Context-Aware Power Management

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A thesis submitted to the University of Dublin, Trinity College

in partial fulfillment of the requirements for the degree of

Doctor of Philosophy (Computer Science)

September 2006

Declaration

I, the undersigned, declare that this work has not previously been submitted to this or any other University, and that unless otherwise stated, it is entirely my own work.

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Dated: 14th September 2006

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Acknowledgements

I would like to sincerely thank my supervisor, Prof. Vinny Cahill, for all of his help, encouragement and insights over the past four years. It has been an invaluable learning experience. I would also like to thank the Irish Research Council for Science, Engineering and Technology who provided the funding for this research.

To everyone who volunteered to take part in the user studies, I would like to say a huge thank you for your openness and willingness to participate. I would particularly like to thank Dr. Myra O'Regan for her help with the data analysis and Neil O'Connor for his assistance with the object-range sensors. I would also like to thank the Department's support staff for making everything run so smoothly. In particular, Tom Kearney and the technicians for their help with the many hardware issues.

A big thank you to all my colleagues in the Distributed Systems Group (DSG). It has been great to be part of such a social group as DSG. I have fond memories of the canoe trips, the Chinese meals, the coffee breaks and the friday football.

To my parents, brother and sisters, thank you for your support, love and friendship throughout the years. Finally, thank you Helene for the love, patience and understanding you have shown during the time it has taken to complete this research.

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September 2006

Abstract

With more and more computing devices being deployed in buildings there has been a steady rise in buildings' electricity consumption. These devices not only consume electricity but also produce heat, which increases loading on ventilation systems, further increasing electricity consumption. At the same time there is a pressing need to reduce overall building energy consumption. For example, the European Union's strategy for security of energy supply highlights energy saving in buildings as a key target area. One approach to reducing energy consumption of devices in buildings is to improve the effectiveness of their power management.

Current state-of-the-art computer power management is predominantly focused on extending battery life for mobile computing devices. The majority of policies are low-level and are used to manage sub-components within the overall computing device. The key trade-off for these policies is device performance versus increased battery life. In contrast, stationary computing devices do not have battery limitations and typically the most significant energy savings are achieved by switching the entire device to standby. However, switching to a deep standby state can cause significant user annoyance due to the relatively long resume time and possible false power downs. Consequently these energy saving features are typically not enabled (or used with long timeouts). To increase enablement, policies for stationary devices need to operate in a near transparent fashion, i.e., operate automatically and with little user-perceived performance degradation.

Context-aware pervasive computing describes a vision of computing everywhere that seamlessly assists us in our daily tasks, i.e., many functions are intelligently automated. Information display, computing, sensing and communication will be embedded in everyday objects and within the environment's infrastructure. Seamless interaction with these devices will enable a person to focus on their task at hand while the devices themselves vanish into the background. Realisation of this vision could exacerbate the building energy problem as more stationary computing devices are deployed but it could also provide a solution. Context information (e.g., user location information) likely to be available in such pervasive computing environments could enable highly effective power management for many of a building's electricity consuming devices. We term such power management techniques as context-aware power management (CAPM), their principal objective being to minimise overall electricity consumption while maintaining user-perceived device performance. The current state of the art in context-aware computing focuses on developing inference techniques for determining high-level context from low-level, noisy, and incomplete sensor data. Possible approaches include rule-based inference, Bayesian inference, fuzzy control, and hidden Markov models. Successful inference enables the vision of computing services interfacing seamlessly and transparently with users' daily tasks. One such desirable, transparent service is context-aware power management.

We have identified several key requirements and designed a framework for CAPM. At the core of the framework, a Bayesian inference technique is employed to infer relevant context from a given range of sensors. We have identified the principal context required for effective CAPM as being (i) when the user is NOT USING and (ii) when the user is ABOUT TO USE a device. Accurately inferring this user context is the most challenging part of CAPM. However, there is also a balance between how much energy additional context can save and how much it will cost both monetarily and energy wise. To date there has been some research in the area of CAPM but to our knowledge there has been no detailed study as to what granularity of context is appropriate and what are the potential energy savings.

We have conducted an extensive user study to empirically answer these questions for CAPM of desktop PCs in an office environment. The sensors used are keyboard/mouse input, user presence based on Bluetooth beaconing, near presence based on ultrasonic range detection, face detection, and voice detection. Results from the study show that there is wide variability of usage patterns and that there is a balance whereby adding more sensors actually increases the energy consumption. For the desktop PC study, idle time, user presence, and near presence are sufficient for effective power management coming within 6-9% of the theoretical optimal policy (on average). Beyond this face detection and voice detection consumed more than they saved. The evaluation further demonstrates the use of Bayesian inference as a viable technique for CAPM.

Publications Related to this Ph.D.

[1] C. Harris and V. Cahill. Power Management for Stationary Machines in a Pervasive Computing Environment. In *38th Annual Hawaii International Conference on System Sciences (HICSS'2005).* Hawaii Big Island, January 2005.

[2] C. Harris and V. Cahill. Exploiting User Behaviour for Context-Aware Power Management. In *International Conference On Wireless and Mobile Computing, Networking and Communications*, Montreal, Canada, August 2005.

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Chapter 1

Introduction

This thesis investigates the potential for context information (e.g., user location information), likely to be available in future pervasive computing environments, to enable highly effective device power management. The principal objective of such context-aware power management (CAPM) is to minimise the overall electricity consumption of an environment's stationary devices, while maintaining acceptable user-perceived device performance. Secondary benefits are reduced noise and heat gain. The thesis focuses on a future pervasive computing office environment containing sensing devices such as location tags, imaging, audio, object detection, and stationary devices such as video displays, desktop PCs, printers, photocopiers, ventilation, and lighting.

