost function can be any functions of input data x and the network output $f(x)$. The specific cost function chosen depends on the task and *a priori* assumptions. For example, the cost function can be defined as the mean square error between the input and the output data. Tasks utilizing unsupervised learning are generally estimation problems, including clustering, the estimation of statistical distributions, and filtering.

In reinforcement learning, input data x are usually not given, but generated by an agent's interactions with the environment[99]. The aim is to discover a policy for selecting actions that minimize some measure of a long-term cost, i.e. the expected cumulative cost. The environment's dynamics and the long-term cost for each policy are usually unknown, but can be estimated. Thus, reinforcement learning is particularly suitable for problems that include a long-term versus short-term reward tradeoff. It has been applied successfully to various problems, including computer chess game, robot control, and telecommunications, i.e., any sequential decision making task.

Artificial neural networks are especially suitable in applications where they are able to infer a function from existing observations (using supervised learning). This is particularly useful in applications where the complexity of the data or task makes the design of such a function by hand impractical.

4.8 Evaluation Criteria Applied to Data Fusion

The data fusion process will produce an output, namely a determination of occupancy at a given time slot. This output should be as close as possible to the truth, which can be expressed as the correspondence between predicted and actual measured occupancy. The correspondence with truth can also be expressed through the total occupied time, the number of false switching actions (false-ons and false-offs) that are observed, and a statistical measure of the association between binary variables, namely the φ correlation[100-106]. These criteria will be used to evaluate the effectiveness of the different data fusion methods.

4.8.1 Total occupied time

The total occupied time is the time of occupancy as measured by each sensor or determined by a calculation method during a specified period (e.g., one day, one week or one month). Total occupied time is useful in calculating energy savings, as energy consumption is the product of power and operating time. When operating time is reduced, energy savings are achieved.

4.8.2 Accuracy (φ)

While the total occupied time measured by sensors is useful, it is imprecise, as sensors do not always respond to occupancy (i.e., do not pulse even though a space is occupied), and sometimes pulse even though a space is unoccupied. A coefficient that takes into account both correct and incorrect measures to characterize the correspondence between occupancy measured by individual sensors and true occupancy (measured via some other method) is useful. Since occupancy and sensor data can be coded dichotomously (where "1" indicates occupancy, and "0" indicates empty), the φ correlation provides a suitable measure of the association between measured value and the truth. The φ coefficient is a special case of Pearson's product moment correlation coefficient used to show the correspondence between two dichotomous variables.

The φ correlation is given in cross-table format[100,105], as in Table 4-3.

Table 4-3. Cross table for the calculation of φ correlation

Truth \ Measured	1	0	
1	N_{11}	N_{10}	$r_1=N_{11}+N_{10}$
0	N_{01}	N_{00}	$r_2=N_{01}+N_{00}$
	$c_1=N_{11}+N_{10}$	$c_2=N_{10}+N_{00}$	

$$\varphi = \frac{N_{11}N_{00} - N_{10}N_{01}}{\sqrt{r_1 r_2 c_1 c_2}} \tag{4. 15}$$

where N_{11} is the number of minutes when the space is occupied, and the sensor detects motion; N_{10} is the number of minutes when the space is occupied, but the sensor does not detect motion; N_{01} is the number of minutes when the space is vacant, but the sensor measures occupancy; and finally, N_{00} is the number of minutes when the space is vacant, and the sensor also indicates it is unoccupied.

The marginal values can be calculated as the sum of the row or column. For example, r_1 in Table 4-3 represents the true occupied time, while c_1 is the measured occupied time.

Table 4-4 shows a sample sensor measured and true occupancy data time series, where a "1" in the "Measured" column represents motion as detected by the sensor, while a "1" in the "Truth" column means the space is occupied., The corresponding cross table is described in Table 4-5:

Table 4-4. Sample sensor and true occupancy data

Sensor	Truth
0	0
0	0
1	0
0	0
0	0
0	0
1	1
1	1
1	1
1	0
0	0
0	0

Table 4-5. Sample cross table for the calculation of φ correlation

Truth \ Measured	1	0	
1	3	0	3
0	2	7	9
	5	7	

And applying equation 4.15, as follows:

$$\varphi = \frac{N_{11}N_{00} - N_{10}N_{01}}{\sqrt{r_1 r_2 c_1 c_2}} = \frac{3\times 7 - 2\times 0}{\sqrt{3\times 9\times 5\times 7}} = 0.683$$

The maximum value of φ correlation is 1, which occurs when the two arrays of binary variables in comparison are identical (both N_{10} and N_{01} equal to 0). The minimum value of φ correlation is -1, which occurs when none of the corresponding elements in the two arrays are the same (both N_{11} and N_{00} equal to 0).

4.8.3 Number of false switches

Increased accuracy implies a reduction in error. In occupancy measurement, there can be two types of errors: a false-off, and a false-on. A false-off occurs when a switching action is initiated in an occupied space. False-offs result in user complaints, and in extreme cases will lead users to disable sensors and control systems. Table 4-6 illustrates how the false-offs are counted in this research. A false-off is counted only when the sensor status changes from “1” to “0”, and the corresponding true occupancy status is 1”. The example shows one false-off.

Table 4-6. Counting of false-offs, showing 1 false-off

	Sensor	Truth
	0	0
	1	1
	1	1
	1	1
False-off →	0	1
	1	1
	1	1
	1	1

In contrast, false-ons occur when a space is vacant but the sensor pulses. In a control application, this error results in the switching on of services in empty spaces: energy is wasted. Table 4-7 shows how the false-ons are counted in this research. A false-on is counted only when the sensor status changes from “0” to “1”, and the corresponding true occupancy status is 0”. The example shows one false-on.

Table 4-7. Counting of false-ons, showing 1 false-on

	Sensor	Truth
	0	0
	0	0
False-on →	1	0
	0	0
	0	0
	1	1
	1	1
	0	0

Ideally, both types of errors should be eliminated to achieve maximum energy savings and user satisfaction. However, as the literature review shows, it is not always possible to accurately measure occupancy using a single sensor. In current occupancy sensor applications, the elimination of false-offs is of primary importance. In current practice, applying a long time delay before switching off the lights reduces the number of false-offs. This strategy eliminates most false-offs, but prolongs system use in vacant spaces, compromising energy savings.

4.9 Summary

Having proposed that a network of sensors may provide superior occupancy measurement than is possible using a single detector, this chapter discussed several analysis techniques for application to the sensor network data stream, and described metrics that can be applied to evaluate the effectiveness of occupancy determination by sensor network.

Eight data fusion methods were described in this chapter. One salient difference between these various methods is that they can be divided into three groups, based on their dependency on pre-existing occupancy and sensor response data.

The following methods do not require pre-existing data: logical functions (AND, MAJORITY, and OR) and the moving average method. These methods extend the spatial coverage of single sensors, but like single-sensor applications, are not able to self-diagnose and self-adjust. They may yield good system output, but performance depends on sensor status, and cannot be guaranteed.

The following methods need prior knowledge about the general occupancy pattern or sensor characteristics: rule-based reasoning and belief network. The rule-based reasoning method defines rules based on general knowledge about the system. The effectiveness of this method depends on how well the system is understood.

Bayesian belief networks, which define the relationship between variables and the conditional probabilities of each variable (e.g. sensor pulsing probability given different time of day and sensor status), can reduce uncertainty and identify abnormally behaving sensors, and thus have the ability to self-adjust. The output of the belief network depends on the graphic structure and the probabilities attached to the network. It can be implemented without measured truth data, but requires more general information concerning the behavior of properly functioning sensors (so-called sensor models).

Finally, the least squares estimation and neural network methods (with supervised learning) need pre-existing data to "train" the system with parameters to achieve best performance. These two methods are good at adjusting parameters based on measured truth data, and generating an output close to the truth. However, if truth data are not available, the application of these methods is limited.

Generally, the parameters of rule-based reasoning, belief network, least squares estimation, and neural network methods can be tuned and optimized if the general knowledge of system performance, or the "Truth" is given, and all will perform better than the algorithms that do not need any pre-existing data. However, truth data can be difficult to obtain in real applications, and thus the optimization of a training-data dependent algorithm is seldom achieved. An algorithm that incorporates the general character of the system, but does not need real-time training (e.g. belief network method) will be most appropriate to the occupancy sensing application.

The chapter described three metrics that will be applied to evaluate the effectiveness of the data fusion methods as these are applied to a sensor network data stream. These are the total occupied time, φ coefficient, and the number of times that a controller using the associated method would have taken an inappropriate action (i.e., switching the lights off in an occupied space (a false-off) or switching the lights on in a vacant space).

The following chapters describe application of these methods to actual occupancy data.

5 Pilot Study

5.1 Introduction

This chapter describes a pilot study conducted to evaluate the prospects for sensor networks applied to the problem of lighting control. This study had two goals. The first goal was to evaluate the utility of using more than one sensor to detect occupancy. If a single measurement point is sufficient to accurately characterize occupancy in a given space, the total occupied time as measured by several independent detectors monitoring that space should be about the same. On the other hand, observed differences in occupancy measured by several independent detectors suggests that each detector, on it's own, provides a less accurate measure of occupancy than might be obtained using a "fused" signal from several individual detectors.

The second goal was to explore the application of the analysis techniques and methods described in the previous chapter to sensor network data. A sensor network is only useful to the extent that an appropriate analysis method can be developed or identified for application to the sensor network data stream, one that results in improved system performance relative to current practice.

5.2 Methods and Procedures

A sensor network was designed and installed in two, 13' x 10' private faculty offices, located at the University of Nebraska's Peter Kiewit Institute, in Omaha, NE. The sensor network consisted of three PIR occupancy sensors, one each mounted on three of the four walls in each room (mounting position and location were selected based on furniture location and the requirement that each detector have a clear view of the occupant's customary work position). Each sensor provides an independent measure of space occupancy, and taken together, the combination of measurements provides a converging and redundant sensor network. Figure 5-1 shows a plan view of the two rooms, and sensor location.

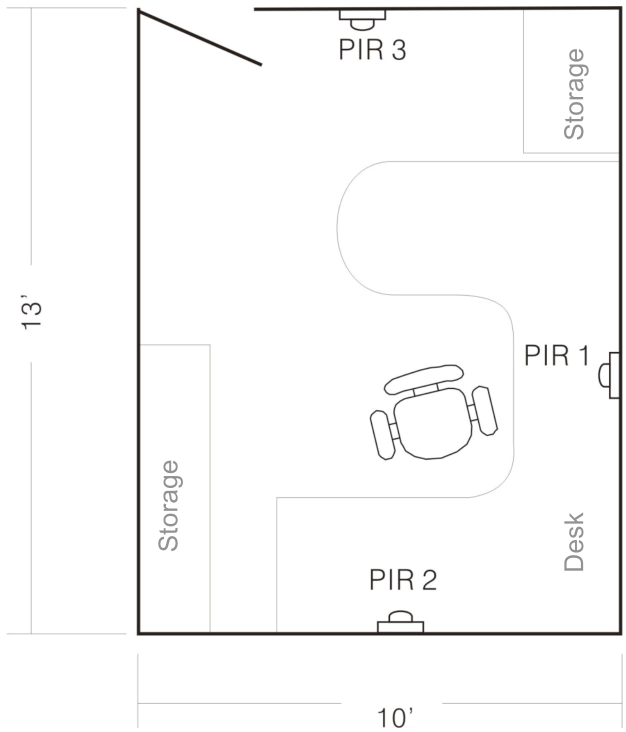


Figure 5-1. Plan view of the private offices used in pilot study

Figure 5-2 shows both sides of the PIR sensors used in the study. This sensor was purchased as a self-assembly kit, and it offered more flexibility with respect to sensitivity setting and signal output wiring than can be achieved with commercially available units sold by home renovation and construction retailers.

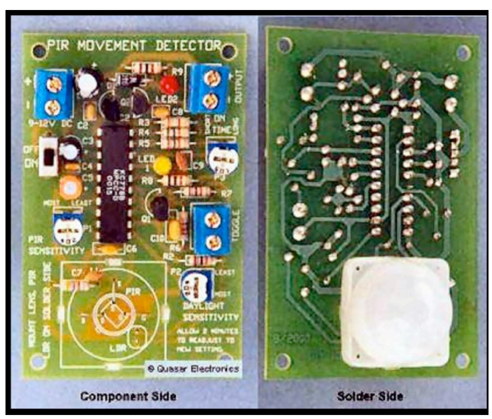


Figure 5-2. Both sides of the assembled PIR sensor used in pilot study

All six PIR sensors were connected to a USB PC-based data acquisition system manufactured by Data Translation, model number DT9806. The electrical signals from the PIR sensors were connected to the digital inputs on the DT9806 terminal block.

The data acquisition and control software was developed using the Data Translation Measure Foundry programming environment. This data acquisition system polled each

PIR sensor every second, writing a single character to a text file to indicate whether or not each respective detector was sending a signal to indicate occupancy (a “0” indicated no signal from the detector, and a “1” indicated a signal – and assumed occupancy – from the detector).

Occupancy data from the six PIR sensors (three in each room) were collected over a two-day monitoring period. The sensor network data were validated by comparing occupancy as determined by the PIR sensors with two independent measures: occupancy as recorded by human observers who monitored entry and exit to each office from a seated position in the hallway outside the two offices, and subsequent review of a digital video record continuously collecting images in each room.

There were three human observers tasked with monitoring occupancy in the two rooms over the two days: one of these three individuals was always present between the hours of 7:00am to 7:00pm on both days. Both monitored rooms were simultaneously visible from the vantage point of the human observer: a large piece of black electrical tape was mounted on the doorframe of each room being monitored, to ensure that the observers only recorded entry and exit from the rooms of interest, and not from adjacent rooms. The human observer recorded the time associated with all occupant entry and exit events occurring over the two-day period.

A digital video record of room occupancy complemented the human observations and PIR data. Apple iSight digital video cameras were mounted in each room diagonally opposite the single door, providing a clear record of each entry and exit event. The software controlling each camera recorded the date and time of each image (in date:hour:minute:second format), writing this information clearly in the lower right area of each image frame. A separate image was collected every two seconds, and individual images were automatically appended to a QuickTime file, which provided a time-lapse movie showing activity in each room over the two-day monitoring period. A human observer, who recorded occupant entry and exit times, manually reviewed the time-lapse movies.

5.3 Results

The discussion of results is divided into two sections. The first section describes individual differences in PIR sensor response to occupancy; the second section focuses on application of the data fusion techniques described in the previous chapter to the PIR sensor network data.

5.3.1 PIR sensor Response to Occupancy

Over the two-day monitoring period, there were 43 events in Room 1 and 36 events in Room 2. Slight differences in event time and duration were apparent in the occupancy data recorded by each method. These are due to asynchrony between the clocks used to record events by the human observers, the computers collecting PIR data, and digital video images. Although an attempt was made to closely synchronize all clocks, it was not possible to achieve exact synchrony.

Table 5-1 shows the start and end time for each event in the two rooms as observed by *in situ* observers and review of the digital video record. Columns 1 and 2 show the original data recorded by the human observers. There were transcription errors related to some events: for example, in the case of event 41 in room 1, the human observer incorrectly noted the event ending on minute 23, when the other two methods showed the event ending sometime between 16:31 and 16:33. In this instance we infer that the human observer incorrectly recorded “23” instead of “32”. In Room 1, 10 out of 86 start/end times were modified to correct transcription errors, and in Room 2, 11 out of 62 start/end times were so modified, as indicated in the shaded cells of the tables. The modified data (showing “corrected clock entries) are shown in column 3 and 4. Data in columns 5 and 6 are based on human review of the digital video. Digital image collection was not initiated in Room 1 until 8:39am, and in Room 2 until 9:52am, so several events are missing from the digital video records for the first day for both rooms.

Table 5-1. Start and end time of occupancy events in pilot study as determined by human observers and video cameras (Shaded cells indicate transcription errors)

Room 1:

	Column Number	1	2	3	4	5	6
	Event number	Human Observer				Video Camera	
		Raw		Modified			
		Start	End	Start	End	Start	End
Day 1	1	7:53:15	7:53:45	7:53:15	7:53:45		
	2	7:54:00	7:55:31	7:54:00	7:55:31		
	3	7:57:55	8:23:05	7:57:55	8:23:05		
	4	8:24:11	8:46:15	8:24:11	8:46:15	8:39:27	8:45:16
	5	8:59:20	8:59:37	8:58:20	8:59:37	8:57:19	8:58:30
	6	9:18:17	9:43:10	9:18:17	9:42:10	9:17:26	9:41:11
	7	9:58:20	10:20:10	9:58:20	10:20:10	9:57:17	10:19:10
	8	10:27:35	10:29:12	10:27:35	10:29:12	10:26:35	10:28:12
	9	11:50:40	11:55:10	11:50:40	11:55:10	11:49:43	11:54:11
	10	12:04:35	12:05:15	12:04:35	12:05:15	12:03:35	12:04:15
	11	12:05:25	12:06:00	12:05:25	12:06:00	12:04:26	12:05:00
	12	13:07:05	14:13:30	13:07:05	14:12:30	13:06:08	14:12:27
	13	14:17:45	14:18:25	14:17:45	14:18:25	14:16:48	14:17:25
	14	14:20:10	14:21:25	14:20:10	14:21:25	14:19:09	14:20:18
	15	14:22:40	14:23:53	14:22:40	14:23:53	14:21:39	14:22:48
	16	14:25:35	15:37:05	14:25:35	15:37:05	14:24:33	15:35:57
	17	15:44:00	16:27:15	15:44:00	16:32:15	15:42:58	16:31:25
	18	16:28:19	16:31:29	16:33:19	16:36:29	16:32:54	16:35:31
Day 2	19	7:44:25	7:44:30	7:44:25	7:44:30	7:43:31	7:43:44
	20	9:36:49	9:38:02	9:36:49	9:38:02	9:35:58	9:37:07
	21	9:42:50	9:50:20	9:42:50	9:50:20	9:41:43	9:49:26
	22	9:50:50	12:24:40	9:50:50	12:24:40	9:49:59	12:23:49
	23	13:30:25	13:30:45	13:30:25	13:30:45	13:29:19	13:29:43
	24	13:32:35	13:33:25	13:32:35	13:33:25	13:31:48	13:32:32
	25	13:34:35	13:52:00	13:34:35	13:52:00	13:33:46	13:51:07
	26	14:22:50	14:23:40	14:22:50	14:23:40	14:21:56	14:22:47
	27	14:24:30	14:28:05	14:24:30	14:28:05	14:23:40	14:27:07
	28	14:28:25	14:41:00	14:28:25	14:41:00	14:27:31	14:40:05
	29	14:45:25	14:47:12	14:45:25	14:47:12	14:44:35	14:46:18
	30	14:47:30	14:47:38	14:47:30	14:47:38	14:46:38	14:46:47
	31	14:49:35	14:50:40	14:49:35	14:50:40	14:48:47	14:49:45
	32	14:51:27	14:59:25	14:51:27	14:58:25	14:50:36	14:57:49
	33	15:01:30	15:04:55	15:01:30	15:04:55	15:00:38	15:04:01
	34	15:06:44	15:09:30	15:06:44	15:09:30	15:05:54	15:08:31
	35	15:10:50	15:18:15	15:09:50	15:18:15	15:08:58	15:17:22
	36	15:21:47	15:24:46	15:21:47	15:24:46	15:20:56	15:23:53
	37	15:25:23	15:26:46	15:25:23	15:26:46	15:24:32	15:25:54
	38	15:40:04	15:35:55	15:35:04	15:35:55	15:34:16	15:35:03
	39	15:39:25	15:47:00	15:39:25	15:47:00	15:38:36	15:46:09
	40	15:49:15	16:17:55	15:49:15	16:17:55	15:48:25	16:17:02
	41	16:21:20	16:23:44	16:21:20	16:32:44	16:20:30	16:31:50
	42	17:00:37	17:03:21	17:00:37	17:03:21	16:59:47	17:02:28
	43	19:00:51	19:01:52	19:00:51	19:01:52	19:00:01	19:01:02

Table 5-1. Start and end time of occupancy events in pilot study as determined by human observers and video cameras (Shaded cells indicate transcription errors) (Cont'd)

Room 2:

Column Number		1	2	3	4	5	6
	Event number	Human Observer				Video Camera	
		Raw		Modified			
		Start	End	Start	End	Start	End
Day 1	1	7:30:18	7:52:15	7:30:18	7:52:15		
	2	7:53:10	7:53:28	7:53:10	7:53:28		
	3	7:54:35	8:25:14	7:54:35	8:25:14		
	4	8:26:15	8:36:25	8:26:15	8:36:25		
	5	8:40:34	8:59:28	8:39:34	8:59:28		
	6	8:59:45	10:06:30	8:59:45	10:06:30	9:52:01	10:07:30
	7	10:07:35	11:59:05	10:07:35	11:59:05	10:08:43	12:00:11
	8	12:00:10	12:39:15	12:00:10	12:39:15	12:01:19	12:40:23
	9	12:42:35	12:42:40	12:42:35	12:42:40	12:43:44	12:43:48
	10	12:44:52	13:09:45	12:43:52	13:09:45	12:45:03	13:10:50
	11	13:36:55	14:34:20	13:36:55	14:34:20	13:38:07	14:35:25
	12	15:28:20	15:29:05	15:28:20	15:29:05	15:29:29	15:30:08
	13	15:29:30	15:31:10	15:29:30	15:31:10	15:30:42	15:32:16
	14	15:33:25	15:51:40	15:33:25	15:51:40	15:34:44	15:52:46
	15	15:52:35	15:59:10	15:52:35	15:58:10	15:53:45	15:59:10
	16	16:00:05	16:35:58	15:59:05	16:34:58	16:00:13	16:36:03
	17	16:38:00	16:38:25	16:38:00	16:38:25	16:39:10	16:39:34
	18	16:39:15	16:57:15	16:39:15	16:57:15	16:40:24	16:58:21
	19	17:02:04	17:13:49	17:02:04	17:12:49	17:03:14	17:13:57
	20	17:15:14	17:21:15	17:15:14	17:21:15	17:16:22	17:22:25
	21	17:24:52	17:27:23	17:23:52	17:27:23	17:25:02	17:28:27
	22	17:29:03	17:57:22	17:29:03	17:56:22	17:30:14	17:57:32
	23	18:02:20	18:04:15	18:01:20	18:04:15	18:02:32	18:05:21
	24	18:05:28	18:49:50	18:05:28	18:48:50	18:06:37	18:49:54
	25	18:53:41	18:58:50	18:52:41	18:58:50	18:53:51	18:59:59
	26					19:04:47	19:06:11
Day 2	27	7:20:20	9:02:50	7:20:20	9:02:50	7:21:28	9:03:57
	28	9:07:12	9:38:15	9:07:12	9:38:15	9:08:21	9:39:17
	29	9:42:15	10:21:25	9:42:15	10:21:25	9:43:21	10:22:33
	30	10:22:20	10:32:08	10:22:20	10:32:08	10:23:30	10:33:07
	31	10:37:28	10:40:05	10:37:28	10:40:05	10:38:39	10:41:12
	32	10:47:17	10:48:00	10:47:17	10:48:00	10:48:27	10:49:07
	33	10:53:05	10:55:25	10:53:05	10:55:25	10:54:02	10:56:31
	34	11:05:45	11:06:15	11:05:45	11:06:15	11:06:58	11:07:23
	35	11:18:05	11:20:25	11:18:05	11:20:25	11:19:03	11:21:31
	36	11:20:35	11:20:58	11:20:35	11:20:58	11:21:43	11:22:07

Table 5-2 shows the cumulative time (in seconds) that each room was occupied, as measured by individual PIR sensors, human observers, and review of digital video. One sensor pulsed continually: these data appear in low contrast gray type, and were not included in further analyses. Although the three PIR sensors faced the occupied area in each room, there were large differences between the measurements of occupied time collected using the different methods. In the most extreme case, the maximum measured occupied time was more than four times the minimum (comparing PIR2 versus PIR3 in Room 2 on the second day).

Table 5-2. Cumulative occupied time (sec) measured by PIR sensors, and human observers

	Room 1 Day 1	Room 1 Day 2	Room 2 Day 1	Room 2 Day 2
PIR1	7021	6889	16709	6193
PIR2	11517	13080	25384	9540
PIR3 (1)	21058	23388	6901	2254
Observer	17723	16789	33881	11494
Video (2)	15085	16766	25829	11543

(1) PIR3 in Room 1 was defective as it pulsed throughout the day (see also Figure 5-3).
(2) Video records in both rooms were not initiated at the same time as data collection by human observers.

While the differences in the total occupied time measured by several sensors monitoring the same room are interesting and potentially meaningful, this analysis ignores the time stamp at each datum, and could therefore be misleading. For example, two sensors could measure the same cumulative occupied time, but this does not mean that the occupancy measured by these two sensors occurred at the exact same time slot (in this case, at the same second). Indeed, with data resolved to the second, it would not be surprising if the measurements were out of phase (not occurring at the exact same second).

Table 5-3 shows the total number of seconds during which 1, 2, or 3 out of the three sensors indicated occupancy when polled by the DAS in Room 2 (data from room 1 were not analyzed, as one of the sensors in this room was faulty). The “Sum” column is the addition of number of sensors pulsing under each of the three conditions (1/3+2/3+3/3) and it shows the total occupied time (in seconds) indicated by any of the three sensors. These data show that almost 39% of the indicated occupancy was the result of a single sensor pulsing alone (14274/36578=0.39), while most of the occupied time was the result of 2 (39%) or 3 (22%) out of three sensors pulsing in any one second.

Table 5-3. Number of sensors pulsing in Room 2

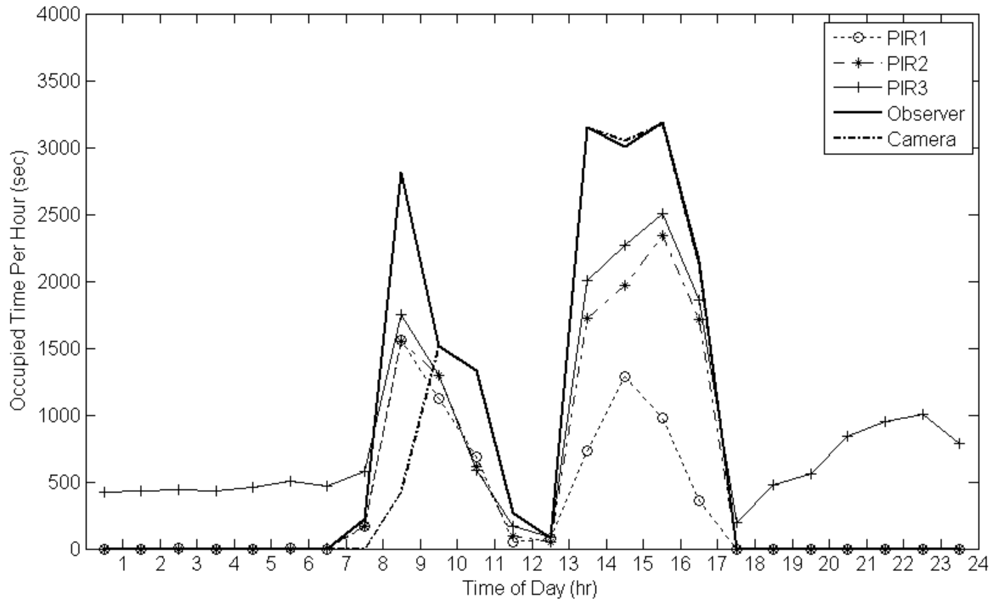
Day	1/3	2/3	3/3	Sum
1	10612	10032	6106	26750
2	3662	4173	1993	9828
Sum	14274	14205	8099	36578

Although there are differences in the occupancy pattern measured by several independent detectors, most of the detectors responded during occupied intervals. This correspondence is striking, given the fine temporal resolution of the data.

The large differences in measured occupied time between sensors suggests that different control actions would have occurred in the two rooms if the lighting systems had been controlled by only one of the three sensors in each room.

We now turn to compare the occupied time measured by the sensors in each room, with the occupied time measured by the human observers. The occupied time as measured by review of the digital video for the first day was lower than the other measures, because video collection started after the human observers took their post: digital video collection in Room 1 was started about 40 minutes after the room was occupied, and in Room 2 it was not initiated until about 2 hours and 20 minutes after the first occupancy event. Figure 5-3 depicts the hourly occupancy measured by the different methods. Inspection of this figure shows that except for the beginning part of the first day, the occupied time measured by the human observers and review of the digital video were very similar. In the remainder of the chapter, we will take the data from the *in situ* human observers as showing the true occupancy profile over the two monitored days.

Room 1, Day 1



Room 1, Day 2

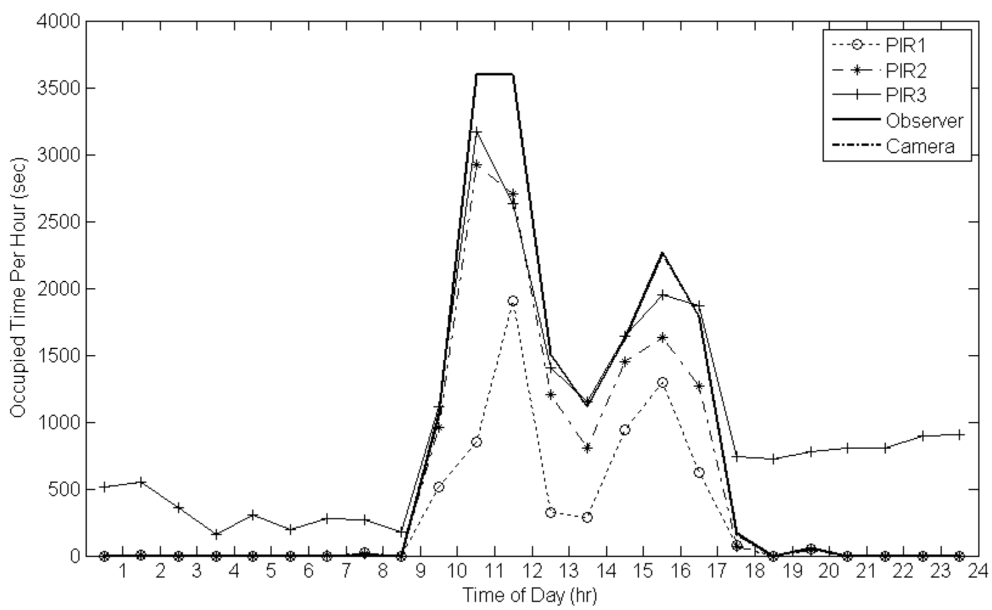
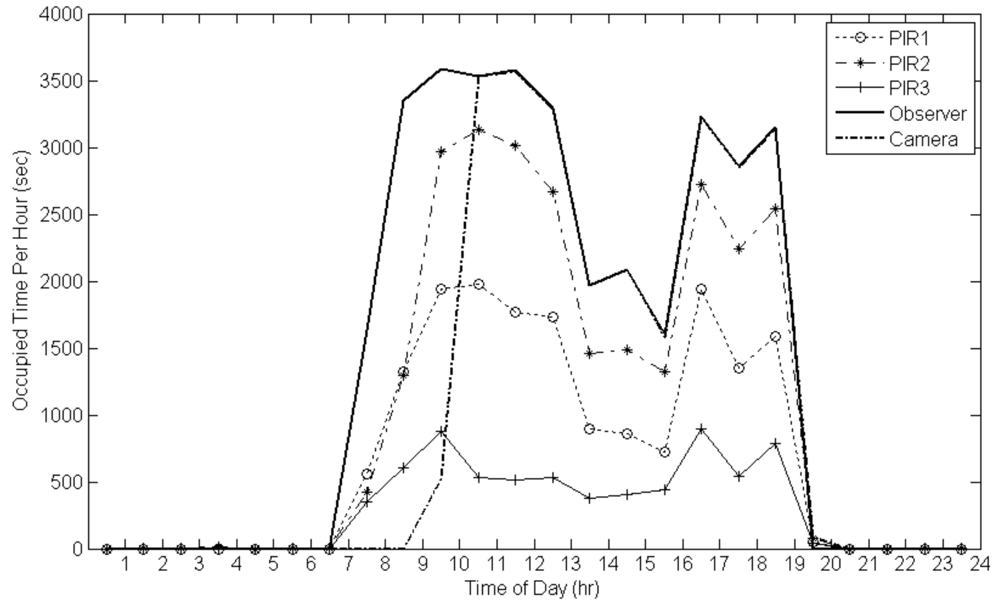


Figure 5-3. Number of occupied seconds in each hour measured by PIR sensors, human observers and video cameras

Room 2, Day 1



Room 2, Day 2

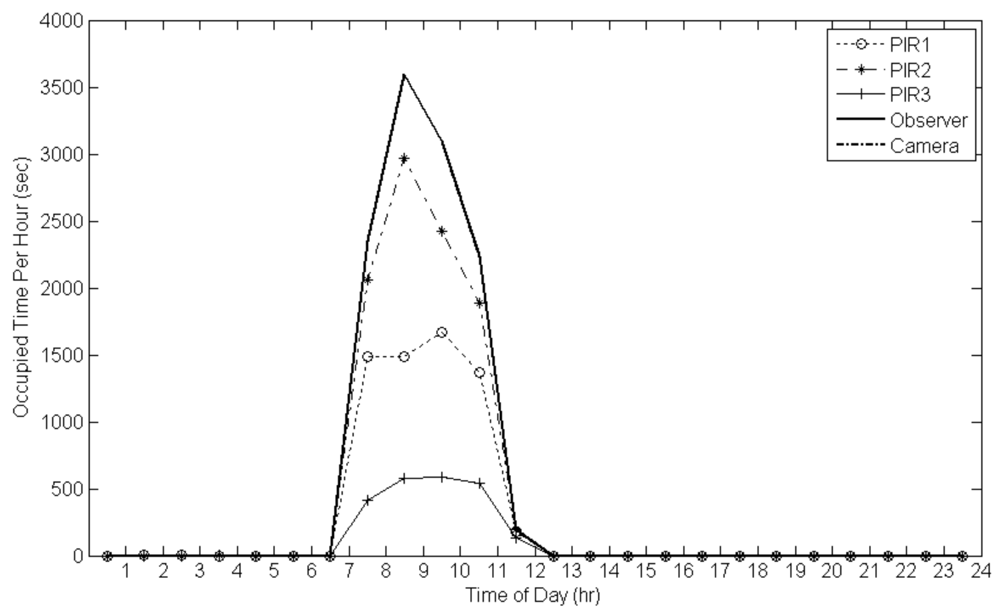


Figure 5-3. Number of occupied seconds in each hour measured by PIR sensors, human observers and video cameras (Cont'd)

On both days in both rooms, there is better agreement between the occupied times measured by humans (whether observed in real time *in situ*, or via subsequent review of digital video record), than there is between occupancy as measured by the three PIR sensors in each room. Further, individual sensors consistently underestimate occupancy. The reason for this is that the data collected by human observers show all elapsed time during occupied intervals, whereas the PIR data show occupancy at the second polling was initiated by the data acquisition system. Consequently, the PIR data do not uniformly show occupancy throughout any occupied interval.

For example, Figure 5-4 compares measurements taken by PIR sensors versus the truth (as determined by the human observer *in situ*), over a single hour in Room 2 Day 2. Note the spikes in the PIR occupancy record within each occupied interval, compared to the data from the human observer. The PIR sensors do not usually pulse continuously, and as a result, there are "gaps" in sensor response within each occupancy event.

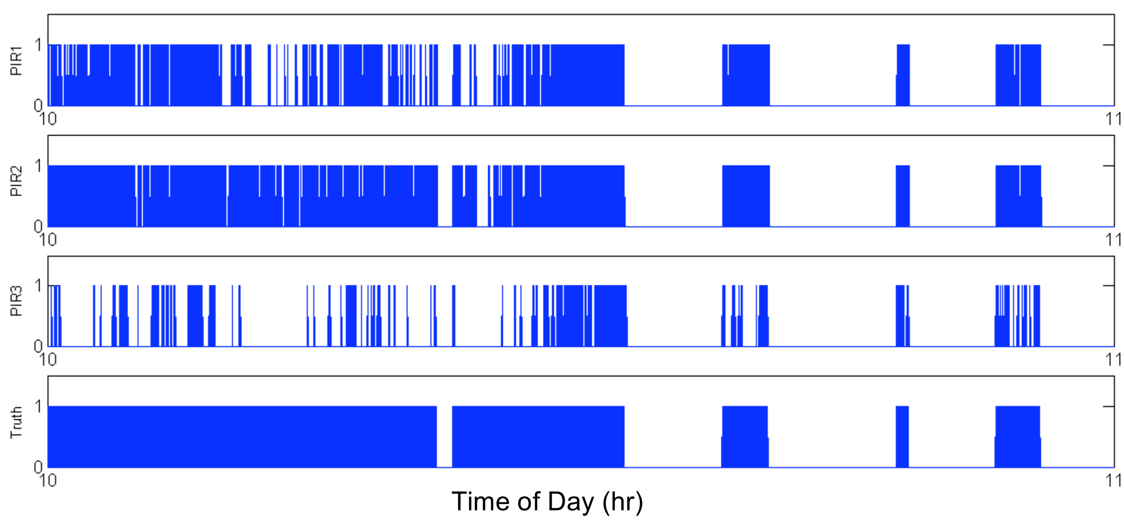


Figure 5-4. Detail of Room 2 occupancy profile from morning of Day 2 as measured by PIR sensors, and video image (Truth)

While it is possible to manually recode PIR data to show continuous occupancy, this agreement is achieved only through the application of a *post hoc* correction to the sensor network data, based on the information collected by the human observers *in situ*. This will be problematic for a real control application, because it assumes knowledge of the actual occupied state to optimize the performance of the sensor network, which would not be available.

Further analysis shows that temporal aspects of the sensor network data stream can be used to define an objective measure to determine whether or not the space is actually occupied. The proposed measure takes into account the duration and frequency of time slots that the space was actually occupied (as indicated by human observer in this study), but during which the PIR sensors indicated it was vacant (which for the purpose of this discussion we call the sensor network *silent interval*).

Figure 5-5 depicts the observed frequency of silent intervals of different durations for each sensor over the two-day period, where the x-axis is the duration of the silent interval, and the y-axis is the frequency of occurrence. Each bar in the histograms represents a 5-second class interval. For example, for PIR1 in room 1, there were about 1000 silent intervals lasting between 1 to 5 seconds. Most of the silent intervals lasted between 1 and 15 seconds, but they could last as long as 6 minutes (e.g., PIR 2 Room 1, PIR 3 Room 2).

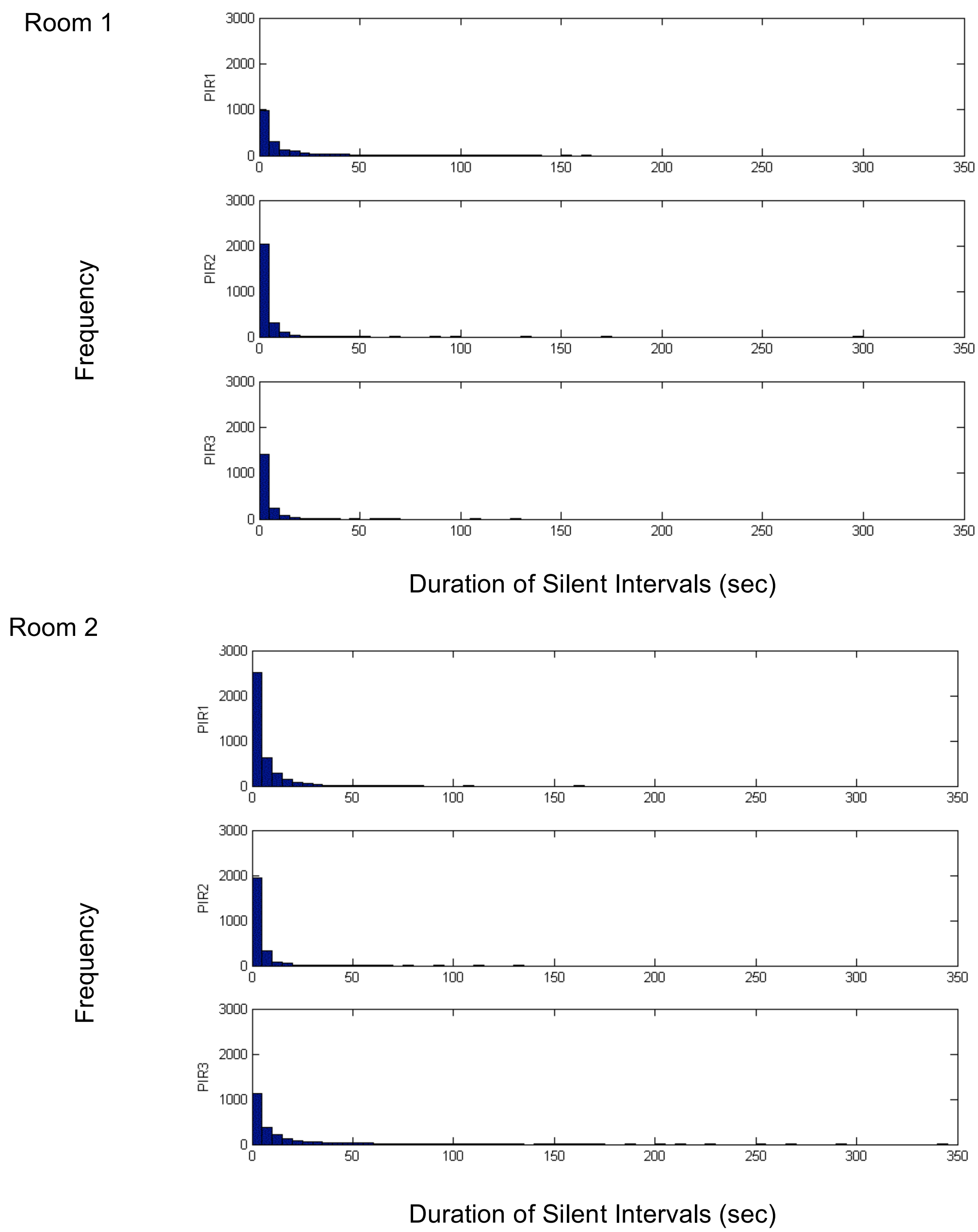


Figure 5-5. Frequency distribution of silent intervals of each sensor used in pilot study

The duration of the silent interval may provide an objective method that can be used to help define the control system time delay setting: recall that the time delay setting is the period of time that must elapse before lights are switched off.

As discussed in the literature review, current systems use long time delay settings (typically 15 to 30 minutes), due to the uncertainty associated with the determination of occupancy using a single detector. The analysis of the durations of the silent intervals reported here suggests that much shorter time delay settings are possible with a sensor network, as opposed to a system that uses a single sensor. For example, Figure 5-5 suggests that silent intervals of less than 5 seconds in duration can be ignored, as the probability is high that the space is still occupied. As the duration of the silent interval increases, the probability that the space is actually occupied decreases significantly, and the appropriate control actions related to building systems can be initiated. However, with a sensor network, since there were no silent intervals longer than six minutes in these data, it would be possible to significantly reduce the duration of the time delay used to switch off lights from the 20 to 30 minutes currently used in most systems.

Figure 5-6 extends this analysis, showing the relationship between the percent deviation from actual occupied time (measured in seconds), as a function of the time delay setting. In this analysis, the effect of the time delay setting on assumed occupancy is modeled by transforming the raw occupancy data measured by PIR sensors to include time delay of varying duration. Intervals in the raw data file having a duration of less than or equal to the modeled time delay are marked as occupied rather than unoccupied, and the new value of assumed occupancy using the defined time delay setting is calculated.

Table 5-4 provides an example, and shows how the application of a three-second time delay affects the duration of assumed occupancy and system use over a short time series: the transformed data are highlighted in bold type. In this example, a “1” indicates a sensor network signal indicating occupancy, a “0” indicates no signal from the sensor network, and the space is assumed to be empty. The raw data show 5 seconds occupancy. Applying a 3-second delay replaces each 3 second unoccupied interval with an occupied signal, thereby increasing the total occupancy to 13 seconds.

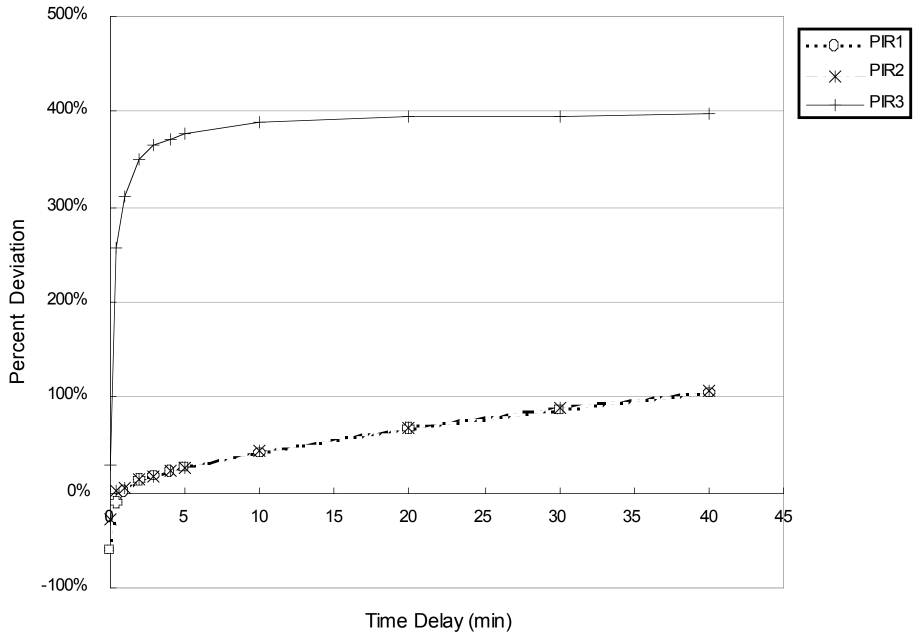
Table 5-4. Raw and transformed occupancy pattern assuming three-second time delay

	Raw Data (sec)	Three Seconds Time Delay
	1	1
	0	**1**
	0	**1**
	1	1
	1	1
	1	1
	0	**1**
	0	**1**
	0	**1**
	0	0
	0	0
	1	1
	0	**1**
	0	**1**
	0	**1**
Sum	5	13

Figure 5-6 shows the percent deviation of occupied time from true occupancy, measured by each individual sensor at different time delay settings ranging from 30 seconds to 40 minutes. In Room 1, PIR3 was faulty (pulsing continuously), and so application of defined delays to the time series for this sensor resulted in large increases in occupied time. As noted above (i.e., Figure 5-4), PIR sensors do not pulse continually within each occupied event, so the raw sensor data underestimate occupied time: in the case of PIR1 in Room 1, the raw data underestimated true occupancy by as much as 80%. As the modeled time delay was increased, the assumed occupied time in the space increased: applying a 20 to 30-minute time delay to PIR1 and PIR2 increased the modeled occupied time in Room 1 by 70% to nearly 100%.