1.1 Motivation

The European Union (EU) strategy for security of energy supply [13] highlights three main issues:

1. The EU will become increasingly dependent on external energy sources; enlargement will reinforce this trend. Based on current forecasts, if measures are not taken, import dependence will reach 70% of total energy consumption in 2030, compared to 50% today.

2. At present, greenhouse gas emissions in the EU are on the rise, making it difficult to respond to the challenge of climate change and to meet the EU's commitments under the Kyoto protocol [45].

3. The EU has very limited scope to influence energy supply conditions. It is essentially on the demand side that the EU can intervene, mainly by promoting energy savings in buildings and in the transport sector.

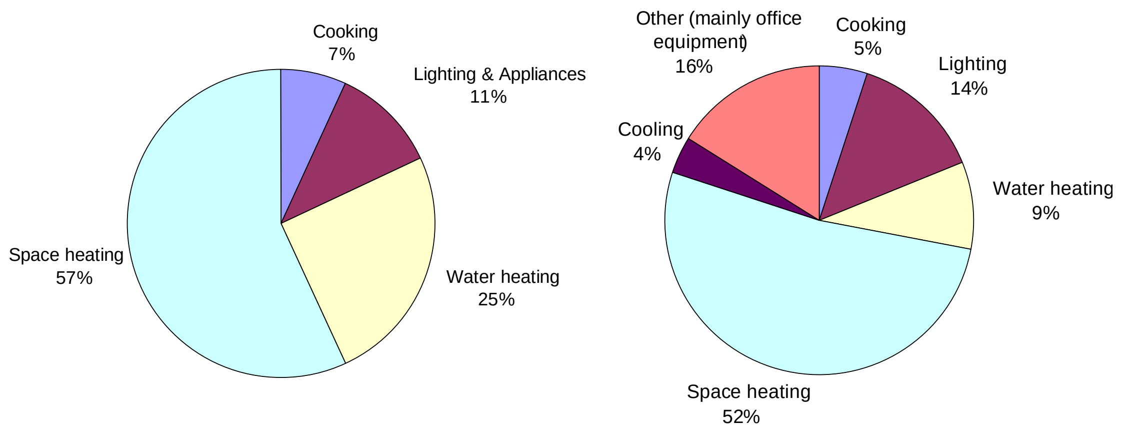


Figure 1.1: Residential and commercial energy consumption [14]

The EU's demand for energy has been growing at a rate of between 1% and 2% a year since 1986. While industrial demand has remained stable, households and the tertiary sector have increased their demand for electricity, transport, and heat. In particular demand for electricity has grown much more rapidly than any other type of energy and is predicted to track gross domestic product (GDP) growth closely until 2020 [13]. The total energy consumption of the EU in 1997 was estimated at 10,815 Tera-Watt hours (TWh). Of this total, 40% was used in the building sector and 32% in the transport sector [14]. Within the building sector residential properties consume 70% and commercial buildings consume 30%. Figure 1.1 shows the breakdown of how energy is consumed in both residential and commercial buildings.

The charts show that commercial buildings consume slightly less energy for heating but significantly more energy for lighting and other uses (mainly office equipment and building services' pumps and fans at about 8% each [47]). The current trend is that while buildings are gradually becoming better insulated reducing heat demand, increasing demand for appliances and services often offset heating efficiency gains. Furthermore, improved energy efficiency in electrical devices (e.g., energy saving light bulbs, and flat-screen monitors) has been more than offset by growing demand.

We conducted an analysis of electrical energy consumption for all buildings within Trinity College to compare with the estimates and trends above[1]. The stock of office equipment operating within the university was estimated from asset registers, sales records and network addresses for the year 2003. Multiplying the number of devices by their corresponding unit energy cost (UEC) (see Figure 1.3 below) gives a total energy cost (TEC) of around 0.003 TWh for office equipment within the university for 2003. This equates to 14.7% of the College's total electricity consumption or around

[1]The analysis was conducted as part of an EU pilot action for procurement of energy-efficient office equipment [15].

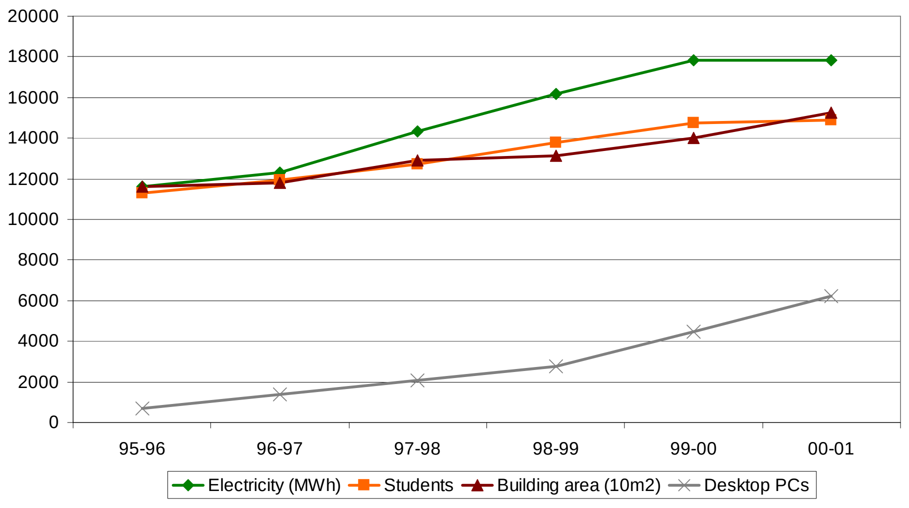
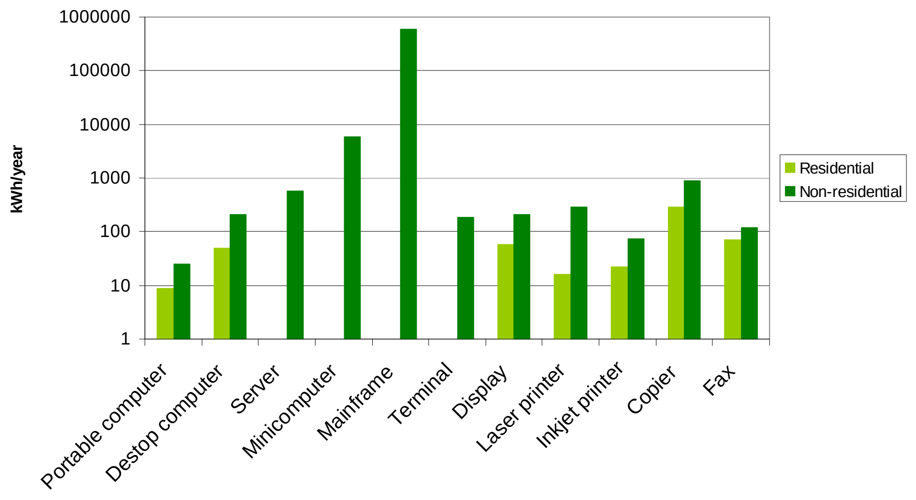


Figure 1.2: Trinity College Dublin electricity consumption [15]

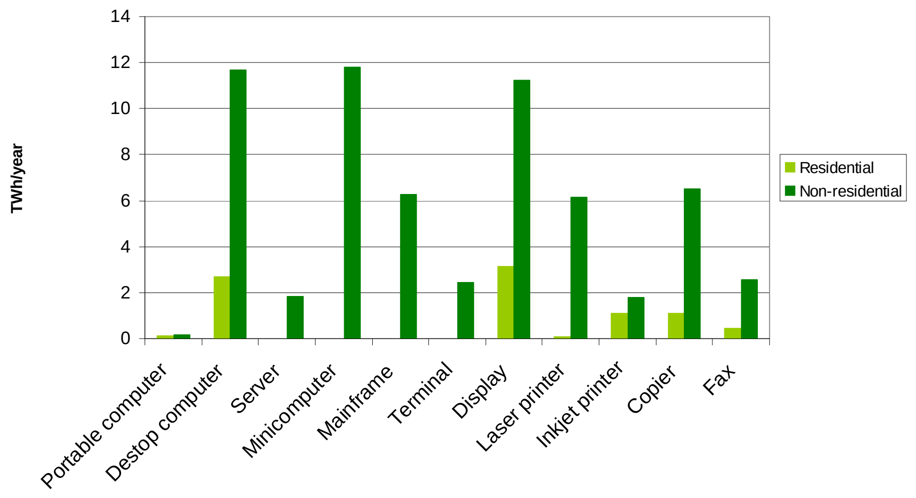
euro 190,000 in financial cost. Figure 1.2 shows electricity consumption, student numbers, building area and number of desktop PCs from 1995 to 2001. Electricity consumption has increased by over 50% in this period outstripping the increase in students and building area. At the same time the number of desktop PCs increased by 800%.

Part of this trend of increased electrical energy consumption in buildings is due to the increased numbers of computing devices (office equipment) being deployed in buildings. The Lawerence Berkeley National Laboratory (LBNL) provides detailed estimates of energy consumed by office and network equipment in the United States as of 1999 [33]. The office equipment is divided into 11 types of device and categorised into residential and non-residential sectors as usage varies between the sectors. Figure 1.3 details the estimated unit energy cost and total energy cost for each device type over a period of a year for both the residential and non-residential sectors. UEC is charted in kilo-Watt hours per year (kWh/year) and the scale is logarithmic to include the minicomputer and mainframe devices which consume 5,840 and 58,400 kWh/year respectively.

The UEC figures are multiplied by the estimated number of devices existing in the residential and non-residential sectors to give the total energy cost for each device type in TWh/year. The charts highlight that even though the unit energy cost of the minicomputer and mainframe far exceed other office equipment, both the desktop computer and the desktop display unit have the two highest total energy costs, due to the shear number of them (estimated 109,110 desktop computers and 109,180 displays in the USA in 1999 compared to 2,020 minicomputers and 107 mainframes). The total energy

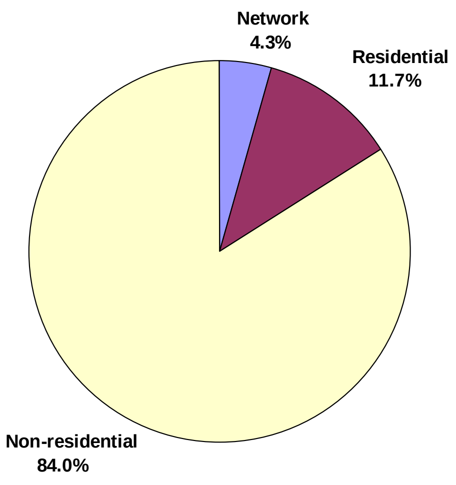


(a) Annual unit energy cost per device type (kWh/year)



(b) Annual total energy cost per device type (TWh/year)

Figure 1.3: Unit energy cost and total energy cost per device type for USA [33]



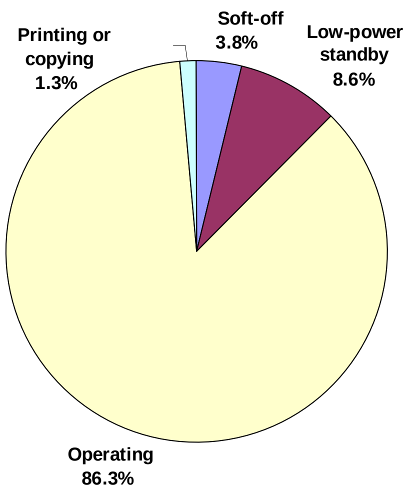


Figure 1.4: Percentage energy cost per sector and per power state [33]

cost of network equipment is estimated to be 3.22 TWh/year, which includes routers, switches, access devices and hubs for wide area and local area networks.