Similar trends were observed in Room 2. All three sensors functioned properly in this room over the two day monitoring period. Again, the raw time series from the sensor network underestimated true occupancy, and applying time delays to these data resulted in different increases in the assumed occupied time in the space for the three sensors: in this case applying a 20 to 30-minute time delay to the sensor time series data produced increases in modeled occupancy from between 30% (PIR3) to 75% (PIR2)

Room 1



Room 2

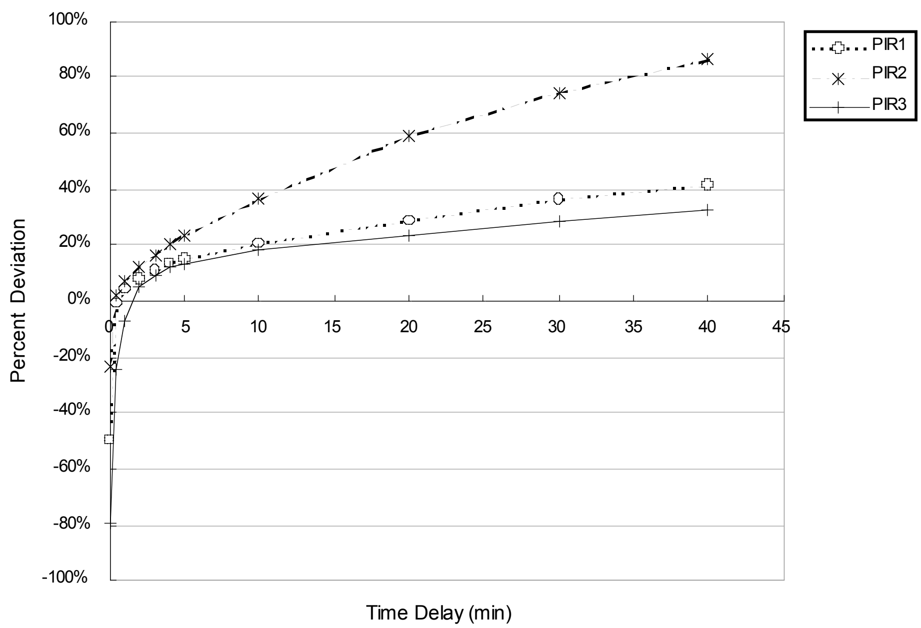


Figure 5-6. Effect of time delay settings on accuracy of total occupied time determination. Plots show time delay settings of 0, 0.5, 1, 2, 3, 4, 5, 10, 20, 30, 40 minutes

The analysis reported in this section shows the following:

- There is considerable uncertainty associated with the determination of occupancy using measurements from a single detector mounted at a potentially non-optimal location.
- The particular PIR detectors used in this study underestimated occupancy relative to "Truth".
- The uncertainty and underestimated occupied time together account for the requirement for long time delay used in commercial control systems.

A network of sensors monitoring the same space would reduce uncertainty because data from other detector provides converging information that can be used to determine if a space is occupied or vacant.

While a network of sensors may help eliminate the uncertainty associated with individual sensor measurements, the usefulness of the network depends on the analysis techniques applied to the data stream, and the ability of these techniques to produce results that correspond to occupancy better than current systems. The next section discusses the application of the 8 data fusion methods described in Chapter 4 to these occupancy data.

5.3.2 Fusion of PIR sensor data

In Chapter 4, several data fusion techniques that may reduce the uncertainty associated with the measurement of occupancy were described in detail. These data fusion techniques are:

- Three logical functions (OR, AND and MAJORITY);
- Moving average;
- Rule-based reasoning;
- Belief network (BN)
- Least squares estimation (LSE), and;
- Artificial neural network (NN).

The moving average method, as introduced in section 4.3, averages readings from each individual sensor over a past time period, and then sums the averaged output from all three sensors. A 5-second averaging period was initially used in the moving average calculations, and later this period was expanded to 60, 300, 600, and 1200 seconds, respectively, to further smooth out the data.

The rule-based reasoning method described in section 4.4 essentially takes into account the performance of most sensors and the time persistence of occupancy status. In this study, if the space is judged by the rule as occupied during a single second, it will be considered occupied for the next five seconds.

The belief network is constructed based on a general model of room occupancy and conditional probabilities associated with sensor pulsing, as described in section 4.5. The construction and the parameter determination of the network are described in 11Appendix A.

Two of these methods require training data to refine system parameters (least squares estimation, described in section 4.6, and the feed-forward back-propagation supervised neural network, described in section 4.7). The first-day readings from three PIR sensors along with the "Truth" data collected by the human observers comprised the training data, and parameters were calculated and then applied to the PIR readings over both days to calculate the sensor network output. The length of the training period is arbitrary in an actual application, and the training period could be several hours, or even several days duration.

As discussed in Chapter 4 (section 4.8), the estimated occupancy using each of the eight data fusion methods were compared against several criteria, as follows:

- The true occupied time ("Truth"), as measured by the human observers who monitored the two spaces (in seconds);
- The percentage deviation of the predicted occupied time from the truth. Ideally, the occupied times calculated by each individual method should be close to the truth, and this percentage deviation should be close to zero;
- The accuracy in terms of φ correlation, and the four occupancy status components of φ (namely N_{11} , N_{10}, N_{01} and N_{00}: where N_{11} is the number of seconds when the space is occupied, and the sensor detects a motion; N_{10} is the number of seconds when the space is occupied, but the sensor does not detect a motion; N_{01} is the number of seconds when the space is vacant, but the sensor measures occupancy; and finally, N_{00} is the number of seconds when the space is vacant, and the sensor also indicates it was unoccupied). The maximum value of φ is 1, representing perfect agreement between the measured value and the truth. The desired N_{11} equals the true occupied time, and the desired N_{00} is the total number of seconds in a day (86400) minus the occupied seconds. These two desired values again depict the situation in which the calculated value perfectly matches the truth. N_{10} and N_{01} represent the time (in seconds) when a false-off or a false-on occurs, respectively. N_{01} is useful in energy saving calculations, since it essentially represents "wasted on-time" (the number of seconds when the space is vacant, but sensor measures occupancy, and ambient systems remain switched on in a vacant space), and obviously should be minimized.
- The number of false switches (false-ons occurring when lights are switched on in an unoccupied space; false-offs occurring when lights are switched off in an occupied space).

The eight data fusion methods were applied to the sensor network data collected in the two rooms, and the results are shown in Table 5-5, which depicts results for each room and each day.

The columns identified as PIR1, PIR2 and PIR3 show direct readings from each sensor. As in Table 5-2, differences in occupied time measured by each sensor show that the performance of individual sensors varied even though they were measuring the same phenomena in the same space. Except for the defective sensor (PIR3 in Room 1), each individual sensor underestimated the total occupied time.

Table 5-5. Comparison of data fusion techniques

Room 1, Day 1

Criteria	Truth (Desired)	PIR1	PIR2	PIR3	OR	AND	MAJORITY	Moving Average	Rule-Based	BN	LSE	NN
Occupied Time (sec)	17723	7021	11517	21058	23213	5161	11222	12936	16181	13750	12267	13014
PCT Dev. from Truth	0	-60.4%	-35.0%	18.8%	31.0%	-70.9%	-36.7%	-27.0%	-8.7%	-22.4%	-30.8%	-26.6%
Accuracy (φ)	1	0.57	0.76	0.53	0.63	0.49	0.75	0.81	0.92	0.78	0.79	0.81
N_{11} (Truth=1, Measured=1)	17723	6865	11400	12304	14430	5073	11066	12736	15857	12835	12103	12838
N_{10} (Truth=1, Measured=0)	0	10858	6323	5419	3293	12650	6657	4987	1866	4888	5620	4885
N_{01} (Truth=0, Measured=1)	0	156	117	8754	8783	88	156	200	324	915	164	176
N_{00} (Truth=0, Measured=0)	68677	68521	68560	59923	59894	68589	68521	68477	68353	67762	68513	68501
No. of False-offs	0	787	1313	968	824	841	1124	427	121	255	1193	1155
No. of False-ons	0	20	15	2807	2813	11	16	12	11	272	18	22

Room 1, Day 2

Criteria	Truth (Desired)	PIR1	PIR2	PIR3	OR	AND	MAJORITY	Moving Average	Rule-Based	BN	LSE	NN
Occupied Time (sec)	16789	6889	13080	23388	25101	5448	12808	14760	16977	16813	13631	14055
PCT Dev. from Truth	0	-59.0%	-22.1%	39.3%	49.5%	-67.6%	-23.7%	-12.1%	1.1%	0.1%	-18.8%	-16.3%
Accuracy (φ)	1	0.58	0.85	0.61	0.69	0.51	0.84	0.91	0.97	0.87	0.87	0.88
N_{11} (Truth=1, Measured=1)	16789	6712	12927	13840	15510	5332	12637	14519	16524	15015	13435	13846
N_{10} (Truth=1, Measured=0)	0	10077	3862	2949	1279	11457	4152	2270	265	1774	3354	2943
N_{01} (Truth=0, Measured=1)	0	177	153	9548	9591	116	171	241	453	1798	196	209
N_{00} (Truth=0, Measured=0)	69611	69434	69458	60063	60020	69495	69440	69370	69158	67813	69415	69402
No. of False-offs	0	1026	1233	836	528	1122	1160	346	34	154	1119	1010
No. of False-ons	0	10	20	3169	3175	11	8	2	4	415	16	19

Table 5-5. Comparison of data fusion techniques (Cont'd)

Room 2, Day 1

Criteria	Truth (Desired)	PIR1	PIR2	PIR3	OR	AND	MAJORITY	Moving Average	Rule-Based	BN	LSE	NN
Occupied Time (sec)	33881	16709	25384	6901	26750	6106	16138	20764	29983	21435	25384	26750
PCT Dev. from Truth	0	-50.7%	-25.1%	-79.6%	-21.0%	-82.0%	-52.4%	-38.7%	-11.5%	-36.7%	-25.1%	-21.0%
Accuracy (φ)	1	0.60	0.79	0.35	0.82	0.33	0.58	0.68	0.89	0.71	0.79	0.82
N_{11} (Truth=1, Measured=1)	33881	16531	25070	6714	26394	5990	15931	20482	29569	21318	25070	26394
N_{10} (Truth=1, Measured=0)	0	17350	8811	27167	7487	27891	17950	13399	4312	12563	8811	7487
N_{01} (Truth=0, Measured=1)	0	178	314	187	356	116	207	282	414	117	314	356
N_{00} (Truth=0, Measured=0)	52519	52341	52205	52332	52163	52403	52312	52237	52105	52402	52205	52163
No. of False-offs	0	2809	1855	1692	1804	1564	2616	1098	264	708	1855	1804
No. of False-ons	0	23	44	40	49	27	26	12	8	14	44	49

Room 2, Day 2

Criteria	Truth (Desired)	PIR1	PIR2	PIR3	OR	AND	MAJORITY	Moving Average	Rule-Based	BN	LSE	NN
Occupied Time (sec)	11494	6193	9540	2254	9828	1993	6166	7965	10869	4934	9540	9828
PCT Dev. from Truth	0	-46.1%	-17.0%	-80.4%	-14.5%	-82.7%	-46.4%	-30.7%	-5.4%	-57.1%	-17.0%	-14.5%
Accuracy (φ)	1	0.70	0.89	0.41	0.91	0.39	0.70	0.81	0.96	0.62	0.89	0.91
N_{11} (Truth=1, Measured=1)	11494	6156	9491	2228	9767	1975	6133	7916	10772	4878	9491	9767
N_{10} (Truth=1, Measured=0)	0	5338	2003	9266	1727	9519	5361	3578	722	6616	2003	1727
N_{01} (Truth=0, Measured=1)	0	37	49	26	61	18	33	49	97	56	49	61
N_{00} (Truth=0, Measured=0)	74906	74869	74857	74880	74845	74888	74873	74857	74809	74850	74857	74845
No. of False-offs	0	1020	633	653	546	610	979	373	65	169	633	546
No. of False-ons	0	5	4	7	9	4	3	2	3	6	4	9

It is interesting to note that sometimes the percent deviation of occupied time from truth does not coincide with accuracy (φ). For example, in Room1, Day2, the percent deviation and accuracy for rule-based reasoning method are 1.1% and 0.97, respectively. The occupied time determined by belief network method is closer to the truth (deviation from truth = 0.1%), but the measurement is less accurate ($\varphi = 0.87$). The occupied time is useful in determining system usage, but since it ignores the time stamp (it simply equals to $N_{11} + N_{01}$), sometimes it is misleading, as this example shows. In contrast, accuracy accounts for all four possible sensor status conditions (N_{11}, N_{10}, N_{01} and N_{00}): "correct measurements" (N_{11} and N_{00}) increase accuracy, while "incorrect measurements" (N_{10} and N_{01}) reduce accuracy.

The three logical functions combine the outputs from three sensors without any additional knowledge (of the operating characteristics of individual sensors, or other probabilities related to occupancy). The predictive accuracy of the logical functions depends on the operating properties of individual sensors. In terms of occupied time, the OR function always yields a result higher than or equal to the largest value measured by any individual sensor; the AND function always generates a value lower than or equal to the smallest number as determined by any individual sensor, and; the MAJORITY function always outputs a value in between these two.

Since individual sensors underestimate occupied time, the OR function will be most close to the truth among the three logical functions, as can be seen from the Room 2 data (assuming, of course, that all sensors are functioning correctly). However, if any sensor within a sensor network is prone to false triggering, the OR function will overestimate occupancy, based on the response of the most sensitive (in this case faulty) sensor. This is demonstrated by the Room 1 data.

The AND function defines occupancy only when all sensors pulse. Since each individual sensor underestimates occupancy, this function will always underpredict occupied time. In this data set, this function shows a large deviation from the truth (-69.3% in Room 1 and -82.2% in Room 2) and a low accuracy (φ=0.5 in Room 1 and φ=0.35 in Room2).

Of the three logical functions, the MAJORITY is the "safest" method. It eliminates signals from failed sensors in determining occupancy (it is unlikely that a majority of sensors monitoring a space will fail). This algorithm yielded moderate accuracy in the two rooms (φ=0.79 in Room 1 and φ=0.64 in Room 2).

The moving average method, which averaged the measurements from three sensors over the past 5 seconds, enhanced the accuracy of individual sensors (φ=0.86 in Room 1 and φ =0.75 in Room 2). The results still showed unnecessary short fluctuations (as demonstrated by the 387 and 736 daily false-offs). This suggests that a longer moving average interval (greater than 5 seconds) is required.

Among the eight data fusion methods, the rule-based reasoning method most accurately estimated the occupancy (with φ=0.95, percent deviation from truth = -3.9% in Room 1 and φ=0.92, percent deviation from truth = -10% in Room 2). This is reasonable since the rule was defined after examining the patterns of sensor measurements, and tuned for best performance. A five-second "sensor performance persistence" rule was also defined in the algorithm and filled out most of the silent intervals, so it is not surprising that this method yielded the smallest number false-offs.

The belief network method, based on a general model of room occupancy and conditional probabilities associated with sensor pulsing, shows good agreement with the truth in Room 1 (φ =0.83), but only moderate agreement in Room2 (φ =0.66). The measurements from all sensors during a single time slot are the most important factor in determining occupancy in a belief network (other factors that are included are time of the day, sensor status persistence, and occupancy status persistence). Thus during typical office hours, a belief network yields a result similar to majority voting. Two sensors in Room 2 (PIR1 and PIR3) underestimated the occupied time (by 49.5% and 79.8%, respectively), and these explain why the output from the belief network was not satisfactory.

The least squares estimation and neural network methods both utilized truth data from the first day as the training data, and both show good agreement with the truth ($\varphi \approx$ 0.85 in both rooms). This is not surprising since the system parameters were tuned based on the true occupancy from the same data set used to evaluate the method (i.e., the training data were highly correlated with the evaluated data set). In any real application, the training data would also be highly correlated with the actual application data, and it is not unreasonable to assume that a longer training period would have improved the performance of these two algorithms. Nevertheless, neither of these two methods was able to eliminate false-offs.

None of the methods achieved satisfactory performance in terms of the number of false switches. The high frequency of false-offs and ons observed after application of all methods indicated that if the lighting system had been controlled by any of these methods as applied to sensor network data, lights would have been frequently and inappropriately switched on and off. At least in this data set, a supplementary time delay is required, because even correctly functioning sensors do not pulse continually during occupied periods (since people do not continually move when they are in an office – e.g., Figure 5-4), and the application of all processing algorithms to the data stream eliminated neither false-offs nor false-ons. The next section describes the effects of an application of time delay to fused occupancy data.

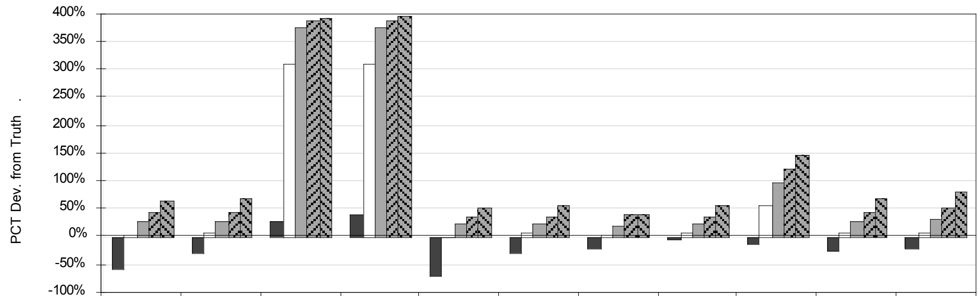
5.3.3 Effects of time delay on fused occupancy data

Time delay settings of 1, 5, 10 and 20 minutes were applied to the fused data, using the same method described in Table 5-4, with the goal of modeling the effects of different time delay settings on fused data. This method was applied to all the algorithms except the moving average method, for which no time delay was applied, but a different duration was used to average the data. Consequently, at the four time delay settings, data were averaged over the last 60, 300, 600, 1200 steps (seconds). Generally, a longer duration in moving average calculation further smoothes out the raw data.

Since the ultimate goal of this research is to achieve energy efficiency and user satisfaction, the correspondence between true occupied time and false-offs, as a function of time delay settings applied to the fused data are of particular interest. Figure 5-7, Figure 5-8 and Figure 5-9 show the results of the modeling in terms of percent deviation of total occupied time from the truth, accuracy (φ) and number of false-offs, respectively.

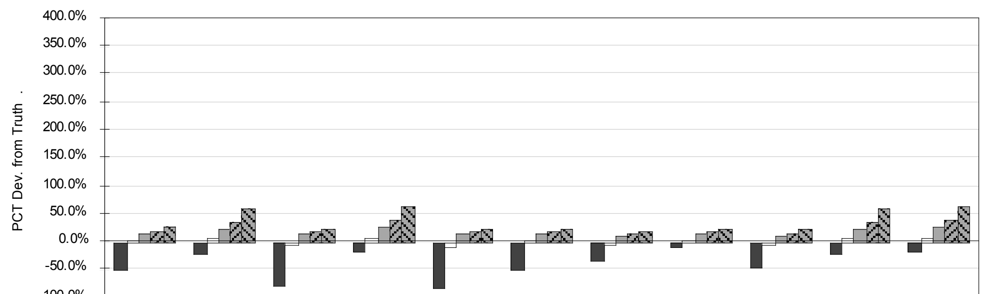
Figure 5-7 shows the percent deviation from truth for time delay settings of 1, 5, 10 and 20 minutes. As expected, with a time delay of 1 minute, the occupied time calculated by most methods (except "AND"), was closer to the truth than all the other time delay settings. However, as shown by Figure 5-9, with a time delay of 1 minute, the existence of many false-offs shows this short delay will not be long enough to ensure user satisfaction.

Room 1



	PIR1	PIR2	PIR3	OR	AND	MAJORITY	Moving Average	Rule-Based	BN	LSE	NN
No time delay	-59.7%	-28.6%	29.1%	40.2%	-69.2%	-30.2%	-19.5%	-3.8%	-11.1%	-24.8%	-21.4%
1-min time delay	2.5%	6.3%	311.0%	311.8%	-1.0%	7.0%	2.1%	8.1%	56.2%	7.8%	8.8%
5-min time delay	26.5%	27.0%	376.4%	377.3%	22.6%	23.8%	21.1%	24.3%	99.6%	27.3%	30.8%
10-min time delay	42.4%	43.9%	388.1%	389.9%	35.1%	37.2%	39.1%	37.6%	121.4%	44.1%	51.2%
20-min time delay	67.0%	69.1%	393.5%	396.0%	53.7%	57.1%	40.3%	57.4%	145.0%	69.3%	81.7%

Room 2

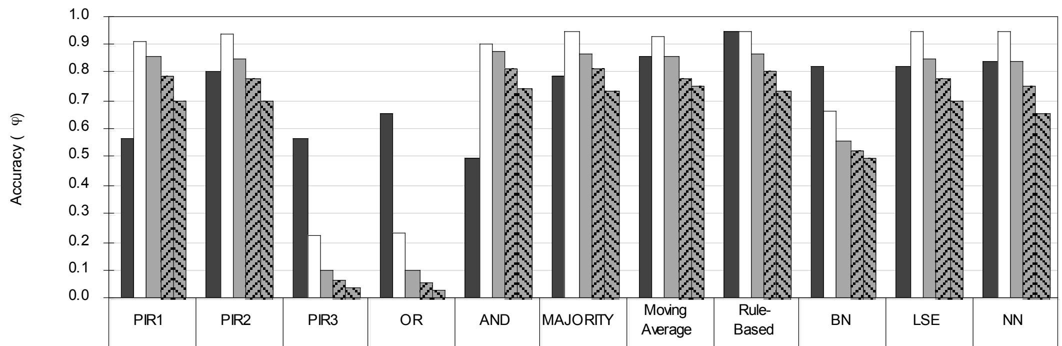


	PIR1	PIR2	PIR3	OR	AND	MAJORITY	Moving Average	Rule-Based	BN	LSE	NN
No time delay	-48.4%	-21.0%	-80.0%	-17.8%	-82.3%	-49.4%	-34.7%	-8.5%	-46.9%	-21.0%	-17.8%
1-min time delay	4.4%	7.2%	-6.7%	8.7%	-10.5%	3.8%	-3.7%	4.5%	-6.0%	7.2%	8.7%
5-min time delay	15.1%	23.7%	13.7%	25.1%	13.6%	13.8%	9.4%	14.0%	9.2%	23.7%	25.1%
10-min time delay	20.8%	36.6%	18.1%	39.3%	18.1%	18.1%	13.7%	18.2%	16.1%	36.6%	39.3%
20-min time delay	29.0%	59.1%	23.7%	64.4%	23.7%	23.7%	17.9%	23.8%	22.0%	59.1%	64.4%

Figure 5-7. Percent deviation of occupied time from truth as measured by each sensor and determined by 8 data fusion algorithms

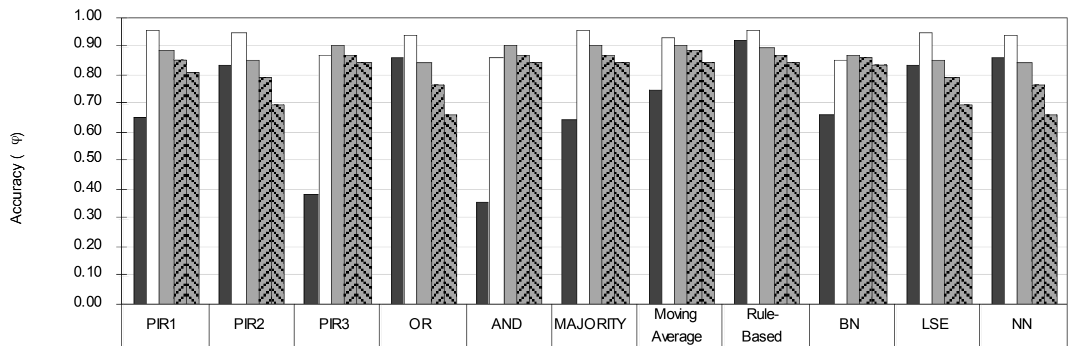
As expected, data from a defective sensor (PIR3) fused with the OR function showed large deviation from the true occupied time (Figure 5-7, Room 1) and low accuracy (Figure 5-8, Room 1) at all time delay settings. For all the data fusion algorithms, the percent deviation from the occupied time increased as the time delay increased, demonstrating that a long time delay setting is unfavorable to energy savings.

Room 1



	PIR1	PIR2	PIR3	OR	AND	MAJORITY	Moving Average	Rule-Based	BN	LSE	NN
No time delay	0.57	0.80	0.57	0.66	0.50	0.79	0.86	0.95	0.83	0.83	0.85
1-min time delay	0.92	0.94	0.23	0.23	0.91	0.95	0.93	0.95	0.67	0.95	0.95
5-min time delay	0.86	0.86	0.10	0.10	0.88	0.87	0.86	0.87	0.56	0.86	0.84
10-min time delay	0.79	0.79	0.07	0.06	0.82	0.81	0.78	0.81	0.53	0.79	0.76
20-min time delay	0.71	0.70	0.05	0.04	0.75	0.74	0.76	0.74	0.50	0.70	0.66

Room 2

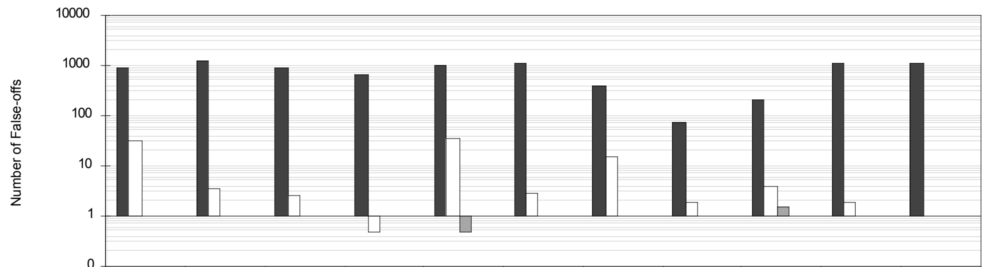


	PIR1	PIR2	PIR3	OR	AND	MAJORITY	Moving Average	Rule-Based	BN	LSE	NN
No time delay	0.65	0.84	0.38	0.86	0.36	0.64	0.75	0.92	0.66	0.84	0.86
1-min time delay	0.96	0.95	0.87	0.94	0.86	0.96	0.93	0.96	0.86	0.95	0.94
5-min time delay	0.89	0.85	0.90	0.84	0.90	0.90	0.90	0.90	0.87	0.85	0.84
10-min time delay	0.85	0.79	0.87	0.77	0.87	0.87	0.89	0.87	0.86	0.79	0.77
20-min time delay	0.81	0.70	0.84	0.67	0.84	0.84	0.85	0.84	0.84	0.70	0.67

Figure 5-8. Accuracy (φ) of each sensor and each data fusion algorithm

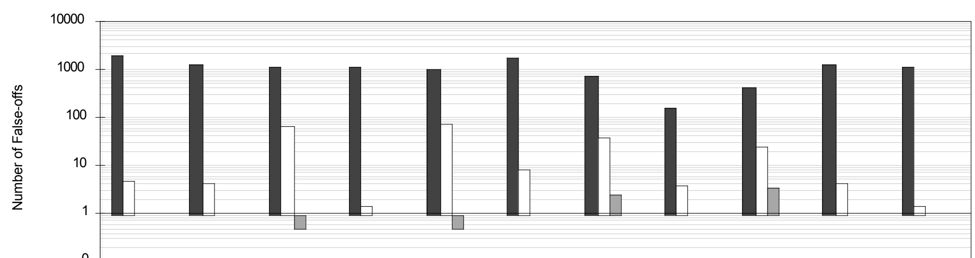
The accuracy of most methods (Figure 5-8) peaks when the time delay equals 1 minute, and then decreases as the time delay setting was increased. The decreased accuracy observed under the longer time delay settings is due to the increased time that lights are on in an empty space (wasted on-time) that prevails under these conditions.

Room 1



	PIR1	PIR2	PIR3	OR	AND	MAJORITY	Moving Average	Rule-Based	BN	LSE	NN
No time delay	907	1273	902	676	982	1142	387	78	205	1156	1083
1-min time delay	32	4	3	1	36	3	16	2	4	2	1
5-min time delay	0	0	0	0	1	0	0	0	2	0	0
10-min time delay	0	0	0	0	0	0	0	0	0	0	0
20-min time delay	0	0	0	0	0	0	0	0	0	0	0

Room 2



	PIR1	PIR2	PIR3	OR	AND	MAJORITY	Moving Average	Rule-Based	BN	LSE	NN
No time delay	1915	1244	1173	1175	1087	1798	736	165	439	1244	1175
1-min time delay	5	5	68	2	73	9	39	4	25	5	2
5-min time delay	0	0	1	0	1	0	3	0	4	0	0
10-min time delay	0	0	0	0	0	0	0	0	0	0	0
20-min time delay	0	0	0	0	0	0	0	0	0	0	0

Figure 5-9. Number of false-offs as measured by each sensor and determined by eight data fusion algorithms

Finally, the number of false-offs (Figure 5-9) were plotted on logarithmic axes, because when the length of the time delay was increased, the number of false-offs drops exponentially. Figure 5-9 shows that at a time delay setting of 10 minutes, all false-offs have been eliminated by all the fusion algorithms. This indicates that a time delay setting shorter than the currently used settings of between 20 to 30 minutes is possible, if a sensor network is used instead of a single sensor.

5.4 Discussion

The two goals of the pilot study described in this chapter were to evaluate the utility of using more than one sensor to detect occupancy, and to explore the application of the analysis methods described in Chapter 4 to sensor network data.

If a single measurement point is sufficient to accurately characterize occupancy in a given space, the total occupied time as measured by several independent detectors monitoring that space should be about the same. On the other hand, observed differences in occupancy measured by several independent detectors suggests that each detector, on it's own, provides a less accurate measure than might be obtained using a "fused" signal from several detectors.

An examination of raw sensor data collected from three different PIR sensors in each of two rooms over a two-day monitoring period revealed that the occupancy patterns measured by these sensors were different, even though they faced the occupied area(s) in each room. Thus, there is considerable uncertainty about the occupancy status if a single sensor is used.

This uncertainty can be reduced if a network of more than one sensor is used to monitor occupancy: further analysis comparing the sensor network response against true occupancy showed that there were no intervals longer than six minutes duration during which the space was occupied but there were no pulses from at least one of the three sensors in the network (the sensor network silent interval). The duration of the silent interval in a sensor network that is being used for occupancy-based control can be used to more precisely define (and in fact reduce) the time interval that must elapse before the system initiates a control action. In this data set, properly functioning sensors *always* underestimated the occupied time, because the sensors did not pulse continuously even though the space was occupied. Thus, a time delay setting will always be needed, even for fused sensor network data.

The second goal was to explore the application of the analysis techniques and methods described in Chapter 4 to sensor network data. A sensor network is only useful to the extent that an appropriate analysis method can be developed or identified for application to the sensor network data stream, one that results in improved system performance relative to current practice. The two most important performance criteria that can be applied to evaluate the performance of the sensor network relate to the number of false-offs observed under a given set of operating conditions, and wasted on-time observed under a given set of operating conditions. With a proper data fusion algorithm, which combines the outputs from several sensors, it is possible to improve the accuracy of occupancy measurement and apply a shorter time delay. We can expect greater energy savings achieved from a sensor network since with a shorter time delay, less wasted on-time will result.

The results described in this chapter show that the different data fusion methods could be fruitfully applied to the time series data produced by a network of PIR sensors.

Generally, in terms of φ correlation, the more *a priori* information about the response of individual sensors to occupancy that is provided, the more accurate the fusion algorithm will be. The eight individual algorithms studied here can be divided into three groups based on how much previous knowledge they need. The first group, consisting of rule-based reasoning, neural network, and least squares estimation, provided the most accurate estimates of occupancy in both offices. The next most accurate estimates were provided by the belief network (which models occupancy using a probabilistic model of office occupancy and sensor response) and moving average methods (which assumes that no short-term fluctuations will exist in an occupancy event). Finally, the logical functions (OR, AND, MAJORITY) fall to the last group providing the least accurate estimates of occupancy.

Most false-offs were eliminated with a time delay setting of 5 minutes for all the data fusion methods. This is reasonable since only one silent interval longer than 5 minutes was observed in these two rooms over the two-day period.

While these results are encouraging, additional work is necessary to confirm the main findings reported in this chapter given the small sample size and monitoring period used in the pilot study.

6 Study II: Sensor Networks for Occupancy Detection

6.1 Introduction

The pilot study suggested that with proper data fusion techniques, the output from a sensor network might characterize occupancy more reliably and more accurately than the output from any individual sensor. The study also demonstrated that there were large variations between the occupancy patterns measured by different sensors installed in a single private space, which implies that a single detection point cannot guarantee optimal sensor performance. These conclusions were based on a small sample of offices measured over a very short period (two-day data collection in two private offices), so more extensive data and analysis are required to generalize the results and conclusions.

The goal of the work described in this chapter, therefore, is to confirm and extend the findings from the pilot study. Occupancy sensor networks were installed in a sample of private and open-plan offices, and monitored for about two months. There were two goals for this study. The first was to study and confirm the performance differences between the individual sensors installed in the same space, as were observed in the pilot study. If a single sensor can accurately characterize occupancy, measures from each individual sensor should be similar, as long as the monitored space is within the coverage area for the sensor. If the occupancy measured by each sensor is different, then a combined output from the sensor network may be more accurate than any single sensor.

The second goal of this study was to characterize possible reductions in system use that can be produced using a shorter time delay setting. Since it is possible to more accurately characterize occupancy with a sensor network, a shorter time delay setting should be possible, which will reduce operating time while maintaining user satisfaction. That is, there might be less "wasted on time" if a space is controlled by a sensor network instead of a single point of detection: further, since occupancy is characterized more accurately by a sensor network, fewer false-offs are expected, even though the time delay is shorter.

6.2 Methods and Procedures

Sensor networks were designed, installed, and monitored in a sample of private offices and open plan work areas located at the University of Nebraska's Peter Kiewit Institute, located in Omaha, NE, and at the University of California's Lighting Technology Center, located in Davis, CA. Ten private faculty offices and 23 cubicle workstations in an open-plan work area were studied at the University of Nebraska (monitored for 59 days and 63 days, respectively). In the open-plan work area, a digital video record of office occupancy complemented the sensor data: four AXIS digital video cameras were mounted at ceiling level in the four corners of the room. The software controlling each camera recorded the date and time of each image (in date:hour:minute:second format), writing this information clearly in the lower right area of each image frame. A separate image was collected every two seconds, and these separate images were automatically appended to a QuickTime file, which provided a time-lapse movie showing activity in the room. These time-lapse movies were manually reviewed by a human observer, who recorded the maximum number of occupants who were in the room at each minute of the day. As described in the results, the maximum number of occupants in the room was compared with the number of PIR sensor pulses that occurred each minute.

The sample of work areas monitored at the University of California included six private offices, three partially open laboratory, technology demonstration and storage areas, and one corridor (all monitored for 71 days).

The sensor network monitoring each respective area consisted of three commercially available wireless PIR occupancy sensors. Sensor mounting positions varied as each space included slightly different arrangements of furniture, equipment and other materials; however, all sensors were mounted so they had a direct and unobstructed view of the customarily occupied area in the space. Each detector sent a wireless signal to a centrally located data acquisition system whenever a change in occupancy was detected. The sensor network recorded space occupancy every minute: when a signal was received from any of the three PIR sensors in a space, the space was considered occupied for the duration of that minute.

The occupancy sensors used in this study were different from those used in the pilot study because this system and components functioned more reliably over the data collection period. The wireless occupancy detectors used were Activehome X10 model RMS18 PIR sensors, as shown in Figure 6-1. These commercially available devices are intended for use by home automation hobbyists, and each requires two 1.5V AAA batteries. Individual sensors are identified by a user-programmable alphanumeric address: this unique alphanumeric address was recorded by a computer-based data acquisition system used to collect occupancy data over the monitoring period.

Figure 6-1. Wireless PIR sensor

The signals transmitted by these PIR sensors are received by a model number W800RF32 310mhz antenna, connected via an RS232 serial to USB computer interface that records the signals from the sensors, using a commercially available home automation software control package called XTension, which runs under the Apple Macintosh OS X operating system. Figure 6-2 shows the computer system logging activity.

Figure 6-2. Wireless data acquisition system (DAS)

An entry recording the date, time and unique sensor identification number was recorded to a computer hard disk log file when each wireless signal was received. Figure 6-3 shows part of a sample log file.

```
Fri, May 13, 2005 5:49:20 PM Received ON for B6 (w)
Fri, May 13, 2005 5:49:21 PM Received ON for C5 (w)
Fri, May 13, 2005 5:49:24 PM Received ON for C2 (w)
Fri, May 13, 2005 5:49:25 PM Received ON for C4 (w)
Fri, May 13, 2005 5:49:32 PM Received ON for C4 (w)
Fri, May 13, 2005 5:49:33 PM Received ON for C1 (w)
Fri, May 13, 2005 5:49:40 PM Received ON for C1 (w)
Fri, May 13, 2005 5:49:41 PM Received ON for C4 (w)
Fri, May 13, 2005 5:49:42 PM Received ON for C3 (w)
Fri, May 13, 2005 5:49:44 PM Received ON for C2 (w)
Fri, May 13, 2005 5:49:45 PM Received ON for B6 (w)
Fri, May 13, 2005 5:49:48 PM Received ON for C4 (w)
```

.

Figure 6-3. A sample log file showing the status of individual sensors

For the purposes of this analysis, the raw log file was converted to one-minute resolution time series data: if a sensor was logged "ON" for a particular time within a minute, the sensor output of that minute was considered ON and coded as "1". Otherwise, the sensor status was coded as "0", indicating no signal was received or an "OFF" signal was received from the detector for that minute. In the previous study, data were collected at a resolution of one-second, which is too fine for a control application. Since the time delays applied for the purposes of control are typically on the order of (at least) tens of minutes, data collected at a resolution of one minute are acceptable to adequately characterize occupancy.

6.3 Results

The description of the results is divided into four sections. The first section examines the differences among occupied time (in minutes) measured by each sensor. The second section describes the relationship between sensor pulse rate and occupancy in the data set collected from the open-plan work area at the University of Nebraska. The third section describes the sensor network outputs from six data fusion methods as applied to the data collected from private offices at the University of Nebraska. Finally, occupied times as determined by individual sensors and the sensor network are compared at different time delay settings, and the savings that result from the use of the fused sensor network signal (compared to individual sensors), are described as applied to the data collected from private offices at the University of Nebraska.

6.3.1 Individual differences in sensor performance

Table 6-1 shows the total occupied time (in minutes) measured by each of the three detectors mounted in each work area over the monitoring period. The percent difference was calculated as (max-min)/max, since the maximum is the most conservative estimate of occupancy.

Table 6-1. Occupied time (min) measured by three PIR occupancy detectors Occupied time (min) in 10 private offices over 59 days (University of NE)

Room	PIR 1	PIR 2	PIR 3	Percent Difference
1	1620	3533	3427	54.1
2	156	599	423	74
3	3763	6702	7268	48.2
4	3503	6756	8573	59.1
5	6018	6408	4356	32
6	3216	1618	3296	50.9
7	4804	4940	3653	26.1
8	1058	2603	913	64.9
9	7179	6279	6025	16.1
10	8462	9005	10794	21.6

Table 6-1. Occupied time (min) measured by three PIR occupancy detectors (cont'd)
Occupied time (min) in 10 work areas over 71 days (University of CA)

Area	PIR 1	PIR 2	PIR 3	Percent Difference
1	9769	2334	1543	84.2
2	6368	7412	6529	14.1
3	11508	994	1504	91
4	10671	16076	3555	33.6
5	8157	1599	6364	--
6	991	14494	10483	93.2
7	593	1829	1219	--
8	3616	1601	1416	60.8
9	1	1619	729	55
10	8462	9005	10794	21.6

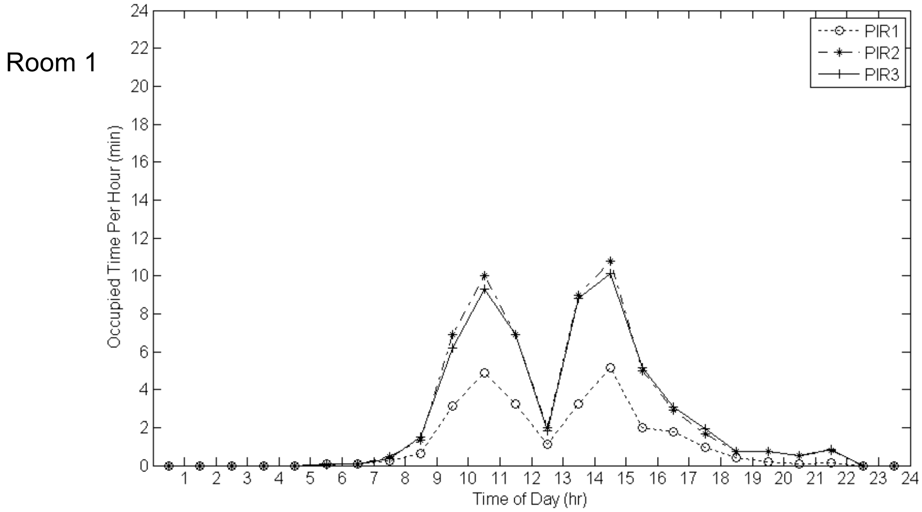
Table 6-1. Occupied time (min) measured by three PIR occupancy detectors (cont'd)
Occupied time (min) in 23 cubicle workstations over 63 days (University of NE)

Workstation	PIR 1	PIR 2	PIR 3	Percent Difference
1	3210	1101	1005	68.7
2	5065	5300	2734	48.4
3	5800	9457	4720	50.1
4	4936	6170	2451	60.3
5	8123	2328	726	68.8
6	2849	2670	2451	14
7	11740	12223	6568	46.3
8	7196	8455	6099	27.9
9	7225	7122	3155	56.3
10	667	535	76	88.6
11	5	2727	2012	26.2
12	1832	4295	1628	62.1
13	3898	0	7506	48.1
14	3935	5142	3393	34
15	960	666	146	84.8
16	2585	1508	0	41.7
17	5312	4554	2564	51.7
18	3846	6300	3397	46.1
19	2991	4387	2731	37.7
20	1801	4743	2667	62
21	2466	4816	1920	60.1
22	2663	5074	3124	47.5
23	1520	8257	3352	81.6

Large individual differences in sensor response to occupancy were observed in all monitored areas. Some of these differences were the result of sensor failure, or caused by sensors falling or being moved from their original mounting locations by occupants (this was especially true for data collected at the University of CA). Occupancy times measured by these sensors have not been included in the analyses, and are identified in the Tables in low contrast gray type.

Even excluding these data, the differences in measured occupancy among sensors monitoring the same space are quite noticeable: the percent difference in occupied time for sensors measuring the ten private offices at the University of NE ranged from 16.1% to 74.0%, with an average of 44.7%. For the eight work areas with valid data monitored at the University of CA, the differences ranged from 14.1% to 93.2%, with an average of 56.7%. Finally, the differences between detectors monitoring individual cubicle workstations monitored at the University of NE ranged from 14% to 91%, with an average difference between detectors of 53.7%. Over all three data sets, the differences ranged from 14% to 93.2%, with an overall mean difference of 51.7%.

More detailed analysis of the data collected from the ten private offices at the University of Nebraska helps elucidate the nature of the individual differences in sensor response. The differences among the sensors were examined in terms of hourly distribution of occupied time. Figure 6-4 shows the average daily profile of occupied time (in minutes) over the 59 days in each of the ten private offices as measured by each sensor. Most PIR sensors in the same room measured similar shapes of occupancy, specifically, showing routines of coming to the office, having lunch and leaving the office at the end if the working day.