Breaking down the energy cost per sector shows clearly that non-residential is the main energy consumer for office equipment and breaking down into device power states shows that the majority of energy is consumed by devices during their operating state (see Figure 1.4). The study took a simplified model of device power states assuming that each device has one *operating* state, one *low-power standby* state, and a *soft-off* state (many electrical devices still consume energy when physically switched off and still connected to the mains). The *printing or copying* state models the power consumed by devices when they are printing or copying[2]. Furthermore, LBNL note that the main potential for savings due to power management are in displays, desktop computers, and copiers, which currently have low enablement of their power management features (estimated to be about 25% enabled).

Another reason for increased electrical energy consumption in buildings is the increased deployment of air conditioning and mechanical ventilation (fans) to cool building environments during the summer months. The increasing numbers of computing devices adds to ventilation loading, which further increases electricity consumption. Roughly speaking the heat energy dissipated from a device is equivalent to its energy consumption. So, a 45 Watt (W) LCD display will dissipate about 45 W of heat energy and a 60 W desktop computer will dissipate around 60 W of heat. An air conditioned space with a 200% efficiency will consume 52.5 W to dissipate the heat from the one display and

[2]The power consumed when printing or copying is significantly higher than in the normal operating state.

desktop computer.

Natural ventilation is an alternative technique that maximises use of windows and natural airflows to passively ventilate and cool the environment, significantly reducing energy consumption for cooling and ventilation. Natural ventilation is particularly suited to temperate climates which have moderate temperature variations throughout the year. Given a suitable climate, the principal factor in the viability of natural ventilation is the heat gain in the space. The primary internal heat sources are people, lighting, and small power devices (e.g., office equipment). Table 1.1 gives figures for typical internal heat gains in an office environment for low, medium and high densities of the three factors.

Gains (W/m2)	Low	Medium	High
People	5-8	8-11	11-15
Lights	3-5	6-9	10-14
Small power	0-6	6-12	12-20
Total	6-16	18-30	30-50

Table 1.1: Internal heat gains [68]

For overheating to be controlled by ventilation, there is a limit to the allowable heat gains within the space. This is because the cooling energy coming from the cooler external air is not controllable and the thermal mass of the building (which at night time stores the cooling energy) is limited. Figure 1.5 shows the cooling potential of ventilation for given internal/external temperature difference (Delta T) and ventilation rates in litres per second per person (l/s/p). Typical high-density internal heat gains from Table 1.1 range from 30 to 50 W/m^2. The ECON19 benchmark [47] specifies a target energy efficient mechanical ventilation rate for cooling of 40 l/s/p. From the figure it can be seen that 30 W/m^2 cooling would be just achievable for the night time 6 degree temperature difference but no where near achievable for a typical day time 2 degree temperature difference.

In summary, we believe that effective device power management will provide several significant benefits for both the operators and users of commercial buildings. It will contribute to significant energy savings in lighting and appliances (22% of commercial building energy) and it will reduce the need for air conditioned and mechanically ventilated spaces significantly reducing energy consumed by ventilation and cooling (12% of commercial building energy). For the users, it will enable a more pleasant working environment with more naturally ventilated spaces and reduced noise levels through less need for mechanical fans and air-conditioning units and more computing devices in silent standby modes. Many example building projects cite building users wanting a more user friendly “open” building where they can open windows to control their environment as opposed to their sealed

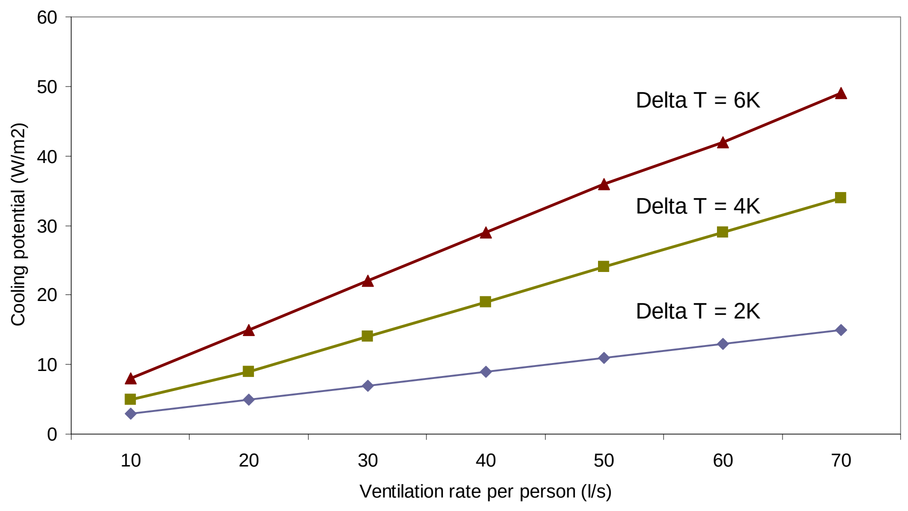


Figure 1.5: Cooling potential of ventilation for given internal/external delta temperature and ventilation rate[68]

air-conditioned building [68].

1.2 Dynamic Power Management

Research into dynamic power management [2] dates back to the 1980s, the main driver being to extend battery life in mobile computers. It is an effective technique that simply powers down a device (or some of its sub-components) during idle periods that occur during its operation. The two fundamental assumptions are that (i) idle periods will occur during the device's operation and (ii) these periods can be predicted with a degree of certainty. What makes dynamic power management difficult is that typically power state transitions have a significant cost. Possible costs are (i) extra energy is consumed, (ii) device performance is degraded, and (iii) device lifetime is reduced. Break-even time is the minimum time a device must spend in a lower power state to justify the cost of transitioning down to that state and back again. The resume time is the time taken for the device to resume to the operating state.

The current state of the art is predominantly focused on developing policies for mobile computing devices. The majority of mobile policies use low-level information and manage sub-components within the computing device. For example, a policy may observe the pattern of hard disk requests to predict when to power off the hard disk component [51]. The key trade-off for these policies is device performance versus increased battery life. The hard disk may be aggressively power managed to extend battery life but its performance will deteriorate as it will be slower to respond to user requests. These low-level mobile policies can only predict short idle periods and are not able to predict the time of the next user request, hence they incur a performance delay the next time the user requests the device. Therefore, they are only suitable for managing devices or sub-components which have relatively short break-even and resume times (order 10 and 1 seconds respectively [20]).

Typically, the most significant power savings for stationary devices are achieved by switching the entire device to standby. However, switching to a deep standby state has two implications as the device break-even and resume times are significantly longer. Firstly, since break-even times are longer, policies need to accurately predict longer idle periods (order 1 to 10 minutes). Second, switching to low-power standby states can cause significant user annoyance as resume times are longer (order 10 seconds) and there is the possibility of false power downs. Furthermore, stationary computing devices do not have battery limitations so users expect little or no performance degradation. Therefore, policies need to be near certain before powering down and they need to predict the time of the next user request to avoid resume time delays.

Currently, the standard policy for power managing stationary devices is the threshold policy, which simply waits a certain threshold period of idleness before powering down the device. It is neither able to predict long idle periods nor the time of the next user request. As a result of these inadequacies deeper standby energy saving features are typically not enabled (or set to a long timeout). To increase enablement of these features, policies for stationary devices need to operate in a near transparent fashion (i.e., operate automatically with little user-perceived performance degradation).

1.3 Pervasive Computing

Pervasive or ubiquitous computing is heralded as the next stage in the evolution of computing [66, 58]. Instead of today's situation where people use dedicated computing devices (e.g., desktop computers) to access information and perform their "computing" tasks, pervasive computing envisions information display, computing, sensing, and communication existing all around, embedded in everyday objects and the environment's infrastructure[3]. The objective of this being to assist people with their everyday tasks by providing information, computing, and services in an "intelligent", seamless manner. This seamless integration enables people to focus on their task at hand while the computers themselves vanish into the background. They need not be explicitly aware of the computing devices involved

[3]We view smart spaces as a subset of pervasive computing which deals specifically with adding "intelligence" to building environments.

in their daily tasks and so the computing becomes transparent. The vision relies on the availability of cheap computing, communication, sensing, and display devices pervasively deployed within the environment and the ability to "intelligently" integrate services with users' everyday tasks.

We are already seeing the beginnings of the vision today with the almost saturated deployment of mobile phones (many with significant computing capability) and many shops and public buildings using large video displays to display information. There are also many embedded computing devices in everyday objects such as home appliances, cars, and street furniture (e.g., bus stops). What still has to be achieved is the seamless interaction of all these devices to provide users with useful services in a transparent manner.

However, realisation of this pervasive computing vision could exacerbate the building energy problem as more computing, communication, sensing, and display devices are deployed in buildings. Weiser [66] considers the type of devices that might become common in a typical office environment. He cites one issue of crucial importance being scale. Devices will come in different sizes, each suited to a particular task. The devices he experimented with are tabs (post-it note size), pads (A4 paper size), and boards (bulletin board size). He envisaged a typical office containing more than 100 tabs, 10 to 20 pads and one or two boards. The tabs and pads are battery powered requiring recharging periodically while the boards are stationary. The boards can serve a number of functions such as bulletin boards for displaying information, white boards for collaboration in a meeting and electronic bookcases from which a user might download some information to their pad or tab. Satyanaraynan [58] envisions public spaces augmented with "surrogate" servers to provide computing service for handheld device users. Increasing numbers of these stationary devices are a real concern for increasing energy consumption in buildings. Furthermore, Jain [31] cites energy consumption due to mobile devices as a significant environmental concern for pervasive computing. "While mobile devices are becoming more energy efficient, the overall energy consumption due to such devices continues to increase as their total number increases rapidly."

These are well-founded concerns for pervasive computing. However, on the other hand pervasive computing could possibly provide a solution by enabling more "intelligent" device power management. For example, user location information, likely to be available in pervasive computing environments could enable highly effective power management for many of a building's electricity consuming devices. We have termed such techniques that make use of "context" as context-aware power management (CAPM) [26]. It is enabled by research being carried out in the areas of dynamic power management and context-aware computing.

1.4 Context-aware computing

Context-aware computing is one of the fundamental components in realising the pervasive computing vision. Context describes the state of the environment in which an application operates and the state of the user (or users). In general, context typically consists of location, identity, user activity, environmental properties, and available resources [3]. Being context-aware can be defined as the ability to sense and react to context, enabling autonomous, proactive operation by reducing or eliminating the need for explicit user input to the application.

Satyanarayanan [58] describes a scenario for this proactive, seamless context-aware computing. "Fred is preparing a presentation on his desktop PC. Being late for the meeting he grabs his handheld PC and leaves the office. The presentation is automatically transferred to the handheld so he can continue editing while walking across campus to the meeting. The system infers Fred is going to the meeting from his calendar information and the location tracking service. Before entering the meeting the presentation is downloaded to the projection PC and the projector is switched on to warm up. During the presentation face detection cameras in the room detect unfamiliar people, the system warns Fred not to present a slide which contains sensitive information." The scenario shows things being seamlessly/proactively automated for the user, *downloading* the presentation, *switching on* the projector, *warning* Fred not to present a sensitive slide. They all require the system to be context-aware, aware of the state of the environment and what the user is doing or going to do.