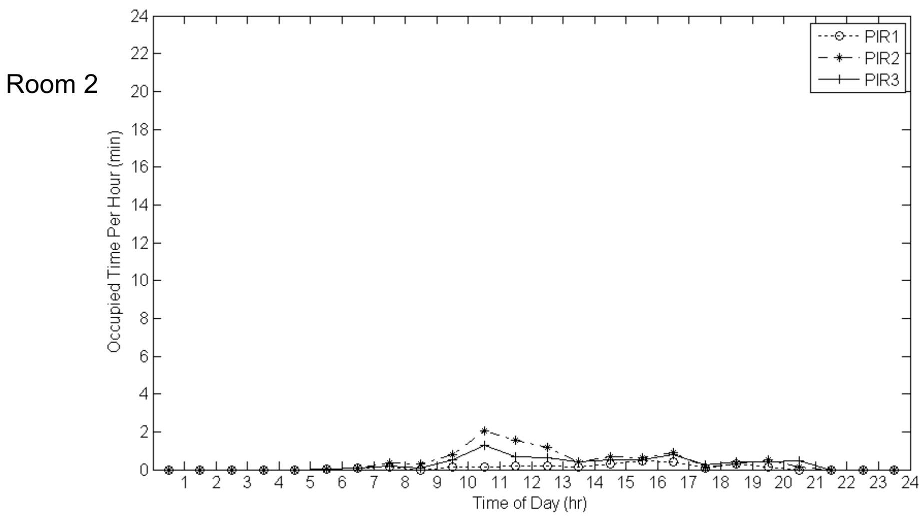
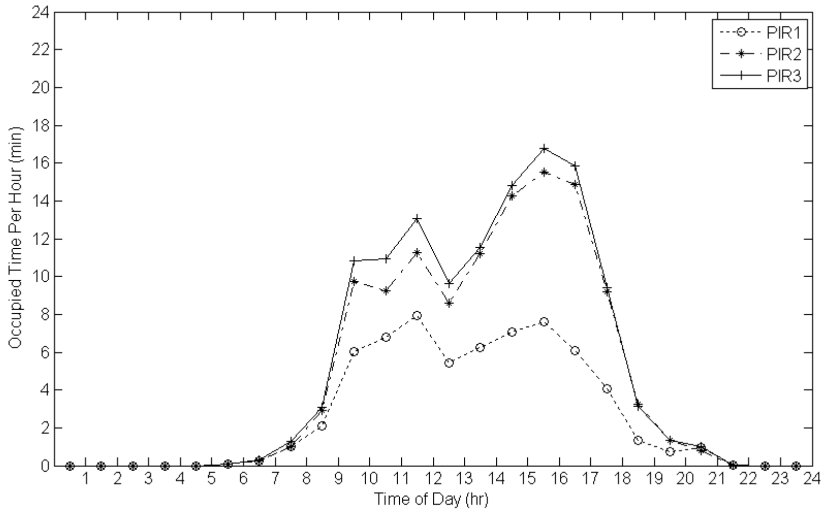


Figure 6-4. Hourly occupied time (min) of each room over 59 days

Room 3



Room 4

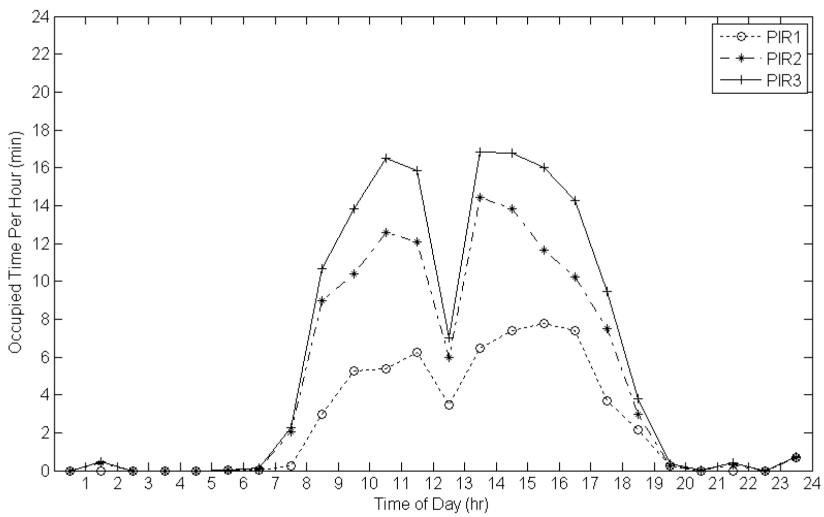
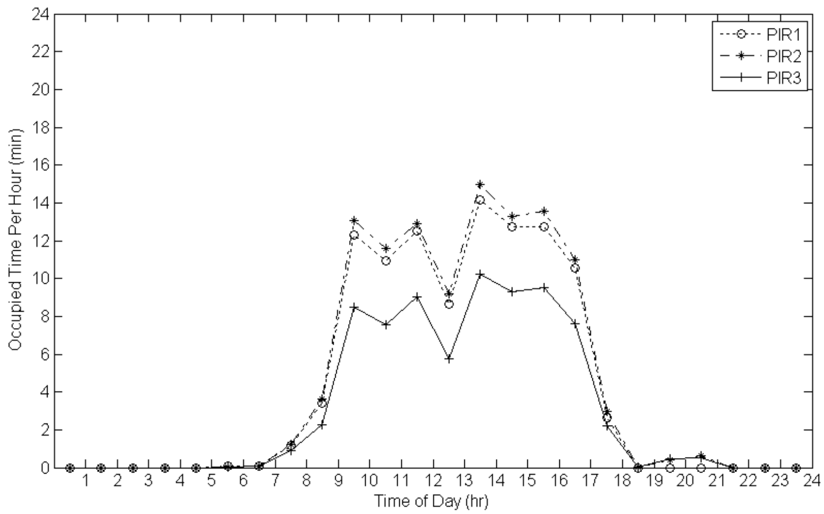


Figure 6-4. Hourly occupied time (min) of each room over 59 days (Cont'd)

Room 5



Room 6

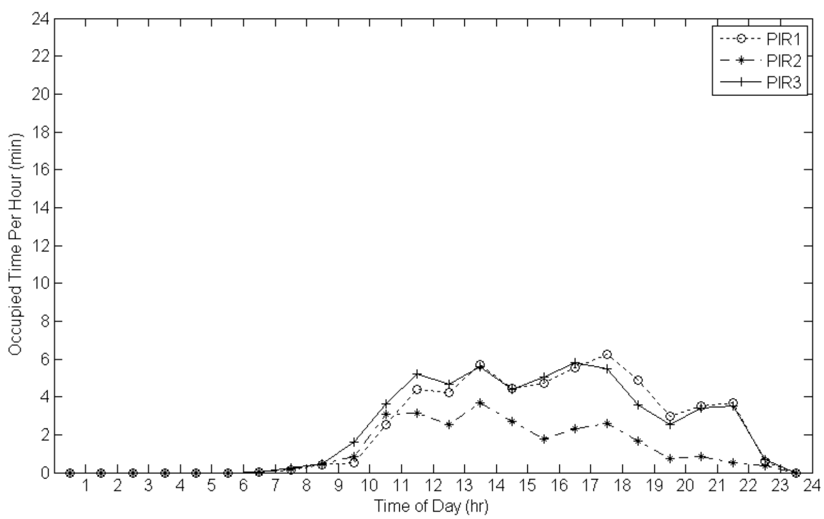
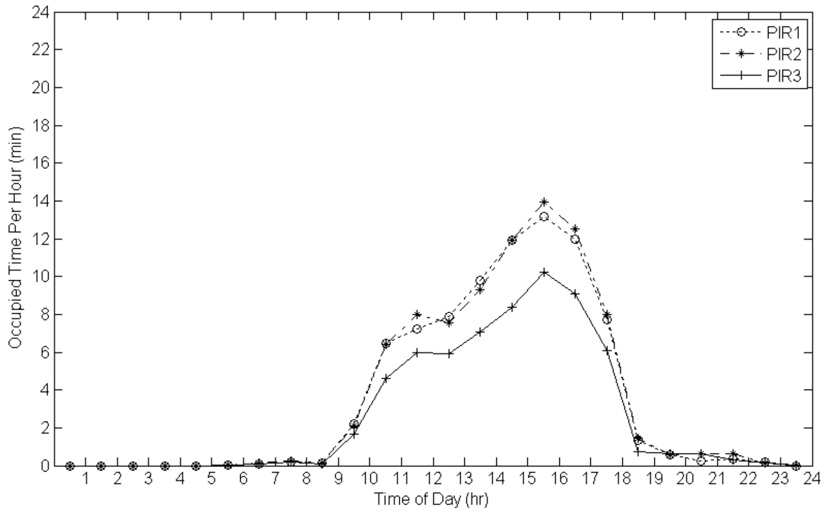


Figure 6-4. Hourly occupied time (min) of each room over 59 days (Cont'd)

Room 7



Room 8

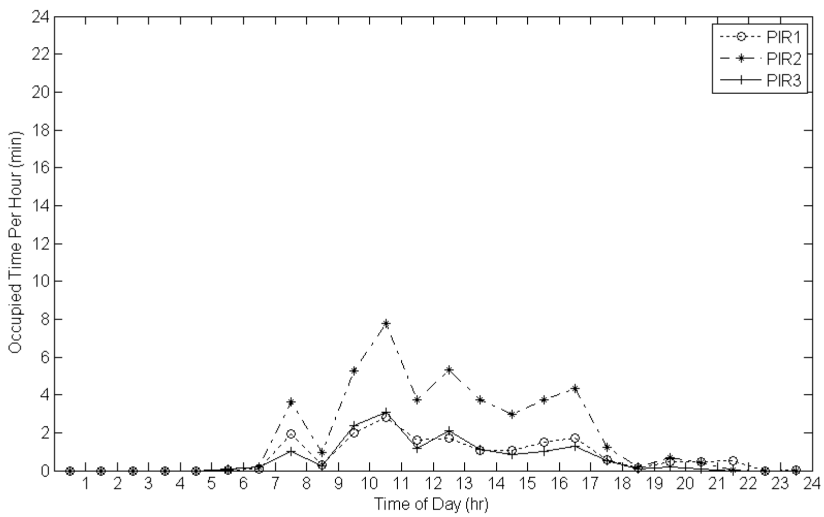
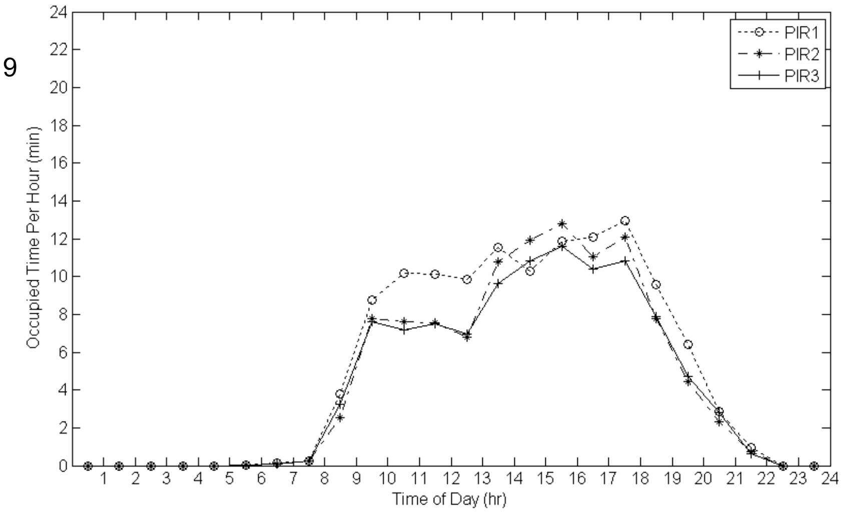


Figure 6-4. Hourly occupied time (min) of each room over 59 days (Cont'd)

Room 9



Room 10

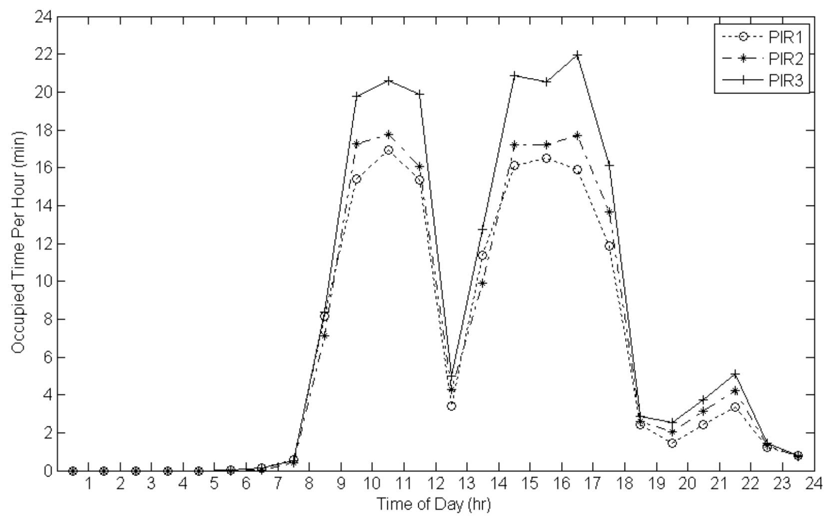


Figure 6-4. Hourly occupied time (min) of each room over 59 days (Cont'd)

Differences between individual sensors were also noticeable: some sensors were consistently less sensitive than others (for example, PIR1 in Room 1 was less sensitive than PIR2 and PIR3). Consequently, sensors measuring different occupied time would have different durations and frequencies of silent intervals (recall that silent interval is the interval that the space was actually occupied, but the PIR sensor did not pulse). To achieve maximum energy savings, different time delays would be required for different sensors, to fill up silent intervals and eliminate false-offs, i.e., a longer time delay would be needed in the case of a less sensitive sensor. Since sensor performance usually cannot be determined before installation, the safe solution is to apply a long time delay to all sensors. In other words, the uncertainty in occupancy measurement is typically compensated for in real applications with long time delays, and sometimes, by professional commissioning to find the best mounting position, viewing angle and time delay.

The average hourly occupancy (in minutes), depicted in Figure 6-4, was generally low (the maximum occupied time was around 22 minutes, in Room 10). These occupancy rates are due to the fact that the first month of data collection occurred during the university summer break, when university faculty are frequently away from their offices. In addition, the data set included weekends, during which occupancy was very low (coded in the data as mostly zeros).

Figure 6-5 depicts the daily occupied time over the monitoring period for all ten offices, over the complete 59-day monitoring period. As expected, measured occupancy was higher during the weekdays than over the weekends. Furthermore, as the left panel demonstrates, during the summer months, occupancy is lower than would be expected in a more traditional office setting. Once the academic term commenced (right panel), observed occupancy in these offices increased as expected.

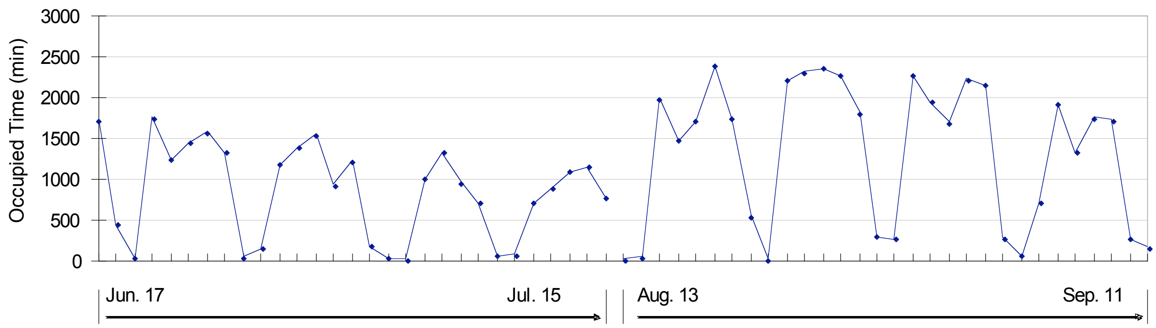


Figure 6-5. Total occupied time (min) per day of 10 rooms over 59 days

6.3.2 Relationship between sensor pulse rate and occupancy

A network of sensors provides more extensive measures of occupancy than single sensors, and it may also be possible that the sensor network response to occupancy could be used to differentiate between one or more occupants in a monitored space. Figure 6-6 depicts the relationship between room occupancy and PIR sensor pulse rate over the monitoring period in the data collected from the open-plan work area at the University of Nebraska. The relationship between sensor pulse rate and occupancy was weak. This is due to two factors, one related to human behavior, the second related to limitations with the sensors and DAS used to collect these data.

In the case of few occupants, even a single person can generate many sensor pulses within a minute if they walk around the space. This often occurred early in the mornings in this space when a custodial staff member entered the room to vacuum the carpet and empty the trash. In these instances, occupancy was low, but the number of sensor pulses received at the DAS was high because the occupant moved throughout the entire space, triggering pulses from all sensors. This aspect of these data also prevented the fruitful application of more extensive data fusion to this set of data.

When the room was more heavily occupied, limitations in the wireless communications protocol used by these sensors to transmit signals to the DAS reduced the number of signals recorded by the DAS. This is apparent in Figure 6-6, which shows fewer pulses received by the DAS once occupancy reached about 11 persons in the space. The wireless sensors employed to collect these data use a relatively unsophisticated communications protocol: if two signals were received at the DAS at the same time, neither was recorded. As room occupancy increased, it became more likely that two or more signals arrived at the DAS at the same instant. When this occurred, none of the signals were recorded by the DAS, and as a result the recorded sensor pulse rate, and the absolute number of sensor pulses received, fell slightly relative to occupancy.

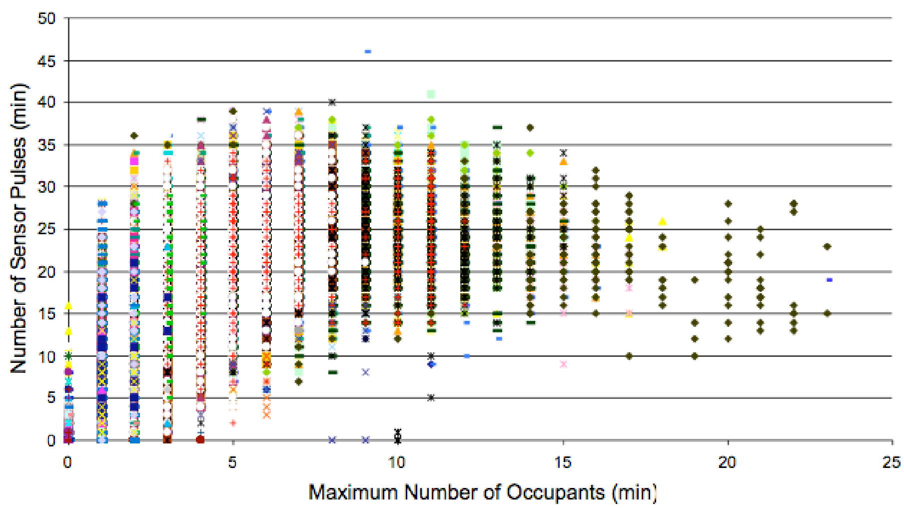


Figure 6-6. Relationship between sensor pulse rate and occupancy

Better communications protocols that include signal error checking and verification are required before the relationship between occupancy and sensor network pulse rate can be established, but even with these improvements, the correlation between pulse rate and occupancy is still likely to remain weak.

6.3.3 Comparison of individual measurements and sensor network outputs

Fusing the measurements from a network of sensors to produce a more accurate determination of occupancy might reduce the uncertainty associated with individual sensors. In the pilot study, eight data fusion techniques were utilized to calculate the sensor network output. This section describes the application of the following data fusion methods to the data collected from the ten private offices located at the University of Nebraska:

- Three logical functions (OR, AND and MAJORITY);
- Moving average;
- Rule-based reasoning, and;

- Belief network (BN).

The moving average was initially calculated as averaging back one step, i.e., the average of the current and the immediately past minute. The rule-based reasoning assumed 1-minute time persistency of sensor status, that is, if the algorithm determined occupancy at one particular minute, it assumed the space will be continuously occupied for another minute.

The belief network method adopted the same parameters as were used in the pilot study. These parameters include the probabilities of sensor pulsing conditional on sensor status and time of day, and the probabilities of time persistence of occupancy and sensor status.

Table 6-2 shows the average daily occupied time (in minutes) measured by each of the three detectors mounted in each room, along with the total occupied time (in minutes) determined by the six data fusion algorithms over the monitoring period.

Table 6-2. Average occupied time (min) for 10 private offices monitored over 59 days.

Room Number	PIR1	PIR2	PIR3	OR	AND	MAJORITY	Moving Average	Rule-Based	BN
1	27.5	59.9	58.1	67.4	24.1	54.0	78.1	78.5	71.4
2	2.6	10.2	7.2	12.3	1.8	5.8	17.8	12.4	10.0
3	63.8	113.6	123.2	143.5	50.9	106.2	166.5	163.2	152.5
4	59.4	114.5	145.3	154.4	40.3	124.5	168.3	166.2	147.3
5	102.0	108.6	74.0	114.8	68.0	101.8	124.9	124.3	117.4
6	54.5	27.4	55.9	87.8	9.0	41.1	109.4	88.2	82.4
7	81.4	83.7	61.9	109.7	42.0	75.3	132.8	131.5	123.6
9	121.7	106.4	102.1	157.7	57.3	115.3	181.8	184.4	160.0
10	143.4	152.6	183.0	210.5	94.3	174.2	235.5	236.1	215.3

It is interesting to note that although the occupied times determined by each sensor were quite different, varying on average by 44.7% (calculated as (max-min)/max), the results determined by the logical function OR, moving average, rule-based reasoning and belief network, were more similar, varying only by 18.0%.

As discussed in the pilot study, a functioning sensor always underestimates the total occupied time. Thus, among the three logical functions, OR yields results closest to the truth, if all sensors work properly: however, although it combines the output from all sensors, the logical function OR would still be expected to underestimate the occupied time. Unlike the pilot study, none of the sensors collecting occupancy data from private faculty offices at the University of NE were defective, so we can infer that the true occupied time will still be higher than the results calculated by the logical function OR (for example, in Room 2 of the pilot study, OR function underestimated true occupied time by about 20%).

The fusion methods of moving average, rule-based reasoning and belief network all generally yielded similar and slightly higher occupied time than the OR function. Although we cannot make the statement that these methods are more accurate than any individual sensor measurements at this point, since truth data were not available, the statement is consistent with data previously described in Chapter 5.

The other two logical functions, AND and MAJORITY, should have underestimated the occupied time, given the fact that no sensor failures were observed in this data set.

6.3.4 Modeling the effects of different time delays

Chapter 5 argued that if occupancy could be more accurately determined, a shorter time delay could be applied to achieve greater energy savings. Table 6-3 shows the modeled occupied time (in minutes) after the application of 5, 10, and 20-minute time delays to the data described in Table 6-2 (this is the same analysis as described in section 5.3.3). For the moving average method, data were averaged over intervals of 5, 10, and 20 minutes, respectively, instead of applying the corresponding time delay.

Table 6-3. Average occupied time (min) for 10 private offices monitored over 59 days with 5, 10, 20-minute time delay.

Time Delay (min)	Room Number	PIR1	PIR2	PIR3	OR	AND	MAJORITY	Moving Average	Rule-Based	BN
5	1	65.9	95.8	92.4	97.9	63.0	88.2	93.8	90.1	90.9
	2	6.2	27.4	24.3	35.5	5.3	16.0	31.4	17.2	22.6
	3	138.2	172.2	183.8	200.3	115.5	170.4	194.0	178.4	177.4
	4	75.3	174.3	188.8	194.9	66.1	175.0	189.7	181.7	173.7
	5	134.3	139.8	131.0	146.2	121.7	133.3	142.0	134.4	135.5
	6	99.1	80.9	104.8	149.1	30.9	88.1	141.7	109.1	125.9
	7	138.6	149.7	135.9	162.9	104.5	137.6	157.7	147.0	149.1
	8	54.3	67.8	46.7	77.7	28.8	57.4	72.5	63.5	66.1
	9	181.6	196.5	195.8	215.4	147.2	195.6	209.4	203.2	191.9
	10	197.4	242.3	254.3	266.4	171.3	247.0	260.9	251.4	246.9
10	1	86.2	113.5	109.7	115.6	83.1	102.3	107.2	103.4	103.9
	2	9.1	41.3	37.8	55.3	7.8	23.5	26.1	23.9	33.4
	3	176.7	191.7	202.4	227.6	148.3	187.3	190.5	192.3	191.5
	4	83.0	195.4	210.2	216.3	74.3	195.3	201.4	203.0	191.2
	5	147.5	157.1	154.1	164.4	139.8	146.3	150.5	146.8	147.9
	6	116.2	114.6	127.5	178.2	45.8	109.9	143.6	129.5	152.7
	7	155.0	171.6	162.8	183.2	131.5	157.3	161.1	161.5	162.4
	8	74.3	85.0	69.1	102.1	43.3	75.3	76.8	77.5	84.2
	9	204.9	226.3	223.0	240.3	184.7	218.2	218.2	221.7	209.9
	10	213.7	262.3	274.8	290.8	189.5	264.4	265.5	266.9	265.7
20	1	112.6	143.9	138.5	146.3	108.9	124.1	115.7	124.6	125.4
	2	15.1	67.3	62.5	93.1	12.7	36.7	30.2	37.4	53.3
	3	223.8	223.7	233.9	272.7	186.6	211.2	208.5	214.1	215.2
	4	93.7	228.7	242.6	249.6	86.5	225.9	214.3	233.3	217.8
	5	168.7	187.6	186.0	196.9	160.7	167.3	161.6	168.9	169.2
	6	138.7	162.9	159.5	216.8	69.6	139.4	158.0	167.8	189.3
	7	177.7	202.1	196.0	214.7	162.6	180.9	173.4	182.3	183.1
	8	102.6	109.3	99.8	137.8	65.9	98.4	84.4	112.0	109.1
	9	240.2	265.9	258.8	278.0	225.4	248.6	242.4	250.9	239.0
	10	240.1	288.2	305.8	330.3	207.0	288.9	277.8	297.0	295.8

The predictions of occupied time (in minutes) determined by every method increased as the time delay increased, as expected. If the sensor network determines occupancy more accurately, potential savings might arise from reductions in the time delay setting. Tables Table 6-4Table 6-5 model the reductions in occupied time that would have been achieved had these ten offices been controlled using a network of three PIR sensors using a 5 or 10-minute time delay setting, versus the operating time that would have been observed using a single sensor with a 20-minute time delay.

Table 6-4. Total occupied time (min) and percent reductions in cumulative occupied time between sensor network outputs plus 5-minute time delay, versus the maximum occupied time determined by individual sensor plus 20-minute time delay.

Room Number	Occupied minutes					Percent Reduction			
	Max of PIR + 20	OR + 5	Moving Average + 5	Rule-Based + 5	BN + 5	OR + 5	Moving Average + 5	Rule-Based + 5	BN + 5
1	143.9	97.9	93.8	90.1	90.9	-32.0%	-34.8%	-37.4%	-36.8%
2	67.3	35.5	31.4	17.2	22.6	-47.2%	-53.3%	-74.5%	-66.4%
3	233.9	200.3	194.0	178.4	177.4	-14.4%	-17.1%	-23.7%	-24.1%
4	242.6	194.9	189.7	181.7	173.7	-19.7%	-21.8%	-25.1%	-28.4%
5	187.6	146.2	142.0	134.4	135.5	-22.1%	-24.3%	-28.3%	-27.8%
6	162.9	149.1	141.7	109.1	125.9	-8.4%	-13.0%	-33.0%	-22.7%
7	202.1	162.9	157.7	147.0	149.1	-19.4%	-22.0%	-27.3%	-26.2%
8	109.3	77.7	72.5	63.5	66.1	-28.9%	-33.6%	-41.9%	-39.5%
9	265.9	215.4	209.4	203.2	191.9	-19.0%	-21.3%	-23.6%	-27.8%
10	305.8	266.4	260.9	251.4	246.9	-12.9%	-14.7%	-17.8%	-19.3%
Average						-22.4%	-25.6%	-33.3%	-31.9%

$$\text{Percent reduction (\%)} = \frac{\text{(Fused output + 5 min delay) - (Maximum of individual measurements + 20 min delay)}}{\text{Maximum of individual measurements + 20 min delay}} \quad (6.\ 1)$$

Table 6-5. Total occupied time (min) and percent reductions in cumulative occupied time between sensor network outputs plus 10-minute time delay, versus the maximum occupied time determined by individual sensor plus 20-minute time delay.

Room Number	Occupied minutes					Percent Reduction			
	Max of PIR + 20	OR + 10	Moving Average + 10	Rule-Based + 10	BN + 10	OR + 10	Moving Average + 10	Rule-Based + 10	BN + 10
1	143.9	115.6	107.2	103.4	103.9	-19.6%	-25.5%	-28.1%	-27.8%
2	67.3	55.3	26.1	23.9	33.4	-17.8%	-61.1%	-64.5%	-50.3%
3	233.9	227.6	190.5	192.3	191.5	-2.7%	-18.5%	-17.8%	-18.1%
4	242.6	216.3	201.4	203.0	191.2	-10.8%	-17.0%	-16.3%	-21.2%
5	187.6	164.4	150.5	146.8	147.9	-12.4%	-19.8%	-21.7%	-21.2%
6	162.9	178.2	143.6	129.5	152.7	9.4%	-11.8%	-20.5%	-6.2%
7	202.1	183.2	161.1	161.5	162.4	-9.3%	-20.3%	-20.1%	-19.6%
8	109.3	102.1	76.8	77.5	84.2	-6.5%	-29.7%	-29.1%	-22.9%
9	265.9	240.3	218.2	221.7	209.9	-9.6%	-18.0%	-16.6%	-21.1%
10	305.8	290.8	265.5	266.9	265.7	-4.9%	-13.2%	-12.7%	-13.1%
Average						-8.4%	-23.5%	-24.7%	-22.2%

$$\text{Percent reduction (\%)} = \frac{\text{(Fused output + 10 min delay) - (Maximum of individual measurements + 20 min delay)}}{\text{Maximum of individual measurements + 20 min delay}} \quad (6.\ 2)$$

Tables Table 6-4Table 6-5 show that using an output from a sensor network for system control would have produced reductions in system use, relative to what would have been observed if the systems in these offices were controlled using any of the three single points of detection applied in this study (differences between the sensor network +5 minutes signal and the maximum observed for the three individual sensors +20 minutes range from -22.4% to -33.3%; differences between the sensor network +10 minutes signal and the maximum observed for the three individual sensors +20 minutes range from -8.4% to -24.7%). Since no *a priori* information is available which of the three detectors provides the best measure of occupancy, it is appropriate to use the maximum total occupied time obtained from the three individual sensors, because this value provides the most conservative estimate that would have been obtained, had these ten spaces been monitored and controlled by any single points of detection.

6.4 Discussion

The two goals of this chapter were to confirm and extend the findings from the pilot study that showed individual differences in sensor performance, and to explore the reductions in system use that would result from application of a shorter time delay setting. Results confirmed that for single-point detection, there are large uncertainties associated with individual sensor performance. Thus, each individual sensor is less capable at characterizing occupancy than a sensor network consisting of several individual detectors. Six of the data analysis techniques introduced in Chapter 4 were applied to a subset of the raw data to calculate the sensor network output.

We concluded from the pilot study that properly functioning sensors always underestimate the occupied time, because sensors do not pulse continually even though the space is occupied. Four of the fusion methods, namely logical function OR, moving average, rule-based reasoning and belief network, yielded occupancies that are higher than any individual measurements, and close to each other. With more accurate occupancy measurements, shorter time delays can be applied to reduce system operating time and save energy. In the pilot study, the application of a 5-minute time delay to the sensor network resulted in a similar number of false-offs (i.e., similar degree of user satisfaction) as were observed through control with a single-detector and a 20-minute time delay. If a 5-minute time delay was applied to the sensor network instead of the typical 20 minutes in current single sensor applications, operating time would be reduced by an *additional* 22.4% to 33.3% (relative to the reductions that would have resulted from use of a single optimally placed sensor). A longer time delay of 10 minutes applied to the sensor network data stream eliminates false-offs (as demonstrated in the pilot study), and produces reductions of 8.4% to 24.7%, relative to the reduction that would have resulted from use of a single sensor with a 20-minute time delay.

7 Study III: Effects of Sensor Type and Mounting Position on Measured Occupancy

7.1 Introduction

The work described so far has revealed that there can be considerable uncertainty associated with the measurement of occupancy by individual occupancy sensors; consequently, long time delay settings are used by current systems to compensate for this uncertainty. A sensor network with proper data fusion methods, on the other hand, can characterize occupancy more accurately, and a shorter time delay can be applied. This can result in greater energy savings without increasing the number of false-offs when the sensor network is applied to lighting control.

This chapter describes a round-robin study conducted to directly compare occupancy measured by PIR sensors from several different manufacturers, mounted at different locations in a private office. This study had four goals. The first was to confirm that differences in measured occupancy would also be observed using sensors intended for use in commercial applications, rather than for home automation.

The second goal was to evaluate the effects of sensor position on measured occupancy. Previous studies described in this report show large differences in measured occupancy for the same brand of sensor; however, whether these differences are due to mounting position or individual sensor characteristics is unclear. This study was designed to evaluate the effect of sensor type and mounting position on measured occupancy.

The third goal was to confirm the advantages of sensor networks with more extensive truth data. The pilot study (described in Chapter 5) showed that a sensor network provided more accurate and reliable measurement of occupancy than a single sensor, but this conclusion was based on only two days data: in this chapter, the data collection period was extended to six weeks.

The fourth goal was to confirm the findings concerning possible reductions in system use that result from shorter time delay settings that can be applied to the sensor network, versus time delay applied to single sensors. The study described in Chapter 6 suggested that further reductions in system use were possible using shorter time delays applied to sensor network control, in addition to the savings that would have resulted from application of a 20-minute time delay when using a single sensor, and it would be useful to confirm this finding.

7.2 Methods and Procedures

The experiment was conducted in two private faculty offices located at the University of Nebraska's Peter Kiewit Institute, in Omaha, NE. Four groups of occupancy sensors were mounted on three of the four walls in each office to record occupancy over a six-week data collection period. At the end of every week, all sensors were moved to an adjacent wall in the same office. The occupancies measured by different sensor types at respective locations were compared to evaluate the effects of sensor type and mounting location on measured occupancy.

A set of four sensors was mounted on each of three walls in each office. Each set of four sensors consisted of a commercially available wall sensor, one assembled sensor, and two wireless sensors mounted adjacent to one another on one wall, as shown in Figure 7-1.

Figure 7-1. Sensor arrangement on one wall in the round-robin study

Specific details on each sensor are summarized in Table 7-1. Two of the same brand wireless sensors were mounted on each wall, to test the variation within this sensor type. Since an identical set of four sensors was deployed on three walls, each office was monitored by a total of 12 sensors.

Table 7-1. Sensors used in round-robin study

Sensor Type	Picture	Model	Manufacturer	Number used in each office
Commercial		Motion Sensing Wall Switch 6105	Cooper Wiring Devices	3
Assembled		DIY Kit 30. PIR Detector	Packed by A1parts	3
Wireless		PMS18 Indoor Occupancy Sensor	X10 Inc.	6

The commercial and the assembled sensors were connected to the same DAS described in Chapter 5; the wireless sensors sent signals to the DAS described in Chapter 6.

All sensors were set at maximum sensitivity. The commercial and assembled sensors were equipped with photosensors that prevent pulsing, and thereby switching lights on, in the event of adequate lighting at the sensor. This feature was disabled to ensure that the sensors always responded to motion.

Apple iSight digital video cameras were mounted in each room diagonally opposite the single door, providing a clear record of each entry and exit event. A separate image was collected every two seconds, and individual images were automatically appended to a QuickTime file, which provided a time-lapse movie showing activity in each room over the two-day monitoring period. A human observer manually reviewed the time-lapse movies, and occupancy within each minute was recorded in a spreadsheet file, for later comparison with the occupancy data collected by the sensors.

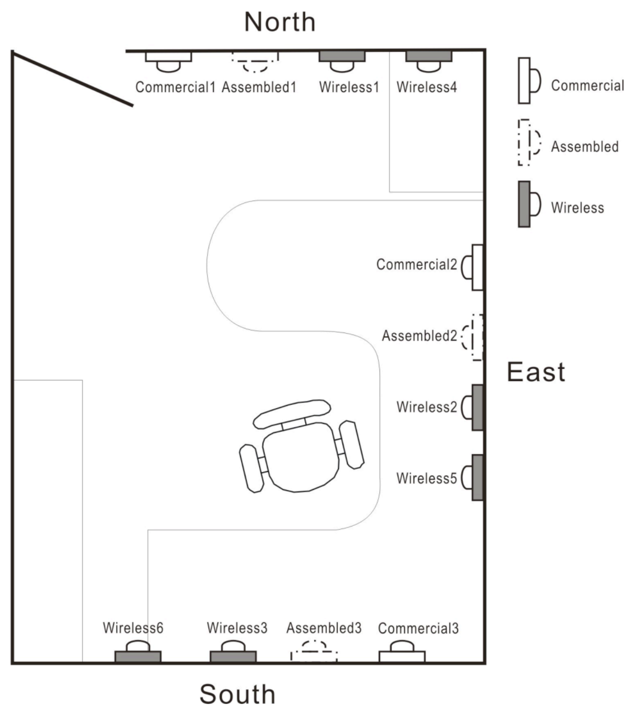
Raw data collected by both data acquisition systems were converted to time-series data with one-minute resolution. The data conversion rule was the same as used in the previous chapter: if a sensor pulsed within a minute, the sensor output for that minute was coded as "1", otherwise, the sensor status was coded as "0" for that minute.

The room dimensions and overall sensor arrangement are shown in Figure 7-2. Each of the shaded boxes in the figure represents the location of each set of four sensors shown in Figure 7-1. From Figure 7-2 we can see that sensors mounted on the East and South walls were closer to the occupant than those mounted on the North wall, for the "customary" seating position in each office.

Figure 7-2. Room dimensions and overall sensor arrangement. Each of the shaded areas represents the mounting location of a set of four sensors.

At the beginning of each week, the four sensor sets were rotated in a clockwise fashion, as shown in Figure 7-3.

Week 1 & 4



Week 2 & 5

Figure 7-3. Round-robin rotation of sensor mounting positions. The mounting positions in the sketches are not to scale; all four sensors mounted on the same wall were in a much smaller area, as Figure 7-2 shows.

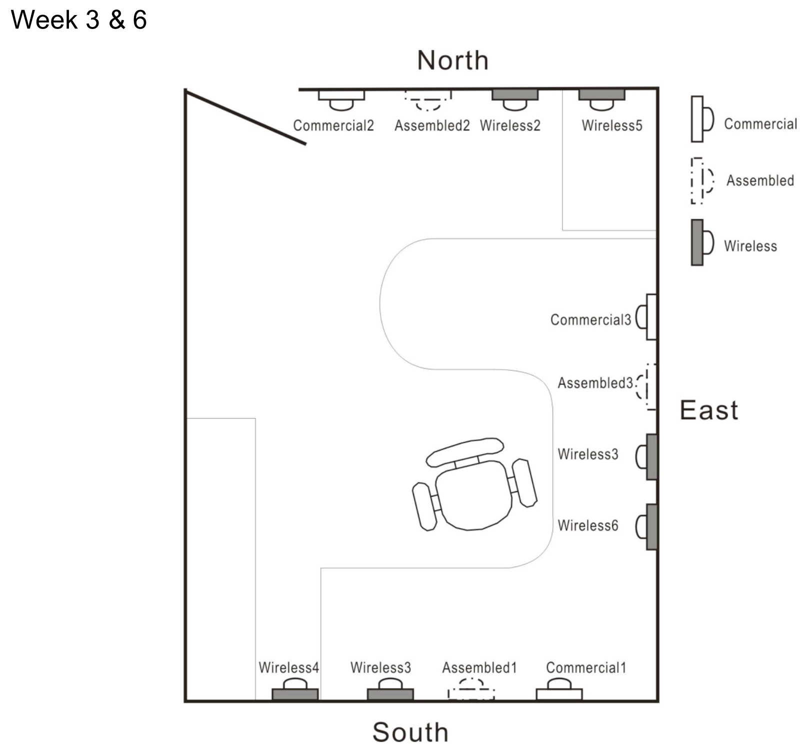


Figure 7-3. Round-robin rotation of sensor mounting positions. The mounting positions in the sketches are not to scale; all four sensors mounted on the same wall were in a much smaller area, as Figure 7-2 shows. (Cont'd)

During the first three weeks, two of the assembled sensors in Room 2 were defective, pulsing continually throughout the day: these two sensors were replaced at the beginning of the fourth week, and data collection continued.

7.3 Results

The discussion of the results is divided into four sections. The first section summarizes the occupied time (in minutes) measured by each sensor. This analysis showed the general occupancy pattern in these two offices during the data collection period, and identified defective sensors. The second section reports the results of a mixed-design ANOVA[109], which was applied to evaluate the effects of sensor type and mounting position on measured occupancy. The third section compares the occupancy determined by individual sensors versus the sensor network. Finally, the fourth section compares the energy savings that can be achieved through the use of a sensor network versus a single sensor.

7.3.1 Occupied time

The occupied time (in minutes) measured each day as a function of sensor type is presented in Table 7-2. Occupied The first day in each week is Sunday, and the last day is Saturday. The data are arranged such that numbers in the same column represent the measured occupancy from the same sensor. The sensor location listed in the first column indicates the arrangement of sensors at that week. For example, "ESN" means Sensor 1 was mounted on the East wall, Sensor 2 was on the South wall, and Sensor 3 was on the North wall. The true occupied time (in minutes), as determined by human review of the digital video, is also listed in the table.

Table 7-2. Occupied time (min) measured by each sensor in each day

Room 1:

Location	Days	Truth	Commercial			Assembled			Wireless1			Wireless2		
			1	2	3	1	2	3	1	2	3	1	2	3
	1	5	4	5	5	6	6	5	4	5	6	5	5	5
	2	415	44	93	202	281	398	406	21	134	129	20	129	65
	3	437	38	106	185	220	422	420	23	186	143	29	178	83
Week1 N E S	4	445	38	115	207	154	412	425	26	147	135	30	166	64
	5	428	47	106	225	150	413	416	191	149	162	34	178	54
	6	386	38	113	157	139	363	382	17	157	101	27	178	47
	7	0	0	0	0	1	1	0	0	2	1	1	1	1
	8	177	49	106	31	142	177	106	77	45	31	94	38	27
	9	435	116	172	29	259	430	259	136	52	36	125	56	25
	10	402	90	176	40	290	386	255	141	76	32	129	55	21
Week2 E S N	11	451	112	181	48	312	447	316	200	81	49	185	63	27
	12	435	105	230	45	351	431	331	202	93	33	173	73	27
	13	416	93	173	32	268	395	220	143	64	25	148	55	17
	14	0	0	0	0	0	0	1	0	2	1	1	1	1
	15	0	0	0	0	1	0	0	0	1	1	1	1	1
	16	398	214	23	115	387	343	380	195	23	237	173	22	159
	17	507	270	55	119	497	416	482	214	43	272	230	38	204
Week3 S N E	18	334	140	52	107	325	264	307	162	39	136	122	30	120
	19	365	185	35	119	358	286	354	157	33	172	141	28	140
	20	387	224	53	117	360	273	361	176	40	193	149	39	134
	21	0	0	0	0	0	4	0	0	1	1	1	1	1
	22	5	4	4	5	7	9	75	3	4	6	3	4	4
	23	210	65	113	166	133	204	207	38	151	99	53	127	82
	24	214	66	127	180	151	216	212	34	158	123	52	131	95
Week4 N E S	25	314	135	179	281	221	311	298	91	230	203	104	234	153
	26	28	17	20	25	22	27	30	14	18	21	13	21	18
	27	183	107	132	165	145	186	181	78	136	104	80	131	96
	28	2	3	2	3	2	3	135	0	1	4	1	1	3
	29	6	6	6	5	9	52	43	4	6	4	5	8	4
	30	332	223	252	149	335	334	280	200	140	122	227	182	89
	31	276	129	191	46	290	294	191	136	121	27	153	115	20
Week5 E S N	32	234	154	201	102	236	235	205	176	136	100	172	163	83
	33	299	210	237	110	300	303	249	206	145	117	218	171	86
	34	212	155	183	120	218	220	209	146	123	80	149	120	76
	35	0	0	0	0	0	36	2	0	1	1	1	2	1
	36	7	7	4	7	32	12	8	4	3	5	6	2	3
	37	251	243	149	222	252	242	259	201	157	214	205	153	201
	38	142	119	38	93	146	127	146	126	18	79	91	27	78
Week6 S N E	39	404	348	151	293	364	361	390	273	175	271	302	152	224
	40	215	186	69	154	196	207	221	154	65	152	141	64	120
	41	119	118	71	101	117	111	124	102	49	107	106	50	83
	42	0	0	0	0	0	0	0	0	1	1	1	1	1
Weekday Average		322	134	127	132	249	302	284	133	105	122	126	104	90
PCT Dev. From Truth			-58.4%	-60.8%	-59.1%	-22.7%	-6.4%	-12.0%	-58.9%	-67.6%	-62.0%	-60.9%	-67.7%	-72.2%

Table 7-2. Occupied time (min) measured by each sensor in each day (Cont'd)

Room 2:

Location	Days	Truth	Commercial			Assembled (1)			Wireless1			Wireless2		
			1	2	3	1	2	3	1	2	3	1	2	3
Week1 N E S	1	0	0	0	0	1015	1	1137	0	1	1	1	1	1
	2	2	2	2	2	1020	3	1168	1	3	1	2	1	2
	3	181	51	176	146	1069	190	1183	42	150	105	38	127	156
	4	15	15	15	15	1037	17	1138	15	15	15	15	14	14
	5	146	70	148	121	1142	154	1223	57	132	102	53	104	118
	6	159	100	160	130	1055	176	1181	82	149	107	76	118	127
	7	0	0	0	0	1044	2	1167	0	1	1	1	1	1
Week2 E S N	8	0	0	0	0	812	2	951	0	1	1	1	1	1
	9	309	249	172	135	918	348	928	266	256	45	216	187	42
	10	546	401	272	236	978	540	899	429	426	114	383	244	102
	11	415	266	181	141	912	408	815	340	320	53	253	154	50
	12	267	191	154	134	843	267	779	213	210	75	199	144	60
	13	2	2	2	2	616	3	672	2	5	2	1	5	1
	14	0	0	0	0	677	3	778	0	1	1	1	1	1
Week3 S N E	15	0	0	0	0	1131	2	439	0	1	1	1	1	1
	16	39	32	13	29	1147	36	420	19	8	31	26	6	28
	17	1	0	0	0	1114	1	430	1	2	2	0	3	2
	18	223	245	108	213	1186	217	594	192	86	130	202	67	194
	19	0	0	0	0	1155	1	322	0	1	1	1	1	1
	20	469	425	185	386	1228	419	717	307	93	275	358	67	347
	21	28	28	21	25	1163	30	431	11	5	2	23	5	20
Week4 N E S	22	0	0	0	0	0	2	1	0	1	1	1	1	1
	23	395	110	358	328	159	398	395	83	308	318	67	329	327
	24	286	163	273	249	175	287	289	112	240	241	81	241	247
	25	314	89	275	242	75	314	317	34	228	237	40	223	249
	26	218	89	185	173	96	220	233	48	164	169	43	160	169
	27	351	145	328	276	152	353	362	103	282	279	83	272	292
	28	0	0	0	0	0	2	0	0	2	1	1	1	1
Week5 E S N	29	0	0	0	0	0	7	0	0	1	1	1	1	1
	30	306	286	286	126	283	318	255	229	230	75	205	191	72
	31	374	339	339	101	339	368	321	304	301	79	262	257	84
	32	192	181	183	51	180	204	152	165	168	41	135	119	32
	33	500	421	448	174	454	503	425	384	390	162	332	291	161
	34	363	322	346	158	339	376	344	308	310	155	268	237	154
	35	304	282	269	49	292	302	227	251	270	32	187	188	34
Week6 S N E	36	0	0	0	0	0	1	0	0	2	1	1	1	1
	37	384	382	220	325	363	364	385	290	148	296	311	122	305
	38	371	378	170	315	296	333	366	268	126	261	296	115	267
	39	401	383	182	312	360	384	402	261	131	258	308	105	265
	40	273	302	119	226	275	251	274	207	88	203	247	63	203
	41	358	342	106	286	326	332	356	258	87	242	286	66	261
	42	0	0	0	0	0	0	1	0	1	1	1	1	1
Weekday Average	All 6 weeks	262	199	180	168				167	169	136	160	134	144
	First 3 weeks	185				1028	185	831						
	Last 3 weeks	339				258	334	325						
PCT Dev. From Truth	All 6 weeks		-23.9%	-31.2%	-36.0%				-36.1%	-35.7%	-48.2%	-39.1%	-48.7%	-44.9%
	First 3 weeks					455.9%	0.2%	349.5%						
	Last 3 weeks					-23.9%	-1.6%	-4.1%						

(1) Assembled 1 and Assembled 3 in Room 2 were replaced at the beginning of the fourth week.

Two of the assembled sensors in Room 2 (Assembled 1 and Assembled 3) pulsed continually through the first three weeks of data collection (generating about 1000 pulses per day out of a total of 1440 possible pulses [or minutes] per day). These two sensors were defective and were therefore replaced at the beginning of the fourth week. Data from the defective sensors were not included in subsequent statistical analyses.

Since there was little occupancy during the weekends (and the data file for the weekends were mostly zeros), these time periods were less meaningful in comparing the performance of sensors than the weekday data, so they were also excluded from further analysis. The weekday average occupancies are listed in the bottom row(s) of the table. For the assembled sensors in Room 2, two averages were calculated: before and after the sensor replacement.

In terms of weekday average, all properly functioning sensors underpredicted occupancy. In Room 1, sensors underpredicted occupied time by 6.4% to 72.2%, while in Room 2, the occupied time was underestimated by 1.6% to 48.7%. It is noticeable that when sensors were mounted on the North wall (furthest from the occupant), they pulsed less frequently than when they were mounted on the East or South wall (closest to the occupant).

More detailed analysis of daily occupied time shows that the assembled sensors were most sensitive, and sometimes slightly overestimated occupied time. The daily deviation of occupied time measured by assembled sensors in both rooms ranges from -76.1% (underestimation) to 7.1% (overestimation).

7.3.2 Effects of sensor type and mounting position

To study the differences in sensor performance, the accuracy (φ correlation of measured occupancy compared against truth) was used as the dependent variable instead of the occupied time. The sensors were measuring different days of occupancy when they were mounted at different locations, and so the occupied time (in minutes) can be expected to vary as a function of office and day. While the effect of mounting location and the sensor type are of the most interest, the value of the φ correlation is preferable for use in this analysis because it is a characteristic of the sensor itself, and does not vary with true occupancy.

Table 7-3 shows the summary of weekday average occupied time (in minutes) and the φ correlation. The number in each cell was averaged over data collected from all the properly functioning sensors: for the commercial and wireless sensors, and the assembled sensors in Room 1, data were averaged over six week period; for the assembled sensor in Room 2, only data from the last three weeks was used in calculating the mean since two out of the three assembled sensors were defective during the first three weeks.

Table 7-3. Mean occupied time (min) and accuracy (φ) of the two rooms over six weeks

Sensor Type	Location	Room 1		Room 2	
		Mean Occupied time (in minutes)	Mean Accuracy (φ)	Mean Occupied time (in minutes)	Mean Accuracy (φ)
Commercial	North	67.07	0.4253	106.50	0.6460
	East	131.03	0.6031	222.33	0.8945
	South	194.53	0.7497	218.47	0.8815
Assembled(1)	North	225.37	0.7881	254.53	0.8128
	East	294.50	0.9320	330.00	0.9736
	South	315.13	0.9672	332.33	0.9406
Wireless 1	North	59.87	0.3749	71.60	0.5181
	East	166.17	0.6842	200.33	0.8301
	South	133.70	0.5976	199.77	0.7924
Wireless 2	North	50.53	0.3610	62.37	0.4544
	East	153.83	0.6564	190.53	0.7556
	South	115.67	0.5627	185.50	0.7846
All	North	100.71	0.4873	123.75	0.6078
	East	186.38	0.7189	235.80	0.8635
	South	189.76	0.7193	234.02	0.8498

(1) In Room 2, only data from the last three weeks are used.