The current state of the art in context-aware computing focuses on developing inference techniques for determining high-level contexts from low-level, noisy, and incomplete sensor data. Possible approaches include rule-based inference, Bayesian networks, fuzzy control, and hidden Markov models [56]. Successful inference enables the vision of computing services interfacing seamlessly with users' daily tasks. One such useful, transparent service is context-aware power management.

1.5 Context-aware Power Management

We define context-aware power management as a dynamic power management technique that employs high-level user context to transparently power manage users' devices. It is possible to apply CAPM to manage users' mobile devices but this thesis focuses on the management of stationary devices, the principal objective being to minimise overall electricity consumption while maintaining user-perceived device performance.

In imagining an ideal CAPM scenario, all electricity consuming devices are instantly switched to very low-power standby states when not in use and these devices are restored to their operating states just before the user requests their service again. To develop effective CAPM policies that approach this ideal we need to obtain context from the user of the device. We identify the key context to infer as (i) when the user is NOT USING the device (for the break-even period) and (ii) when the user is ABOUT TO USE the device (at least the resume time beforehand). Determining this user context is the most challenging part of context-aware power management. However, there is also a balance between how much energy additional context can save and how much it will cost both monetarily and energy wise.

We state that it is necessary to investigate what granularity of context is appropriate for CAPM. Intuitively, finer-grained context can be obtained by adding more and different types of sensor into the space. Observing additional features enables detection of more distinct patterns/cues for finer-grained context. Subsequently, this more precise information enables policies to make better and more timely decisions. However, also intuitively, the more hardware sensors there are and the more feature processing, the more energy will be consumed by the policies. In carrying out this research we are trying to discover what types of sensor are useful for CAPM, what are the benefits of adding the sensors and what are the costs. In particular, is there a linear relationship between granularity of sensors and energy saving or are there "sweet spots" where certain types of sensor give near optimal performance for little additional cost. It is possible to leverage some context already available in the pervasive environment such as estimated user location from wireless connections, but in some cases it is necessary to include CAPM-specific sensors to obtain optimal performance.

Finally, the ground work for CAPM is being laid by advances in power management functionality for computing devices. The advanced configuration and power interface (ACPI) [28] is a de facto standard aimed at enabling effective power management for computing devices. The designers of the standard and PC manufacturers have worked successfully towards achieving very low-power standby states and faster resume times for their computing products. Also, moving the power management code from the BIOS[4] into the operating system has dealt with a number of reliability issues making power management more robust [34]. Work is still on going in achieving even lower power states, faster resume times and more robust operation. This will further increase the potential of CAPM.

1.6 Thesis contribution

To date there has been some research in the area of context-aware power management but to our knowledge there has been no detailed study as to what are the potential energy savings from CAPM

[4]The previous advanced power management (APM) standard was implemented in the BIOS.

and what granularity of context is appropriate. The main contribution of our research is to evaluate the potential for context-aware power management within pervasive computing environments. In particular we:

1. Identify requirements for CAPM and what context is useful for CAPM.
2. Design and implement a framework for CAPM.
3. Evaluate the potential of CAPM, in particular:
    (a) What are the potential energy savings of using additional sensors?
    (b) How good a cue are they for predicting the contexts NOT USING and ABOUT TO USE?
    (c) What is the estimated energy cost of the sensor hardware and data processing?
4. Evaluate Bayesian networks as a technique for implementing CAPM. In particular we evaluate the performance of Bayesian networks with that of dynamic Bayesian networks.
5. Provide recommendations for a reasonable approach to CAPM.

We have conducted an extensive user study to empirically answer these questions for CAPM of desktop PCs in an office environment. At the core of the CAPM framework, a Bayesian inference technique is employed to infer relevant context from a range of sensors (user input, Bluetooth beaconing, ultrasonic range detection, face detection, and voice detection). Results from the study show that there is wide variability of usage patterns and that there is a balance whereby adding more sensors actually increases energy consumption. For the desktop PC study, idle time, presence, and near presence are sufficient for effective power management coming within 6-9% of the theoretical optimal policy (on average). Beyond this, face detection and voice detection consumed more than they saved.

Finally, the evaluation showed that use dynamic Bayesian networks made no improvement over the use of standard Bayesian networks.

1.7 Road map

Chapter 2 reviews the state of the art in dynamic power management and context-aware computing. From this we identify the need for research into CAPM, in particular, what are the potential energy savings and what granularity of context is appropriate for CAPM. Chapter 3 presents initial experimental results from which, requirements for CAPM and the framework design are detailed. Included in this chapter is a description of Bayesian inference. Chapter 4 describes the implementation of the sensor hardware and software, selection of the Bayesian inference software and implementation of the CAPM framework. The evaluation is presented in Chapter 5, which includes the design of the user study, data collection, analysis and results. Finally, our conclusions and potential future work are discussed in Chapter 6.

Chapter 2

State of the Art

The thesis spans two broad areas, those of dynamic power management and context-aware power management. This chapter gives an introduction to both of these areas and reviews the current state of the art in each.

2.1 Dynamic power management

There are three complementary steps possible to reduce the energy consumption of devices in a building.

1. Reduce the number of devices. For example, a network computing solution may be more efficient than everyone having their own desktop computer.

2. Reduce the power of the devices' operating and standby states. For example, LCD displays consume less power than CRT displays in both their operating and standby states (typically 35W, and 1.5W compared to 100W, and 20W for equivalent 17 inch displays).

3. Reduce the amount of time devices spend in higher power operating states. For example, desktop computers that spend most of their time in their operating state when not being used consume 60W when they could be in standby consuming 2.5W.