As can be observed from the above table, in each group, the sensors pulsed least frequently, and accuracy was lowest, when they were mounted on the North wall, where sensors were located furthest from the nominal occupant position (refer to Figure 7-2 for a plan view of the offices). Further, the assembled sensors pulsed more frequently than all the other sensor types, suggesting that this particular sensor type was more sensitive than either the commercial or wireless sensors. The assembled sensors were also always more accurate than the two other sensor types. The φ correlation essentially checks the similarities between two series of binary data: for a functioning sensor, more sensitive usually means having more correct and fewer missed pulses, thus the φ correlation is usually higher. Finally, the two groups of wireless sensors behaved similarly to each other, as expected.

These conclusions were confirmed using a mixed design ANOVA[109], with sensor group and room number representing the between-subjects factors, and mounting position representing the within-subjects factor in the analysis. The dependent variable was the accuracy of sensor response, quantified using the φ correlation between the measured value and the truth. Table 7-4 summarizes the results of the between-subjects tests applied to data from the two rooms. This analysis showed statistically significant main effects of sensor type and room on sensor accuracy, and a statistically significant interaction effect between room and sensor type on accuracy, suggesting the effect of sensor type on accuracy in Room 1 was different than in Room 2.

Table 7-4. Tests of between-subjects effects (Sensor Type)

Dependent variable: Accuracy (φ)

Source	Sum of Squares	df	Mean Square	F	Sig.
Intercept	12.022	1	12.022	6377.728	**0.000**
Sensor Type	0.337	3	0.112	59.506	**0.000**
Room	0.104	1	0.104	55.336	**0.000**
Room * Sensor Type	0.033	3	0.011	5.789	**0.007**
Error	0.030	16	0.002		

Figure 7-4 plots the mean φ correlation with 95% confidence interval in each room for all sensor types, and Table 7-5 describes the results of the post-hoc ANOVA paired comparison tests.

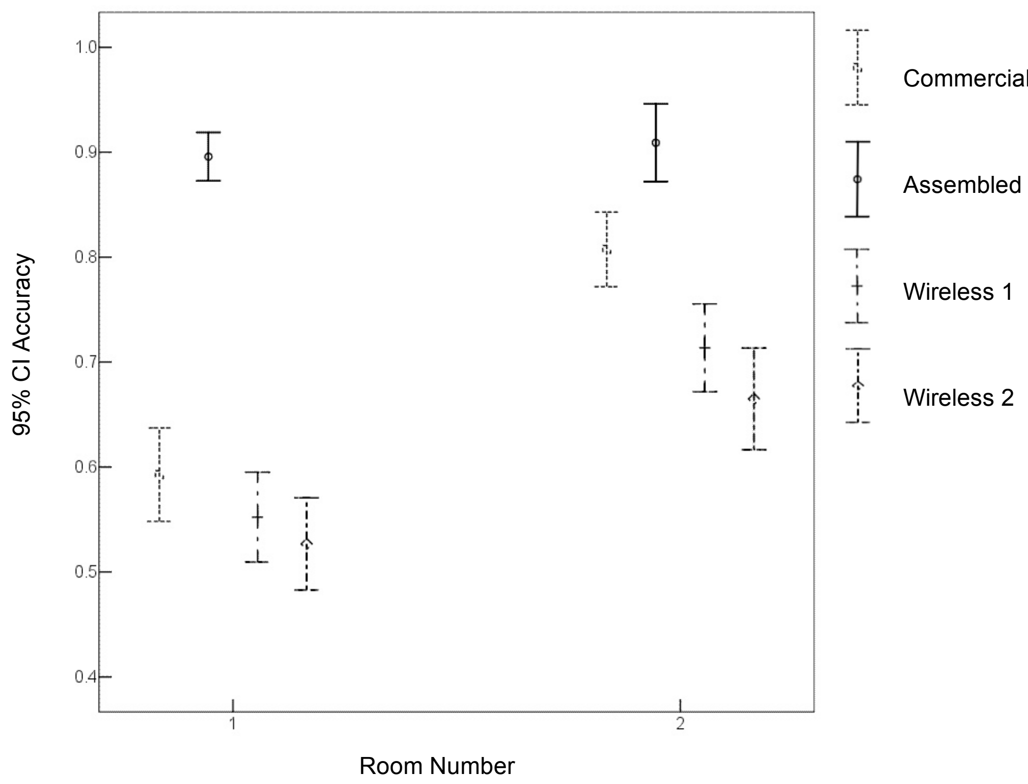


Figure 7-4. Estimated marginal means of accuracy (*φ*) by sensor type and room with error bar showing 95% confidence interval of accuracy (*φ*)

Table 7-5. Pairwise comparisons of accuracy (φ) by sensor type

Room	(I) Sensor Type	(J) Sensor Type	Mean Difference (I-J)	Std. Error	Sig.(a)
1	Commercial	Assembled	-0.303	0.035	**0.000**
	Commercial	Wireless1	0.041	0.035	0.270
	Commercial	Wireless2	0.066	0.035	0.081
	Assembled	Wireless1	0.344	0.035	**0.000**
	Assembled	Wireless2	0.369	0.035	**0.000**
	Wireless1	Wireless2	0.026	0.035	0.481
2	Commercial	Assembled	-0.102	0.035	**0.011**
	Commercial	Wireless1	0.094	0.035	**0.018**
	Commercial	Wireless2	0.142	0.035	**0.001**
	Assembled	Wireless1	0.195	0.035	**0.000**
	Assembled	Wireless2	0.244	0.035	**0.000**
	Wireless1	Wireless2	0.049	0.035	0.189

These analyses show the following:

- The assembled sensors were more accurate than the other sensor types;
- The sensors in Room 2 were slightly more accurate than the sensors in Room 1 (digital video showed that the occupant in Room 2 moved more frequently than the occupant in Room 1);
- The two wireless sensors in each room had almost the same accuracy;
- In Room 2, the commercial sensors were more accurate than the two wireless sensors, but in Room 1, these two types of sensors had almost the same accuracy.

Table 7-6 summarizes the results of the within-subjects test of the two rooms. This analysis showed a statistically significant main effect of mounting position on sensor accuracy, and a statistically significant interaction between mounting position and sensor type on accuracy.

Table 7-6. Tests of within-subjects effects (mounting position)

Dependent variable: Accuracy (φ correlation)

Source	Sum of Squares	df	Mean Square	F	Sig.
Position	0.924	2	0.462	109.069	**0.000**
Position * Room	0.002	2	0.001	0.206	0.815
Position * Sensor Type	0.071	6	0.012	2.810	**0.026**
Position * Room * Sensor Type	0.040	6	0.007	1.556	0.192
Error (Position)	0.136	32	0.004		

Figure 7-5, plots the mean φ correlation at each mounting position for all sensor type and Table 7-7 describes the results of the post-hoc ANOVA paired comparison test.

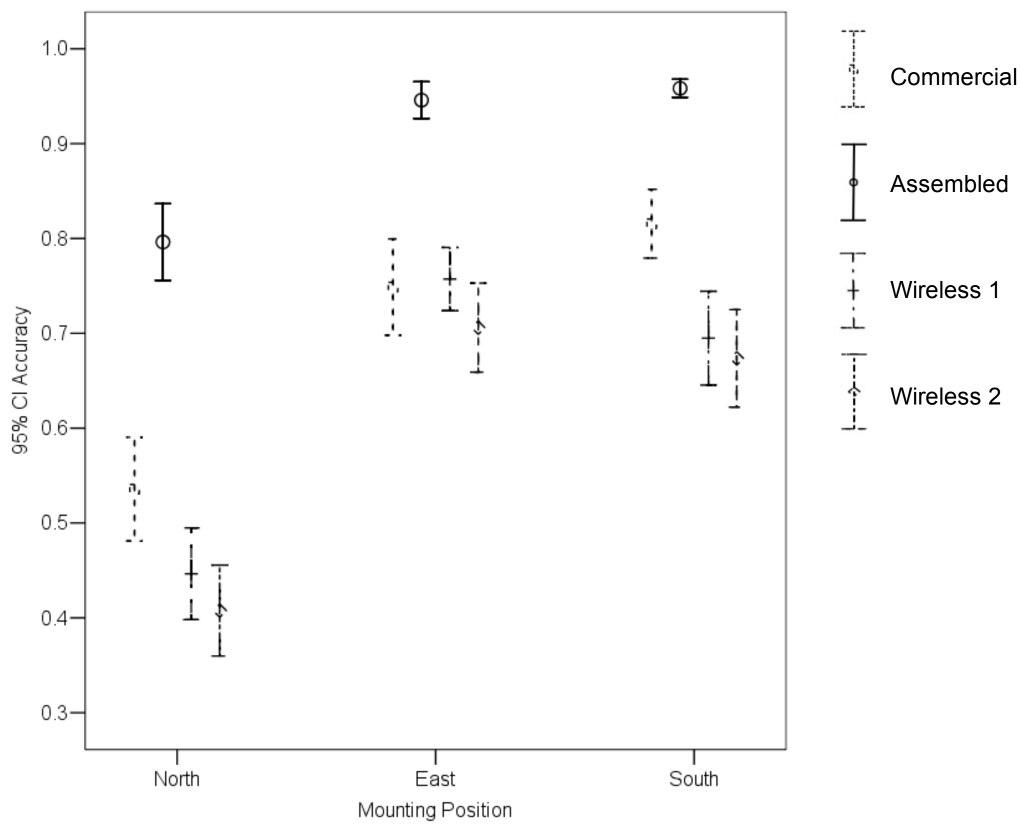


Figure 7-5. Estimated marginal means of accuracy (*φ*) by sensor type and mounting position with error bar showing 95% confidence interval of accuracy (*φ*)

Table 7-7. Pairwise comparisons of accuracy (φ) by mounting position

Position	(I) Sensor Type	(J) Sensor Type	Mean Difference (I-J)	Std. Error	Sig.(a)
North	Commercial	Assembled	-0.265	0.049	**0.000**
	Commercial	Wireless1	0.089	0.049	0.088
	Commercial	Wireless2	0.128	0.049	**0.019**
	Assembled	Wireless1	0.354	0.049	**0.000**
	Assembled	Wireless2	0.393	0.049	**0.000**
	Wireless1	Wireless2	0.039	0.049	0.441
East	Commercial	Assembled	-0.204	0.024	**0.000**
	Commercial	Wireless1	-0.008	0.024	0.731
	Commercial	Wireless2	0.043	0.024	0.091
	Assembled	Wireless1	0.196	0.024	**0.000**
	Assembled	Wireless2	0.247	0.024	**0.000**
	Wireless1	Wireless2	0.051	0.024	**0.047**
South	Commercial	Assembled	-0.138	0.042	**0.004**
	Commercial	Wireless1	0.121	0.042	**0.010**
	Commercial	Wireless2	0.142	0.042	**0.004**
	Assembled	Wireless1	0.259	0.042	**0.000**
	Assembled	Wireless2	0.280	0.042	**0.000**
	Wireless1	Wireless2	0.021	0.042	0.615

These analyses show the following:

- All sensors were less accurate when mounted on the North wall (located furthest from the occupant) compared to East and South wall mounting locations (located closer to the occupant).
- When mounted on the North wall, commercial sensors exhibited about the same accuracy as Wireless 1, but were more accurate than Wireless 2; when mounted on the East wall, commercial and wireless sensors all had almost the same accuracy; however when mounted on the South wall, commercial sensors were more accurate than the wireless sensors.

It is interesting to note that these results confirm the uncertainty associated with single-points of detection, since they show that sensor performance will vary with sensor type and mounting position. A single measurement point provides a less accurate measure of occupancy than a sensor network.

7.3.3 Comparison of individual measurements and sensor network outputs

To reduce the uncertainty associated with individual sensors (due to unpredictable mounting position, for example), the outputs from each sensor in a sensor network can be combined using a fusion technique to produce a more accurate determination of occupancy. In this section, the outputs from different data fusion techniques are compared against one another, and actual occupancy. The eight data fusion techniques applied to these data were:

- Three logical functions (OR, AND and MAJORITY);
- Moving average;
- Rule-based reasoning;
- Belief network (BN);
- Least squares estimation (LSE), and;
- Artificial neural network (NN).

As in Chapter 6, the moving average was initially calculated as averaging back one step (i.e. one minute). The rule-based reasoning method assumed a 1-minute time persistency of sensor status, that is, if the algorithm determined occupancy during one minute, it assumed the space was continuously occupied for the next minute. In subsequent applications of different time delay settings to the fused data, the moving average outputs were calculated by averaging over longer intervals.

The belief network is constructed based on a general model of room occupancy and conditional probabilities associated with sensor pulsing, as described in section 4.5. The determination of network parameters is described in 11Appendix A.

Table 7-8 shows the comparison of measures by various methods. The outcomes of each method are compared by means of total occupied time (in minutes), accuracy, number of false-ons, number of false-offs, as well as the different values in the cross table used to calculate the φ coefficient.

Overall, as already noted, the sensors installed in Room 1 pulsed less frequently than those in Room 2 when the space was occupied, as shown by the over 50% deviation of measured occupied time from truth for the commercial and wireless sensors, while in Room 2, the deviation between sensor measurements and truth was usually from 20% to 50%. Although there might be some individual differences in the sensitivities of sensors from the same group, review of the digital video showed that the occupant in Room 1 was less active than the occupant in Room 2. Since sensors are less responsive to small-sized movements[42], these observations are reasonable since the characteristics of movements will have an impact on the sensor pulsing frequency.

Table 7-8. Comparison of data fusion techniques

Room 1:

	Room 1	Truth (Desired)	Sensor 1	Sensor 2	Sensor 3	OR	AND	MAJORITY	Moving Average	Rule-Based	BN	LSE	NN
Commercial (6 weeks)	Occupied Time (min)	322	134.3	126.5	131.8	201.4	65.8	125.4	258.2	215.6	225.5	201.0	201.1
	PCT Dev. from Truth	0	-58.3%	-60.7%	-59.1%	-37.4%	-79.6%	-61.0%	-19.8%	-33.0%	-30.0%	-37.6%	-37.5%
	Accuracy (φ)	1	0.58	0.56	0.58	0.73	0.40	0.56	0.82	0.73	0.77	0.73	0.73
	N_{11} (Truth=1, Measured=1)	322	132	124	130	198	65	123	246	204	220	198	198
	N_{10} (Truth=1, Measured=0)	0	191	198	193	124	258	200	76	118	103	125	125
	N_{01} (Truth=0, Measured=1)	0	3	2	2	3	1	3	12	11	6	3	3
	N_{00} (Truth=0, Measured=0)	1118	1115	1115	1115	1114	1116	1115	1105	1106	1112	1114	1114
	No. of False-offs	0	36	37	37	48	20	40	27	19	18	48	48
	No. of False-ons	0	1	1	1	1	0	1	1	1	1	1	1
Assembled (6 weeks)	Occupied Time (min)	322	249.2	301.9	283.9	325.2	214.1	295.7	341.8	334.0	344.6	323.9	320.7
	PCT Dev. from Truth	0	-22.6%	-6.2%	-11.8%	1.0%	-33.5%	-8.2%	6.2%	3.7%	7.0%	0.6%	-0.4%
	Accuracy (φ)	1	0.84	0.94	0.90	0.97	0.77	0.93	0.96	0.97	0.95	0.97	0.97
	N_{11} (Truth=1, Measured=1)	322	246	297	280	317	213	293	321	320	322	316	315
	N_{10} (Truth=1, Measured=0)	0	76	25	43	6	109	30	2	2	1	6	8
	N_{01} (Truth=0, Measured=1)	0	3	5	4	9	1	3	21	14	23	8	6
	N_{00} (Truth=0, Measured=0)	1118	1114	1113	1113	1109	1117	1115	1097	1104	1095	1110	1112
	No. of False-offs	0	32	16	23	4	46	19	1	1	0	4	6
	No. of False-ons	0	2	3	3	5	0	1	4	1	7	4	3
Wireless 1 (6 weeks)	Occupied Time (min)	322	132.6	104.6	122.5	216.4	34.1	109.3	282.9	218.6	248.1	215.3	216.4
	PCT Dev. from Truth	0	-58.8%	-67.5%	-62.0%	-32.8%	-89.4%	-66.1%	-12.1%	-32.1%	-23.0%	-33.1%	-32.8%
	Accuracy (φ)	1	0.56	0.50	0.56	0.74	0.29	0.53	0.83	0.75	0.81	0.74	0.74
	N_{11} (Truth=1, Measured=1)	322	127	102	121	207	34	109	262	211	240	206	207
	N_{10} (Truth=1, Measured=0)	0	195	221	201	115	288	214	61	112	82	116	115
	N_{01} (Truth=0, Measured=1)	0	5	3	1	9	0	0	21	8	8	9	9
	N_{00} (Truth=0, Measured=0)	1118	1112	1115	1116	1109	1118	1117	1096	1110	1110	1109	1109
	No. of False-offs	0	50	43	47	54	18	48	25	17	16	55	54
	No. of False-ons	0	3	2	1	6	0	0	4	0	2	5	6
Wireless 2 (6 weeks)	Occupied Time (min)	322	126.0	104.3	89.7	192.4	31.7	96.0	258.6	188.0	214.0	191.4	192.4
	PCT Dev. from Truth	0	-60.9%	-67.6%	-72.1%	-40.2%	-90.2%	-70.2%	-19.7%	-41.6%	-33.5%	-40.6%	-40.2%
	Accuracy (φ)	1	0.56	0.51	0.47	0.71	0.28	0.49	0.81	0.68	0.76	0.71	0.71
	N_{11} (Truth=1, Measured=1)	322	124	103	89	188	32	95	244	180	210	188	188
	N_{10} (Truth=1, Measured=0)	0	198	220	234	134	291	227	78	143	112	135	134
	N_{01} (Truth=0, Measured=1)	0	2	2	1	4	0	1	14	8	4	4	4
	N_{00} (Truth=0, Measured=0)	1118	1116	1116	1116	1114	1117	1117	1103	1109	1114	1114	1114
	No. of False-offs	0	46	43	40	56	17	40	29	15	18	56	56
	No. of False-ons	0	2	1	1	3	0	1	3	1	1	3	3

Table 7-8. Comparison of data fusion techniques (Cont'd)

Room 2:

	Room 2	Truth (Desired)	Sensor 1	Sensor 2	Sensor 3	OR	AND	MAJORITY	Moving Average	Rule-Based	BN	LSE	NN
Commercial (6 weeks)	Occupied Time (min)	262	199.4	180.2	167.7	241.5	102.9	202.9	266.0	271.9	257.1	223.4	238.6
	PCT Dev. from Truth	0	-23.9%	-31.2%	-36.0%	-7.8%	-60.7%	-22.6%	1.5%	3.8%	-1.9%	-14.7%	-8.9%
	Accuracy (Ψ)	1	0.81	0.78	0.75	0.91	0.58	0.84	0.93	0.94	0.93	0.87	0.91
	N_{11} (Truth=1, Measured=1)	262	192	176	165	233	102	199	249	253	245	216	230
	N_{10} (Truth=1, Measured=0)	0	70	86	97	29	160	63	13	9	17	46	32
	N_{01} (Truth=0, Measured=1)	0	7	4	3	9	1	4	17	19	12	8	8
	N_{00} (Truth=0, Measured=0)	1178	1171	1174	1175	1169	1177	1174	1161	1159	1166	1170	1170
	No. of False-offs	0	22	28	32	17	33	31	6	2	4	17	18
	No. of False-ons	0	2	1	1	3	0	2	2	1	2	3	3
Assembled (last 3 weeks)	Occupied Time (min)	339	258.1	333.7	325.1	347.8	244.3	324.8	362.6	351.5	345.1	345.0	342.9
	PCT Dev. from Truth	0	-23.9%	-1.6%	-4.1%	2.6%	-27.9%	-4.2%	7.0%	3.7%	1.8%	1.8%	1.2%
	Accuracy (Ψ)	1	0.83	0.96	0.95	0.97	0.81	0.97	0.95	0.97	0.96	0.97	0.97
	N_{11} (Truth=1, Measured=1)	339	255	326	320	335	243	323	338	338	331	335	334
	N_{10} (Truth=1, Measured=0)	0	84	13	19	4	96	16	1	1	8	4	5
	N_{01} (Truth=0, Measured=1)	0	3	8	5	13	1	2	25	14	14	10	9
	N_{00} (Truth=0, Measured=0)	1101	1098	1093	1096	1088	1100	1099	1076	1087	1087	1091	1092
	No. of False-offs	0	28	9	11	3	34	12	1	1	0	3	4
	No. of False-ons	0	2	3	1	6	0	0	5	0	2	4	4
Wireless 1 (6 weeks)	Occupied Time (min)	262	167.3	168.6	135.8	238.9	55.9	176.8	271.4	256.0	255.5	235.6	218.6
	PCT Dev. from Truth	0	-36.1%	-35.7%	-48.2%	-8.8%	-78.7%	-32.5%	3.6%	-2.3%	-2.5%	-10.1%	-16.6%
	Accuracy (Ψ)	1	0.75	0.75	0.67	0.90	0.42	0.78	0.93	0.94	0.94	0.90	0.86
	N_{11} (Truth=1, Measured=1)	262	164	164	133	230	56	175	252	246	245	228	211
	N_{10} (Truth=1, Measured=0)	0	99	98	129	32	206	87	10	16	17	34	51
	N_{01} (Truth=0, Measured=1)	0	4	4	3	9	0	2	20	10	10	8	8
	N_{00} (Truth=0, Measured=0)	1178	1174	1174	1175	1169	1178	1177	1158	1168	1168	1170	1170
	No. of False-offs	0	34	34	36	22	26	43	6	5	3	24	28
	No. of False-ons	0	2	3	2	6	0	1	5	1	2	5	5
Wireless 2 (6 weeks)	Occupied Time (min)	262	159.6	134.4	144.4	232.2	47.9	158.3	268.6	247.2	246.2	229.7	230.6
	PCT Dev. from Truth	0	-39.1%	-48.7%	-44.9%	-11.4%	-81.7%	-39.6%	2.5%	-5.6%	-6.0%	-12.3%	-12.0%
	Accuracy (Ψ)	1	0.72	0.66	0.69	0.89	0.39	0.74	0.92	0.92	0.92	0.88	0.88
	N_{11} (Truth=1, Measured=1)	262	155	131	142	223	48	157	249	239	236	222	222
	N_{10} (Truth=1, Measured=0)	0	107	131	120	39	214	105	13	23	26	40	40
	N_{01} (Truth=0, Measured=1)	0	5	3	3	9	0	2	20	9	10	8	9
	N_{00} (Truth=0, Measured=0)	1178	1173	1175	1175	1169	1178	1177	1158	1169	1168	1170	1170
	No. of False-offs	0	37	40	34	25	24	46	8	7	4	26	26
	No. of False-ons	0	3	2	2	6	0	1	5	1	2	6	6

Table 7-8 also shows that, on average, all sensors underestimated the total occupied time. In the most extreme case, the total occupied time was underestimated by over 70% (Room 1, Wireless 2, Sensor 3). The assembled sensors pulsed more often than the other types of sensors. When the data were fused using the logical function OR, since the assembled sensors were slightly "over sensitive", this resulted in higher total occupied time than the truth (as shown in Table 7-8, on average, the OR function overestimated the occupied time by 1.0% in Room 1, and 2.6% in Room 2 for the last three weeks). This contradicts our previous conclusion that for proper functioning sensors, the OR function will always underestimate the total occupied time. Recall that we used the same assembled sensors in the round-robin study as the ones used in the pilot study, however, in the pilot study, the data were resolved to one-second intervals, whereas in this study, the data were resolved to one minute intervals. The conversion rule was that if the sensor pulsed at any second within a minute, that minute was considered occupied. As demonstrated in the pilot study, most silent intervals lasted less than one minute (Figure 5-5), thus after conversion, most silent intervals were deemed occupied. Although each of the individual assembled sensors still underestimated occupied time, the combination of the three, plus some false triggering, resulted in slightly higher estimates of occupied time than the truth.

The other two logical functions, as already seen from previous studies, underestimated the occupied time. The AND function underestimated occupancy by 27.9% to 90.2%, while the MAJORITY function underestimated occupancy by 4.2% to 70.2%. The deviations from truth were larger as the sensor sensitivity decreased.

The moving average, rule-based reasoning and belief network methods generally generated accurate estimates of occupancy, since they considered the general occupancy pattern or the characteristics of individual sensors. The moving average and rule-based reasoning methods take into account a 1-minute time delay, and so they sometimes slightly overestimated occupied time. The occupied time determined by the moving average method deviated from truth by -19.8% to 7.0%, while the occupied time determined by rule-based reasoning deviated from truth by -41.6% to 3.8%. A similar range in deviation was found for the results generated by the belief network method, as the percent deviation ranged from -33.5% to 7.0%. The moving average method had the highest accuracy among all the methods (over 0.8 for all sensors installed in Room 1, and over 0.9 for sensors installed in Room 2). These methods were also better at eliminating false-offs than other fusion algorithms: the number of false-offs in Room 1 was reduced from around 40 to around 20; in Room 2, false-offs were reduced from around 30, to fewer than 10.

The least squares estimation and neural network methods, both utilized the first-day data from each week as the training data, and parameters were defined based on the truth, generated results similar to the OR function: slightly improved performance for commercial and wireless sensors, and these marginally overestimated the occupied time measured by assembled sensors.

Recall that during the first three weeks in Room 2, two out of the three assembled sensors were defective, and their measurements were therefore not included in the ANOVA. However, these data are useful in discussing the effectiveness of data fusion algorithms since they challenge the ability of the various methods to correctly handle data from faulty sensors. The results of various algorithms applied to these data are shown in Table 7-9.

Table 7-9. Comparison of data fusion techniques when two out of three sensors were defective

Room 2		Truth (Desired)	Sensor 1	Sensor 2	Sensor 3	OR	AND	MAJORITY	Moving Average	Rule-Based	BN	LSE	NN
Assembled (first 3 weeks)	Occupied Time (min)	185	1028.0	185.3	831.3	1097.7	165.7	781.1	1293.0	1230.4	271.0	211.7	179.1
	PCT Dev. from Truth	0	455.7%	0.2%	349.3%	493.4%	-10.4%	322.2%	598.9%	565.1%	46.5%	14.4%	-3.2%
	Accuracy (φ)	1	0.22	0.95	0.26	0.20	0.92	0.33	0.13	0.16	0.75	0.88	0.96
	N_{11} (Truth=1, Measured=1)	185	180	178	167	183	162	180	185	185	176	178	176
	N_{10} (Truth=1, Measured=0)	0	5	7	17	2	23	5	0	0	9	7	9
	N_{01} (Truth=0, Measured=1)	0	848	8	664	915	3	601	1108	1046	95	34	3
	N_{00} (Truth=0, Measured=0)	1255	407	1248	591	340	1252	654	147	210	1160	1221	1252
	No. of False-offs	0	4	5	13	2	16	4	0	0	0	5	7
	No. of False-ons	0	213	4	226	192	2	244	78	75	5	28	2

When applied with two faulty sensors, the OR and MAJORITY functions, moving average and rule-based reasoning methods all failed, overestimating occupied time by

322.2% to 598.9%. The OR function returned TRUE when any of the three sensors pulsed, so it is not surprising that it generated a higher deviation from truth than any of the individual sensors. The MAJORITY function, moving average and rule-based reasoning methods essentially adopted the majority sensor responses: since two of the three sensors were faulty, all these methods output unusually high estimates of occupied time.

The AND function, belief network, least squares estimation and neural network methods, however, generated more accurate estimates of occupied time. The AND function was the only acceptable logical function, since in this two-sensor failure case, its output was similar to the only functioning sensor. Remember that in the more general cases, when all or most of the sensors work properly, the AND function exaggerates the silent intervals, and underestimates the occupied time, so the performance of AND function is not guaranteed.

The output from the belief network was moderately accurate (φ =0.75) in this case, and it overestimated occupancy by 46.5% (however, defective sensors overestimated the occupied time by 455.7% and 349.3%, respectively). In defining belief network parameters, sensors are deemed less likely to pulse during the night, thus when those two sensors pulsed continuously at night, they were defined as defective by the algorithm. Since the pulsing patterns remained constant during the day, the condition of these two sensors was locked at “defective”, and they were weighted less in outputting the fused results.

The least squares estimation and neural network methods yielded the most accurate estimates in this case, as they defined parameters by comparing the measured and truth data, and thus these two methods have the ability to self-diagnose and identify faulty sensors. The measurements from the faulty sensors were greatly different from the true occupancy data determined by human observer, so they were neglected by these two methods. The outputs from the least squares estimation and neural network methods were then similar to the measurements from Sensor 2, the only properly functioning sensor. These methods are most reliable and robust, however, their applications are limited by the availability of truth data.

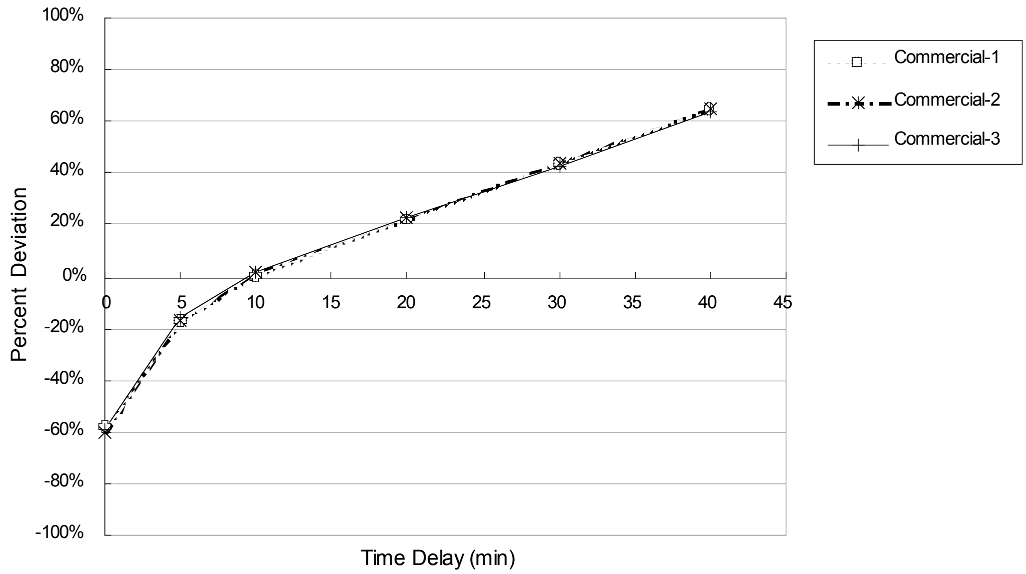
In both cases (whether or not data from faulty sensors were included), the fusion algorithms generated more accurate outputs than obtained from individual sensors, and reduced the number of false-offs, especially for the methods that incorporate knowledge about the system or true occupancy data. However, the number of false-offs was still at the scale of tens, which is not acceptable. Different time delay settings are applied to the individually measured and the fused data, and the results are compared in the next section.

7.3.4 Modeling the effects of different time delays

Figure 7-6 shows the percent deviation of occupied time from true occupancy, measured by each individual sensor at different time delay settings ranging from 5 to 40 minutes. Only data from the properly functioning sensors are included. The curves describing the sensors of the same type are similar, since the data were averaged over all the three mounting locations, and the effect of mounting location was eliminated.

PIR sensors do not pulse continually within each occupied event, so the raw sensor data underestimate occupied time (in one case up to 72.1%). As the modeled time delay was increased, the assumed occupied time in the space increased: applying a 20-minute time delay to the commercial and wireless sensors, the occupied time increased by approximately 20% in both rooms. For the more sensitive assembled sensors, the increment is even larger, at about 40%. Almost all sensors measured the “correct” occupied time (with 0% deviation) with a time delay between 5 and 10 minutes, except the most sensitive assembled sensors, which measured the “correct” occupied with a time delay less than 5 minutes. This suggests that a short time delay is possible, with a proper data fusion method.

Room 1, Commercial



Room 1, Assembled

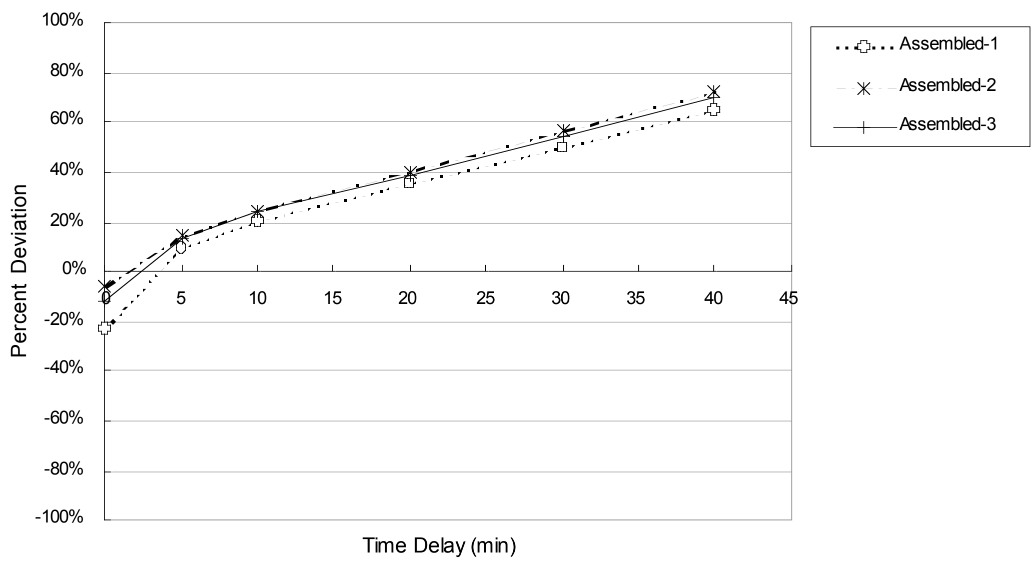
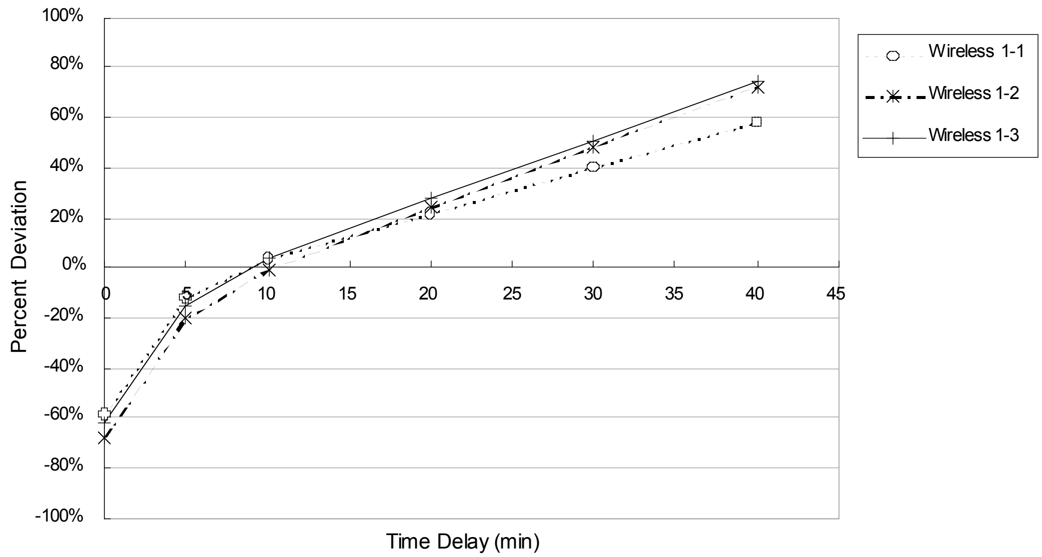


Figure 7-6. Effect of time delay settings on total occupied time determination. Plots show time delay settings of 0, 5, 10, 20, 30, 40 minutes

Room 1, Wireless 1



Room 1, Wireless 2

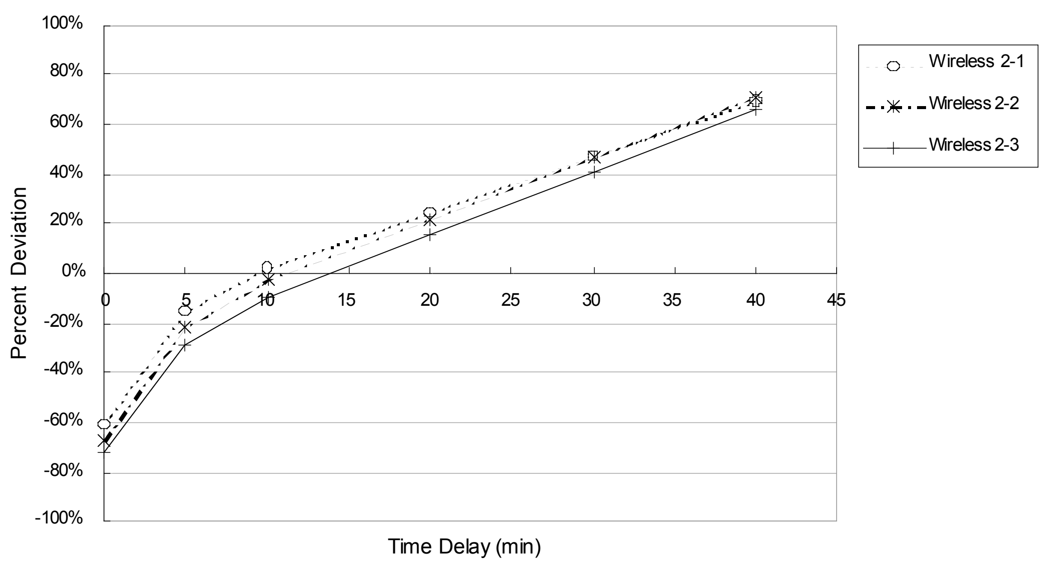
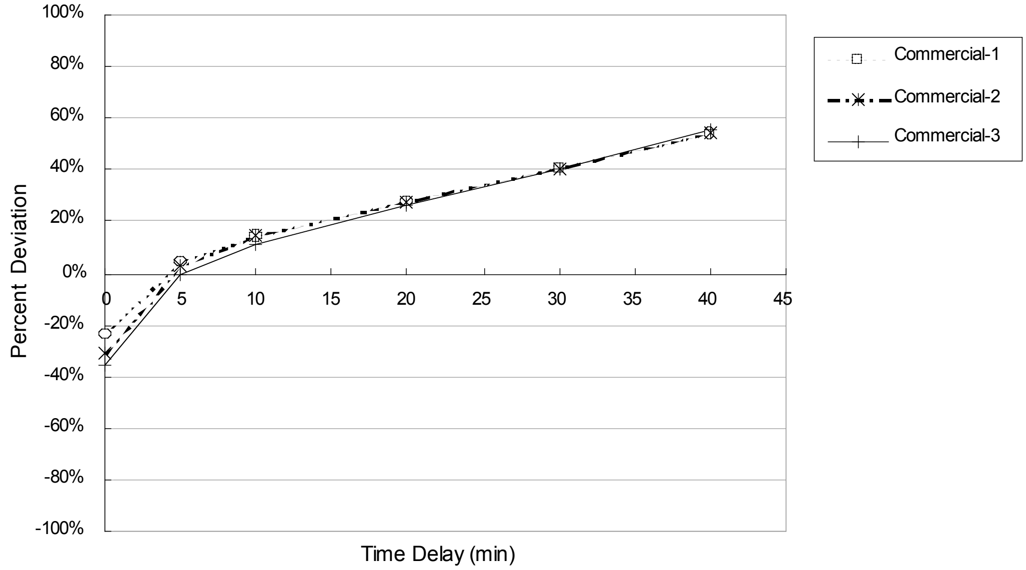


Figure 7-6. Effect of time delay settings on total occupied time determination. Plots show time delay settings of 0, 5, 10, 20, 30, 40 minutes (Cont'd)

Room 2, Commercial



Room 2, Assembled

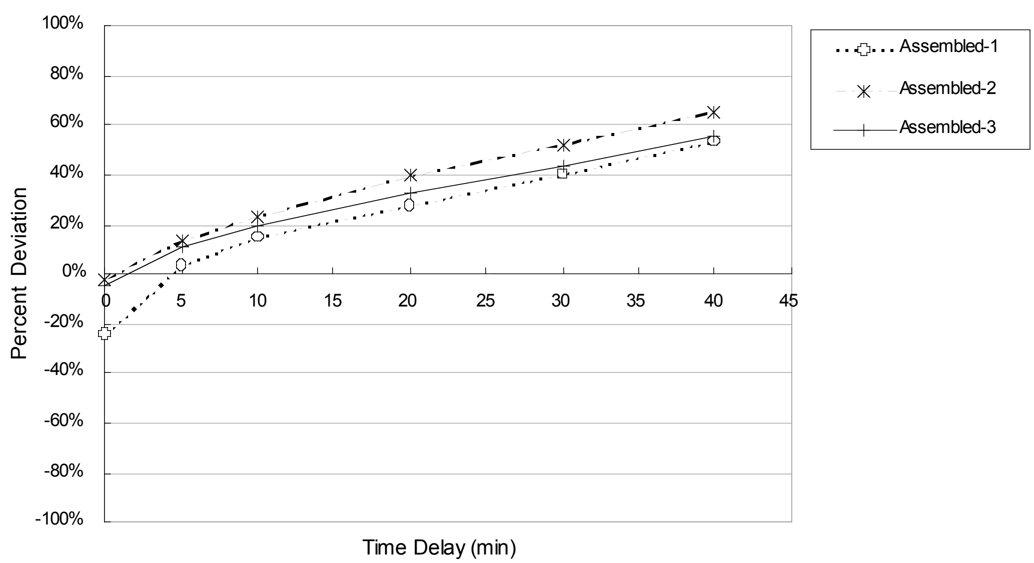
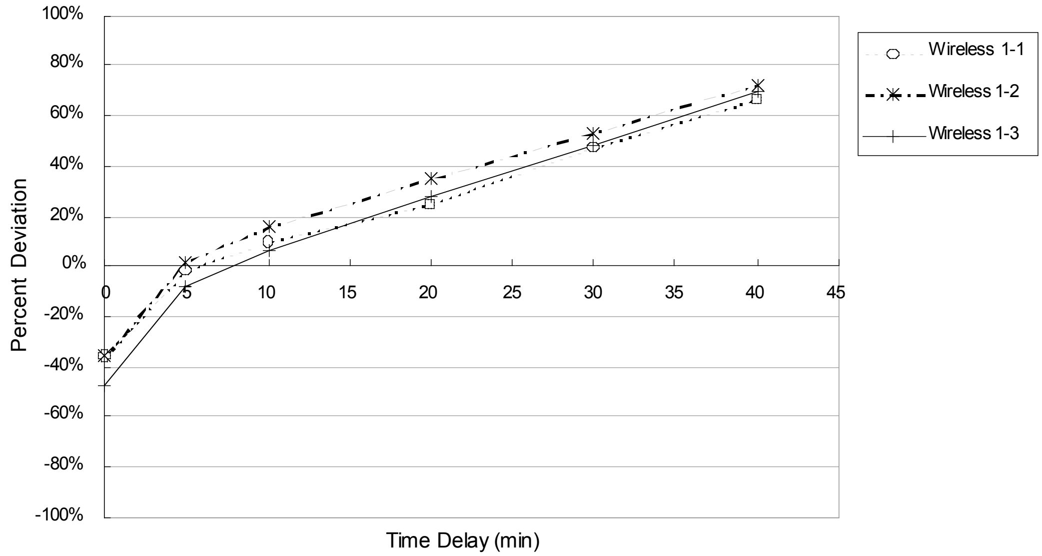


Figure 7-6. Effect of time delay settings on total occupied time determination. Plots show time delay settings of 0, 5, 10, 20, 30, 40 minutes (Cont'd)

Room 2, Wireless 1



Room 2, Wireless 2

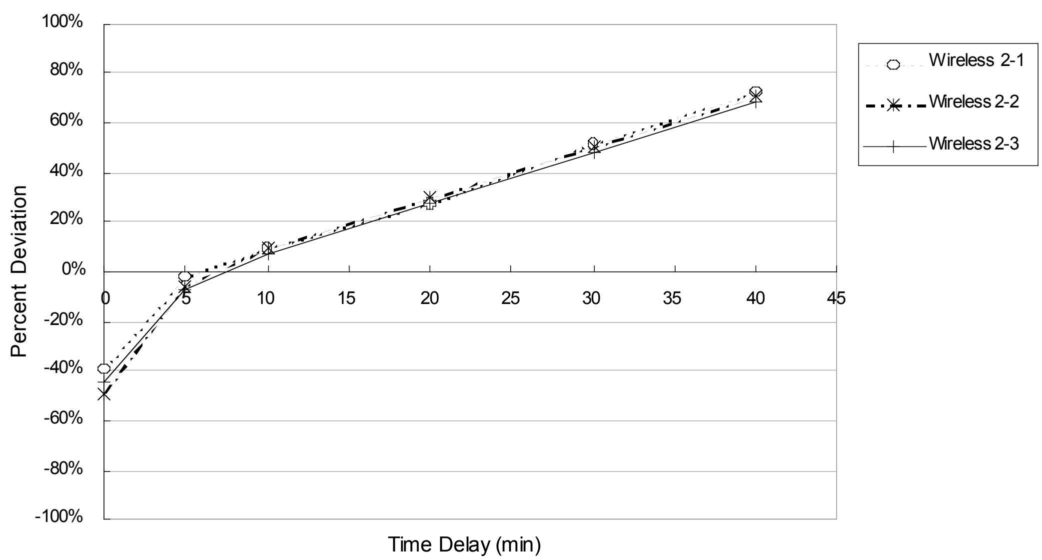


Figure 7-6. Effect of time delay settings on total occupied time determination. Plots show time delay settings of 0, 5, 10, 20, 30, 40 minutes (Cont'd)

Similar results were observed in the pilot study (as depicted on Figure 5-6, page 49). The pilot study showed that false-offs could not be eliminated with a 5-minute time delay (Figure 5-9), so time delays of 5 minutes or less are not recommended in control applications. For the study described in this chapter, only time delay settings greater than or equal to 5 minutes were applied. Figure 7-7 summarizes the effect of time delay setting found in both the pilot and round-robin studies. The figure shows the average percent deviation of occupied time from true occupancy as a function of time delay. Each line plots average effects across all properly functioning sensors installed in the space (i.e., Pilot Study Room 1 was averaged over two functioning sensors; Pilot Study Room 2 was averaged over all three installed sensors; Round-robin Study Room 1 was averaged over all the 12 commercial, assembled, and wireless sensors for the six-week data collection period; Round-robin Study Room 2 was averaged over commercial and wireless sensors for the six-week data collection period, but assembled sensors only for the last three weeks of the data collection period).