All three approaches are necessary to significantly reduce device energy consumption. This thesis focuses on the third approach, which in computing research is termed *dynamic power management* [2] as it power manages the device dynamically during its runtime operation. Even though this research has been applied to power management of computing devices, the principles can equally be applied to other electrical devices such as lighting and ventilation. We therefore use the term *device* to generalise all electrically powered devices that provide some service or function to the user. So, a device could be a computing device such as a display, desktop computer (we view the display and computer as separate devices), a ceiling light, a ventilation unit, or a desktop fan. Furthermore, a device could also be a sub-component of another device, for example, the hard disk in a desktop computer or its network card. Research into dynamic power management dates back to the 1980s, the main driver being to extend battery life in mobile computers.

Dynamic power management can significantly reduce device energy consumption by taking advantage of the idle periods that occur during the operation of a device. For example, a device that spends three quarters of its time idle could save up to 75% of the energy it consumes being left on all the time. The two fundamental assumptions are that (i) idle periods will occur during the device's operation and (ii) these periods can be predicted with a degree of certainty [2]. Figure 2.1 shows a graph of device usage for a device over time (the dashed line). The power management policy (thick grey line) must decide whether to power down during the idle periods. Some power management policies also attempt to power up the device just before the next user request. In general, the performance of a particular policy will vary depending on the usage of the device. For example, a device that is used continuously will have little scope for energy savings, whereas a device that is used infrequently will have significant potential savings.

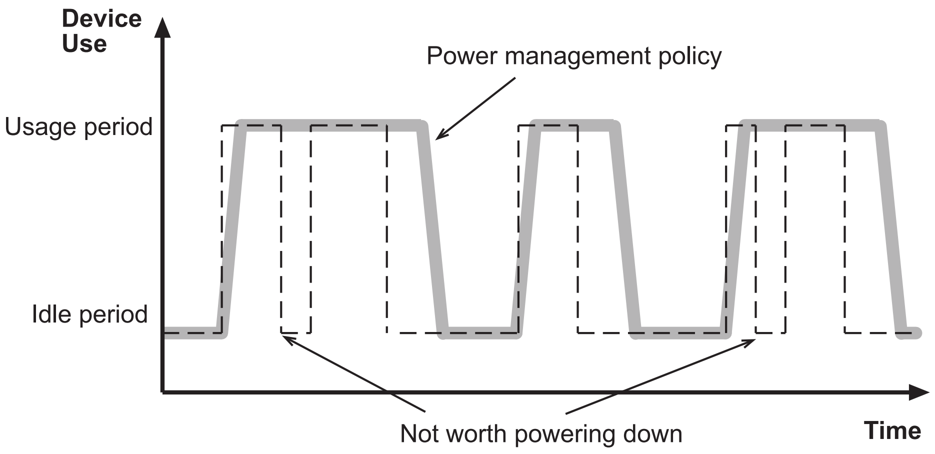


Figure 2.1: Usage periods and idle periods for a device

What makes it difficult to achieve the full potential savings is the fact that for most devices power state transitions have a significant cost. Typically a power state transition may:

1. Consume extra energy. For example, a PC consumes extra energy in writing its state to hard

disk before powering down to the hibernate state and a hard disk consumes extra energy in mechanically powering up its disks.

2. Reduce device performance. For example, a user may have to wait for their display to resume and worse still is the possibility of falsely powering down the display, which can cause significant user annoyance.

3. Reduce device lifetime. Some devices wear out faster when they are switched on and off frequently. For example, hard disks incur mechanical wear in spinning up and down their disks and fluorescent lighting incurs electrical wear when igniting the fluorescent gas.

Therefore not all idle periods are long enough to justify powering down the device. The primary task of the power management policy is to predict whether the current idle period will be long enough to justify the transition cost. Secondarily, if the policy can predict when the next user request will be, it can reduce the time the user has to wait for the device to resume.

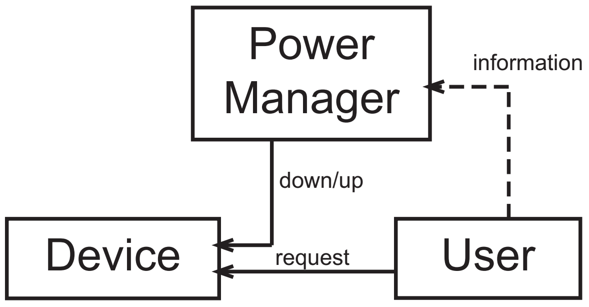


Figure 2.2: Dynamically power managed device

Figure 2.2 shows a simple model of a dynamically power-managed device. The user generates requests that must be serviced by the device while the power manager implements policies that decide when the device should be powered down/up. Power management policies use information they receive from the user of the device to make their decisions. This information can be either observed or explicitly passed to the power manager by the user. The model can be viewed at different levels. For instance, the device could be a low-level device such as a hard disk or a collection of devices such as a desktop computer. Also, the user of the device can be viewed at different levels. For example, the user could be viewed as a low-level device driver, the operating system, a software application or the actual human user of the device.

All devices can be modelled by a number of power states (S_0, S_1, S_2, S_3, ...). In the highest power state, S_0, the device operates at full performance. Lower power states operate at reduced performance levels. Either the device performance has been "throttled" and it operates more slowly or it is in a standby state. For example, a central processing unit (CPU) can have a number of reduced power operating states [67]. These are achieved by reducing the processor clock frequency, which enables the voltage and hence the power to be dropped[1]. Each lower power state has an associated break-even and resume time (see Table 2.1). The break-even time (T_{be}) is the minimum time the component must be in the lower power state to amortise the cost of the state transition. The resume time (T_r) is the time taken to transition back to the S_0 operating state. The deeper the power state, the lower the power consumed but the greater the break-even and resume times. For devices that are composed of a number of sub-devices, the power states are simply a combination of the power states of the sub-devices themselves. For example, a desktop computer has a number of power states which map to the power states of the CPU, hard disk, network card, peripherals, and motherboard.