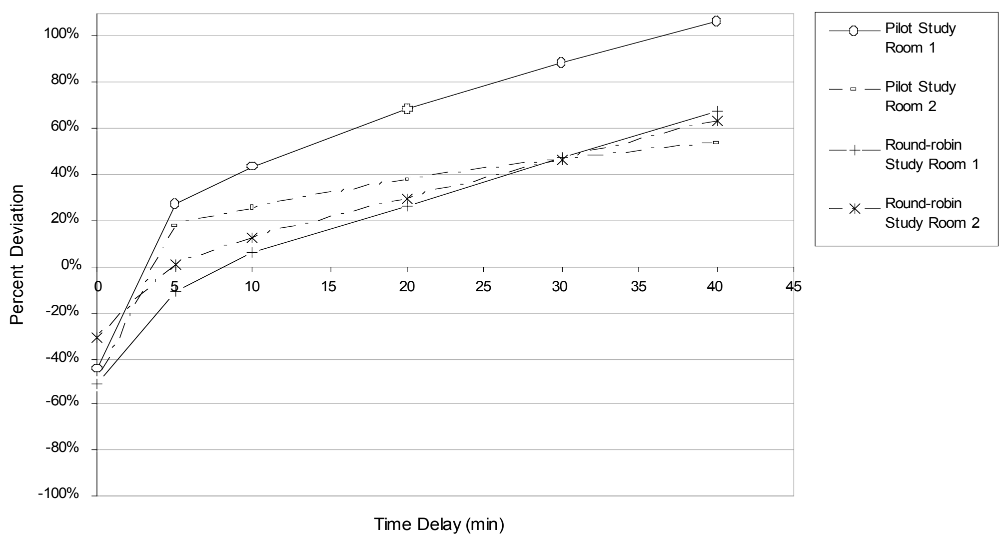


Figure 7-7. Effect of time delay settings on total occupied time in two studies

The remainder of this section concludes the analysis of data by comparing the performance of data fusion algorithms with shorter time delays of 5 and 10 minutes, versus a single sensor with a conventional 20-minute delay, not only in terms of occupied time, but also accuracy (φ correlation), and the number of false switches.

Table 7-10 shows the percent deviation of occupied time that would have resulted had these two offices been controlled using a network of three PIR sensors using 5 or 10-minute time delay settings, versus the operating time that would have been observed using a single sensor with a 20-minute time delay.

In both rooms, the AND rule underestimated the occupied time with 5 and 10-minute time delays, and in Room 1, the MAJORITY rule also underestimated the occupied time with a 5-minute delay for all except the assembled sensors.

In the case of Room 2, Table 7-10 plots the outputs observed when two faulty sensors (Assembled 1 and Assembled 3) were providing input to the data stream, showing the large difference in the effectiveness of the eight algorithms. Simple fusion algorithms, such as logical functions OR and MAJORITY, moving average and rule-based reasoning cannot account for sensor malfunction, and so generate a larger deviation from true occupied time.

Table 7-10 Percent deviation of occupied time from truth of individual sensors with 20-minute time delays versus fusion algorithm with 5 or 10-minute time delays

Room 1

Sensor	Sensor 1	Sensor 2	Sensor 3	OR		AND		MAJORITY		Moving Average		Rule-Based		BN		LSE		NN	
Type	+20	+20	+20	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10
Commercial (6 weeks)	21.9%	22.6%	22.6%	7.4%	19.5%	-41.7%	-27.0%	-8.7%	9.3%	4.8%	15.4%	0.8%	14.2%	1.7%	16.0%	7.4%	19.5%	7.4%	19.5%
Assembled (6 weeks)	35.3%	40.5%	39.2%	18.5%	30.0%	6.5%	17.7%	12.2%	20.7%	10.9%	20.2%	14.5%	22.5%	24.3%	35.6%	16.9%	27.3%	15.1%	24.9%
Wireless 1 (6 weeks)	21.6%	23.8%	27.3%	15.8%	29.6%	-66.1%	-30.6%	-15.4%	4.0%	0.6%	17.3%	4.3%	9.6%	6.4%	19.4%	15.4%	29.0%	15.8%	29.6%
Wireless 2 (6 weeks)	24.5%	21.9%	15.8%	10.3%	25.2%	-67.6%	-32.6%	-15.0%	-3.4%	6.1%	13.9%	7.8%	29%	5.8%	10.7%	9.7%	24.3%	10.3%	25.2%

Room 2

Sensor	Sensor 1	Sensor 2	Sensor 3	OR		AND		MAJORITY		Moving Average		Rule-Based		BN		LSE		NN	
Type	+20	+20	+20	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10
Commercial (6 weeks)	27.6%	27.7%	26.1%	12.1%	18.8%	-14.4%	4.5%	8.3%	16.5%	10.4%	16.3%	11.2%	18.0%	10.5%	17.3%	3.7%	9.5%	11.2%	17.9%
Assembled (first 3 weeks)	678.2%	46.6%	677.2%	673.7%	678.1%	136%	22.3%	631.0%	667.6%	669.5%	677.4%	662.8%	674.2%	60.5%	68.2%	83.3%	122.8%	13.8%	22.7%
Assembled (last 3 weeks)	27.7%	39.7%	32.3%	17.1%	27.2%	22%	13.3%	9.9%	16.8%	15.0%	17.2%	11.7%	18.3%	10.8%	17.4%	15.2%	25.0%	14.4%	22.5%
Wireless 2 (6 weeks)	24.5%	34.5%	27.3%	17.5%	27.8%	-41.0%	-20.5%	7.1%	15.5%	15.1%	18.0%	10.1%	17.0%	10.5%	17.9%	15.6%	24.7%	13.9%	23.9%
Wireless 2 (6 weeks)	27.1%	30.0%	27.9%	18.2%	29.1%	-46.0%	-26.1%	3.5%	13.1%	15.6%	16.4%	8.1%	15.3%	8.0%	15.8%	16.6%	26.6%	17.4%	27.9%

The AND function outputs a positive signal only when all sensors pulse, so it generated a good result similar to the only functioning sensor (Assembled 2). The more complicated methods, least squares estimation, belief network and neural network methods identify faulty sensors, and generate acceptable results (reducing the over 600% deviation to around 100%). The neural network methods only overestimate the occupied time by 13.8% at 5-minute time delay when majority of the sensors fail, demonstrating superior performance in occupancy measurements.

For functioning sensors, fused results with a short time delay of 5 minutes are always closer to the truth, as compared to individual measurements with a long time delay. The percent deviation from truth of fused sensor network data with a 10-minute time delay is similar to that of individual sensors with a 20-minute time delay.

The plots of the percent deviation from true occupied time were complemented by the accuracy of each method, as shown in Table 7-11. When compared with Table 7-10, it is clear that the larger the deviation from the truth, the less accurate the method. Furthermore, the fused outputs with a 5-minute time delay were slightly more accurate than the individual sensors with a 20-minute delay. When a longer time delay of 10 minutes was applied to the sensor network data stream, the accuracy generally decreased slightly, as compared to fused sensor network data with a 5-minute time delay.

Table 7-11. Accuracy (φ) of individual sensors with 20-minute time delays versus fusion algorithm with 5 or 10-minute time delays

Room 1

Sensor	Sensor 1	Sensor 2	Sensor 3	OR		AND		MAJORITY		Moving Average		Rule-Based		BN		LSE		NN	
Type	+20	+20	+20	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10
Commercial (6 weeks)	0.75	0.75	0.75	0.89	0.86	0.50	0.57	0.76	0.80	0.84	0.85	0.81	0.81	0.85	0.84	0.89	0.86	0.89	0.86
Assembled (6 weeks)	0.81	0.79	0.80	0.89	0.82	0.90	0.86	0.92	0.86	0.93	0.86	0.91	0.85	0.87	0.79	0.90	0.83	0.91	0.84
Wireless 1 (6 weeks)	0.81	0.79	0.80	0.89	0.82	0.90	0.86	0.92	0.86	0.93	0.86	0.91	0.85	0.87	0.79	0.90	0.83	0.91	0.84
Wireless 2 (6 weeks)	0.72	0.72	0.68	0.87	0.82	0.40	0.47	0.70	0.75	0.81	0.84	0.74	0.76	0.83	0.82	0.88	0.83	0.87	0.82

Room 2

Sensor	Sensor 1	Sensor 2	Sensor 3	OR		AND		MAJORITY		Moving Average		Rule-Based		BN		LSE		NN	
Type	+20	+20	+20	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10
Commercial (6 weeks)	0.84	0.85	0.84	0.92	0.85	0.79	0.80	0.92	0.86	0.93	0.86	0.92	0.85	0.91	0.85	0.89	0.90	0.92	0.85
Assembled (first 3 weeks)	0.01	0.80	0.01	0.03	0.54	0.93	0.76	0.10	0.36	0.04	0.41	0.05	0.08	0.71	0.62	0.69	0.57	0.93	0.75
Assembled (last 3 weeks)	0.84	0.79	0.82	0.90	0.85	0.89	0.88	0.94	0.90	0.91	0.90	0.93	0.89	0.91	0.87	0.91	0.86	0.91	0.87
Wireless 2 (6 weeks)	0.82	0.81	0.77	0.90	0.77	0.64	0.69	0.93	0.84	0.91	0.83	0.93	0.83	0.91	0.81	0.91	0.79	0.91	0.79
Wireless 2 (6 weeks)	0.79	0.81	0.79	0.89	0.77	0.61	0.71	0.92	0.88	0.90	0.82	0.93	0.87	0.90	0.81	0.90	0.78	0.90	0.77

Another parameter important to justify selection of a fusion algorithm is the number of false-offs. The occupied time relates to the energy savings that could be achieved for a given method, while the number of unwanted switch offs while a space is occupied is associated with user satisfaction.

Table 7-12. Number of false-offs for individual sensors with 20-minute time delays versus fusion algorithm with 5 or 10-minute delays

Room 1

Sensor	Sensor 1	Sensor 2	Sensor 3	OR		AND		MAJORITY		Moving Average		Rule-Based		BN		LSE		NN	
Type	+20	+20	+20	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10
Commercial (6 weeks)	2	2	1	1	0	6	3	5	3	2	0	4	0	2	0	1	0	1	0
Assembled (6 weeks)	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Wireless 1 (6 weeks)	1	2	2	1	0	5	2	5	0	2	0	3	0	2	0	1	0	1	0
Wireless 2 (6 weeks)	2	2	2	1	0	5	2	3	0	3	0	4	0	2	0	1	0	1	0

Room 2

Sensor	Sensor 1	Sensor 2	Sensor 3	OR		AND		MAJORITY		Moving Average		Rule-Based		BN		LSE		NN	
Type	+20	+20	+20	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10
Commercial (6 weeks)	0	0	1	0	0	9	2	1	0	1	0	1	0	1	0	1	0	1	0
Assembled (first 3 weeks)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Assembled (last 3 weeks)	0	0	0	0	0	4	2	0	0	0	0	0	0	0	0	0	0	0	0
Wireless 2 (6 weeks)	1	0	1	0	0	9	4	2	0	0	0	1	0	0	0	0	0	1	0
Wireless 2 (6 weeks)	1	1	1	0	0	9	4	3	0	1	0	1	0	1	0	0	0	1	0

As Table 7-12 shows, the number of false-offs for the fused data with a short time delay (5 minutes) is comparable to the number of false-offs observed for single-sensor control with a longer time delay (20 minutes). With a time delay of 10 minutes, all false-offs are eliminated for all the fusion methods, except for the logical functions AND and MAJORITY. Since the logical functions AND and MAJORITY underestimate occupancy, longer time delays are required to eliminate false-offs, so these two functions are not recommended for occupancy sensor data fusion.

Table 7-13. Number of false-ons for individual sensors with 20-minute time delays versus fusion algorithm with 5 or 10-minute delays

Room 1

Sensor	Sensor 1	Sensor 2	Sensor 3	OR		AND		MAJORITY		Moving Average		Rule-Based		BN		LSE		NN	
Type	+20	+20	+20	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10
Commercial (6 weeks)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Assembled (6 weeks)	1	1	1	3	3	0	0	1	1	1	1	1	1	2	2	2	2	1	1
Wireless 1 (6 weeks)	0	1	1	2	2	0	0	0	0	1	1	0	0	1	1	2	2	2	2
Wireless 2 (6 weeks)	1	1	1	2	2	0	0	0	0	1	1	0	0	0	0	2	2	2	2

Room 2

Sensor	Sensor 1	Sensor 2	Sensor 3	OR		AND		MAJORITY		Moving Average		Rule-Based		BN		LSE		NN	
Type	+20	+20	+20	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10	+5	+10
Commercial (6 weeks)	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Assembled (first 3 weeks)	0	1	1	4	1	1	1	24	5	8	1	9	2	3	1	16	10	2	1
Assembled (last 3 weeks)	0	2	1	3	3	0	0	0	0	3	0	0	0	1	0	2	2	2	1
Wireless 2 (6 weeks)	0	1	1	3	2	0	0	0	0	3	1	0	0	1	0	2	1	2	2
Wireless 2 (6 weeks)	1	1	1	3	2	0	0	0	0	3	1	0	0	1	0	2	2	3	2

While minimizing false-offs is key to user satisfaction, false-ons (the number of times lights are switched on in an empty space) may also be problematic. Table 7-13 shows the number of false-ons for the fused data with shorter time delays (5 and 10-minutes), compared to the number of false-ons observed for single-sensor control with a longer time delay (20 minutes).

In the case of Room 1, if the lighting were controlled by any one of the three individual sensors, lights would have been switched on in an empty space for an additional 20 minutes (all sensor types showed one false-on, and the lights would have remained switched on for the duration of the 20 minute time delay setting). This would have been exceeded by only one of the fusion algorithms (OR+10 minutes), which would have left the lights on in an empty space for 30 minutes, a ten minute increase. Room 2 included sensors that did not function properly: if these had been controlling the lights, there would have been numerous false-ons, with concomitant increase in light use. However, one benefit of a sensor network is that it can diagnose faulty sensors. Ignoring data from faulty sensors in this room shows that if the lighting were controlled by one of the individual sensors, the lights would have been switched on in an empty space for an additional 40 minutes (two false-ons for Assembled Sensor 2 at 20 minutes each). None of the fusion algorithms applied to the sensor network data would have resulted in the lights being switched on in a vacant space for this length of time.

Table 7-14 and Table 7-15 show the percentage reductions in system use (characterized by occupied time) by applying 5 or 10-minute time delays, versus a single sensor with a 20-minute delay. The comparisons are carried out between the maximum occupied time measured by an individual sensor, and the occupied time after application of each fusion algorithm. The logical functions AND and MAJORITY have not been included since their application does not correspond well with measured occupancy, and they are not recommended for use in control applications.

Table 7-14 models the reductions in occupied time that would have been achieved had these two offices been controlled using a network of three PIR sensors using a 5-minute time delay setting, versus the operating time that would have been observed using a single sensor with a 20-minute time delay. Table 7-14 shows that using an output from a sensor network for system control would have produced reductions in system use, relative to what would have been observed if the systems in these offices were controlled using single points of detection (differences between the sensor network +5 minutes signal and the maximum observed for the three individual sensors +20 minutes range from -12.3% to -17.0%).

Table 7-14. Total occupied time (min) and percent reductions in cumulative occupied time between sensor network outputs plus 5-minute time delay, versus the maximum occupied time determined by individual sensor plus 20-minute time delay

	Group	Occupied Time (minutes)							Percent Reduction					
		Max of Individual Sensor +20	OR +5	Moving Average +5	Rule-Based +5	BN +5	LSE +5	NN +5	OR +5	Moving Average +5	Rule-Based +5	BN +5	LSE +5	NN +5
Room 1	Commercial (6 weeks)	394.9	345.9	337.6	324.7	327.4	345.9	345.9	-12.4%	-14.5%	-17.8%	-17.1%	-12.4%	-12.4%
	Assembled (6 weeks)	452.6	381.5	357.1	368.7	400.2	376.6	370.8	-15.7%	-21.1%	-18.5%	-11.6%	-16.8%	-18.1%
	Wireless 1 (6 weeks)	409.8	372.8	324.1	335.9	342.6	371.5	372.8	-9.0%	-20.9%	-18.0%	-16.4%	-9.3%	-9.0%
	Wireless 2 (6 weeks)	400.9	355.2	341.7	347.1	340.7	353.2	355.2	-11.4%	-14.8%	-13.4%	-15.0%	-11.9%	-11.4%
Room 2	Commercial (6 weeks)	334.6	293.6	289.3	291.3	289.5	271.7	291.4	-12.2%	-13.5%	-12.9%	-13.5%	-18.8%	-12.9%
	Assembled (1) (first 3 weeks)	1439.6	1431.3	1423.6	1411.1	296.9	339.1	210.6	-0.6%	-1.1%	-2.0%	-79.4%	-76.4%	-85.4%
	Assembled (last 3 weeks)	473.7	397.1	389.8	378.7	375.7	390.4	387.7	-16.2%	-17.7%	-20.1%	-20.7%	-17.6%	-18.2%
	Wireless 1 (6 weeks)	352.4	307.9	301.7	288.4	289.5	303.0	298.5	-12.6%	-14.4%	-18.2%	-17.9%	-14.0%	-15.3%
	Wireless 2 (6 weeks)	340.6	309.6	302.8	283.1	283.0	305.6	307.7	-9.1%	-11.1%	-16.9%	-16.9%	-10.3%	-9.7%
Average									-12.3%	-16.0%	-17.0%	-16.1%	-13.9%	-13.4%

(1) Data from assembled sensors during the first 3 weeks were not included in the average calculation.

Table 7-15 models the reductions in occupied time that would have been achieved had these two offices been controlled using a network of three PIR sensors using a 10-minute time delay setting, versus the operating time that would have been observed using a single sensor with a 20-minute time delay. Table 7-15 shows that using an output from a sensor network for system control would have also produced reductions in system use, relative to what would have been observed if the systems in these offices were controlled using single points of detection (differences between the sensor network +10 minutes signal and the maximum observed for the three individual sensors +20 minutes range from -3.6% to -12.3%).

Table 7-15. Total occupied time (min) and percent reductions in cumulative occupied time between sensor network outputs plus 10-minute time delay, versus the maximum occupied time determined by individual sensor plus 20-minute time delay

	Group	Occupied Time (minutes)							Percent Reduction					
		Max of Individual Sensor +20	OR +10	Moving Average +10	Rule-Based +10	BN +10	LSE +10	NN +10	OR +10	Moving Average +10	Rule-Based +10	BN +10	LSE +10	NN +10
Room 1	Commercial (6 weeks)	394.9	384.9	371.7	367.7	373.4	384.9	384.9	-2.5%	-5.9%	-6.9%	-5.5%	-2.5%	-2.5%
	Assembled (6 weeks)	452.6	418.6	386.9	394.6	436.7	409.9	402.1	-7.5%	-14.5%	-12.8%	-3.5%	-9.4%	-11.2%
	Wireless 1 (6 weeks)	409.8	417.4	377.7	352.9	384.5	415.3	417.4	1.9%	-7.8%	-13.9%	-6.2%	1.3%	1.9%
	Wireless 2 (6 weeks)	400.9	403.3	366.8	331.2	356.3	400.2	403.3	0.6%	-8.5%	-17.4%	-11.1%	-0.2%	0.6%
Room 2	Commercial (6 weeks)	334.6	311.4	304.7	309.3	307.4	286.8	308.8	-6.9%	-8.9%	-7.6%	-8.1%	-14.3%	-7.7%
	Assembled (1) (first 3 weeks)	1439.6	1439.4	1438.1	1432.2	311.2	412.3	227.1	0.0%	-0.1%	-0.5%	-78.4%	-71.4%	-84.2%
	Assembled (last 3 weeks)	473.7	431.3	397.3	400.9	397.9	423.9	415.4	-9.0%	-16.1%	-15.4%	-16.0%	-10.5%	-12.3%
	Wireless 1 (6 weeks)	352.4	334.9	309.1	306.6	308.8	326.6	324.7	-5.0%	-12.3%	-13.0%	-12.4%	-7.3%	-7.9%
	Wireless 2 (6 weeks)	340.6	338.2	304.9	302.0	303.0	331.6	335.2	-0.7%	-10.5%	-11.3%	-11.0%	-2.6%	-1.6%
Average									-3.6%	-10.6%	-12.3%	-9.2%	-5.7%	-5.1%

(1) Data from assembled sensors during the first 3 weeks were not included in the average calculation.

The savings that result from the sensor network with a 10-minute time delay are less than those from the system with a shorter 5-minute time delay, the 10-minute time delay eliminates false-offs.

Table 7-16 compares the measured occupied time of sensors and data fusion with no time delay, while Table 7-17 shows the same data compared to the actual occupied time ("Truth). As previously noted, these data show that most individual sensors underpredict occupied time, with the exception of the assembled sensors. We have previously speculated that this may be due to an artifact of the data processing, or the fact that all the other sensors have been designed to be less sensitive (to avoid false-ons), since they are all commercially available products.

Table 7-16. Total occupied time (min) and percent differences in cumulative occupied time between sensor network outputs versus the maximum occupied time determined by individual sensors

	Group	Occupied Time (minutes)							Percent Difference					
		Max of Individual Sensor	OR	Moving Average	Rule-Based	LSE	BN	NN	OR	Moving Average	Rule-Based	LSE	BN	NN
Room 1	Commercial (6 weeks)	134.3	201.4	258.2	215.6	201.0	225.5	201.1	50.0%	92.3%	60.6%	49.6%	67.9%	49.8%
Room 1	Assembled (6 weeks)	301.9	325.2	341.8	334.0	323.9	344.6	320.7	7.7%	13.2%	10.6%	7.3%	14.1%	6.2%
Room 1	Wireless 1 (6 weeks)	132.6	216.4	282.9	218.6	215.3	248.1	216.4	63.1%	113.3%	64.8%	62.3%	87.0%	63.1%
Room 1	Wireless 2 (6 weeks)	126.0	192.4	258.6	188.0	191.4	214.0	192.4	52.7%	105.2%	49.2%	51.8%	69.8%	52.7%
Room 2	Commercial (6 weeks)	199.4	241.5	266.0	271.9	223.4	257.1	238.6	21.1%	33.4%	36.4%	12.1%	28.9%	19.7%
Room 2	Assembled* (first 3 weeks)	1028.0	1097.7	1293.0	1230.4	211.7	271.0	179.1	6.8%	25.8%	19.7%	-79.4%	-73.6%	-82.6%
Room 2	Assembled (last 3 weeks)	333.7	347.8	362.6	351.5	345.0	345.1	342.9	4.2%	8.7%	5.3%	3.4%	3.4%	2.8%
Room 2	Wireless 1 (6 weeks)	168.6	238.9	271.4	256.0	235.6	255.5	218.6	41.7%	61.0%	51.9%	39.8%	51.6%	29.7%
Room 2	Wireless 2 (6 weeks)	159.6	232.2	268.6	247.2	229.7	246.2	230.6	45.5%	68.3%	54.9%	44.0%	54.3%	44.5%
Average									35.8%	61.9%	41.7%	33.8%	47.1%	33.6%

(1) Data from assembled sensors during the first 3 weeks were not included in the average calculation.

Table 7-17. Total occupied time (min) and percent differences in cumulative occupied time between sensor network outputs versus the true occupied time

	Group	Occupied Time (minutes)							Percent Difference					
		Truth	OR	Moving Average	Rule-Based	LSE	BN	NN	OR	Moving Average	Rule-Based	LSE	BN	NN
Room 1	Commercial (6 weeks)	322	201.4	258.2	215.6	201.0	225.5	201.1	-37.4%	-19.8%	-33.0%	-37.6%	-30.0%	-37.5%
Room 1	Assembled (6 weeks)	322	325.2	341.8	334.0	323.9	344.6	320.7	1.0%	6.2%	3.7%	0.6%	7.0%	-0.4%
Room 1	Wireless 1 (6 weeks)	322	216.4	282.9	218.6	215.3	248.1	216.4	-32.8%	-12.1%	-32.1%	-33.1%	-23.0%	-32.8%
Room 1	Wireless 2 (6 weeks)	322	192.4	258.6	188.0	191.4	214.0	192.4	-40.2%	-19.7%	-41.6%	-40.6%	-33.5%	-40.2%
Room 2	Commercial (6 weeks)	262	241.5	266.0	271.9	223.4	257.1	238.6	-7.8%	1.5%	3.8%	-14.7%	-1.9%	-8.9%
Room 2	Assembled* (first 3 weeks)	185	1097.7	1293.0	1230.4	211.7	271.0	179.1	493.4%	598.9%	565.1%	14.4%	46.5%	-3.2%
Room 2	Assembled (last 3 weeks)	339	347.8	362.6	351.5	345.0	345.1	342.9	2.6%	7.0%	3.7%	1.8%	1.8%	1.2%
Room 2	Wireless 1 (6 weeks)	262	238.9	271.4	256.0	235.6	255.5	218.6	-8.8%	3.6%	-2.3%	-10.1%	-2.5%	-16.6%
Room 2	Wireless 2 (6 weeks)	262	232.2	268.6	247.2	229.7	246.2	230.6	-11.4%	2.5%	-5.6%	-12.3%	-6.0%	-12.0%
Average									-16.9%	-3.9%	-12.9%	-18.3%	-11.0%	-18.4%

(1) Data from assembled sensors during the first 3 weeks were not included in the average calculation.

The intent of the data and analyses described throughout this report is to show benefits of networking versus single sensors. Table 7-18 and Table 7-19 show the true occupied time (in minutes) and the increases in occupied time that would result from sensor network control with 5 and 10-minute time delay settings. These data characterize the increases in light use that would be observed in the case of a retrofit from no occupancy detection to a networked sensor system, rather than an upgrade from a single detector to a networked system.

Table 7-18. Total occupied time (min) and percent differences in cumulative occupied time between sensor network outputs plus 5-minute time delay versus the true occupied time

		Occupied Time (minutes)							Percent Difference					
	Group	Truth	OR +5	Moving Average +5	Rule-Based +5	BN +5	LSE +5	NN +5	OR +5	Moving Average +5	Rule-Based +5	BN +5	LSE +5	NN +5
Room 1	Commercial (6 weeks)	322	345.9	337.6	324.7	327.4	345.9	345.9	7.4%	4.8%	0.8%	1.7%	7.4%	7.4%
	Assembled (6 weeks)	322	381.5	357.1	368.7	400.2	376.6	370.8	18.5%	10.9%	14.5%	24.3%	16.9%	15.1%
	Wireless 1 (6 weeks)	322	372.8	324.1	335.9	342.6	371.5	372.8	15.8%	0.6%	4.3%	6.4%	15.4%	15.8%
	Wireless 2 (6 weeks)	322	355.2	341.7	347.1	340.7	353.2	355.2	10.3%	6.1%	7.8%	5.8%	9.7%	10.3%
Room 2	Commercial (6 weeks)	262	293.6	289.3	291.3	289.5	271.7	291.4	12.1%	10.4%	11.2%	10.5%	3.7%	11.2%
	Assembled (1) (first 3 weeks)	185	1431.3	1423.6	1411.1	296.9	339.1	210.6	673.7%	669.5%	662.8%	60.5%	83.3%	13.8%
	Assembled (last 3 weeks)	339	397.1	389.8	378.7	375.7	390.4	387.7	17.1%	15.0%	11.7%	10.8%	15.2%	14.4%
	Wireless 1 (6 weeks)	262	307.9	301.7	288.4	289.5	303.0	298.5	17.5%	15.1%	10.1%	10.5%	15.6%	13.9%
	Wireless 2 (6 weeks)	262	309.6	302.8	283.1	283.0	305.6	307.7	18.2%	15.6%	8.1%	8.0%	16.6%	17.4%
Average									14.6%	9.8%	8.6%	9.7%	12.6%	13.2%

(1) Data from assembled sensors during the first 3 weeks were not included in the average calculation.

Table 7-19. Total occupied time (min) and percent differences in cumulative occupied time between sensor network outputs plus 10-minute time delay versus the true occupied time

	Group	Occupied Time (minutes)							Percent Difference					
		Truth	OR +10	Moving Average +10	Rule-Based +10	BN +10	LSE +10	NN +10	OR +10	Moving Average +10	Rule-Based +10	BN +10	LSE +10	NN +10
Room 1	Commercial (6 weeks)	322	384.9	371.7	367.7	373.4	384.9	384.9	19.5%	15.4%	14.2%	16.0%	19.5%	19.5%
	Assembled (6 weeks)	322	418.6	386.9	394.6	436.7	409.9	402.1	30.0%	20.2%	22.5%	35.6%	27.3%	24.9%
	Wireless 1 (6 weeks)	322	417.4	377.7	352.9	384.5	415.3	417.4	29.6%	17.3%	9.6%	19.4%	29.0%	29.6%
	Wireless 2 (6 weeks)	322	403.3	366.8	331.2	356.3	400.2	403.3	25.2%	13.9%	2.9%	10.7%	24.3%	25.2%
Room 2	Commercial (6 weeks)	262	311.4	304.7	309.3	307.4	286.8	308.8	18.8%	16.3%	18.0%	17.3%	9.5%	17.9%
	Assembled (1) (first 3 weeks)	185	1439.4	1438.1	1432.2	311.2	412.3	227.1	678.1%	677.4%	674.2%	68.2%	122.8%	22.7%
	Assembled (last 3 weeks)	339	431.3	397.3	400.9	397.9	423.9	415.4	27.2%	17.2%	18.3%	17.4%	25.0%	22.5%
	Wireless 1 (6 weeks)	262	334.9	309.1	306.6	308.8	326.6	324.7	27.8%	18.0%	17.0%	17.9%	24.7%	23.9%
	Wireless 2 (6 weeks)	262	338.2	304.9	302.0	303.0	331.6	335.2	29.1%	16.4%	15.3%	15.6%	26.6%	27.9%
Average									25.9%	16.8%	14.7%	18.7%	23.2%	23.9%

(1) Data from assembled sensors during the first 3 weeks were not included in the average calculation.

Finally, Table 7-20 shows the minimum time delay settting at which false-offs were eliminated for all sensor types and fusion methods. In all cases the time delay was less than 10 minutes, considerably less than used in current systems.

Table 7-20. Minimum time delay at which false-offs are eliminated and corresponding occupied time (min), and percent difference from truth

	Group	Truth	OR			Moving Average			Rule-Based			BN			LSE			NN		
			Min Time Delay	Occupied Time (min)	Pct. Diff.	Min Time Delay	Occupied Time (min)	Pct. Diff.	Min Time Delay	Occupied Time (min)	Pct. Diff.	Min Time Delay	Occupied Time (min)	Pct. Diff.	Min Time Delay	Occupied Time (min)	Pct. Diff.	Min Time Delay	Occupied Time (min)	Pct. Diff.
Room 1	Commercial (6 weeks)	322	8	352.0	9.3%	8	344.3	6.9%	7	339.4	5.4%	6	349.8	8.6%	7	367.0	14.0%	9	346.1	7.5%
	Assembled (6 weeks)	322	2	338.7	5.2%	2	342.1	6.2%	2	335.1	4.1%	1	325.1	0.9%	3	359.3	11.6%	2	365.4	13.5%
	Wireless 1 (6 weeks)	322	7	381.6	18.5%	8	347.8	8.0%	8	352.0	9.3%	9	360.9	12.1%	7	386.8	20.1%	7	383.2	19.0%
	Wireless 2 (6 weeks)	322	9	401.0	24.5%	9	354.8	10.2%	6	337.3	4.8%	8	345.4	7.3%	8	384.8	19.5%	8	379.3	17.8%
Room 2	Commercial (6 weeks)	262	6	293.8	12.1%	8	296.2	13.0%	9	300.9	14.9%	9	289.8	10.6%	8	273.7	4.5%	7	300.8	14.8%
	Assembled (1) (first 3 weeks)	185	1	1206.2	552.0%	0	1301.1	603.3%	0	1280.0	591.9%	1	222.5	20.3%	2	272.4	47.2%	1	185.6	0.3%
	Assembled (last 3 weeks)	339	1	363.6	7.2%	1	380.5	12.2%	1	364.4	7.5%	3	366.5	8.1%	1	364.9	7.7%	4	380.2	12.2%
	Wireless 1 (6 weeks)	262	9	315.0	20.2%	7	304.9	16.4%	7	301.2	14.9%	8	297.1	13.4%	7	326.2	24.5%	9	303.6	15.9%
	Wireless 2 (6 weeks)	262	8	332.6	26.9%	8	304.5	16.2%	8	301.2	15.0%	6	294.4	12.4%	8	331.4	26.5%	9	324.2	23.8%
Average					15.5%			11.2%			9.5%			9.2%			16.0%			15.5%

(1) Data from assembled sensors during the first 3 weeks were not included in the average calculation.

7.4 Discussion

The goals of the study described in this chapter were to explore the sources of variation among sensor measurements and confirm the advantages of a sensor network versus single sensors in terms of accuracy and reduced system operating time.

Both mounting position and sensor type were shown to have significant effects on measured occupancy. When sensors were mounted on the North wall, where they were furthest from the normal sitting position of the occupant, they pulsed less frequently than in the other two mounting locations, although the occupant position was always within the coverage area claimed for the sensor at all mounting locations. This indicates that since sensors are less sensitive as the distance between the sensor and the target increases, mounting position will be critical to sensor performance.

Manufacturers of occupancy sensors rarely address the importance of mounting location. Most previous research concluded that commissioning and tuning were necessary to ensure the best performance[19, 45, 48, 44], but the mounting location of sensors in these studies, and indeed in practice, is quite arbitrary. A point that can "see" the whole controlled space is usually randomly selected, and the mounting location remains static. Past research and application has assumed that measured occupancy would not vary with mounting position; however, these results clearly show that mounting position can have a significant effect on measured occupancy, even in small enclosed office spaces.

We utilized three types of sensors in this study, and only the assembled sensors were significantly more sensitive than the other sensors. The commercial and wireless sensors used in this study were less sensitive than the assembled sensors; it is possible they were designed deliberately to reduce false-ons. Most of the time they only respond to middle and large movements, ignoring small but typical office movements such as typing, reading, and even hand waving. The commercial and wireless sensors are therefore prone to false-offs, and as such these individual sensors will require long time delay settings.

These results confirm that a sensor network provides superior occupancy detection. When all sensors function properly, a simple algorithm, such as logical function OR will provide a reasonably accurate prediction of occupancy, and the network performance will always be better than that provided by any individual sensor. The AND and MAJORITY functions always underestimate occupancy, and both functions are not recommended for use in a sensor network analysis algorithm.

Moving average and rule-based reasoning yielded similar results in total occupied time. These two methods were better at reducing false-ons since they considered the persistence of sensor performance to some extent. Neither the logical functions, nor the moving average, nor rule-based reasoning methods, include the ability to handle faulty sensor data. These simple algorithms will fail to determine occupancy accurately if one or more of the sensors in a network are not functioning properly.

Least squares estimation and neural networks are able to "learn" from true occupancy data, and can provide good results even in cases of sensor failure. However, pre-existing occupancy data are needed to "train" new systems, which is usually not available in real applications.

Bayesian belief networks, which define the relationships between variables and the conditional probabilities associated with each variable, such as the sensor pulsing probability given different time of day and sensor status, can also identify abnormally behaving sensors.

The least squares estimation and neural network methods identify defective sensors based on the large differences between that sensor measurement and the truth, while the belief network identifies the abnormally behaved sensors based on predefined conditional probabilities. Thus the effectiveness of the belief network will depend on the accuracy of the defined sensor model.

If occupancy is more accurately determined, it is possible to apply shorter time delay and achieve greater savings. Data described here showed that with a time delay of 5 minutes, the outputs from the sensor network were more accurate than those of individual sensors with a 20-minute time delay, and produced a similar number of false-offs. By switching from the single-detector based system to the sensor network with 5-minute time delay, with the same level of user satisfaction, a reduction of 12.3% to 17.0% in system use could be achieved. If a time delay of 10 minutes was applied to the sensor network, all the false-offs could be eliminated by the data fusion methods, and a reduction of 3.6% to 12.3% was possible. Although these reductions are not as large as the percentages calculated from the second study (Chapter 6), which showed reductions of 22.4% to 33.3% at 5-minute time delay and 8.4% to 24.7% at 10-minute time delay, they are also remarkable since they are *in addition to* the savings already achieved by the application of single sensor.

The next chapter describes the implementation of a prototype sensor network for lighting control in a small sample of work areas.

8 A Prototype Sensor Network for Lighting Control

8.1 Introduction

The final phase of the project involved the development and application of a prototype sensor network lighting control system. The sensor network is expected to allow for more accurate switching because it measures occupancy more accurately than any individual sensor. Improved accuracy means that the time delay parameter used to specify when the lights are switched off in an empty space can be shortened.

A control system was implemented based on the same home automation technologies used to collect the occupancy data described in previous chapters. This solution supplemented the wireless occupancy sensors with additional power control modules that were individually addressed and switched in response to signals from the wireless occupancy sensors used in previous phases of the project.

8.2 Methods and Procedures

Space occupancy was monitored using three wireless passive infrared (PIR) occupancy detectors (Activehome X10 model RMS18), each sensor facing the customarily occupied area in the controlled space. Wireless signals transmitted by these sensors were received using a Power Linc Model 1132 CU Controller, connected to a personal computer via an RS232 serial to USB computer interface. This unit was capable of receiving occupancy signals, *and* sending powerline carrier control signals to switch power on and off to connected luminaires.

The alphanumeric addresses associated with pulses from wireless sensors received in response to space occupancy were recorded on a personal computer using a commercially available home automation software package called Indigo, which runs under the Apple Macintosh OS X operating system. For the purposes of subsequent analyses, the raw log files were converted to one-minute resolution time series data: if a signal from a PIR sensor was logged "ON" for a particular time within a minute, the sensor output of that minute was considered ON and coded as "1". Otherwise, the sensor status was coded as "0", indicating no signal was received or an "OFF" signal was received from the detector for that minute.

Besides recording occupancy data, features of the Indigo home automation software package were used to switch power to a single luminaire using the sensor network data stream as the basis for the control signal. A single luminaire was powered using an X10 plug-in module (3-pin Appliance Module Model AM466), which was in turn connected to the same electrical circuit into which the wireless interface was plugged and powered.

Indigo was configured to send a signal to switch off power to the luminaire module three minutes after the sensor network data stream indicated that the room was vacant.

Light usage in each room was monitored using commercially available HOBO U9 Light On/Off data loggers from Onset Computer Corporation (Figure 8-1). These relatively small and compact devices (1.8 x 2.38 x 0.77 inches) are intended for mounting in close proximity to a light source. A light sensitive detector protrudes from one side of the device (circled in the figure), and is used to detect the time associated with changes in the state of the light source. The time associated with every state change was recorded to the logger onboard memory. A USB interface cable is used to download the raw state change data to a personal computer for further analysis. For the purposes of this analysis, the raw log file was converted to one-minute resolution time series data. The status of the lighting system being monitored by a lighting logger was coded as "ON" (with a value of "1"), for all minutes after the light was switched "ON" until the raw log file indicated that the state of the light sensor changed to the "OFF" condition. All other minutes were coded as "0", indicating that the light being monitored was switched off during these minutes.

Figure 8-1. Lighting data logger

Three rooms were included in this study. Each room incorporated different lighting systems, as follows. Room 1 was illuminated by two independent systems: a recessed ceiling-mounted direct-indirect fluorescent system provided ambient lighting; this system was complemented by a halogen wall-wash system that provided accent lighting along one wall. The second room was illuminated by four independent lighting systems. Ambient illumination was provided by a suspended direct fluorescent system. A halogen wall-wash system providing accent lighting along one wall complemented this system. This room also incorporated two additional lighting systems that were designed to showcase features of the ceiling and plenum, using two independently controlled indirect fluorescent systems. All illumination in the third room was provided by a suspended direct fluorescent system. In the case of rooms with more than one lighting system, light use was coded as "ON" if any of the systems in the room were switched on. Lighting control in all three rooms was provided by manual wall switches; a time clock system in the second room automatically turned the lights on and off at specific times throughout the day.

Occupancy and light usage were monitored in these spaces for about 1 month during the spring of 2007. The number of days each room was monitored differed slightly, as follows: room 1, 47 days; room 2, 31 days; room 3, 38 days.

After the initial monitoring period, our original plan had been to implement sensor network lighting control in each room, but the control system did not perform reliably enough to be installed in all three rooms, despite a period of apparently successful laboratory bench testing. When the system was initially installed in two of the three rooms, repeated episodes of power cycling to the controlled luminaires in both rooms were observed, in which the control system repeatedly switched the luminaire on and off: this was only remedied by turning off all power to the system, and then turning it back on again. In addition, on two separate mornings the occupant of one room arrived to find the lights switched on: further examination of the log files revealed that the lights had been switched on late the previous evening and they had remained on overnight, despite the fact that the room was unoccupied during the overnight period. In these cases, manually switching the luminaire on and off was sufficient to correct the problem.

As a result of these performance failures, the decision was made to implement the sensor network lighting control system in only one room, and monitor occupancy and light usage in this space for another month. Data collection continued in the other two spaces, and the sensor network lighting control policy was applied to the occupancy and light usage data, to outline the usage patterns that would have arisen in these spaces if the lighting systems had been controlled by sensor network as well.

8.3 Results

Table 8-1 summarizes occupancy and light usage collected from the three rooms prior to the installation of the sensor network.

Table 8-1. Occupancy and light use in three rooms over about one month

(A) Room 1 (47 days)

Condition	Minutes	Percent Total
Empty, Lights Off	61263	91
Empty, Lights On	2893	4.3
Occupied, Lights Off	2017	3
Occupied, Lights On	1507	2.2

(B) Room 2 (31 days)

Condition	Minutes	Percent Total
Empty, Lights Off	36900	82.7
Empty, Lights On	3436	7.7
Occupied, Lights Off	873	2
Occupied, Lights On	3431	7.7

(C) Room 3 (38 days)

Condition	Minutes	Percent Total
Empty, Lights Off	53353	97.5
Empty, Lights On	620	1.1
Occupied, Lights Off	179	0.3
Occupied, Lights On	568	1

Occupancy and light use in all three rooms was very low, which as we have previously discussed is due to the fact that the rooms were occupied by university faculty and staff, who have more flexible schedules than other office workers and spend large portions of their days in classrooms teaching or in laboratories.

Table 8-2 summarizes occupancy and light usage observed in Room 1 after the sensor network was installed to control one of the luminaires in the room. Even though monitoring in the space continued for a month, actual occupancy and light usage were observed in the space for only 19 days over the course of the month.

Table 8-2. Room 1 occupancy and lighting use (19 days)

Condition	Minutes	Percent Total
Empty, Lights Off	25696	93.9
Empty, Lights On	451	1.6
Occupied, Lights Off	1000	3.7
Occupied, Lights On	213	0.8
Occupied	1213	4.4
Sensor Network	1388	5.1
Lights	664	2.4

In this case, the luminaire controlled by the sensor network remained switched on for slightly more than twice the time than any of the manually controlled lights in the room were illuminated (the luminaire controlled by the sensor network was switched on for 1,388 minutes, while the manually controlled luminaires were switched on for 664 minutes. Nevertheless, this somewhat unexpected result at least demonstrated that the sensor network was able to closely tailor the lighting use to actual occupancy, because the usage time (at 1,388 minutes) is relatively close to the occupied time (at 1,213 minutes).

Table 8-3 shows occupancy and light usage data in Room 2 observed in the second monitoring period.

Table 8-3. Room 2 occupancy and lighting use (32 days)

Condition	Minutes	Percent Total
Empty, Lights Off	30076	65.3
Empty, Lights On	11893	25.8
Occupied, Lights Off	521	1.1
Occupied, Lights On	3590	7.8
Occupied	4111	8.9
Sensor Network	4363	9.5
Sensor Network + 5 Minutes	4426	9.6
Sensor Network + 10 Minutes	4712	10.2
Sensor Network + 20 Minutes	5207	11.3
Sensor Network + 30 Minutes	5596	12.1
Lights	15483	33.6

The lights in this room remained switched on even though the space was empty for a significant portion of the monitored period (nearly 26%). Modeling shows that in this case application of the sensor network to control the lighting with a 5 or 10 minute time delay would have resulted in less than a 2% increase (from 8.9% to 10.2%, with a 10-minute time delay applied to the sensor network data). This small increase contrasts with the light usage of nearly 34% (of which nearly 26% occurred in an empty space. Hence, if a sensor network with a 10 minute time delay had controlled the lights in this space, light usage would have been reduced by about 46% ([11,893-4,712]/15,483).

Table 8-4 shows occupancy and light usage data in Room 3 observed in the second monitoring period.

Table 8-4. Room 3 occupancy and lighting use (33 days)

Condition	Minutes	Percent Total
Empty, Lights Off	44896	94.5
Empty, Lights On	530	1.1
Occupied, Lights Off	504	1.1
Occupied, Lights On	1590	3.3
Occupied	2094	4.4
Sensor Network	2306	4.9
Sensor Network + 5 Minutes	2354	5.0
Sensor Network + 10 Minutes	2585	5.4
Sensor Network + 20 Minutes	2975	6.3
Sensor Network + 30 Minutes	3311	7.0
Lights	2120	4.5

Occupants in this room used the manual control effectively, as the lights were switched on just slightly longer than the time that the room was occupied (lights on for 2,120 minutes, room occupied for 2,094 minutes). Therefore, applying the sensor network control policy to the lighting in the space would have resulted in small increases to the lighting use.

Finally, modeled light usage that would have prevailed with sensor network lighting control in the room containing the 23 cubicle workstations (open-plan work area studied at the University of Nebraska, monitored for 63 days, and described in Chapter 6) is described in Table 8-5. In this room, application of sensor network lighting control with a 5 minute time delay would have increased light usage by just over 10%; a 20 minute time delay would have increased light usage by about third, and a 30 minute time delay applied to the occupancy data collected in this space would have increased light usage by 42.5%. A very short time delay could have been applied in this space, because the room was monitored by 69 independent detectors (3 in each of the 23 cubicle workstations located in the room).

Table 8-5. Modeled light usage under sensor network lighting control in room containing 23 cubicle workstations lighting use (63 days)

Condition	Minutes	Percent Total
Occupied	26848	N/A
Sensor Network	29476	9.8
Sensor Network + 5 Minutes	29945	11.5
Sensor Network + 10 Minutes	32077	19.5
Sensor Network + 20 Minutes	35536	32.4
Sensor Network + 30 Minutes	38267	42.5

8.4 Discussion

The results of this phase of the project were disappointing. The prototype sensor network developed to control the lighting did not function well enough to deploy in more than one space, and in this space, lighting control by sensor network showed an increase relative to use of the manually switched luminaires that were available to the occupant. This finding was at least in part due to the fact that the study was carried out during the summer months, when plentiful daylight was available in the monitored space, and the occupant did not use the manually switched luminaires. Nevertheless this unexpected result at least demonstrated that the sensor network was able to tailor the lighting use to actual occupancy.

Savings from the application of any lighting control strategy will only accrue if the lights remain switched on in an empty space. Few savings were observed in the two rooms that had low occupancy and lighting use, whereas larger savings were modeled for the room in which the lights remained switched on for long time periods even though the space was empty. Thus, we conclude from these results that a compelling demonstration of the actual benefits of sensor network control of lighting in a real application is still needed.

8.5 Future Work

When this project was proposed in 2002, our goal was to improve the performance of occupancy sensing control systems through the application of more extensive sensing.

The results reported in earlier chapters of the document show that more extensive sensing leads to more accurate measurement of occupancy. As a result, the time delay applied by occupancy sensing control systems to switch off systems can be shortened, leading to greater potential savings than can be achieved using current control systems.

The time delay parameter is the key to system performance and savings. In current systems, the time delay is manually set (usually using dip switches on the sensor itself) at installation, and thereafter remains unchanged. In rare occasions, the time delay setting is adjusted as part of post-installation commissioning, but even in these cases the time delay setting remains unchanged after commissioning has been completed. Throughout this project, our own work has been focused on establishing the shortest, but fixed, time delay setting that would lead to savings without compromising occupant satisfaction (as occurs when lights are switched off in occupied rooms).

At the conclusion of this project, we believe that the technologies developed and described herein offer the possibility of more sophisticated control, even though the results described in this chapter were disappointing. At the conclusion of the project we extended the control system described in this chapter so that the time delay interval could be dynamically set, and indeed individually tuned, in response to occupant behavior in the space. Thus, the time delay interval using this newest technology is not fixed (as in current systems), but is dynamic, and set in response to occupant behavior.

With this new control strategy, each individual space has the possibility to operate under a unique control setting tuned to take account of occupant behavior. Control settings can also automatically adjust to changes in occupancy patterns that might result from changes in furniture layout, or if a new occupant moves into a space.

Our immediate plan is to undertake experimental work to evaluate two aspects of the performance of this new control strategy. First, we expect that much shorter time delay settings should be established, and indeed hypothesize that the optimization process should converge on a setting of between 5 and 10 minutes, based on the data described in Figure 7-7, which shows that a sensor network measures the “correct” occupied time with a 5 to 10 minute time delay. We also expect that the new system should converge on an optimal time delay setting based on actual occupancy relatively quickly (in less than 2 weeks).

9 Summary

The research described in this report is based on the simple notion that a network of occupancy sensors will provide more accurate and reliable measurements of building occupancy, and building system control, than are provided by current occupancy sensing systems that rely on single points of detection. More extensive sensing and more sophisticated control algorithms are required to maximize energy efficiency and user satisfaction.

The effectiveness of traditional single-point detection is restricted by sensor mounting position and inherently simple detector technologies. A sensor network, consisting of several independent detectors monitoring the same space, provides more information about occupancy than is possible from a single point of detection. In contrast to technologies that use single-points of detection, a sensor network estimates occupancy based on measurements from all the networked sensing elements, and combines these measurements using a robust data fusion technique that can also take into account, for example, the history of performance of individual sensors in the network, and/or the typical occupancy pattern of a specific space.

This chapter concludes the report, summarizing results from the studies described in the report, presenting a discussion of the economics associated with the sensor network approach (based on occupancy and cost data collected as part of this project and published elsewhere[110-116]), and discussing some technology developments that will be required for wide implementation of sensor networks for building control and management[117-122].

9.1 Summary of studies

The effectiveness of a sensor network for occupancy monitoring and lighting control was evaluated in several studies. The first study was conducted in two relatively small private offices over a two day period, and was designed to evaluate the utility of using a network of sensors to detect occupancy, and explore data fusion methods that could be applied to determine occupancy. Three PIR sensors were deployed in each office, and all the sensors were wired to a central computer that recorded the occupancy data from these sensors. The data from the sensors was complemented by two other "true" measures of occupancy: a digital video record collected from each office over the two day period, and occupancy records collected by human observers who monitored the status of each office during working hours over the two day period.

If a single sensor can accurately characterize occupancy, the occupied times measured by the different methods (individual PIR sensors, digital video and human observers), should all be about the same. In fact, results showed differences in occupied time measured by the three different sensors in each office, while the occupied times measured by the human observers and digital video were more similar.

The deviations between occupied times measured by the sensors versus the true total occupied time (measured by the human observers) ranged from -17% to -80%. Single sensors underestimated occupied time, and there were also differences in measured occupied time between the three sensors located in each office. For example, in the most extreme case, there was a 76.4% difference in the occupied time measured by two of the sensors in one room on the second monitored day.

Given that these results were obtained in relatively small private offices with a single occupant, the differences in measurements between sensors accentuate the difficulty in obtaining an accurate measure of occupancy with a single sensor. The performance of a single sensor will be affected by numerous factors, such as sensor type, mounting position and occupant behavior patterns. As a result of the operation of these factors, there can be considerable uncertainty in the determination of occupancy by a single sensor.

Control applications that use occupancy sensors compensate for these uncertainties with a long time delay setting (e.g., 20 to 30 minutes). The long time delay setting ensures that services are not inadvertently switched off in an occupied space (a so-called "false-off": the use of additional sensors helps reduce this uncertainty, and the number of false-offs. False offs should be avoided if at all possible, as they sometimes lead occupants to disable control systems). However, a long time delay also means energy waste, as energy is the product of power and time. Conventional time delay settings of 20 to 30 minutes, while eliminating many false-offs, can considerably increase the operating time.

Data collected from all three sensors installed in the same space were fused to generate a sensor network output. The results were encouraging: sensor network outputs were more reliable than any single-point detection in terms of accuracy and ability to reduce number of false-offs. Because occupancy could be determined more accurately using fused sensor network data, shorter time delays could be applied, and more energy savings would result without sacrificing user satisfaction.

To confirm and extend the findings observed in the pilot study, PIR sensor networks were deployed in a larger sample of work areas for a longer monitoring period in the second study. The results from the first study were confirmed. There were large differences in the measured occupied time between the three individual sensors monitoring occupancy in each office: the differences in total occupied time measured by individual sensors ranged from 14% to 93.2%, with an overall mean difference of 51.7%.

A subset of these data were then used to model the system use that would have resulted had the lighting systems in these spaces been controlled by any one of the three sensors alone (with a longer [20 minute] time delay), versus the on-time that would have prevailed using the sensor network for control (using a shorter [5 or 10 minutes] time delay). Applying a 5 or 10-minute time delay to occupancy measured by the sensor network resulted in reductions of 22.4% to 33.3% or 8.4% to 24.7%, respectively, relative to the maximum on-time that would have prevailed in the space using single point occupancy measurement, with a longer time delay of 20 minutes.

Although the first two studies concluded that individual sensors installed in the same space behaved differently, and that shorter time delay settings that result in greater energy savings are possible, the differences in measured occupancy between more than one sensor monitoring the same space could come from random individual sensor characteristics, or some other factor, such as sensor mounting position and/or sensor type. If all sensors mounted in a single room perform the same anywhere in the space, then the solution for best occupancy determination might be several sensors placed adjacent to one another anywhere in the space, instead of the widely spaced mounting used in the first two studies (which was used to ensure the whole space was covered). A third study was therefore designed and completed to evaluate the effects of sensor type and mounting location on occupancy measurements.

This "round-robin" study involved three sensor types (wired self-assembly kits, wired commercial sensors and wireless sensors) and three mounting positions, conducted in two private offices over a six week monitoring period. Signals from each sensor, as well as the true occupancy data recorded by video cameras were collected during the study. The true occupancy data were compared with the individual sensor measurements and fused data network occupancy estimates to evaluate the accuracy of these measurements. At the start of each week over the 6-week data collection period, all sensors were removed from the wall they were mounted on, and then moved to the next adjacent wall in a clockwise direction. The occupancy data measured by the three different sensor types at their respective locations were compared to evaluate the effects of sensor type and mounting location.

Statistical analysis (ANOVA) showed that sensor mounting position and sensor type had significant effects on sensor performance. Generally, the wired self-assembled sensors pulsed more often than the wireless and commercial sensors at all mounting positions, while the wireless and commercial sensors measured about the same occupancy when mounted adjacent to one another on the same wall. All three types of sensors pulsed more often when they were mounted closer to occupants. The finding that there were significant differences in measured occupancy as a function of mounting location underlines the difficulty and uncertainty associated with occupancy measurement using a single randomly mounted sensor, even though the control areas of all the sensors used were well within the coverage area claimed by the manufacturer. This explains why post installation commissioning is important in real situations, and why long time delays are required to ensure satisfactory control.

The sensor network produced good estimates of occupancy, even when two out of the three wired sensors were observed defective in the first half of the round robin study. The results confirmed that an appropriate algorithm applied to the sensor network data stream has the ability to self-diagnose, and thus sensor network control can be more robust than control using a single sensor, which would have no additional information to use in diagnosing sensor performance.

As in the second study, outputs from the sensor network with a 5 or 10-minute time delay were compared with the measures from each individual sensor with a 20-minute delay.

At these settings, control by sensor network with a 5-minute time delay versus individual sensors with a 20-minute time delay produced the same number of false-offs, and the system usage with the sensor network could be reduced by 12.3% to 17.0%. At a 10-minute time delay, false-offs were eliminated, and control by sensor network would have reduced system use by 3.6% to 12.3%, compared with individual sensors with a 20-minute time delay.

Table 9-1. Summary of the three studies

		Pilot Study	Study II	Round-robin Study
Sample size (Number of private office studied)		2	10[1]	2
Data collection period		2 days	59 days	42 days
Difference in measured occupied time between individual sensors [2]		66.7% to 76.4%	16.1% to 74.0%	5.8% to 82.0%
Deviation of measured occupied time from truth [3]		-80.4% to 39.3%	N/A	-72.1% to 455.7%
Percentage of the reduced system time (5 vs. 20) [4]	All sensors were functioning	21.4% to 31.3%	22.4% to 33.3%	12.3% to 17.0%
	One or two sensors were defective[5]	59.6% to 75.5%	N/A	76.4% to 85.4%
Percentage of the reduced system time (10 vs. 20) [6]	All sensors were functioning	12.5% to 28.6%	8.4% to 24.7%	3.6% to 12.3%
	One or two sensors were defective[5]	55.1% to 72.1%	N/A	71.4% to 84.2%

(1) Only data collected from private faculty offices at the University of NE are summarized here.

(2) Calculated as (max-min)/max.

(3) Calculated as (Measured-Truth)/Truth. A sensor usually underestimates the occupied time; the overestimation (percentage>0) therefore often indicates a sensor malfunction.

(4) Modeled reduction in on time using sensor network with 5-minute time delay versus single sensor with 20-minute time delay, calculated as ((max of individually measured time + 20-min delay) - (output from sensor network + 5-min delay))/ (max of individually measured time + 20-min delay).

(5) Only considered results from data fusion methods that can identify faulty sensor(s), i.e., for the pilot study, moving average, rule-based reasoning, BN, LSE and NN methods were considered; for the round-robin study, only BN, LSE and NN methods were considered.

(6) Modeled reduction in on time using sensor network with 10-minute time delay versus single sensor with 20-minute time delay, calculated as ((max of individually measured time + 20-min delay) - (output from sensor network + 10-min delay))/ (max of individually measured time + 20-min delay).

Table 9-1 summarizes findings from the three studies. The results in the table demonstrate that the occupied time measured by individual sensors varies significantly, and therefore each individual sensor will be a poor predictor of occupied time, as demonstrated by the large deviation between the occupied time measured by the sensors versus the "true" occupied time measured directly by human observers or by human review of digital video. Properly functioning sensors usually *underestimate* the occupied time and do not pulse continuously in an occupied space (in contrast to malfunctioning sensors, which were observed to pulse continually, even when the space was unoccupied).

Long time delay settings are used in traditional control applications to compensate for this uncertainty. When occupancy is measured more accurately using a network of sensors, 5-minute time delay can be applied to achieve the same user satisfaction, reducing system use by a further 12.3% to 33.3%, relative to the savings that could be achieved using a single detector with a longer time delay. While a single sensor with 20-minute time delay produces about 0.8 false-offs/day (observed in the round-robin study), a sensor network with a 5-minute delay produces about 0.6 false-offs/day (also observed in the round-robin study). Applying a time delay of 10 minutes can eliminate false-offs and reduce system use by 3.6% to 28.6%.

Sensor failure is hard to predict and prevent in real applications. Numerous sensor failures were observed in the course of this work. The whole control system would have failed if only a single sensor was used, but with a proper data fusion method, it was possible to identify defective sensors.

9.2 Summary of Data Fusion Algorithms

Eight data fusion techniques were applied to evaluate the performance of the sensor network in the pilot and the round-robin studies, and these were introduced in Chapter 4. They were: logical functions OR, AND and MAJORITY, moving average, rule-based reasoning and Bayesian belief network, least squares estimation and neural network methods. Since the true occupancy data were not collected as part of the second study, the data fusion methods that require supervised training (least squares estimation, and neural network) were not applied. Instead, the three logical functions, moving average, rule-based reasoning and Bayesian belief network methods were applied to this data set.

The comparison of the effectiveness of the 8 different methods to predict occupancy was made by means of total occupied time, the accuracy (in terms of φ correlation) and the number of false-ons and false-offs. If all sensors function properly, a simple algorithm such as logical function OR produces a more accurate prediction of occupancy better than any single detector, because the combination of the underestimates from each individual sensor is always closer to the truth. However, in the case of sensor failure, simple algorithms fail to identify faulty sensor(s), and so produce an incorrect result. To ensure system performance, more sophisticated methods that take into account additional factors are recommended.

The data fusion techniques described and applied in this report can be classified into three groups. The first group is composed of methods that do not need any *a priori* information about the system and true occupancy: these include logical functions OR, AND and MAJORITY, and the moving average method. Occupancy predictions using these methods are inaccurate in the case of sensor failure. However, if all sensors function correctly, the logical function OR and the moving average methods usually generate accurate prediction of occupancy that are closer to the truth than any single measurements.

Methods in the second group require some general knowledge about the expected occupancy pattern or general sensor response to occupancy: these include rule-based reasoning and Bayesian belief network methods. The rule-based reasoning method defines rules based on observed sensor behavior. For example, a rule can be defined as: during the day, the space is considered occupied if one sensor pulses, while during the night, two sensors must pulse at the same time to indicate occupancy. This rule is based on the knowledge that all sensors do not pulse at the same time, even when the space was occupied (e.g. Table 5-3), and that there is a higher probability of occupancy during the day than at night. The effectiveness of this method depends on the understanding of the system and the definition of the rules

The belief network method needs similar information, but rather than defining some "rule", this method interprets the propositions making up the rule statement statistically in terms of conditional probabilities. Depending on the definition of the belief network structure, various conditional probabilities are required. For example, we need to know the probability of sensor pulsing when a room is occupied and the sensor in that room is functioning correctly. Again, the effectiveness of this method depends on the understanding of the system and the definition of the network structures and the characteristics of sensors (sensor model).

The third group of data fusion algorithms requires "true" occupancy data to train parameters used to complete the fusion algorithm. These include: least squares estimation and neural network methods. Basically, these methods used a sample of sensor network measurements and the true occupancy information as inputs to calculate values for parameters that ideally map sensor readings to the truth. The calculated parameters were then applied to other sensor readings, and a predicted occupancy was calculated. Back propagation supervised learning was applied to the neural network methods used in this report. Although neural networks can also be trained in an unsupervised fashion (no training data used), the networks developed in this research used true occupancy data to train the network.

Table 9-2. The accuracy (φ) of algorithms in the pilot and round-robin studies

Study	Pilot Study		Round-robin Study								
Room Number	1	2	1			2					
Sensor Type	Assembled (1)	Assembled	Commercial	Assembled	Wireless (3)	Commercial	Assembled1 (2)	Assembled	Wireless (3)	Average	Variance
Logic Function *AND*	0.50	0.36	0.42	0.78	0.29	0.64	0.93	0.80	0.49	0.58	0.048
Logic Function *MAJORITY*	0.79	0.64	0.59	0.94	0.54	0.86	0.34	0.97	0.79	0.72	0.042
Logic Function *OR*	0.66	0.86	0.76	0.97	0.75	0.92	0.24	0.97	0.86	0.78	0.051
Moving Average	0.86	0.75	0.83	0.94	0.83	0.92	0.18	0.95	0.87	0.79	0.058
Rule-based Reasoning	0.95	0.92	0.75	0.96	0.74	0.92	0.20	0.97	0.92	0.81	0.061
Belief Network	0.83	0.66	0.80	0.95	0.81	0.94	0.67	0.96	0.92	0.84	0.013
Least Squares Estimation	0.83	0.84	0.76	0.97	0.75	0.93	0.86	0.97	0.87	0.86	0.007
Neural Network	0.85	0.86	0.76	0.97	0.75	0.92	0.95	0.97	0.85	0.88	0.007

(1) One out of the three sensors installed in this room was malfunctioning.
(2) Two out of the assembled sensors were malfunctioning.
(3) This column shows the average of two groups of wireless sensors.

Table 9-2 summarizes the accuracy of the eight data fusion methods as applied in two studies with true occupancy data. The accuracy is designated by φ correlation: a special case of Pearson's r, which describes the similarity between two sets of dichotomous data. In this study, φ correlation was used to compare the measured or estimated data with the truth, and the higher the φ value (with a maximum of 1), the more accurate the method. Only data from the pilot and the round-robin tests were evaluated here since the accuracy calculation cannot be applied to data from the second study due to the absence of truth data. The data fusion methods were ordered by increasing accuracy, and interestingly, this order is coincident with the complexity of the methods. The simple methods that do not need expert knowledge and parameter training have low accuracy and high variance, which indicates unstable performance. As the fusion algorithm utilizes more information, the application of that algorithm produces more accurate and reliable estimates of occupancy. This should not be surprising.

In conclusion, to guarantee accurate occupancy measurement, at least one of the following three conditions should be satisfied: 1) Accurate definition of sensor model (probability of sensor pulsing under occupied versus empty space conditions); 2) Real occupancy data for calibration (training data) is available, and; 3) The general occupancy patterns associated with specific building types is known (e.g., the probability of occupancy in each hour of the day in private offices). When values for these parameters can be defined, advanced algorithms such as Bayesian belief networks, or neural networks, can be constructed and will generate good predictions about occupancy.

9.3 Limitations and Suggestions

9.3.1 Limitations in network topology

The sensor network developed and deployed in this research is only a prototype; many improvements are needed before commercialization is possible. The system described here used a centralized network structure, or a so-called "star" network topology: all sensors were connected to a central processor where the decision concerning occupancy was made, and there was no communication between the sensors themselves, as depicted in Figure 9-1.

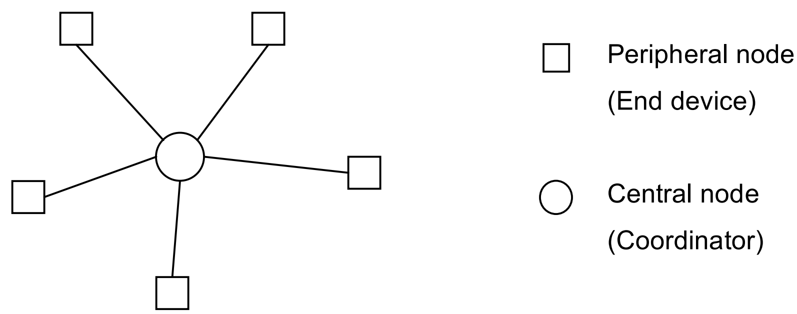


Figure 9-1. Star network topology

A node is a connection point in a network, which can be a computer, a router, or a hub, for example. A coordinator is the processing center of the whole network. It maintains overall network knowledge, and needs most computing power of the three node types. Each network only has one coordinator. An end device usually has limited functionality. It can be a sensor, controller or an actuator. Each end device communicates directly with a network coordinator in a star network structure.

This structure improves the accuracy of decision and reduces the probability of a network failure relative to a single sensor since the redundant information provided by the peripheral nodes (PIR sensors) are all considered at the central node (computer). The failure of a transmission line linking any peripheral node to the central node will result in the isolation of that peripheral node from all others, but the remaining peripheral nodes will be unaffected. Decisions can still be made based on the remaining nodes, so the structure is more robust than a single sensor. However, the failure of the central node will cause the failure of the whole system. Furthermore, data transmission is restricted by distance; if a node is located far away from the central processor, it will result in extra wiring cost or weak wireless signal.

So-called "mesh" or "peer- to-peer" networks provide more effective data transmission and processing. Nodes within a mesh network can communicate with each other to form a mesh, and data processing in a mesh network can be completed by many different nodes in the network. Thus, mesh networking enables the most efficient use of processing power, and full services remain available regardless of the failure of individual parts of the network. Figure 9-2 illustrates the layout of a mesh network and the three common types of nodes within a mesh network. The router acts as a junction between two or more network nodes to buffer and transfer data packets among them. It can communicate with all three types of nodes. The end device only communicates with a network coordinator or router.

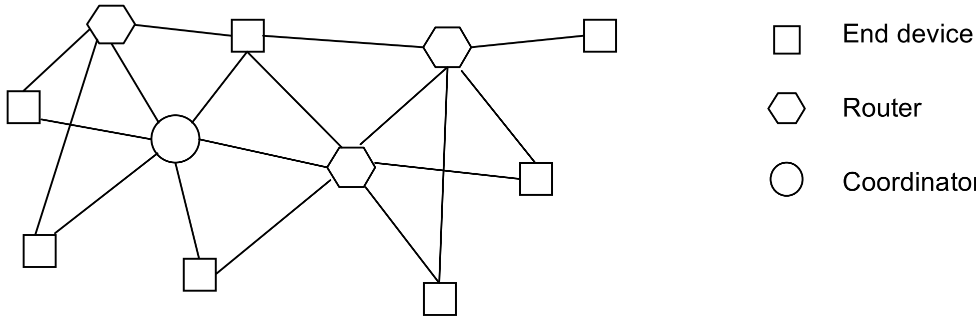


Figure 9-2. Mesh network topology

Mesh networks enable high degrees of reliability and robustness. There is usually a choice of more than one route that one part of the network can communicate with the coordinator. If a malfunction occurs in one section of a network, then another route can be used, and the network still maintains the maximum functionality. In the future, a wireless mesh network is preferable for occupancy monitoring, due to improved effectiveness, robustness and low installation cost.

Another limitation of the current sensor network relates to the communications protocols used in the research. The occupancy sensors used in the research were either self-assembly kits for electronic amateurs, commercially available products, or wireless sensors used by home automation hobbyists. The wired sensors (self-assembled, or commercially available) differentiate an "occupied" from an "unoccupied" signal by sending a change in voltage to a data acquisition system or controller, while the wireless sensors send a signal based on the X10 protocol, a narrowband communication protocol used primarily for home automation. The X10 protocol is typically used in powerline carrier applications (relatively few of the devices currently available have wireless capability), and it uses a small address space with no error checking or correction.

To commercialize a sensor network for lighting control, faster data communication mechanisms and more reliable communication protocols are required. For example, BACnet is a data communications protocol for building automation and control networks. Currently, it is an ASHRAE, ANSI, and ISO standard protocol. LonWorks is another networking platform specifically created for building control applications. LonWorks is based on a low bandwidth protocol for networking devices over media such as twisted pair, power lines, fiber optics, and radio frequency. It is popular for the automation of various functions within buildings such as lighting and HVAC. ZigBee is a suite of high-level communication protocols using small, low-power digital radios based on the IEEE 802.15.4 standard for wireless personal area networks (WPANs). Since wireless sensors are preferable in our sensor network due to ease of installation, and low power consumption, ZigBee might be a good choice for future distributed occupancy sensor networks. Compared with wireless standards such as Wi-Fi and Bluetooth, ZigBee is focused on building monitoring and control and, in theory, offers unlimited network size, high reliability, low power consumption and low cost[117-121] .

Power management is important in a sensor network. The wired sensors used in this research were powered by 9V DC adapters and the wireless sensors need two 1.5V AAA batteries. These may be suitable for small scale or home automation uses but is not acceptable for large commercial applications. Battery replacement is impractical and uneconomical, so complementary power management devices and protocols will be required in a sensor network for measuring occupancy. Again, ZigBee enables low-power data transmission and so would be a good candidate for commercial occupancy sensor network applications. Other solutions that do not require batteries, such as photovoltaics, which convert solar energy directly into electricity, or EnOcean technology[122], which harvests environmental energy fluctuation (such as change in pressure and temperature) and converts it into electricity, may also be useful.

9.3.2 Limitations in algorithms and criteria

This research investigated the application of several algorithms to occupancy sensor network data. Algorithms that incorporate information about general occupancy patterns and sensor characteristics, such as the belief network algorithm, enhance the performance of the sensor network in terms of accurately predicting occupancy, and diagnosing and accounting for the existence of sensors generating faulty or inaccurate data. Although this algorithm is better at determining occupancy and identifying faulty sensors than data from a single sensor, the belief network algorithm requires information concerning the probability of occupancy at different times: in this research, these data were determined empirically, and from occupancy data published roughly 20 years ago by ASHRAE Standard 90.1-1989. A larger sample of more contemporary occupancy data would help improve the performance of this algorithm. This study concentrated on commercial buildings, and intuitively, industrial and residential buildings can also be benefit from the sensor network, if a suitable occupancy patterns are available and can be incorporated into the data fusion algorithm.

Other advanced algorithms, like the supervised neural network method, need training information to refine the parameters incorporated in the methods. Future research is encouraged to integrate this algorithm within a more preferable network structure (e.g. mesh network). The system, for example, might have a “Training On/Off” button at the router, which also includes one of the three occupancy sensors installed in a single space. The commissioning staff or the occupant would be instructed to stay in the space when the system training mode was enabled. When the “Training On/Off” button is pushed, enabling the training mode, the system assumes the space is occupied, and adjusts the sensitivity and time delay settings based on this “true occupancy” information. The user would disable the training mode by pushing the “Training On/Off” button again, thus storing the new parameters. A longer training process would be expected to increase the accuracy of the system parameters.

The criteria used in this research to evaluate the performance of the sensor network can also be improved. The two major criteria used in this study were accuracy (in terms of φ correlation), and the number of false-offs. Recall the formulation of the φ correlation is as follows:

Measured / Truth	1	0	
1	N_{11}	N_{10}	r_1=N_{11}+N_{10}
0	N_{01}	N_{00}	r_2=N_{01}+N_{00}
	c_1=N_{11}+N_{10}	c_2=N_{10}+N_{00}	

$$\varphi = \frac{N_{11}N_{00} - N_{10}N_{01}}{\sqrt{r_1 r_2 c_1 c_2}} \tag{4.15}$$

N_{11} and N_{00} relate to correct measurements, while N_{10} and N_{01} represent incorrect measurements: N_{10} is the number of instances the space was occupied but the sensor(s) did not detect motion, while N_{01} is the number of instances when the space was vacant, but the sensor(s) measured occupancy. When the time delay was increased, N_{01} also inevitably increased, and the overall accuracy decreased. The formula does not distinguish between the two kinds of incorrect measurements: N_{10}, which is closely related to false-offs, should be more highly weighted in the calculation, since it is the major source of user complaints.

For example, the accuracy of the belief network algorithm for wireless sensors in Room 2 in the round-robin study was 0.94 (N_{10}=16.9, N_{01}=10.4) without any time delay (and which underestimated the occupied time by 2.5%). If a 5-minute time delay was applied, the accuracy decreased slightly to 0.91 (N_{10}=7.7, N_{01}=35.2), and in this case, the operating time exceeded the true occupied time by 10.5%. Adding a 5-minute time delay reduced the number of false-offs to 0.4 (from 3.1, with no time delay). The reduction in the number of false-offs is preferred, but it is not reflected in the change in the value of φ from 0.94 to 0.91. If N_{10} is given a weighting of 1.5, and N_{01} a weighting of 0.5, the φ values change to 0.92 (no time delay) and 0.93 (5-minute time delay), which may be a more reasonable description of the measurement accuracy.

User satisfaction was only evaluated in terms of the number of false-offs. Research shows that dimming lights, rather than switching them off completely, might also be acceptable, and save noticeable amount of energy[36-40]. The sensor network, with enhanced capability endowed with an advanced network topology, might also consider the energy saving and user satisfaction in a more effective manner.

9.4 Economic Analysis

This section provides an economic analysis associated with the application of sensor networks. Previously in this document, energy savings were discussed in terms of reduced operating time. A more sophisticated analysis incorporating all the initial and operating costs is provided in this section. Simple payback periods for single-point detection and sensor network systems are calculated in this section as estimates of the economic advantage of the sensor networks. The simple payback period is calculated by Equation 8.1.

$$\text{Payback Period (in years)} = \frac{\text{Incremental Investment}}{\text{Annual Savings}} \tag{9. 1}$$

where the incremental investment is the increase in initial cost of switching from one system to another, and the annual savings is the reduction in operating costs under the alternative system.

Occupancy sensors used in current building systems are usually used to control lighting systems only, so the economic analysis in this section is restricted to lighting systems. If occupancy-based building control were expanded to all applicable systems, greater energy savings and shorter payback periods would be expected because of the reduction in overall operating time and associated costs for these other systems.

The analysis in this section involves three building types, one based on data collected in this report, the other two based on data provided by DOE. The studies described in this report were carried out in small private offices used by university faculty. Compared with the office data provided by DOE, occupancy in these offices is usually lower. Thus, they might result in different payback periods.

Two other building types were defined by DOE[112]. DOE classified office buildings into two general groups: large with floor area greater than 25,000 ft^2 (having power densities of 1.3-1.8 watts/ft^2, and lighting usage of 4190 hours per year), versus small, with floor area less than 25,000 ft^2, power densities of 1.7-2.2 watts/ft^2, and annual lighting usage of 3340 hours.

In each building type, the lighting system control options compared were: a manual wall switch, a single PIR wall switch, a single ceiling or wall mounted dual-technology sensor, and the sensor network. The initial and operating costs for the four control strategies were calculated and compared, using the manual wall switch as the baseline for economic analysis.

9.4.1 Initial cost

The initial costs of the control system included the material cost of the switch, sensors, and all ancillary material (wiring, conduit, junction boxes, etc.), and the installation labor cost. Table 9-3 shows total prices for typical manual switches and occupancy sensors. Prices were obtained from major manufacturers, and are described in Appendix D. Costs for accessories (electric metallic tubing conduit (EMT), wire, steel outlet box and plaster ring, wall plate) and labor come from RSMeans 2006 electrical cost data[116]. Occupancy sensors are assumed to have the same tubing and wiring requirements as manual switches. Ceiling or wall mounted sensors usually operate at low voltage (24 or 12 VDC), and a power pack is needed to transform the line voltage to the sensor operating voltage. The material and installation costs of power packs are therefore also included in the total cost of ceiling or wall mounted sensors.

The costs of mounting and wiring sensors can exceed the cost of the sensors themselves. As Table 9-3 shows, labor for tubing and wiring alone costs around $120 ($88.44+$29.93), while the cost of a manual switch itself is only $1.35. The high material and labor costs make a wireless solution desirable.

Table 9-3. Material and installation costs for manual wall switches and occupancy sensors

	Unit Price	Quantity	Unit	Material	Installation	Total
Manual wall switch						
Electric metallic tubing conduit (EMT)	$1.09	22	Ft	$23.98	$88.44	$112.42
Wire	$16.70	0.63	CLF	$10.52	$29.93	$40.45
Steel outlet box	$2.59	1	Ea.	$2.59	$26.00	$28.59
Steel outlet box plaster rings	$2.76	1	Ea.	$2.76	$8.15	$10.91
Wall plate	$0.34	1	Ea.	$0.34	$6.55	$6.89
Manual switch	$1.35	1	Ea.	$1.35	$13.05	$14.40
Total				**$41.54**	**$172.12**	**$213.66**
PIR wall switch						
Electric metallic tubing conduit (EMT)	$1.09	22	Ft	$23.98	$88.44	$112.42
Wire	$16.70	0.63	CLF	$10.52	$29.93	$40.45
Steel outlet box	$2.59	1	Ea.	$2.59	$26.00	$28.59
Steel outlet box plaster rings	$2.76	1	Ea.	$2.76	$8.15	$10.91
Wall plate	$0.34	1	Ea.	$0.34	$6.55	$6.89
PIR occupancy sensor	$60.00	1	Ea.	$60.00	$14.65	$74.65
Total				**$100.19**	**$173.72**	**$273.91**
Ceiling/Wall mounted dual-technology sensor						
Electric metallic tubing conduit (EMT)	$1.09	22	Ft	$23.98	$88.44	$112.42
Wire	$16.70	0.63	CLF	$10.52	$29.93	$40.45
Steel outlet box	$2.59	1	Ea.	$2.59	$26.00	$28.59
Steel outlet box plaster rings	$2.76	1	Ea.	$2.76	$8.15	$10.91
Wall plate	$0.34	1	Ea.	$0.34	$6.55	$6.89
Dual-tech occupancy sensor	$150.00	1	Ea.	$150.00	$50.00	$200.00
Power pack	$40.00	1	Ea.	$40.00	$10.00	$50.00
Total				**$230.19**	**$219.07**	**$449.26**

For the sensor network, costs are largely unknown, as a sensor network for lighting control does not yet exist. The analysis is therefore based on a combination of known and estimated costs, as follows.

The wireless sensors used in this research cost $13.00 each. Installation costs for wireless sensors are lower than for wired sensors or switches, as they involve no EMT or wire, and therefore less associated labor. While the installation labor fee for the manual switch is $13.05, this analysis conservatively estimates the labor per sensor in a sensor network at $10.00 per sensor, since it involves no wiring. In our research, wireless sensors were mounted to the wall surface using a product called "sticky wax", which adds material cost of $1.00, and labor costs of $5.00, for each of the 3 sensors used in each office. Computer hardware and software at $480.00 were required for data acquisition and control in 10 offices (consisting of a $400.00 Macintosh computer and $80.00 software). Costs to commission the system are estimated at about $50.00 per office. A lamp module that provides X10 switching capability currently costs about \$14.00. The installation cost of this module is assumed to be \$5.00.

We have suggested that ZigBee networks would be preferable for this application, and so calculations for network hardware costs are based on the current prices of ZigBee components. A ZigBee network consists of one coordinator and several routers and end devices. The retail price of a ZigBee compliant end device module is about \$3.00 as of 2006[118]. The ZigBee end device module would be incorporated into an occupancy sensor, and the same unit cost as the X10 based wireless sensors used in this study is assumed (\$13.00 each). Commercially available ZigBee routers cost about \$60.00. Each office needs two end devices (i.e., occupancy sensors) and one router (which also incorporates a third occupancy sensor). In a commercialized ZigBee-based lighting control network, a ZigBee compatible ballast would also be required. A ZigBee compatible ballast adds \$5.00 to material costs [119], and does not affect the installation cost.

Mounting accessories are needed to install wireless sensors. These include the same products as needed for a wired sensor (including material and labor costs associated with a metal box in which to place the sensor, plaster ring and wall plate). No EMT or wires are required. The end devices and routers (all of which incorporate an occupancy sensor), communicate with a ZigBee-enabled coordinator, which is anticipated to include software to manage the data stream from the sensor network, and switch lights. Costs for the coordinator and control center are estimated at \$5,500.00. Fifty offices are assumed to share one coordinator in a small office building, while in a large building, one coordinator is assumed to control 500 offices: note that costs for the control center are divided by the number of offices controlled by the device. Table 9-4 lists all the above-mentioned devices and labor costs associated with the sensor network used in the research project, and estimated costs for a commercially available system in generic large and small office buildings.

Table 9-4. Material and installation costs per office for sensor networks

Prototype sensor network (Private faculty office)	Unit Price	Quantity	Unit	Material	Installation	Total
Wireless sensor (X10 protocol)	$13.00	3	Ea.	$39.00	$30.00	$69.00
Mounting accessory	$1.00	3	Ea.	$3.00	$15.00	$18.00
Control Module	$14.00	1	Ea.	$14.00	$5.00	$19.00
Central computer	$480.00	0.1	Ea.	$48.00	$50.00	$98.00
Total				**$104.00**	**$100.00**	**$204.00**
Sensor network (General small office)						
Electric metallic tubing conduit (EMT)	$1.09	0	Ft	$0.00	$0.00	$0.00
Wire	$16.70	0	CLF	$0.00	$0.00	$0.00
Steel box	$2.59	3	Ea.	$7.77	$78.00	$85.77
Steel box plaster rings	$2.76	3	Ea.	$8.28	$24.45	$32.73
Wall plate	$0.34	3	Ea.	$1.02	$19.65	$20.67
Incremental cost for Zigbee ballast	$5.00	4	Ea.	$20.00	$0.00	$20.00
Wireless sensor (Zigbee module)	$13.00	2	Ea.	$26.00	$20.00	$46.00
Zigbee router	$60.00	1	Ea.	$60.00	$10.00	$70.00
Control center	$5,500.00	0.02	Ea.	$110.00	$0.00	$110.00
Total				**$233.07**	**$152.10**	**$385.17**
Sensor network (General large office)						
Electric metallic tubing conduit (EMT)	$1.09	0	Ft	$0.00	$0.00	$0.00
Wire	$16.70	0	CLF	$0.00	$0.00	$0.00
Steel box	$2.59	1	Ea.	$2.59	$78.00	$80.59
Steel box plaster rings	$2.76	1	Ea.	$2.76	$24.45	$27.21
Wall plate	$0.34	1	Ea.	$0.34	$19.65	$19.99
Incremental cost for Zigbee ballast	$5.00	4	Ea.	$20.00	$0.00	$20.00
Wireless sensor (Zigbee module)	$13.00	2	Ea.	$26.00	$20.00	$46.00
Zigbee router	$60.00	1	Ea.	$60.00	$10.00	$70.00
Control center	$5,500.00	0.002	Ea.	$11.00	$0.00	$11.00
Total				**$122.69**	**$152.10**	**$274.79**

9.4.2 Operating cost

Lighting load (Power density)

Lighting loads are expressed as lighting power density, the electrical load per unit area. The power density of the private faculty offices used in this research was approximately 2.0 watts/ft^2. Power densities applicable to general small and large commercial buildings have been determined by DOE survey (DOE 2006 Buildings Energy Data Book) to be 1.7-2.2 watts/ft^2, and 1.3-1.8 watts/ft^2, respectively[112]. We therefore use 2.0 watts/ft^2 as a "typical" value for small buildings and 1.5 watts/ft^2 for large buildings. This 1.5 watts/ft^2 also coincides with the allowable lighting power density set by ASHRAE 90.1, which has been adopted by more than 30 states. For a 200 ft^2 private office, the load will be 400 watts (small building) or 300 watts (large building) respectively.

Hours of usage (Time)

Baseline lighting use of 3340 hours per year for small commercial, buildings and 4190 hours per year for large commercial buildings are from DOE (2006) Buildings Energy Data book.

Past research shows that single-sensor control typically reduces operating time by 25%. Further reductions are possible by the utilization of a sensor network, as documented in this report. With a 5-minute time delay, reductions of 21.4% to 31.3%, 22.4% to 33.3%, and 12.3% to 17.0% were found in the three studies of this research, respectively, and similar user satisfaction was achieved as compared to a single sensor with 20-minute time delay. With a 10-minute time delay, reductions of 12.5% to 28.6, 8.4% to 24.7%, and 3.6% to 12.3% of were found, and all false-offs were eliminated. This economic analysis therefore assumes a further 20% or 10% reduction applicable to the sensor network, at time delay settings of 5 or 10 minutes, respectively.

For the private faculty offices in our project, DOE specified lighting hours for small offices (3340 hours/year) are adopted as the baseline, and the actually measured operating time for the single-point detection sensor and the sensor network are used to calculate the payback periods for corresponding systems.

HVAC interaction

While there might be additional savings from reductions in the cooling load due to lights, we have not included these effects in this analysis. Sezgen and Koomey have noted “the net reduction in HVAC bills due to a reduction in lighting is about 3.4% of the change in lighting bill … However, for the … commercial building area, the change in HVAC source energy due to lighting/HVAC interactions is approximately zero.”[113] They further noted that although reducing lighting energy can lead to a reduction in cooling, this can sometimes produce a slight increase in required heating, hence the net effect of lights depends on building characteristics and climate, and for the “75% of the commercial building area in the US” they surveyed, Sezgen and Koomey concluded that “a reduction in lighting energy that is well-distributed geographically and across building types will induce neither significant savings nor significant penalties in HVAC primary energy and small benefits in HVAC energy expenditures.” Nevertheless, there may be potential for energy savings in controlling HVAC operation (air distribution) based upon occupancy. Conditioning (i.e., heating and cooling) and ventilation (i.e., air exchanges) of spaces based on true occupancy offers greater benefit to make this technology feasible, however, the accuracy of the sensor network system would have to advance significantly to support these functions.

Energy cost

As of 2006, the commercial average retail price of electricity per kWh was 8.67 cents for the United States, and was 5.98 cents for Nebraska[111]. Both numbers are used in the payback calculations.

9.4.3 Simple payback period

Table 9-5 summarizes the simple payback period associated with the prototype system deployed in the private faculty offices studied in this research. According to these operating scenarios, since the sensor network cost less than manual switching it generates an immediate saving (and consequently no payback period). While encouraging, these calculations are too optimistic, as the estimated costs associated with a commercial sensor network control system (at about $385.00 and $275.00 per office in small and large commercial buildings, respectively), are higher than those incurred in this research project (at only $204.00 per office).

Table 9-5 Simple payback analysis of manual wall switch, PIR wall switch, ceiling/wall mounted dual-technology sensor, and sensor network in a private faculty office

		Private Faculty Office	Base line (Manual switch)	PIR wall switch	Dual-tech sensor	Sensor network with 5-min delay	Sensor network with 10-min delay
			A	B	C	D	E
Initial	1)	Unit price (dollars)	$41.54	$100.19	$230.19	$104.00	$104.00
	2)	Installation Cost (dollars)	$172.12	$173.72	$219.07	$100.00	$100.00
	3)	Total (dollars) [1+2]	$213.66	$273.91	$449.26	$204.00	$204.00
	4)	**Incremental Cost (dollars)**		**$60.25**	**$235.60**	**-$9.66**	**-$9.66**
	5)			[B3-A3]	[C3-A3]	[D3-A3]	[E3-A3]
Energy	6)	Average electricity cost(dollars/kWh)	$0.0598				
	7)	Load (Watts) [8 X 9]	260				
	8)	Power Density (watts/ft2)	2.0				
	9)	Area (ft2)	130				
	10)	Time of operation (hours)	3340	1717	1717	1374	1545
	11)	Total Energy (kWh) [7 X 10]/1000	868.4	446.4	446.4	357.1	401.8
	12)	Energy Cost (dollars) [6 X 11]	$51.9	$26.7	$26.7	$21.4	$24.0
	13)	**Annual Savings (dollars)**		**$25.2**	**$25.2**	**$30.6**	**$27.9**
	14)			[A12-B12]	[A12-C12]	[A12-D12]	[A12-E12]
	15)	**Payback (years) [13/5]**		**2.4**	**9.3**	**0.0**	**0.0**

Table 9-6 summarizes the simple payback periods associated with the various control options in generic small and large commercial buildings, using more realistic estimates of commercial sensor network control system costs. The table uses the DOE typical private office data (power density and lighting operating hours) as baseline; a 25% reduction is applied to the baseline as the operating time of single sensor, and an additional 20% or 10% reduction is assumed for the sensor networks with 5 or 10-minute time delay, respectively. Estimated costs for a ZigBee based system are used for sensor network.

Table 9-6. Simple payback analysis of manual wall switch, PIR wall switch, ceiling/wall mounted dual-technology sensor and sensor network in a generic small and large commercial building

General Private Office in Small Commercial Buildings			Base line (Manual switch)	PIR wall switch	Dual-tech sensor	Sensor network with 5-min delay	Sensor network with 10-min delay
			A	B	C	D	E
Initial	1)	Unit price (dollars)	$41.54	$100.19	$230.19	$233.07	$233.07
	2)	Installation Cost (dollars)	$172.12	$173.72	$219.07	$152.10	$152.10
	3)	Total (dollars) [1+2]	$213.66	$273.91	$449.26	$385.17	$385.17
	4)	**Incremental Cost (dollars)**		**$60.3**	**$235.6**	**$171.5**	**$171.5**
	5)			[B3-A3]	[C3-A3]	[D3-A3]	[E3-A3]
Energy	6)	Average electricity cost(dollars/kWh)	$0.0867				
	7)	Load (Watts) [8 X 9]	400				
	8)	Power Density (watts/ft ^{2})	2.0				
	9)	Area (ft ^{2})	200				
	10)	Time of operation (hours)	3340	2505	2505	2004	2255
	11)	Total Energy (kWh) [7 X 10]/1000	1336	1002	1002	801.6	901.8
	12)	Energy Cost (dollars) [6 X 11]	$115.8	$86.9	$86.9	$69.5	$78.2
	13)	**Annual Savings (dollars)**		**$29.0**	**$29.0**	**$46.3**	**$37.6**
	14)			[A12-B12]	[A12-C12]	[A12-D12]	[A12-E12]
	15)	**Payback (years) [13/5]**		**2.1**	**8.1**	**3.7**	**4.6**

General Private Office in Large Commercial Buildings			Base line (Manual switch)	PIR wall switch	Dual-tech sensor	Sensor network with 5-min delay	Sensor network with 10-min delay
			A	B	C	D	E
Initial	1)	Unit price (dollars)	$41.54	$100.19	$230.19	$122.69	$122.69
	2)	Installation Cost (dollars)	$172.12	$173.72	$219.07	$152.10	$152.10
	3)	Total (dollars) [1+2]	$213.66	$273.91	$449.26	$274.79	$274.79
	4)	**Incremental Cost (dollars)**		**$60.3**	**$235.6**	**$61.1**	**$61.1**
	5)			[B3-A3]	[C3-A3]	[D3-A3]	[E3-A3]
Energy	6)	Average electricity cost(dollars/kWh)	$0.0867				
	7)	Load (Watts) [8 X 9]	300				
	8)	Power Density (watts/ft2)	1.5				
	9)	Area (ft2)	200				
	10)	Time of operation (hours)	4190	3142.5	3142.5	2514	2828
	11)	Total Energy (kWh) [7 X 10]/1000	1257	942.75	942.75	754.2	848.5
	12)	Energy Cost (dollars) [6 X 11]	$109.0	$81.7	$81.7	$65.4	$73.6
	13)	**Annual Savings (dollars)**		**$27.2**	**$27.2**	**$43.6**	**$35.4**
	14)			[A12-B12]	[A12-C12]	[A12-D12]	[A12-E12]
	15)	**Payback (years) [13/5]**		**2.2**	**8.6**	**1.4**	**1.7**

Under all the scenarios, the simple payback associated with installing a single PIR wall switch instead of a manual switch is similar, at about 2 years. Switching from a manual wall switch to a ceiling/wall mounted dual-technology sensor results in much longer simple payback periods (8 to 9 years).

While the simple payback periods associated with the sensor networks varied with the number of offices controlled by the network, these costs are less than those associated with the ceiling/wall mounted dual-technology sensors. This is because the estimated material and installation costs associated with the sensor network (at about \$385.00 and \$275.00 for small and large buildings, respectively), are lower than those associated with ceiling/wall mounted dual-technology sensors (at about \$449.00). At a time-delay of 10 minutes, the sensor network with a proper data fusion method is able to eliminate all the false-offs, and the payback period is just increased around 25% from the sensor network with a 5-minute time delay.

It is important to note that these calculations were based on conservative assumptions. For example, mounting accessories for wireless sensors might cost considerably less than those used by traditional control systems, as they may not need to take into account code issues related to line voltage, and this might yield lower costs.

Finally, the reduction in electricity usage may also reduce secondary non-financial costs, such as CO_2, SO2 and NO_x emissions from electricity production. The generation of electricity from fossil fuel power plant accounts for a significant part of both air pollutants and greenhouse gas emissions, thus the reduction of electricity consumption can also help environmental conservation.

9.5 Building Applications Enabled by Sensor Network Occupancy Detection

We close the report by briefly considering other commercial and residential applications that could be enabled through the availability of sensor network occupancy data.

Casualty estimates in the days immediately following the September 11th 2001 attacks varied widely. French brothers and filmmakers Jules and Gedeon Naudet were filming a documentary about the experiences of a probationary firefighter. This work took them to the Twin Towers, where they recorded the day's events. This film was subsequently broadcast by CBS in March 2002. One scene depicted a firefighter in the lobby of one of the Towers attempting to determine if any of the elevators in that building were occupied, using a public address system that linked the lobby with the elevators. A dynamically updated building occupancy map stored offsite on Internet servers and updated in real time would have provided vital information to emergency first responders about building occupancy: data from networked occupancy detection systems in elevators could have told firefighters immediately which elevators were occupied.

A prototype of an occupancy monitoring system has been developed to remotely display the current status of each sensor in a sensor network. This system provides an illustrative view of the occupancy status of the whole monitored area. As Figure 9-3 shows, sensor status can be checked by opening a web browser from any computer connected to the Internet. Highlighted cells indicate the sensors sent an "ON" signal and did not send an "OFF" signal, while gray cells mean no signal or an "OFF" signal was received. A detailed description of the program is provided in 11Appendix C. This prototype can also display time-series graphs showing the occupancy profiles for one or more offices/areas over defined time intervals (e.g., last hour, last day, etc.), and provide statistical summaries of the aggregated occupancy profiles.

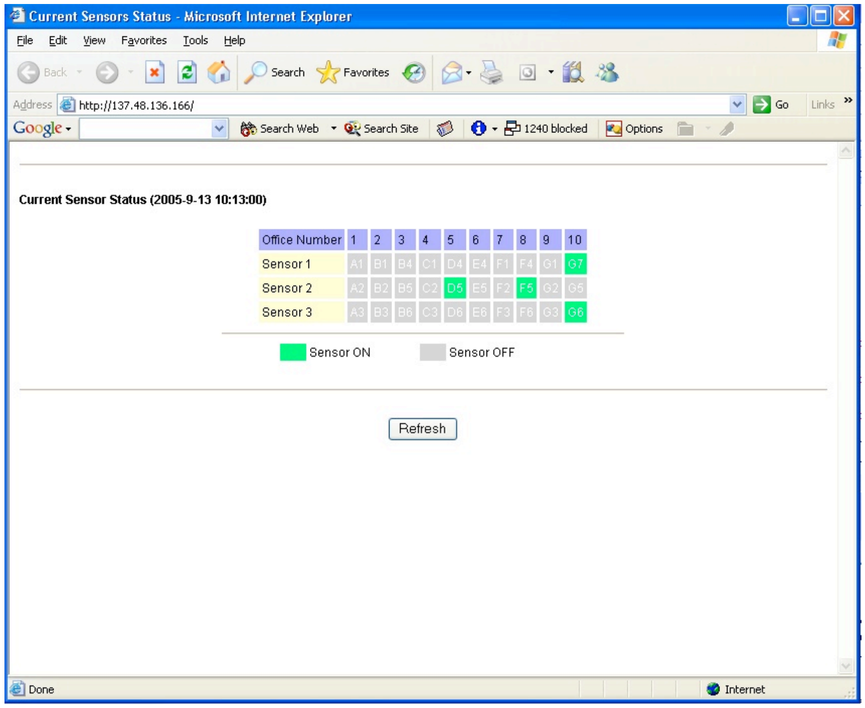


Figure 9-3. Real-time display of PIR sensor status

The prototype system currently only displays raw information sent by the installed PIR sensors, before applying any data fusion algorithm. An extension to the monitoring system would be to incorporate an appropriate inference engine with the basic display that provides an accurate and robust judgment about space occupancy. This web-based monitoring system provides an accurate measurement comparable to video cameras used in security applications, but is considerably less expensive, and provides more anonymity than security video monitoring systems. The anonymous feature makes it useful when occupant identities are not important, and since the system is not as intrusive as a video camera, it is likely to be more acceptable to commercial and residential users.

Sensor networks for occupancy detection can also be used to improve the performance of home security systems. The International Association of Chiefs of Police[123] estimates that 70% of homes and 40% of businesses in the U.S. have security alarm systems: this translates to 7 to 15 million security alarm systems. Each of these systems generates about 2.2 false alarms per year, and security system alarms account for 10-30% of calls for police services. The City of Oxnard CA police have reported that in 1995, only about 2% of security alarms represented an actual or attempted crime. Oxnard police determined that the average cost for police response to an alarm call was $62.04. Since 98% of alarm calls were determined to be false, the cost of police response to false alarms was $424,725.00[124].

Many home security system false alarms are the result of a single sensitive detector responding to the movement of inanimate objects in the field of view of the detector (e.g., curtains above a ventilation duct moving in response to airflow). A sensor network could be designed to respond only to certain patterns of signals from more than one occupancy detector, reducing the cost of false alarms, improving the performance of home security systems, and freeing police officers to deal with more pressing matters.

Sensor networks for occupancy detection could also be used to improve the performance of residential ventilation systems. Temperature stratification in houses is common and costly: depending on the season, lowering or raising a thermostat just 4°F can cost an additional $35.00 to $50.00 per month. Most residential ventilation systems maintain a set temperature at the thermostat itself. The location of the thermostat rarely corresponds with actual occupancy. Consequently, many houses often have unpleasantly hot or cold rooms, which could be more effectively ventilated by redirecting conditioned air from unoccupied areas. Retrofit in-line duct fans are available, which boost airflow to rooms, thereby raising or lowering ambient temperature. These devices are currently controlled thermostatically, or by occupants using a wall switch. A system based on networked occupancy detectors could be designed to control the operation of residential air conditioners, and in-line duct fans so that these devices direct air only to occupied rooms, and only when the residence was actually occupied. Such a system could function in a manner that was completely transparent to users, and would ensure that conditioned air was provided only when and where it was needed, thereby saving energy. Hydronic heating systems, common in Europe, are typically equipped with one thermostatic control valve per zone, and modern thermostatic valves are equipped with digital timers allowing for setback during unoccupied periods. The proposed application would be similar in spirit but applied to forced air heating and cooling typical of North America.

Sensor networks could also be used to reduce the electrical demand due to the operation of residential air conditioning units cooling unoccupied houses during the daytime when homeowners are away. Programmable thermostats allow users to establish different temperature settings at which residential air conditioning units operate at different times of the day, for example, letting the space temperature rise during the day when occupants are at work, then setting a lower temperature just before the normal time that occupants expect to return. These schedules are applied whether or not a house is occupied. Sensor networks could be used to switch off residential air conditioning units during the daytime when houses are vacant, letting the house temperature “float” during the unoccupied hours. Comfort would be maintained by applying an intelligent algorithm to the sensor network occupancy data to start cooling an empty house, based on a probabilistic determination of the likely time that occupants normally return, and the cooling required to achieve the desired temperature setting.

Finally, there are substantial economic and mental health benefits if the elderly live at home as long as possible, rather than in hospitals or nursing homes. The technologies developed as part of this research can facilitate independent living, by providing basic sensors and monitoring systems that will extend the time that the elderly can remain in their own homes (e.g., stoves could be turned off if the kitchen or adjacent spaces have been unattended for a defined period, lights automatically switched on and off as needed, and health monitored when required). A sensor network could be developed to monitor activity in different areas in the home, and display sensor activity on a web page, or notify caregivers by email or telephone in the event of unusual sensor network activity.

10 Acknowledgements

The project was undertaken as a joint effort between the United States Department of Energy National Energy Technology Laboratory (Agreement DE-FC26-04NT41971), the University of Nebraska Center for Building Integration, Johnson Controls, Inc., and Alvine & Associates consulting engineers.

We gratefully acknowledge the assistance of Dr. Robert Dodier, independent technical consultant, and the following Architectural Engineering students who assisted with data collection and analysis: Jarred Craddock, Matthew O'Boyle, Matthew Radik, and Ryan Tushner.

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Appendix A Construction of Belief Network

A.1 Introduction

This appendix describes the construction and the parameter derivation of the belief networks introduced in section 4.5 and applied in Chapters 5 through 7 of this report. Generally, a belief network comprises of a set of variables, and a graphical structure with attached probabilities connecting the variables. The variables incorporated in the occupancy sensor network were: true occupancy, the condition of each sensor (functioning or defective), the output from each sensor, and the time of day. The output from each sensor mostly depends upon true occupancy: if the sensor works properly, then the sensor output is consistent with true occupancy. However, if the sensor is not functioning properly, the relationship between true occupancy and sensor output can be vague. True occupancy is a function of the time of the day, for example, at 03:00, there would be a low probability of occupancy.

Besides the interrelationship between these variables, true occupancy and sensor operating condition are time persistent. For example, if a space is occupied, it is more likely to remain occupied for some time, and vice versa; sensor condition also persists over time, indicating if a given sensor pulses more frequently than others, if will continue to pulse at a higher rate.

The conditional probabilities of sensor output are determined by the measured frequency of sensor pulsing at each sensor condition and occupancy status combination (the pulsing rate when the sensor is functioning and the space is occupied, the pulsing rate when the sensor is functioning and the space is vacant, the pulsing rate when the sensor is defective and the space is occupied, and finally, the pulsing rate when the sensor is defective and the space is vacant). The probability of occupancy conditional on time of day is determined based on true occupancy during the data collecting period of this study, with reference to the general occupancy profile for private offices provided by ASHRAE[42]. The detailed derivation of each conditional probability will be introduced later in this appendix.

A.2 Structure of Belief Network

The variable of interest is whether the space is occupied, and we measure the occupancy using three PIR sensors. Figure A-1 shows the dependency of three sensors on real occupancy, where a shaded oval means an observable variable, and clear oval means a hidden variable.

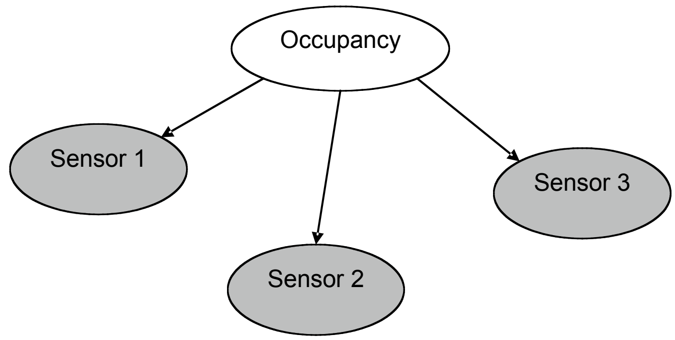


Figure A-1. Belief network showing sensor outputs are conditional on the occupancy

Sensor output is not only affected by true occupancy, but is also affected by the condition of the sensor itself (Figure A-2). If a given sensor is malfunctioning, readings from this device are less likely to reflect real occupancy.

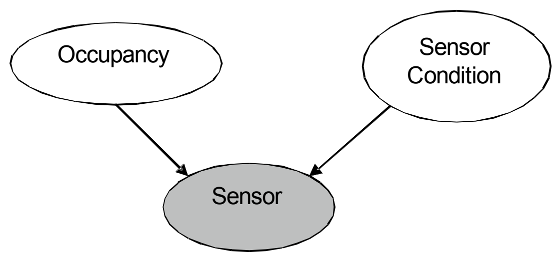


Figure A-2. Belief network showing the measurement of sensor is conditional not only on the actual occupancy, but also on the sensor condition

Figure A-3 shows the time persistency of occupancy. Occupancy information from the last time slot is passed to the current time slot, that is, if the space is occupied at time (t-1), then the probability of occupancy at time (t) is high.

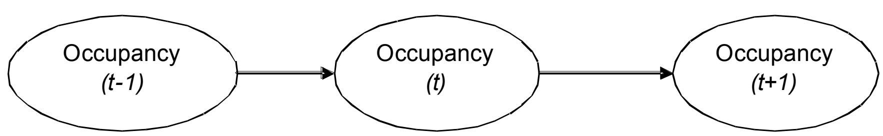


Figure A-3. Belief network showing the occupancy in a space persists over time

Sensor condition also persists over time. If a sensor is properly functioning at time (t-1), then there is a high probability that this sensor will continue to function properly at time (t), as depicted in Figure A-4.

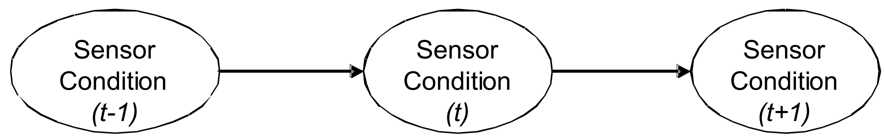


Figure A-4. Belief network showing the sensor status persists over time

The occupancy pattern is affected by other factors, such as time of day, day of week, function of the space, and occupant behavior. This work has focused on private offices. Thus data concerning the probability of occupancy at each hour will be helpful in determining the occupancy pattern (Figure A-5).

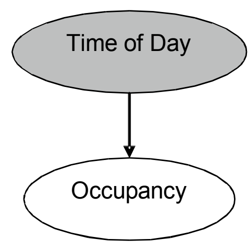


Figure A-5. Belief network showing occupancy is conditional on the time of day

Combining the interrelated relationships described above, a belief network is constructed as shown in Figure A-6.

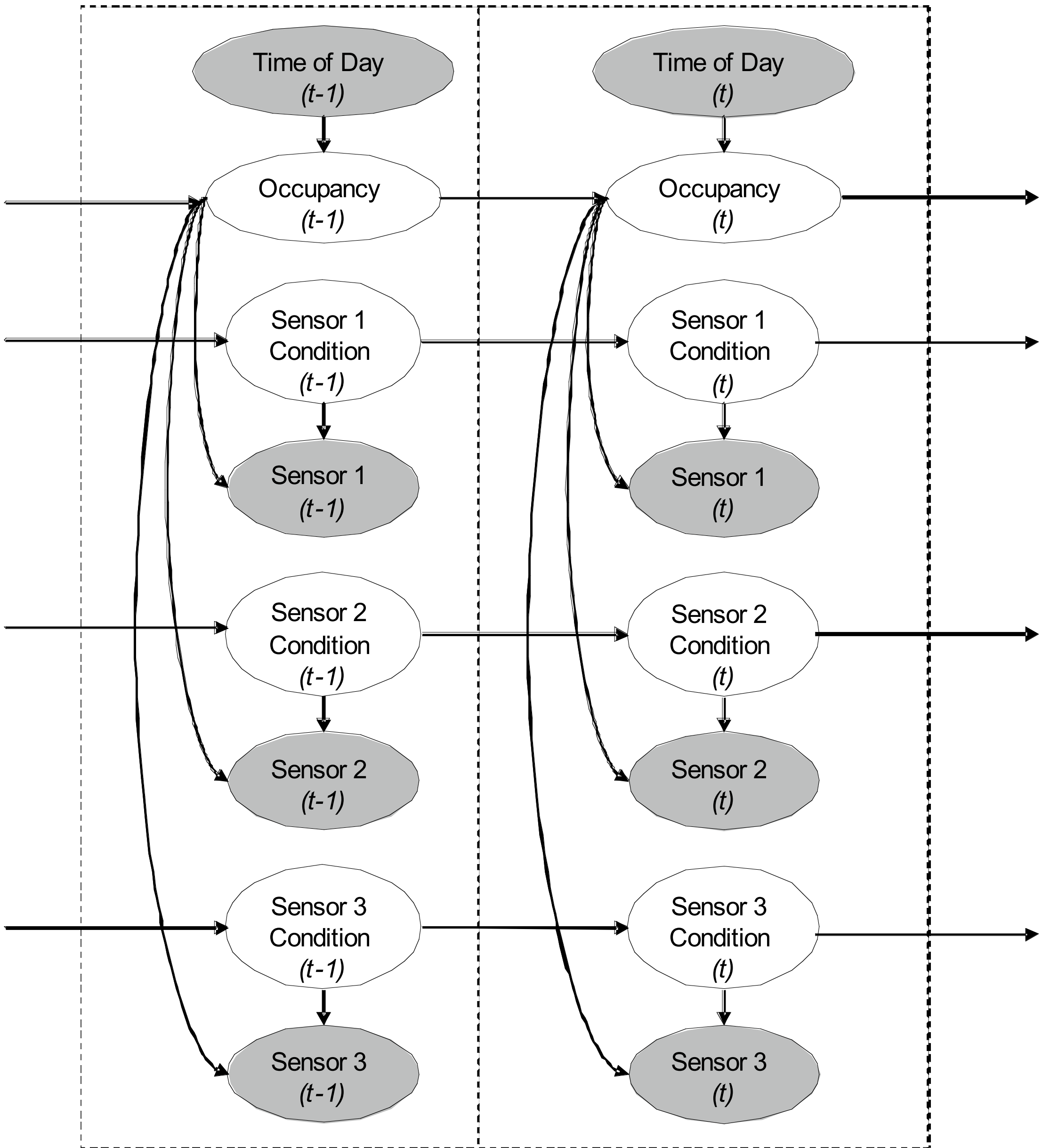


Figure A-6. Belief network to model occupancy, showing that occupancy is affected by the time of day, sensor outputs affected by the occupancy and the sensor condition, and the occupancy and the sensor condition are time persistent.

A.3 Parameter Derivation for the Pilot Study

This section describes the definition of the probabilities of sensor pulsing conditional on occupancy and sensor condition, the probabilities of occupancy conditional on the time of day, and probability of occupancy and sensor condition persistence over time, using the data collected in two offices over two days in the pilot study (Chapter 5). The parameters were applied in the fusion of sensor network data using the belief network method.

A.3.1 Sensor response (conditional on occupancy and sensor condition)

Sensor response (pulse or not pulse) depends on the real occupancy and sensor condition. Occupancy has two possible values: occupied (T) or vacant (F). Sensor condition also has two possible values: functioning (T) or defective (F). For the properly functioning sensors, the probabilities of sensor response associated with real occupancy were modeled using the average pulse rates observed from each functioning sensor in two offices during the two days, as shown in Table A-1.

Table A-1. Average sensor pulsing rate in pilot study

Room	Sensor	Occupied, pulsed (Occupancy=T, Sensor=T)	Occupied, didn't pulse (Occupancy=T, Sensor=F)	Vacant, pulsed (Occupancy=F, Sensor=T)	Vacant, didn't pulse (Occupancy=F, Sensor=F)
1	PIR1	0.393	0.607	0.00234	0.99766
	PIR2	0.704	0.296	0.0019	0.9981
2	PIR1	0.500	0.500	0.00163	0.99837
	PIR2	0.761	0.239	0.00279	0.99721
	PIR3	0.197	0.803	0.00159	0.99841
Average		0.511	0.489	0.0021	0.9980

Ideally, if a sensor always responds when the space is occupied (Occupancy=T, Sensor=T), the pulsing rate would be 1.0, in contrast to the measured 0.511. This low actual pulsing rate means that during more than 40% of the occupied time, individual sensors did not respond. When the space was vacant, the pulsing rate was 0.002, showing a low rate of pulsing in an empty space.

Based on the measured pulsing rate, the probabilities of sensor response are described in Table A-2.

Table A-2. Sensor pulsing probabilities conditional on true occupancy and sensor condition in pilot study

Occupancy	Sensor Status	P(Sensor=F)	P(Sensor=T)
F	F	0.5	0.5
T	F	0.5	0.5
F	T	0.998	0.002
T	T	0.489	0.511

When the sensor functions correctly, it has a probability of 0.511 of pulsing when the space is occupied, and a probability of 0.002 of pulsing when the space is vacant. When the sensor is defective, the pulsing rates are not based on occupancy, and so have an equal probability of pulsing when the space is occupied or vacant, as shown in the table (a probability of 0.5 for all cases).

A.3.2 Persistence of occupancy

The persistence of occupancy was defined as follows: if the space is occupied during one time slot, the probability it will continue to be occupied during the next time slot is 90%; if the space is vacant, it also has 90% probability of remaining vacant during the next time slot. Table A-3 describes these probability values.

Table A-3. Probabilities of occupancy persistence

Occupancy (*t*-1)	P(Occupancy (*t*)=T)	P(Occupancy (*t*)=F)
T	0.9	0.1
F	0.1	0.9

A.3.3 Persistence of sensor status

The probability that the operating condition of a sensor will change is very low, but exists nevertheless and should be included. If a sensor is currently functioning, it will continue to function during the next few time slots, and may remain functioning over the next days or even weeks. The probability of sensor condition change was defined as 10^{-10}, as shown in Table A-4: a properly functioning sensor has a very low probability of becoming defective in the next time slot.

Table A-4. Probabilities sensor status persistence

Sensor Status (*t-1*)	P(Sensor Status(*t*)=T)	P(Sensor Status(*t*)=F)
T	$1\text{-}10^{-10}$	10^{-10}
F	10^{-10}	$1\text{-}10^{-10}$

A.3.4 Occupancy (conditional on time of day)

The occupancy pattern in private offices during weekdays follows routine patterns, for example, between 09:00 and 17:00, there is a high probability that the space is occupied, and the space is likely to be vacant between 20:00 and 05:00. The average fractions of occupied time observed in two offices over two days (pilot study, 5) are plotted in Figure A-7, which also shows the typical office occupancy pattern defined by ASHRAE[42].

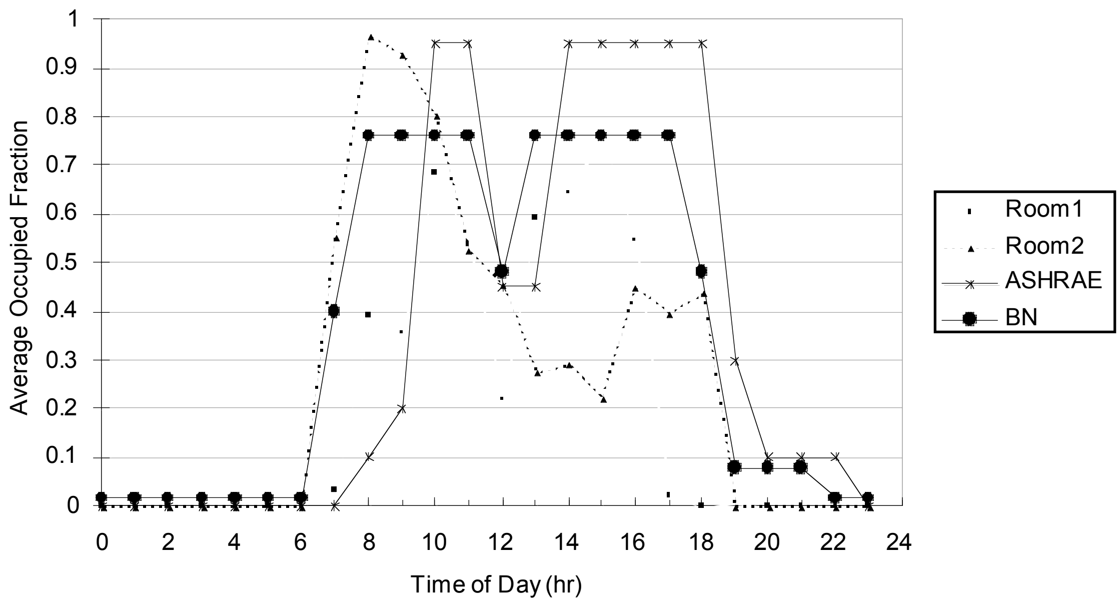


Figure A-7. Occupancy profiles

Based on the measured true occupancy pattern of the two offices and the shape of ASHRAE occupancy profile, the probability of occupancy at different times are described in Table A-5.

Table A-5. Probability of occupancy conditional on time of day in pilot study

Time of Day	P(Occupancy=T)	P(Occupancy=F)
1-6	0.02	0.98
7	0.40	0.60
8-11	0.76	0.24
12	0.36	0.64
13-17	0.76	0.24
18	0.48	0.52
19-21	0.08	0.92
22-24	0.02	0.98

A.4 Parameter Derivation for the Round-Robin Study

In the round-robin study, parameters defining persistence of occupancy and sensor condition were determined in the same manner as parameters used in the pilot study. However, the probabilities of sensor pulsing conditional on occupancy and sensor condition, and the probabilities of occupancy conditional on the time of day were redefined, using the data collected during the round-robin study.

A.4.1 Sensor response (conditional on occupancy and sensor status)

Sensor response (pulse or not pulse) depends on real occupancy and sensor condition. Occupancy has two possible values: occupied (T) or vacant (F). Sensor condition also has two possible values: functioning (T) or defective (F). For properly functioning sensors, the probabilities of sensor response associated with real occupancy were modeled using the average pulse rates observed from each functioning sensor in two offices during the six-week data collection period of the round-robin study, as shown in Table A-6.

Table A-6. Average sensor pulsing rate in round-robin study

Room	Sensor Group	Sensor Number	Occupied, pulsed (Occupancy=T, Sensor=T)	Occupied, didn't pulse (Occupancy=T, Sensor=F)	Vacant, pulsed (Occupancy=F, Sensor=T)	Vacant, didn't pulse (Occupancy=F, Sensor=F)
Room 1	Commercial	1	0.40779	0.59221	0.00251	0.99749
		2	0.38547	0.61453	0.00200	0.99800
		3	0.40180	0.59820	0.00200	0.99800
	Assembled	1	0.76845	0.23155	0.00940	0.99060
		2	0.92330	0.07670	0.01032	0.98968
		3	0.86862	0.13138	0.01456	0.98544
	Wireless1	1	0.39487	0.60513	0.00716	0.99284
		2	0.31600	0.68400	0.00868	0.99132
		3	0.37523	0.62477	0.00131	0.99869
	Wireless2	1	0.38454	0.61546	0.00182	0.99818
		2	0.31828	0.68172	0.00149	0.99851
		3	0.27465	0.72535	0.00101	0.99899
Room 2	Commercial	1	0.73448	0.26552	0.00589	0.99411
		2	0.67201	0.32799	0.00351	0.99649
		3	0.62863	0.37137	0.00257	0.99743
	Assembled (1)	1	0.75147	0.24853	0.00303	0.99697
		2	0.96127	0.03873	0.00702	0.99298
		3	0.94514	0.05486	0.00418	0.99582
	Wireless1	1	0.62405	0.37595	0.00325	0.99675
		2	0.62748	0.37252	0.00354	0.99646
		3	0.50751	0.49249	0.00241	0.99759
	Wireless2	1	0.59148	0.40852	0.00390	0.99610
		2	0.50115	0.49885	0.00266	0.99734
		3	0.54059	0.45941	0.00235	0.99765
Average			0.57934	0.42066	0.00444	0.99481

(1) Only considered the functioning sensor in the last 3 weeks.

Ideally, if a sensor always responds when the space is occupied (Occupancy=T, Sensor=T), the pulsing rate would be 1.0, in contrast to the measured 0.579. This low actual pulsing rate means that during more than 40% of occupied time, sensors did not respond. When the space was vacant, the pulsing rate was 0.004, showing a low possibility of false triggering.

Based on the measured pulsing rate, the probabilities of sensor pulsing are described in Table A-7.

Table A-7. Sensor pulsing probabilities conditional on true occupancy and sensor condition in round-robin study

Occupancy	Sensor Status	P(Sensor=F)	P(Sensor=T)
F	F	0.5	0.5
T	F	0.5	0.5
F	T	0.996	0.004
T	T	0.4	0.6

When the sensor functions correctly, it has a probability of 0.6 of pulsing when the space is occupied, and a probability of 0.004 of pulsing when the space is vacant. When the sensor is defective, the pulsing rates are not based on occupancy, and so have an equal probability of pulsing when the space is occupied or vacant, as shown in the table (a probability of 0.5 for all cases).

A.4.2 Occupancy (conditional on time of day)

The occupancy pattern in private offices during weekdays follows routine patterns, for example, between 09:00 and 17:00, there is a high probability that the space is occupied, and the space is likely to be vacant between 20:00 and 05:00. The average fractions of occupied time observed in two offices over six weeks (round-robin study, 7) are plotted in Figure A-8, which also shows the typical office occupancy pattern defined by ASHRAE[42].

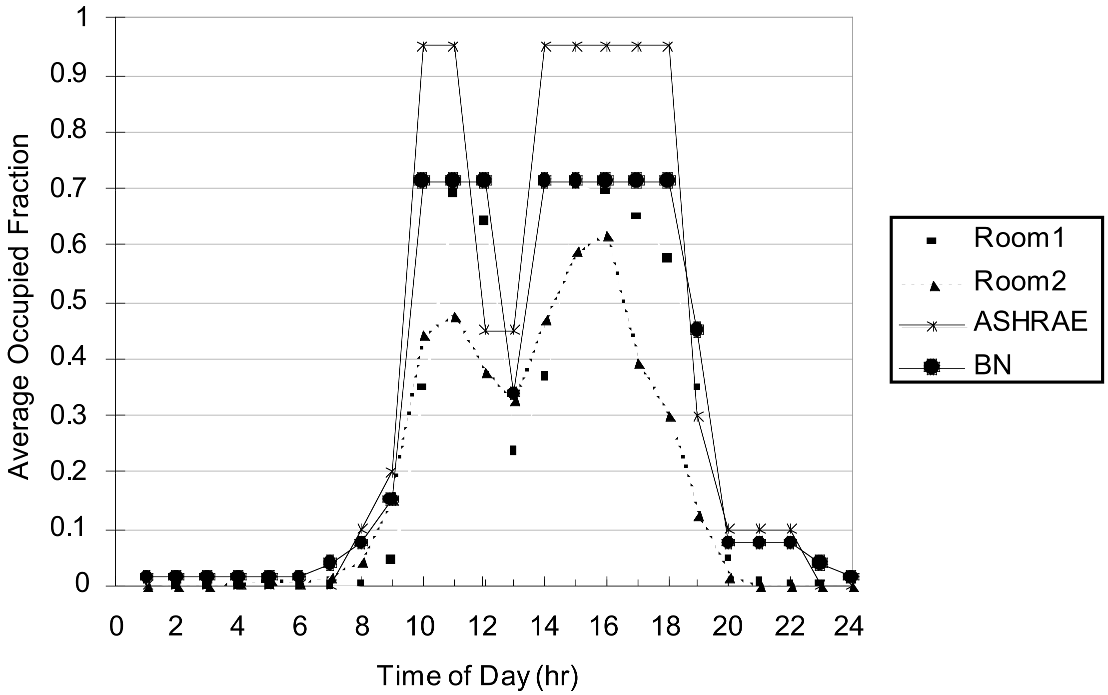


Figure A-8. Occupancy profiles measured in the two rooms in round-robin study, provided by ASHRAE and finally adopted in the belief network

Based on the measured true occupancy pattern of the two offices and the shape of ASHRAE occupancy profile, the probabilities of occupancy at different times are described in Table A-8.

Table A-8. Probability of occupancy conditional on time of day in round-robin study

Time of Day	P(Occupancy=T)	P(Occupancy=F)
1-6	0.02	0.98
7	0.04	0.96
8	0.08	0.93
9	0.15	0.85
10-12	0.71	0.29
13	0.34	0.66
14-18	0.71	0.29
19	0.45	0.55
20-22	0.08	0.92
23	0.04	0.96
24	0.02	0.99

Appendix B Data Fusion Algorithms Source Code

B.1 Moving Average

```
% M-point Moving Average Filter
% In our sensor network, this function firstly smoothing the outputs
from each
% sensor, then sum the results together to get the final out put of
network.

function [averaged]= MovAve3(data,M);   % Define function name and
parameters

num=ones(1,M);              % Create an 1-by-M matrix of ones
for c=1:3
y(:,c)=filter(num,1,data(:,c))/M;   % Use the filter function to
calculate % the moving average of each column of
% matrix "data" over M steps
end

averaged =sum(y,2);             % Sum the averaged results by column
```

B.2 Rule-Based Reasoning

```
% Determine occupancy based on objective criteria
% data: row x 3 matrix, the original outputs from 3 sensors
% Time delay: Time delay to be applied in reasoning

function [result]=ObjCri(data,TimeDelay) % Define function name and
parameters
row = size(data,1);              % Calculate the length of the inputs
result=zeros(row,1);             % Initialize the output
sumcol=sum(data,2);              % Sum the inputs by column
countp=[0 0 0];               % initialize a variable recording the
 % times that a sensor functioned
```

```
 % differently from others
Problem=0;                    % A variable used to record a sensor
 % number if it behaved differently
 % from others
delaycount=TimeDelay;            % initialize the time delay counting

for i=2:row
    if sumcol(i)>1               % If there is at least two sensor
pulsed
        result(i)=1;             % Set the output to be 1
        delaycount=0;            % Starts time delay counting
    elseif sumcol(i)==1          % If only one sensor pulsed
        if result(i-1)==1        % If the system output of the
        % previous time slot is 1
            result(i)=1;             % Set the output to be 1
            delaycount=0;            % Starts time delay counting
        else
            where = find(data(i,:)==1); % Locate which sensor pulsed
differently
% from others
            if where(1,1)==Problem
                countp(where(1,1))=countp(where(1,1))+1;
                        % Count the times that a sensor
                        % functioned differently from others
            else
                Problem=where(1,1);
            end


        end
    else
        if delaycount<TimeDelay     % If none sensor pulses, apply the
time
% delay
            result(i)=1;
            delaycount=delaycount+1;
        end
```

```
    end
end
```

B.3 Least Squares Estimation

```
% A1: training data; A2: new data
function [out,x]=LSE(A1,b,A2)
x=inv(A1'*A1)*A1'*b;             % Solve x for A1*x=b
    % fout2=data*x;
out=A2*x;                    % Apply the calculated x to new data
```

B.4 Belief Network

```
% Define the structure and parameter of the Belief network and
calculate the
% network output
% data: The readings of all three sensors (T x 3 matrix)
% outo: Occupancy prediction (T x 1 array)
% outStn: Status of sensor n (functioning or not) (T x 1 array)


function [outo,outSt1,outSt2,outSt3]=bnt_HMM(data)
occupancy_profile=[0.02 0.02    0.02    0.02    0.02    0.02    0.05
0.1 0.2 0.95    0.95    0.95    0.45    0.95    0.95    0.95    0.95
0.95    0.6 0.1 0.1 0.1 0.05    0.02];
                    % occupancy_profile: probability of occupancy
% at different time of day
occupancy_profile=occupancy_profile*0.75;
% sensor pulsing rate conditional on occupancy and sensor status (Table
A-7)
sensor_profile=[0.5 0.5 0.996 0.4 0.5 0.5 0.004 0.6];


sensor_status=[0.5 0.5];
occupancy_persistence=[0.9 0.1 0.1 0.9]; % Table A-3.  Probabilities of
occupancy persistence
E=1e-12;
status_persistence=[1-E E E 1-E];        %Table A-4.  Probabilities
sensor status persistence
```

```
N=8;                            % # of nodes in each time slot

dag_intra = zeros(N);

O=1; StS1=2; StS2 =3; StS3=4; Time = 5; S1=6; S2=7; S3=8;

            % Number the nodes. Parents should be in front of children


% Following statements define the topology within each time slot

dag_intra(O,Time)=1; % node 1 in slice t connects to node 5 in slice t

dag_intra([O StS1], S1) = 1; % nodes 1 and 2 connect to node 6 (sensor
output

  % is conditional on occupancy and sensor status

dag_intra([O StS2], S2) = 1;

dag_intra([O StS3], S3) = 1;


% Following statements define the topology between time slots

dag_inter = zeros(N);

dag_inter(1,1) = 1;      % node 1 in slice t-1 connects to node 1 in
slice t

dag_inter(2,2) = 1;

dag_inter(3,3) = 1;

dag_inter(4,4) = 1;


node_sizes=[2 2 2 2 24 2 2 2 2];  % Possible number of states of each
node

discrete_nodes = 1:N;        % Discrete hidden variable

onodes = [Time S1 S2 S3];        % Observable nodes (input)

bnet = mk_dbn(dag_intra, dag_inter, node_sizes,'discrete',
discrete_nodes, 'observed', onodes);      % Create the belief network


% Conditional probability distributions are represented as tables

bnet.CPD{O} = tabular_CPD(bnet, O, [0.5 0.5]);

bnet.CPD{Time} = tabular_CPD(bnet, Time,  [1-occupancy_profile;
occupancy_profile]);

bnet.CPD{StS1} = tabular_CPD(bnet, StS1, sensor_status);

bnet.CPD{StS2} = tabular_CPD(bnet, StS2, sensor_status);

bnet.CPD{StS3} = tabular_CPD(bnet, StS3, sensor_status);

bnet.CPD{S1} = tabular_CPD(bnet, S1, sensor_profile);

bnet.CPD{S2} = tabular_CPD(bnet, S2, sensor_profile);
```

```
bnet.CPD{S3} = tabular_CPD(bnet, S3, sensor_profile);


bnet.CPD{9} = tabular_CPD(bnet, 9, occupancy_persistence);
for nm=10:12
    bnet.CPD{nm} = tabular_CPD(bnet,nm, status_persistence);
end

% construct a smoother engine out of lower-level hmm_2TBN_inf_engine to
% implement forward/backward operators

engine = smoother_engine(hmm_2TBN_inf_engine(bnet));

%-----------------------------------------------------------------------
% Apply the defined BNT to data

T=size(data,1);
evidence = cell(N,T);                    % N:slice size; T: number of
slices

% Create evidence: read the time (hour only) and each sensor reading to
the evidence cell
for i=1:T
    evidence(Time,i)=num2cell(ceil(i/60));
end
evidence(S1:S3,:) = num2cell(data(:,1:3)'+1);

% Apply the defined BNT engine to evidence
% The result N x T cell contains the conditional probability of each
node
[engine, ll] = enter_evidence(engine, evidence);
for i=1:T
% compute the probability of occupancy
margo = marginal_nodes(engine, O, i);
outo(i)=margo.T(2);
```

```
% compute the probability of sensor status
margSt1 = marginal_nodes(engine, StS1, i);
margSt2 = marginal_nodes(engine, StS2, i);
margSt3 = marginal_nodes(engine, StS3, i);
outSt1(i)=margSt1.T(2);
outSt2(i)=margSt2.T(2);
outSt3(i)=margSt3.T(2);
end
```

B.4.1 Tabular_CPD

```
%Computation of tabular_CPD (tabular conditional probability
distributions)
%from the Bayes Net Toolbox for Matlab, written by Kevin Patrick Murphy
et al.
% Downloaded from http://www.ai.mit.edu/~murphyk/Software/BNT/bnt.html


function CPD = tabular_CPD(bnet, self, varargin)
% TABULAR_CPD Make a multinomial conditional prob. distrib. (CPT)
%
% CPD = tabular_CPD(bnet, node) creates a random CPT.
%
% The following arguments can be specified [default in brackets]
%
% CPT - specifies the params ['rnd']
%   - T means use table T; it will be reshaped to the size of node's
family.
%   - 'rnd' creates rnd params (drawn from uniform)
%   - 'unif' creates a uniform distribution
% adjustable - 0 means don't adjust the parameters during learning [1]
% prior_type - defines type of prior ['none']
%  - 'none' means do ML estimation
%  - 'dirichlet' means add pseudo-counts to every cell
%  - 'entropic' means use a prior P(theta) propto exp(-H(theta)) (see
Brand)
% dirichlet_weight - equivalent sample size (ess) of the dirichlet
prior [1]
% dirichlet_type - defines the type of Dirichlet prior ['BDeu']
%  - 'unif' means put dirichlet_weight in every cell
```

```
%  - 'BDeu' means we put 'dirichlet_weight/(r q)' in every cell
%    where r = self_sz and q = prod(parent_sz) (see Heckerman)
% trim - 1 means trim redundant params (rows in CPT) when using
entropic prior [0]
% entropic_pcases - list of assignments to the parents nodes when we
should use
%      the entropic prior; all other cases will be estimated using ML
[1:psz]
% sparse - 1 means use 1D sparse array to represent CPT [0]
%
% e.g., tabular_CPD(bnet, i, 'CPT', T)
% e.g., tabular_CPD(bnet, i, 'CPT', 'unif', 'dirichlet_weight', 2,
'dirichlet_type', 'unif')
%
% REFERENCES
% M. Brand - "Structure learning in conditional probability models via
an entropic  prior
%   and parameter extinction", Neural Computation 11 (1999): 1155--1182
% M. Brand - "Pattern discovery via entropy minimization" [covers
annealing]
%   AI & Statistics 1999. Equation numbers refer to this paper, which
is available from
%   www.merl.com/reports/docs/TR98-21.pdf
% D. Heckerman, D. Geiger and M. Chickering,
%   "Learning Bayesian networks: the combination of knowledge and
statistical data",
%   Microsoft Research Tech Report, 1994


if nargin==0
  % This occurs if we are trying to load an object from a file.
  CPD = init_fields;
  CPD = class(CPD, 'tabular_CPD', discrete_CPD(0, []));
  return;
elseif isa(bnet, 'tabular_CPD')
  % This might occur if we are copying an object.
  CPD = bnet;
  return;
end
```

```
CPD = init_fields;

ns = bnet.node_sizes;
ps = parents(bnet.dag, self);
fam_sz = ns([ps self]);
psz = prod(ns(ps));
CPD.sizes = fam_sz;
CPD.leftright = 0;
CPD.sparse = 0;

% set defaults
CPD.CPT = mk_stochastic(myrand(fam_sz));
CPD.adjustable = 1;
CPD.prior_type = 'none';
dirichlet_type = 'BDeu';
dirichlet_weight = 1;
CPD.trim = 0;
selfprob = 0.1;
CPD.entropic_pcases = 1:psz;

% extract optional args
args = varargin;
% check for old syntax CPD(bnet, i, CPT) as opposed to CPD(bnet, i,
'CPT', CPT)
if ~isempty(args) & ~isstr(args{1})
  CPD.CPT = myreshape(args{1}, fam_sz);
  args = [];
end

for i=1:2:length(args)
  switch args{i},
   case 'CPT',
    T = args{i+1};
    if ischar(T)
      switch T
```

```
        case 'unif', CPD.CPT = mk_stochastic(myones(fam_sz));
        case 'rnd',  CPD.CPT = mk_stochastic(myrand(fam_sz));
        otherwise,   error(['invalid CPT ' T]);
       end
     else
       CPD.CPT = myreshape(T, fam_sz);
     end
    case 'prior_type', CPD.prior_type = args{i+1};
    case 'dirichlet_type', dirichlet_type = args{i+1};
    case 'dirichlet_weight', dirichlet_weight = args{i+1};
    case 'adjustable', CPD.adjustable = args{i+1};
    case 'clamped', CPD.adjustable = ~args{i+1};
    case 'trim', CPD.trim = args{i+1};
    case 'entropic_pcases', CPD.entropic_pcases = args{i+1};
    case 'sparse', CPD.sparse = args{i+1};
    otherwise, error(['invalid argument name: ' args{i}]);
  end
end

switch CPD.prior_type
 case 'dirichlet',
  switch dirichlet_type
   case 'unif', CPD.dirichlet = dirichlet_weight * myones(fam_sz);
   case 'BDeu',  CPD.dirichlet = (dirichlet_weight/psz) *
mk_stochastic(myones(fam_sz));
   otherwise, error(['invalid dirichlet_type ' dirichlet_type])
  end
 case {'entropic', 'none'}
  CPD.dirichlet = [];
 otherwise, error(['invalid prior_type ' prior_type])
end

% fields to do with learning
if ~CPD.adjustable
  CPD.counts = [];
  CPD.nparams = 0;
```

```
  CPD.nsamples = [];
else
  %CPD.counts = zeros(size(CPD.CPT));
  CPD.counts = zeros(prod(size(CPD.CPT)), 1);
  psz = fam_sz(1:end-1);
  ss = fam_sz(end);
  if CPD.leftright
    % For each of the Qps contexts, we specify Q elements on the
diagoanl
    CPD.nparams = Qps * Q;
  else
    % sum-to-1 constraint reduces the effective arity of the node by 1
    CPD.nparams = prod([psz ss-1]);
  end
  CPD.nsamples = 0;
end

CPD.trimmed_trans = [];
fam_sz = CPD.sizes;

%psz = prod(fam_sz(1:end-1));
%ssz = fam_sz(end);
%CPD.trimmed_trans = zeros(psz, ssz); % must declare before reading

%sparse CPT
if CPD.sparse
   CPD.CPT = sparse(CPD.CPT(:));
end

CPD = class(CPD, 'tabular_CPD', discrete_CPD(~CPD.adjustable, fam_sz));
%%%%%%%%%%%

function CPD = init_fields()
% This ensures we define the fields in the same order
% no matter whether we load an object from a file,
```

```
% or create it from scratch. (Matlab requires this.)

CPD.CPT = [];
CPD.sizes = [];
CPD.prior_type = [];
CPD.dirichlet = [];
CPD.adjustable = [];
CPD.counts = [];
CPD.nparams = [];
CPD.nsamples = [];
CPD.trim = [];
CPD.trimmed_trans = [];
CPD.leftright = [];
CPD.entropic_pcases = [];
CPD.sparse = [];
```

B.5 Neural Network

```
%input and test: n* number of sensors,typically [86400 X 3]
function [out,net]=neuralnet(input,target,test)

% Define feed forward input-delay back propagation neural network
net = newfftd([0 1; 0 1;0 1],[0 5],[3 1])
input=input';        % Transpose matrix to fit the input requirement
target=target';
test=test';
net.trainParam.show=NaN;
net  = train(net,input,target); % Star train process
out = sim(net,test);            % Apply the trained network to test data
out=out';
```

B.6 Calculate φ Correlation

```
%Phi correlation
%Cross Table
% a:Measured
```

```
% b:Truth

function [N11,N10,N01,N00,PhiCorr]=FuncPhiCross(a,b);

    N11=sum(a & b);      % True occupancy = 1, Measured = 1
    N10=sum(~a & b);     % True occupancy = 1, Measured = 0
    N01=sum(a & ~b);     % True occupancy = 0, Measured = 1
    N00=sum(~(a | b));   % True occupancy = 0, Measured = 0
    % □ is calculated by equation 4.15□
```

$$\varphi = \frac{N_{11}N_{00} - N_{10}N_{01}}{\sqrt{r_1 r_2 c_1 c_2}} \qquad (4.\ 15)$$

```
    den=sqrt((N11+N10)*(N11+N01)*(N10+N00)*(N01+N00));
    if den==0
    PhiCorr=1;
    else
    PhiCorr=(N11*N00-N10*N01)/den;
    end
```

B.7 Miscellaneous Subroutines

B.7.1 Apply time delay

```
% Set time delay as Table 5-4 shows
% OrigData: the original data (MRow x NCol matrix)

function [AfterDelay]=SetTimeDelay(OrigData,TimeDelay)

[MRow,NCol] = size(OrigData); % Get the size of the original data
AfterDelay=zeros(MRow,NCol);  % Initialize the output matrix
for j=1:NCol                  % Start to scan the original matrix
    for i=1:MRow
        if OrigData(i,j)==1   % If reads 1, start to apply time delay
            AfterDelay(i,j)=1;
            for k=1:min(TimeDelay,MRow-i)
```

```
                if OrigData(i+k,j)==0
                    AfterDelay(i+k,j)=1;
                Else
                    i=i+k;
                    break;
                end
            end
        end
    end
end
```

B.7.2 Count occurrence of sub-matrix in another matrix

```
% count how many times matrix B appears in matrix A
function [n]=countm(B,A);
[r1,c1]=size(B);
[r,c]=size(A);
n=0;
for i=1 : r-1
    if B==A(i:i+r1-1,:)
        n=n+1;
        pos(n)=i;
    end
end
```

B.8 Raw Data Conversion

B.8.1 Convert XTension logs to time series data

```
% Sample original XTension log:
% 'Thu, Dec 1, 2005 5:50:30 AM Received ON for A2 (w)';
% They will be converted to [0 1] form
% List of sensors reflect the round-robin setting: the result will be
ordered
% by mounting postion [N E S]

%listSensor = 'B2 B3 B1 B5 B6 B4 A2 A3 A1 A5 A6 A4 ';
%listSensor = 'B1 B2 B3 B4 B5 B6 A1 A2 A3 A4 A5 A6 ';
```

```
listSensor = 'B3 B1 B2 B6 B4 B5 A3 A1 A2 A6 A4 A5 ';
for i=1:21
    fid=fopen(['back\XTension Log ' int2str(i)]); % Open the log for
reading
    sensordata=zeros(1440,10);     % Initialize output
    while 1              % Read line-by-line
        tline = fgetl(fid);
        if ~ischar(tline),   break,   end % Break at the end of line
        ArrayLine=strread(tline, '%s');   % Read the line to array,
separated
                          % by space
        [m,n]=size(ArrayLine);
        if m>7                % If it is a regular log line
            sStatus = ArrayLine(8);   % Get sensor reading (ON or OFF)
            if isequal(sStatus,{'ON'})
           sSensor = ArrayLine(11);  % Read sensor number
                sTime=strcat(ArrayLine(5),ArrayLine(6));
                          % Concatenate strings to get the time
                nTime = Hour(sTime) * 60 + Minute(sTime)+1;
                          % Convert time to number
                nCol = (strfind(listSensor,char(sSensor))-1)/3+1;
                          % Find the right column to write
                if ~nCol==0
                    sensordata(nTime,nCol)=1;   % Write sensor reading
(always 1)
                           % to the right position
                end
            end
        end
    %    disp(tline)
    end
    dlmwrite(['back\Wireless_' int2str(i) '.txt'],sensordata, ' ');
                         % Write results to a text file
    fclose(fid);
end
```

B.8.2 Convert 1-sec resolution to 1-min resolution

```
for d=1:21
    secdata=load(['session2sec\Commercial_' int2str(d) '.txt']);
        % secdata=yout;
    mindata=zeros(1440,21); % Initialize output
    for col=1:21
      for i=1:1440
            for j=1:60

          % Within a minute, if read 1 at any second, the minute is
          % assigned 1.
                if secdata((i-1)*60+j,col)==1
                    mindata(i,col)=1;
                    break;
                end
            end
      end
    end
end
```

Appendix C Web Display Software Programs

This appendix describes software programs used to display and analyze occupancy data on the World Wide Web.

C.1 Real time occupancy monitoring

C.1.1 Introduction

This is a web-based program showing the real time occupancy profile, developed in Mac+Apache+perl environment. This program is essentially a perl CGI script, which reads the current occupancy sensor log file and displays the current sensor status on a web page, as depicted in Figure C-1.

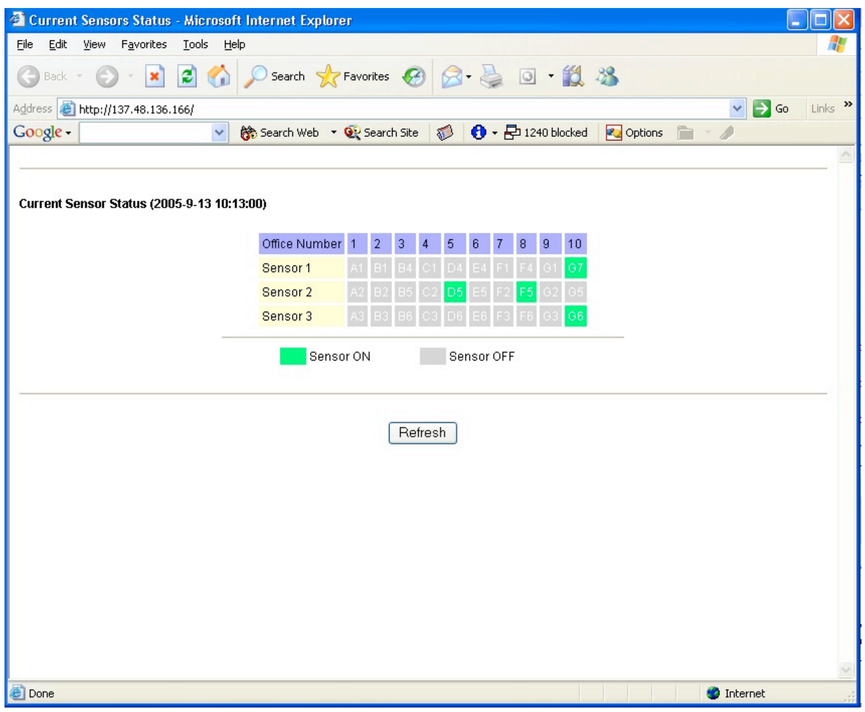


Figure C-1. Web-based real-time occupancy display

C.1.2 Source code

```
#!/usr/bin/perl


# tell the server the results will be displayed as html web page
print "Content-Type: text/html\n\n";
# Specify the file to be read
$path=" /Documents/XTension/XTension Log";
```

```
# String list all the sensor IDs
$listSensor="A1A2A3B1B2B3B4B5B6C1C2C3D4D5D6E4E5E6F1F2F3F4F5F6G1G2G3G7G5
G6";
$ColorON ="#00FF66";  # Green
$ColorOFF="#cccccc";  # Gray

#Following loop initialize all display color to be gray
for ($i=0;$i<30;$i++)
{
    @colors[$i]=$ColorOFF;
    @sensors[$i]=substr($listSensor,$i*2,2);
}

open(logfile,$path) || die print("Can't open $path !");
    # Look back from the bottom of the log file to around 20 lines
    seek(logfile,-1500,2);
    # Put the lines into array  "lines"
    @array = <logfile>;
    @lines=split(chr(13),@array[0]);
    $size=@lines;
#print $size;

for ($i=0;$i<$size;$i++)
{
    #read the space separated line to array "vars"
    @vars=split(" ",@lines[$i]);
    if (@vars[7] eq "ON")
    {
    # if the sensor sent a ON signal, set its corresponding color to
green
        $sTime=@vars[4];
        $nCol=(rindex $listSensor,@vars[10])/2;
        @colors[$nCol]=$ColorON;
    }
    if (@vars[7] eq "OFF")
```

```
        {
    # if the sensor sent a OFF signal, set its corresponding color to
gray
                $sTime=@vars[4];
                $nCol=(rindex $listSensor,@vars[10])/2;
                @colors[$nCol]=$ColorOFF;
        };
}

close(logfile);

#----------------------------------------------------------------------
#Output the results as html format, thus it is viewable from any
computer connected to the internet

# Define the table
print "<table width=\"400\" border=0 cellpadding=3 cellspacing=3>
<br/>";
print " <tr bgcolor=#9999FF align=center >";
print "<td width=\"100\"> Office Number </td>";
for($i=1;$i<11;$i++) {
    print "<td> $i</td>";}

print "</tr><tr><br\/><td bgcolor=#FFFFCC align=center> Sensor1</td>";
for($i=0;$i<10;$i++){
    print "<td bgcolor= @colors[$i*3]> <font color=#FFFFFF size=-1>
@sensors[$i*3] </font></td>"
}
print "</tr> <tr align=center> <td bgcolor=#FFFFCC> Sensor2</td>";
for($i=0;$i<10;$i++){
        print "<td bgcolor= @colors[$i*3+1]> <font color=#FFFFFF size=-
1> @sensors[$i*3+1] </font></td>"
}
print "</tr> <tr align=center> <td bgcolor=#FFFFCC> Sensor3</td>";
for($i=0;$i<10;$i++){
        print "<td bgcolor= @colors[$i*3+2]> <font color=#FFFFFF size=-
1> @sensors[$i*3+2] </font></td>"
```

```
}

print "</tr></table>";
exit;
```

C.2 Web-based querying

C.2.1 Introduction

All sensor readings are stored in a Microsoft Access database. This program is a web-based querying tool that displays hourly occupancy profiles or the total time of each day that satisfies the querying criteria, as shown in Figure C-2 throughFigure C-5.

Figure C-2 depicts the main query interface.

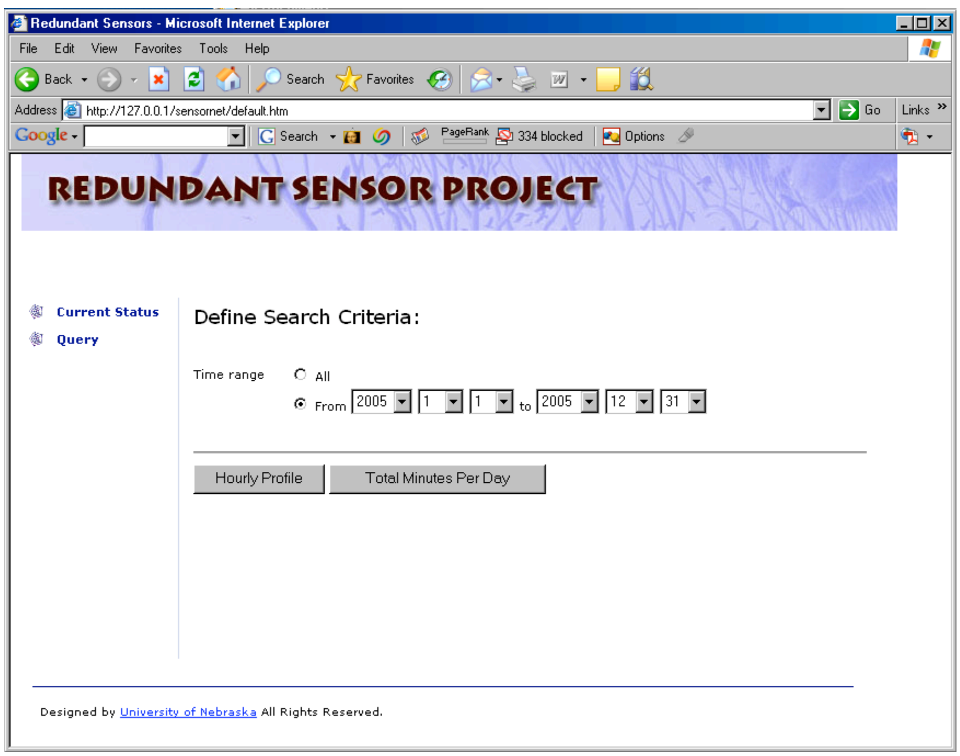


Figure C-2. Web-based occupancy querying interface

If the "Hourly Profile" button is clicked, the hourly distribution of occupancy profiles of each space within the database will be displayed in a new page, as shown in Figure C-3.

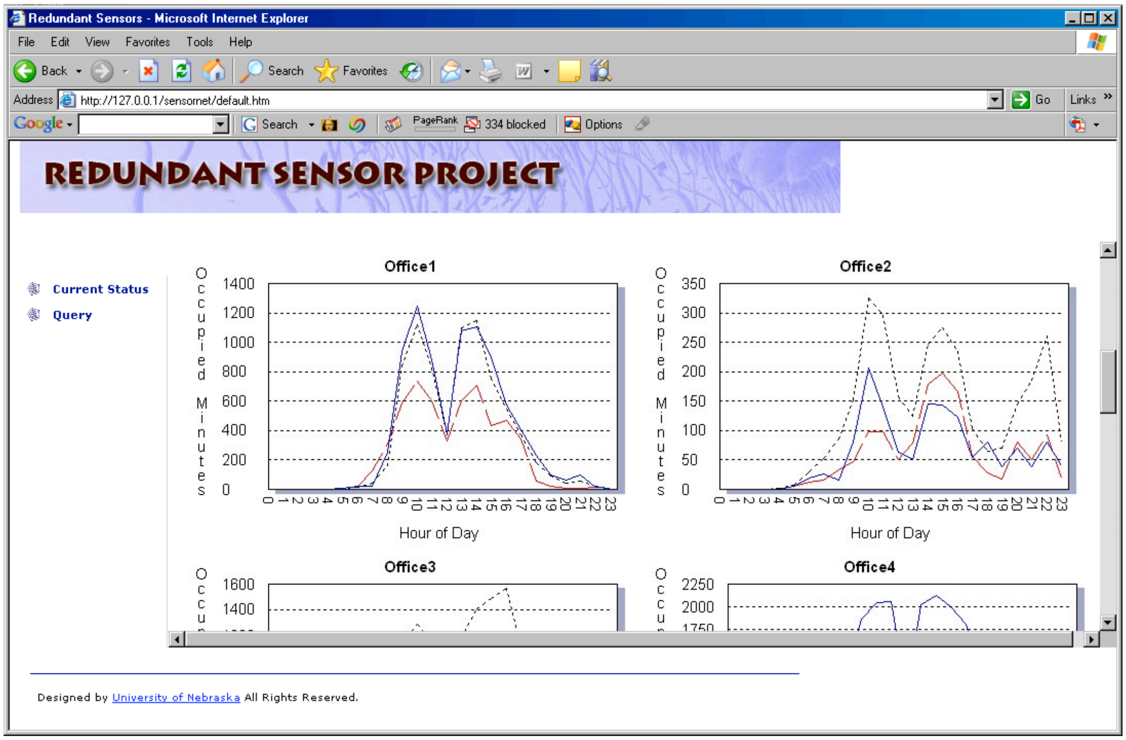
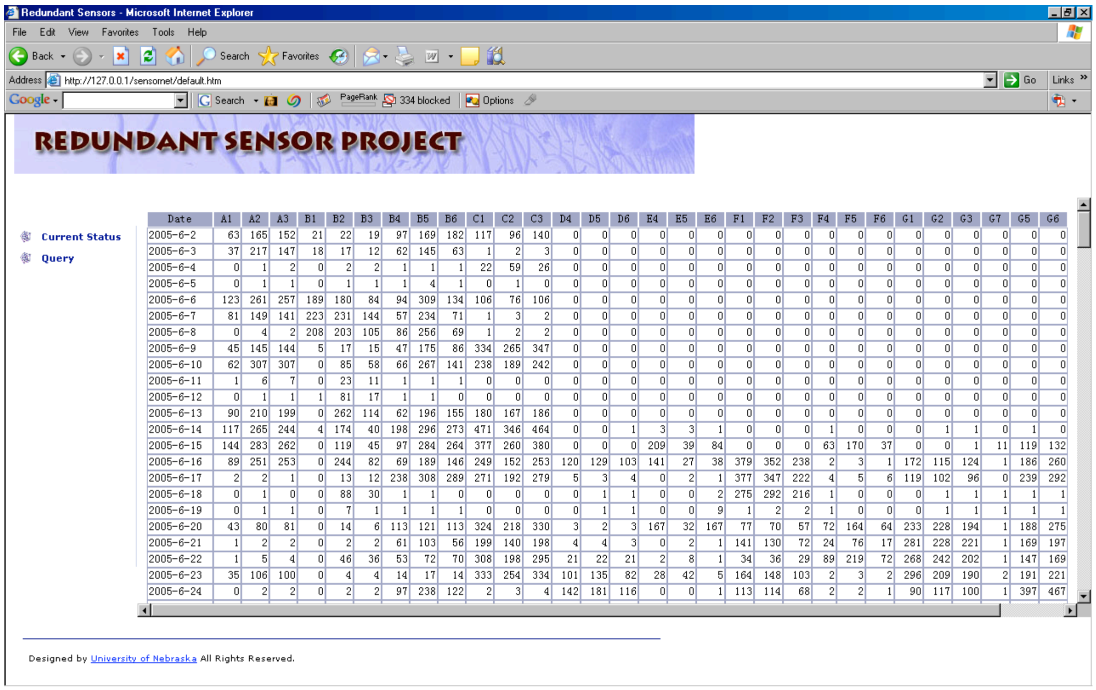


Figure C-3. Query results of hourly occupancy profiles

If the "Total Minutes Per Day" button is clicked, the total occupied time (in minutes) of each day as measured by each sensor will be displayed in a new page. Results can be displayed in tabular (Figure C-4) or graphical form (Figure C-5).



Date	A1	A2	A3	B1	B2	B3	B4	B5	B6	C1	C2	C3	D4	D5	D6
2005-6-2	63	165	152	21	22	19	97	169	182	117	96	140	0	0	0
2005-6-3	37	217	147	18	17	12	62	145	63	1	2	3	0	0	0
2005-6-4	0	1	2	0	2	2	1	1	1	22	59	26	0	0	0
2005-6-5	0	1	1	0	1	1	1	4	1	0	1	0	0	0	0
2005-6-6	123	261	257	189	180	84	94	309	134	106	76	106	0	0	0
2005-6-7	81	149	141	223	231	144	57	234	71	1	3	2	0	0	0
2005-6-8	0	4	2	208	203	105	86	256	69	1	2	2	0	0	0
2005-6-9	45	145	144	5	17	15	47	175	86	334	265	347	0	0	0
2005-6-10	62	307	307	0	85	58	66	267	141	238	189	242	0	0	0
2005-6-11	1	6	7	0	23	11	1	1	1	0	0	0	0	0	0
2005-6-12	0	1	1	1	81	17	1	1	0	0	0	0	0	0	0
2005-6-13	90	210	199	0	262	114	62	196	155	180	167	186	0	0	0
2005-6-14	117	265	244	4	174	40	198	296	273	471	346	464	0	0	1
2005-6-15	144	283	262	0	119	45	97	284	264	377	260	380	0	0	0
2005-6-16	89	251	253	0	244	82	69	189	146	249	152	253	120	129	103
2005-6-17	2	2	1	0	13	12	238	308	289	271	192	279	5	3	4
2005-6-18	0	1	0	0	88	30	1	1	0	0	0	0	0	1	1
2005-6-19	0	1	1	0	7	1	1	1	1	0	0	0	0	1	1
2005-6-20	43	80	81	0	14	6	113	121	113	324	218	330	3	2	3
2005-6-21	1	2	2	0	2	2	61	103	56	199	140	198	4	4	3
2005-6-22	1	5	4	0	46	36	53	72	70	308	198	295	21	22	21
2005-6-23	35	106	100	0	4	4	14	17	14	333	254	334	101	135	82
2005-6-24	0	2	2	0	2	2	97	238	122	2	3	4	142	181	116

Date	E4	E5	E6	F1	F2	F3	F4	F5	F6	G1	G2	G3	G7	G5	G6
2005-6-2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005-6-3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005-6-4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005-6-5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005-6-6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005-6-7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005-6-8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005-6-9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005-6-10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005-6-11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005-6-12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005-6-13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005-6-14	3	3	1	0	0	0	1	0	0	0	1	1	0	1	0
2005-6-15	209	39	84	0	0	0	63	170	37	0	0	1	11	119	132
2005-6-16	141	27	38	379	352	238	2	3	1	172	115	124	1	186	260
2005-6-17	0	2	1	377	347	222	4	5	6	119	102	96	0	239	292
2005-6-18	0	0	2	275	292	216	1	0	0	0	1	1	1	1	1
2005-6-19	0	0	9	1	2	2	1	0	0	0	1	1	1	1	1
2005-6-20	167	32	167	77	70	57	72	164	64	233	228	194	1	188	275
2005-6-21	0	2	1	141	130	72	24	76	17	281	228	221	1	169	197
2005-6-22	2	8	1	34	36	29	89	219	72	268	242	202	1	147	169
2005-6-23	28	42	5	164	148	103	2	3	2	296	209	190	2	191	221
2005-6-24	0	0	1	113	114	68	2	2	1	90	117	100	1	397	467

Figure C-4. Tabulated query results showing total occupied time (min) of each day, each sensor

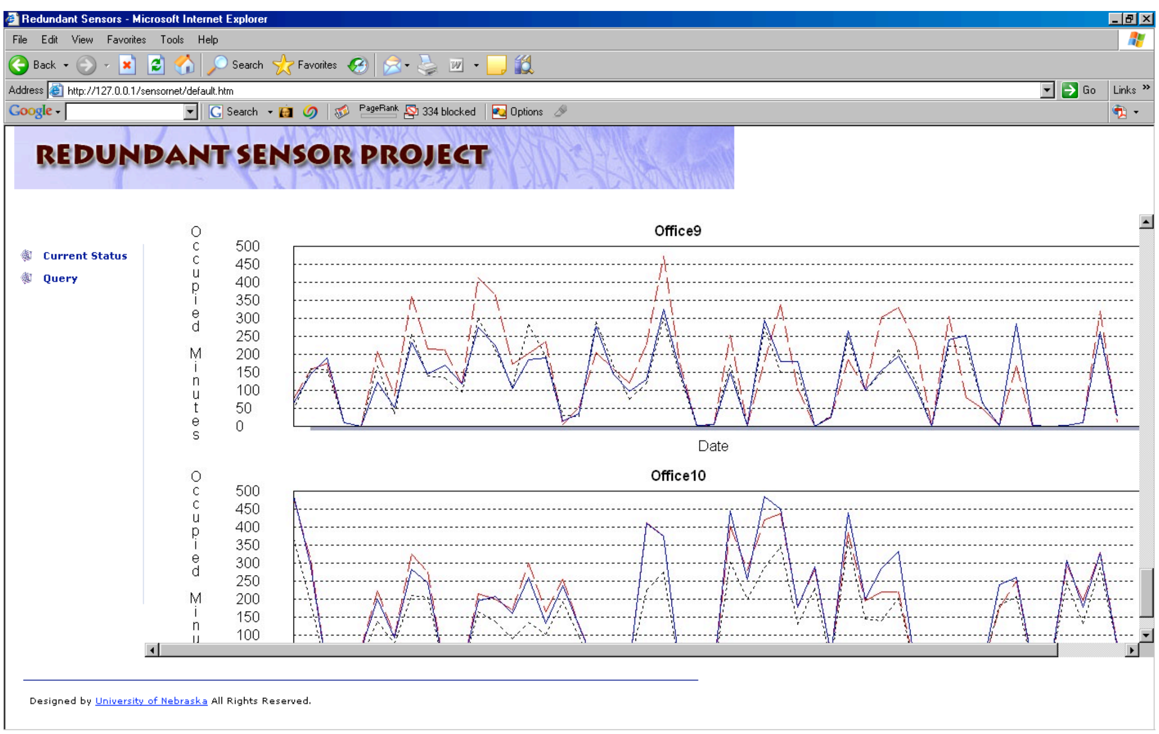


Figure C-5. Graphical query results showing total occupied time (min) of each day, each sensor

C.2.2 Source code - Hourly occupancy profile

```
'queryResultTime.asp
<%@LANGUAGE="VBSCRIPT" CODEPAGE="1252"%>
<!--#include file="Connections/sensornet.asp" -->
<!--#include file="sensorlist.asp" -->
<%
Dim Recordset1
Dim Recordset1_numRows

Set Recordset1 = Server.CreateObject("ADODB.Recordset")
Recordset1.ActiveConnection = MM_sensornet_STRING
Recordset1.Source = "SELECT count(*)  FROM DistinctDay"
Recordset1.CursorType = 0
Recordset1.CursorLocation = 2
Recordset1.LockType = 1
Recordset1.Open()

Recordset1_numRows = 0
%>

<%
Dim result(24,31)
for i=0 to 23
    result(i,0)=i
    for j=1 to 30
        result(i,j)=0
    next
next
%>

<%
Dim rsHourlySum
Dim rsHourlySum_numRows
Set rsHourlySum = Server.CreateObject("ADODB.Recordset")
rsHourlySum.ActiveConnection = MM_sensornet_STRING
```

```
rsHourlySum.Source = GetQuerySQL

'rsHourlySum.Source ="SELECT hour(TTime) AS TimeHour, sum(v01),
sum(v02), sum(v03), sum(v04), sum(v05), sum(v06), sum(v07), sum(v08),
sum(v09), sum(v10), sum(v11), sum(v12), sum(v13), sum(v14), sum(v15),
sum(v16), sum(v17), sum(v18), sum(v19), sum(v20), sum(v21), sum(v22),
sum(v23), sum(v24), sum(v25), sum(v26), sum(v27), sum(v28), sum(v29),
sum(v30) From LogData GROUP BY hour(TTime)"

'rsHourlySum.Source ="SELECT * from hourly"

sqlTemp=sqlTemp & "From LogData"

rsHourlySum.CursorType = 0

rsHourlySum.CursorLocation = 2

rsHourlySum.LockType = 1

rsHourlySum.Open()


rsHourlySum_numRows = 0

%>


<%

 function GetQuerySQL

    mySQL = "SELECT hour(TTime) AS TimeHour"

    for i=1 to 30

        mySQL=mySQL + ",sum(v" & right("0" & CStr(i),2) & ")"

    next

    mySQL=mySQL & " From LogData"

    ' Limit the search result in the time range specified

    DateAndTime = Request.Form("fromYear") & "-" &
Request.Form("fromMONTH") & "-" & Request.Form("fromDAY")

    CFilter = " where (DDate >= CDate('" & DateAndTime & "'))"


    DateAndTime = Request.Form("toYear") & "-" & Request.Form("toMONTH")
& "-" & Request.Form("toDAY")

    CFilter = CFilter & " and (DDate <= CDate('" & DateAndTime & "'))"


     GetQuerySQL = mySQL & CFilter & "GROUP BY hour(TTime)"

End Function


%>
```

```
<%
Dim Repeat1__numRows
Dim Repeat1__index

Repeat1__numRows = -1
Repeat1__index = 0
rsHourlySum_numRows = rsHourlySum_numRows + Repeat1__numRows
%>
<%
'  *** Recordset Stats, Move To Record, and Go To Record: declare stats
variables

Dim Recordset1_total
Dim Recordset1_first
Dim Recordset1_last

' set the record count
Recordset1_total = Recordset1.RecordCount

' set the number of rows displayed on this page
If (Recordset1_numRows < 0) Then
  Recordset1_numRows = Recordset1_total
Elseif (Recordset1_numRows = 0) Then
  Recordset1_numRows = 1
End If

' set the first and last displayed record
Recordset1_first = 1
Recordset1_last  = Recordset1_first + Recordset1_numRows - 1

' if we have the correct record count, check the other stats
If (Recordset1_total <> -1) Then
  If (Recordset1_first > Recordset1_total) Then
    Recordset1_first = Recordset1_total
```

```
  End If
  If (Recordset1_last > Recordset1_total) Then
    Recordset1_last = Recordset1_total
  End If
  If (Recordset1_numRows > Recordset1_total) Then
    Recordset1_numRows = Recordset1_total
  End If
End If
%>

<%
' *** Recordset Stats: if we don't know the record count, manually
count them

If (Recordset1_total = -1) Then

  ' count the total records by iterating through the recordset
  Recordset1_total=0
  While (Not Recordset1.EOF)
    Recordset1_total = Recordset1_total + 1
    Recordset1.MoveNext
  Wend

  ' reset the cursor to the beginning
  If (Recordset1.CursorType > 0) Then
    Recordset1.MoveFirst
  Else
    Recordset1.Requery
  End If

  ' set the number of rows displayed on this page
  If (Recordset1_numRows < 0 Or Recordset1_numRows > Recordset1_total)
Then
    Recordset1_numRows = Recordset1_total
  End If
```

```
  ' set the first and last displayed record
  Recordset1_first = 1
  Recordset1_last = Recordset1_first + Recordset1_numRows - 1

  If (Recordset1_first > Recordset1_total) Then
    Recordset1_first = Recordset1_total
  End If
  If (Recordset1_last > Recordset1_total) Then
    Recordset1_last = Recordset1_total
  End If

End If
%>

<html>
<head>
<title>Untitled Document</title>
<meta http-equiv="Content-Type" content="text/html; charset=iso-8859-
1">
</head>
<body bgcolor="#FFFFFF" text="#000000">
<p align="left"><strong><font size="2">Hourly occupancy profile of all
sensors
  <% if request.form("Time")="All" then %>
  <% dislayTim="All" %>
  <% else
    dislayTime= "from " & Request.form("FromMonth") & "/" &
request.form("FromDay") & "/" & request.form("FromYear") & " to " &
Request.form("ToMonth") & "/" & request.form("ToDay") & "/" &
request.form("ToYear")%>
  <% = dislayTime %>
  <% end if %>
  (
  <%'=(Recordset1.Fields.Item("Expr1000").Value) &  Days%>
  ) </font></strong></p>
```

```
 <%
While ((Repeat1__numRows <> 0) AND (NOT rsHourlySum.EOF))
v_Hr=(rsHourlySum.Fields.Item(0).Value)
for j=1 to 30
    result(v_Hr,j)=(rsHourlySum.Fields.Item(j).Value)
next

  Repeat1__index=Repeat1__index+1
  Repeat1__numRows=Repeat1__numRows-1
  rsHourlySum.MoveNext()
Wend
%>
'Define the output table
<table border="1" cellpadding="1" cellspacing="0"
bordercolor="#FFFFFF">
  <tr>
    <td  width="30" bgcolor="#A3A9C7"><div align="center"><font
size="2">Hours</font></div></td>
    <%for i=1 to 30%>
    <td  width="30" bgcolor="#A3A9C7"><div align="center"><font
size="2"><%=sensors(i)%></font></div></td>
    <%next%>
  </tr>
<%  for i=0 to 23 %>
  <tr bordercolor="#A3A9C7">
      <td>
      <div align="center"><font size="2"><%=result(i,0)%>
</font></div></td>
   <% for j=1 to 30 %>

     <td>
      <div align="right"><font size="2"><%=result(i,j)%>
</font></div></td>
    <%  next%>
  </tr>
 <%next %>
```

```
</table>
<p>

<table width="75%" border="0">
<% for r = 0 to 4 %>
  <tr>
    <td><% GenChartFile(r*2)%></td>
    <td><% GenChartFile(r*2+1)%></td>
  </tr>
 <%next%>

</table>

</p>



<p> </p>

</body>
</html>
<%
Recordset1.Close()
Set Recordset1 = Nothing
%>
<%
rsHourlySum.Close()
Set rsHourlySum = Nothing
%>
```

C.2.3 Source Code - Total occupied time of each day

```
'queryResultMinutes.asp
<%@LANGUAGE="VBSCRIPT" CODEPAGE="1252"%>
<!--#include file="Connections/sensornet.asp" -->
<!--#include file="sensorlist.asp" -->
<%
```

```
Dim rsResultMinutes
Dim rsResultMinutes_numRows

Set rsResultMinutes = Server.CreateObject("ADODB.Recordset")
rsResultMinutes.ActiveConnection = MM_sensornet_STRING
rsResultMinutes.Source =GetQuerySQL
rsResultMinutes.CursorType = 0
rsResultMinutes.CursorLocation = 2
rsResultMinutes.LockType = 1
rsResultMinutes.Open()

rsResultMinutes_numRows = 0
%>
<%
Dim result(500,31)

%>
<%
 function GetQuerySQL
    mySQL = "SELECT DDate"
    for i=1 to 30
        mySQL=mySQL + ",sum(v" & right("0" & CStr(i),2) & ")"
    next
    mySQL=mySQL & " From LogData"
    ' Limit the search result in the time range specified
    DateAndTime = Request.Form("fromYear") & "-" &
Request.Form("fromMONTH") & "-" & Request.Form("fromDAY")
    CFilter = " where (DDate >= CDate('" & DateAndTime & "'))"

    DateAndTime = Request.Form("toYear") & "-" & Request.Form("toMONTH")
& "-" & Request.Form("toDAY")
    CFilter = CFilter & " and (DDate <= CDate('" & DateAndTime & "'))"

     GetQuerySQL = mySQL & CFilter & "GROUP BY DDate"
End Function
```

```
%>
<%
Dim Repeat1__numRows
Dim Repeat1__index

Repeat1__numRows = -1
Repeat1__index = 0
rsResultMinutes_numRows = rsResultMinutes_numRows + Repeat1__numRows
%>

<table border="1" cellpadding="1" cellspacing="0"
bordercolor="#FFFFFF">
  <tr bgcolor="A3A9C7">
    <td width="170"><div align="center"><font
size="2">Date</font></div></td>
    <%for i=1 to 30%>
    <td  width="50" bgcolor="#A3A9C7"><div align="center"><font
size="2"><%=sensors(i)%></font></div></td>
    <%next%>
  </tr>
  <%
While ((Repeat1__numRows <> 0) AND (NOT rsResultMinutes.EOF))
result(Repeat1__index,0)=rsResultMinutes.Fields.Item("DDate").Value
for j=1 to 30
    result(Repeat1__index,j)=rsResultMinutes.Fields.Item(j).Value
next
%>
  <tr bordercolor="#A3A9C7">
    <td><font size="2"><%=result(Repeat1__index,0)%></font></td>
    <%for i=1 to 30%>
    <td><div align="right"><font
size="2"><%=result(Repeat1__index,i)%></font></div></td>
    <%next%>
  </tr>
  <%
```

```
  Repeat1__index=Repeat1__index+1
  Repeat1__numRows=Repeat1__numRows-1
  rsResultMinutes.MoveNext()
Wend
nRow=Repeat1__index
%>
</table>
<table width="75%" border="0">
  <% for r = 0 to 9 %>
  <tr>
    <td><% GenChartFile(r)%></td>
  </tr>
 <%next%>

</table>
<p>
  <%
rsResultMinutes.Close()
Set rsResultMinutes = Nothing
%>
</p>
</body>
</html>
```

Appendix D Sensor Unit Price

Table D-1 lists unit prices for popular commercial occupancy sensors by major manufacturers. The list includes single (PIR or ultrasonic) or dual (PIR+ Ultrasonic or PIR+ Microphonic) technology sensors at various mounting position (wall switch or ceiling/wall mounted).

Table D-1. Occupancy sensor list prices by major manufacturers

Manufacturer	Catalog No.	Technology	Mounting	U.S. List Price ($)	Coverage	View (°)
Wattstopper	CW-100	PIR	Wall switch	33	300 ft^2	180
Wattstopper	CN-100	PIR	Wall switch	37	300 ft^2	180
Wattstopper	WS-200	PIR	Wall switch	58	900 ft^2	180
Wattstopper	WA-300	PIR	Wall switch	84	300 ft^2	180
Wattstopper	WI-300	PIR	Wall switch	84	1000 ft^2	180
Wattstopper	WN-100-120	PIR	Wall switch	58	300 ft^2	180
Wattstopper	WD-180	PIR	Wall switch	80	300 ft^2	180
Wattstopper	WD-270	PIR	Wall switch	84	300 ft^2	180
Wattstopper	WPIR	PIR	Ceiling	72	300 ft^2	360
Wattstopper	CX-100	PIR	Ceiling	106	2000 ft^2	360
Wattstopper	CI-200	PIR	Ceiling	106	1200 ft^2	360
Wattstopper	CI-200-1	PIR	Ceiling	106	500 ft^2	360
Wattstopper	CI-205	PIR	Ceiling	88	1200 ft^2	360
Wattstopper	CI-205-1	PIR	Ceiling	88	500 ft^2	360
Wattstopper	CI-300	PIR	Ceiling	110	1200 ft^2	360
Wattstopper	CI-300-1	PIR	Ceiling	110	500 ft^2	360
Wattstopper	CI-305	PIR	Ceiling	94	1200 ft^2	360
Wattstopper	CI-305-1	PIR	Ceiling	94	500 ft^2	360
Wattstopper	CI-12	PIR	Ceiling	75	1200 ft^2	360
Wattstopper	CI-12-1	PIR	Ceiling	75	500 ft^2	360
Wattstopper	CI-24	PIR	Ceiling	75	1200 ft^2	360
Wattstopper	CI-24-1	PIR	Ceiling	75	500 ft^2	360
Wattstopper	CB-100	PIR	Ceiling	170	1200 ft^2	360
Wattstopper	W-500A	Ultrasonic	Ceiling	96	500 ft^2	360
Wattstopper	W-1000A	Ultrasonic	Ceiling	116	1000 ft^2	360

Manufacturer	Catalog No.	Technology	Mounting	U.S. List Price ($)	Coverage		View (°)
Wattstopper	W-2000A	Ultrasonic	Ceiling	136	2000	ft^2	360
Wattstopper	WT-605	Ultrasonic	Ceiling	104	600	ft^2	360
Wattstopper	WT-600	Ultrasonic	Ceiling	112	600	ft^2	360
Wattstopper	WT-1105	Ultrasonic	Ceiling	124	1100	ft^2	360
Wattstopper	WT-1100	Ultrasonic	Ceiling	132	1100	ft^2	360
Wattstopper	WT-2205	Ultrasonic	Ceiling	144	2200	ft^2	360
Wattstopper	WT-2200	Ultrasonic	Ceiling	152	2200	ft^2	360
Wattstopper	UT-300-1	Ultrasonic	Ceiling	112	500	ft^2	360
Wattstopper	UT-300-2	Ultrasonic	Ceiling	132	1000	ft^2	360
Wattstopper	UT-300-3	Ultrasonic	Ceiling	152	2000	ft^2	360
Wattstopper	UT-305-1	Ultrasonic	Ceiling	104	500	ft^2	360
Wattstopper	UT-305-2	Ultrasonic	Ceiling	124	1000	ft^2	360
Wattstopper	UT-305-3	Ultrasonic	Ceiling	144	2000	ft^2	360
Wattstopper	DT-200	PIR+Ultrasonic	Ceiling/Wall	170	2000	ft^2	360
Wattstopper	DT-205	PIR+Ultrasonic	Ceiling	150	2000	ft^2	360
Wattstopper	DT-355	PIR+Ultrasonic	Ceiling	150	1000	ft^2	360
Sensor switch	WSD	PIR	Wall switch	56.7	20	ft	180
Sensor switch	WSD-NL	PIR	Wall switch	60	20	ft	180
Sensor switch	WSD-PDT	PIR+Micophonic	Wall switch	87.75	50	ft	180
Sensor switch	IPL	PIR	Wall switch	105	70	ft	180
Sensor switch	IPL-PDT	PIR+Micophonic	Wall switch	120	70	ft	180
Sensor switch	LWS	PIR	Wall switch	75	70	ft	180
Sensor switch	LWS-2P	PIR	Wall switch	93.75	70	ft	180
Sensor switch	LWS-PDT	PIR+Micophonic	Wall switch	105	70	ft	180
Sensor switch	LWS-PDT-2P	PIR+Micophonic	Wall switch	114	70	ft	180
Sensor switch	CMR-9	PIR	Ceiling	97.5	12	ft	360
Sensor switch	CMR-9-2P	PIR	Ceiling	127.5	12	ft	360
Sensor switch	CMR-10	PIR	Ceiling	97.5	28	ft	360
Sensor switch	CMR-10-2P	PIR	Ceiling	127.5	28	ft	360
Sensor switch	CMR-PDT	PIR+Micophonic	Ceiling	112.5	12	ft	360
Sensor switch	CMR-PDT-2P	PIR+Micophonic	Ceiling	142.5	12	ft	360
Sensor switch	CMR-PDT-10	PIR+Micophonic	Ceiling	112.5	28	ft	360

Manufacturer	Catalog No.	Technology	Mounting	U.S. List Price ($)	Coverage		View (°)
Sensor switch	CMR-PDT-10-2P	PIR+Micophonic	Ceiling	142.5	28	ft	360
Sensor switch	CMRB-9	PIR	Ceiling	73.5	12	ft	360
Sensor switch	CMRB-9-2P	PIR	Ceiling	103.5	12	ft	360
Sensor switch	CMRB-10	PIR	Ceiling	73.5	28	ft	360
Sensor switch	CMRB-10-2P	PIR	Ceiling	103.5	28	ft	360
Sensor switch	CMRB-PDT-10	PIR+Micophonic	Ceiling	88.5	28	ft	360
Sensor switch	CMRB-PDT-10-2P	PIR+Micophonic	Ceiling	118.5	28	ft	360
Lutron	LOS-SUS	Ultrasonic	Wall switch	108.55	1000	ft^2	180
Lutron	LOS-S2IR-HD	PIR	Wall switch	97.45	1000	ft^2	180
Lutron	LOS-SIR-HD	PIR	Wall switch	72.15	1000	ft^2	180
Lutron	LOS-SIR	PIR	Wall switch	57.15	900	ft^2	180
Lutron	LOS-WDT-R	PIR+Ultrasonic	Wall	151.9	1600	ft^2	110
Lutron	LOS-WDT	PIR+Ultrasonic	Wall	145.5	1600	ft^2	110
Lutron	LOS-WIR	PIR+Ultrasonic	Wall	106.45	1600	ft^2	110
Lutron	LOS-CDT-1000	PIR+Ultrasonic	Ceiling	134.75	1000	ft^2	180
Lutron	LOS-CDT-1000R	PIR+Ultrasonic	Ceiling	143.55	1000	ft^2	180
Lutron	LOS-CDT-2000	PIR+Ultrasonic	Ceiling	148.75	2000	ft^2	360
Lutron	LOS-CDT-2000R	PIR+Ultrasonic	Ceiling	157.5	2000	ft^2	360
Lutron	LOS-CDT-500	PIR+Ultrasonic	Ceiling	105.45	500	ft^2	180
Lutron	LOS-CDT-500R	PIR+Ultrasonic	Ceiling	114.15	500	ft^2	180
Lutron	LOS-CUS-1000	Ultrasonic	Ceiling	116.45	1000	ft^2	180
Lutron	LOS-CUS-2000	Ultrasonic	Ceiling	134.45	2000	ft^2	360
Lutron	LOS-CUS-500	Ultrasonic	Ceiling	101.95	500	ft^2	180
Lutron	LOS-CIR-1500	PIR	Ceiling	81.25	1500	ft^2	360
Lutron	LOS-CIR-450	PIR	Ceiling	86.15	450	ft^2	360
Leviton	ACP10-0L	PIR	Wall switch	82.03	2100	ft^2	180
Leviton	OSSNL-ID	PIR	Wall switch	82.03	2100	ft^2	180
Leviton	OSSMT-MD	PIR+Ultrasonic	Wall switch	91.63	1200	ft^2	180
Leviton	ODS0D-IDW	PIR	Wall switch	114.97	2100	ft^2	180

Manufacturer	Catalog No.	Technology	Mounting	U.S. List Price ($)	Coverage		View (°)
Leviton	ODS10-IDW	PIR	Wall switch	77.74	2100	ft^2	180
Leviton	ODS15-IDW	PIR	Wall switch	81.68	2100	ft^2	180
Leviton	OSC05-M0W	PIR+Ultrasonic	Ceiling	130.25	500	ft^2	180
Leviton	OSC10-M0W	PIR+Ultrasonic	Ceiling	152.37	1000	ft^2	360
Leviton	OSC20-M0W	PIR+Ultrasonic	Ceiling	174.51	2000	ft^2	360
Leviton	OSC05-U0W	Ultrasonic	Ceiling	108.11	500	ft^2	180
Leviton	OSC10-U0W	Ultrasonic	Ceiling	130.25	1000	ft^2	360
Leviton	OSC20-U0W	Ultrasonic	Ceiling	152.37	2000	ft^2	360
Leviton	OSC04-I0W	PIR	Ceiling	88.38	450	ft^2	360
Leviton	OSC15-I0W	PIR	Ceiling	88.38	1500	ft^2	360
Leviton	ODC0S-I1W	PIR	Ceiling	120.64	530	ft^2	360
Leviton	ODC0S-I2W	PIR	Ceiling	120.64	530	ft^2	360
Leviton	ODC0S-I7W	PIR	Ceiling	120.64	530	ft^2	360
Leviton	ODC10-M0W	PIR+Ultrasonic	Ceiling	152.37	1000	ft^2	180
Leviton	ODC10-MRW	PIR+Ultrasonic	Ceiling	185.68	1000	ft^2	180
Leviton	ODC20-MRW	PIR+Ultrasonic	Ceiling	207.63	2000	ft^2	360
Leviton	OSW12-M0W	PIR+Ultrasonic	Wall	174.43	1200	ft^2	110
Leviton	OSWLR-I0W	PIR	Wall	143.46	100	ft	8
Leviton	OSWHB-I0W	PIR	Wall	143.46	120	ft	8
Leviton	OSWWV-I0W	PIR	Wall	121.4	2500	ft^2	110
Leviton	ODW12-MRW	PIR+Ultrasonic	Wall	207.63	1200	ft^2	110

Table D-2 shows the determination of average price of PIR wall switches in the economic analysis (section 9.4). PIR wall switches usually have smaller coverage than the dual-technology sensors and they are recommended to use in small private offices. The four lighting control scenarios assumed in the economic analysis were: manual switch, a simple functioning PIR wall switch, an extended coverage, dual-technology ceiling or wall mounted sensor and the sensor network. Thus, only the simplest (or least expensive) sensor with coverage less than 300 ft^2 are considered in the calculation. The average price of $62.70 was rounded to $60.00 in the economic analysis.

Table D-2. Price of PIR wall switches

Manufacturer	Catalog No.	Technology	Mounting	U.S. List Price ($)	Coverage	View (°)
Wattstopper	CW-100	PIR	Wall switch	33	300 ft^2	180
Wattstopper	CN-100	PIR	Wall switch	37	300 ft^2	180
Wattstopper	WA-300	PIR	Wall switch	84	300 ft^2	180
Wattstopper	WN-100-120	PIR	Wall switch	58	300 ft^2	180
Wattstopper	WD-180	PIR	Wall switch	80	300 ft^2	180
Wattstopper	WD-270	PIR	Wall switch	84	300 ft^2	180
Average				**62.7**		

Table D-3 shows the determination of average price of ceiling or wall mounted dual-technology sensors in the economic analysis (section 9.4). The economic analysis aimed to contrast the simple PIR wall switch with an extended-coverage sensor, so only dual-technology sensors with greater than 1000 ft^2 or 10 ft of coverage are considered in the calculation. The average price of $149.10 was rounded to $150.00 in the economic analysis.

Table D-3. Price of dual-technology ceiling or wall mounted sensors

Manufacturer	Catalog No.	Technology	Mounting	U.S. List Price ($)	Coverage	View (°)
Wattstopper	DT-200	PIR+Ultrasonic	Ceiling/Wall	170	2000 ft^2	360
Wattstopper	DT-205	PIR+Ultrasonic	Ceiling	150	2000 ft^2	360
Wattstopper	DT-355	PIR+Ultrasonic	Ceiling	150	1000 ft^2	360
Lutron	LOS-WDT-R	PIR+Ultrasonic	Wall	151.9	1600 ft^2	110
Lutron	LOS-WDT	PIR+Ultrasonic	Wall	145.5	1600 ft^2	110
Lutron	LOS-WIR	PIR+Ultrasonic	Wall	106.45	1600 ft^2	110
Lutron	LOS-CDT-1000	PIR+Ultrasonic	Ceiling	134.75	1000 ft^2	180
Lutron	LOS-CDT-1000R	PIR+Ultrasonic	Ceiling	143.55	1000 ft^2	180
Lutron	LOS-CDT-2000	PIR+Ultrasonic	Ceiling	148.75	2000 ft^2	360
Lutron	LOS-CDT-2000R	PIR+Ultrasonic	Ceiling	157.5	2000 ft^2	360
Leviton	OSC10-M0W	PIR+Ultrasonic	Ceiling	152.37	1000 ft^2	360
Leviton	OSC20-M0W	PIR+Ultrasonic	Ceiling	174.51	2000 ft^2	360
Leviton	ODC10-M0W	PIR+Ultrasonic	Ceiling	152.37	1000 ft^2	180
Leviton	ODC10-MRW	PIR+Ultrasonic	Ceiling	185.68	1000 ft^2	180
Leviton	ODC20-MRW	PIR+Ultrasonic	Ceiling	207.63	2000 ft^2	360
Leviton	OSW12-M0W	PIR+Ultrasonic	Wall	174.43	1200 ft^2	110
Leviton	ODW12-MRW	PIR+Ultrasonic	Wall	207.63	1200 ft^2	110
Sensor switch	CMR-PDT	PIR+Micophonic	Ceiling	112.5	12 ft	360
Sensor switch	CMR-PDT-2P	PIR+Micophonic	Ceiling	142.5	12 ft	360
Sensor switch	CMR-PDT-10	PIR+Micophonic	Ceiling	112.5	28 ft	360
Sensor switch	CMR-PDT-10-2P	PIR+Micophonic	Ceiling	142.5	28 ft	360
Sensor switch	CMRB-PDT-10	PIR+Micophonic	Ceiling	88.5	28 ft	360
Sensor switch	CMRB-PDT-10-2P	PIR+Micophonic	Ceiling	118.5	28 ft	360
Average				**149.1**		