Table 2.1: Power states, break-even and resume times

State	Power	Break-even time	Resume time
S_0	P_0	-	-
S_1	P_1	T_{be1}	T_{r1}
S_2	P_2	T_{be2}	T_{r2}
S_3	P_3	T_{be3}	T_{r3}
...	...	...	...

2.1.1 The oracle and threshold policies

The *oracle* policy [60] is a theoretical optimal policy that has future knowledge of user requests for the device. This policy will power down the device immediately after a request is serviced to the lowest power state that has T_{be} less than the idle period. If the idle period is not going to be greater than T_{be} for any of the power states, it leaves the device on for the period. If the device is powered down, the policy powers it up to the operating state just before the next request (see Figure 2.3). Since this policy powers up the device before the next request the break-even time only needs to consider transition energy and device lifetime, not performance degradation. This optimal policy is a useful baseline when comparing realisable policies.

The key trade-off in the design of most real-life policies is device energy consumption versus device performance. Figure 2.4 shows a so-called threshold policy that waits a given time T_{idle} before powering down in the idle period. It wastes energy waiting for the timeout and incurs a performance

[1]Significant savings can be made as power is proportional to the square of the voltage.

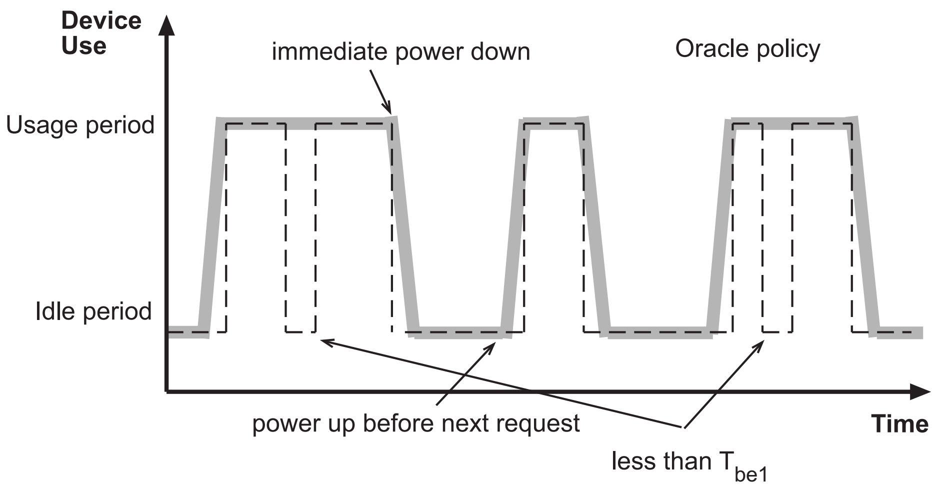


Figure 2.3: The theoretically optimal oracle policy

delay at the next user request. The shorter T_{idle} the more energy saved but the device will power down more often increasing the number of device response delays. There is also the added complexity that for some devices the transitions consume significant extra energy and/or reduce the device lifetime. Therefore an aggressive policy (with very short T_{idle}) could end up consuming more energy and/or cause the device to fail prematurely. For more sophisticated policies, it is also necessary to take into account the potential energy cost of implementing the policy. For example, extra energy may be consumed in the processor execution of a policy [60] or external sensor hardware may be used, which will consume extra energy.

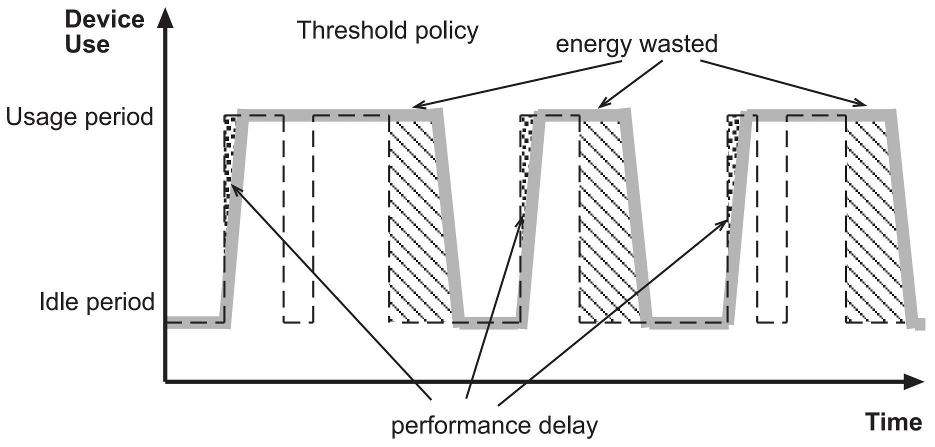


Figure 2.4: Trade off power consumption versus performance

The following section reviews the current state-of-the-art dynamic power management policies. They are predominantly focused on management of mobile devices. The discussion at the end of the section highlights why mobile policies are often inappropriate for management of stationary devices.

2.2 Dynamic power management policies

In this review of dynamic power management policies for computing devices we have identified four levels of policy, device-driver-level, operating system-level, application-level and user-level. A policy is assigned to a level depending on where it gets its input data from. Dynamic power management techniques which are not considered in this review are:

1. Techniques to optimise the behaviour of the user of the device so that it will arrange requests to complement the power management policy. These include operating system optimisations [69] and application optimisations [23] where the operating system or application is tuned to complement the power management policy.

2. Techniques to reduce the performance of the user so that it will make fewer requests, e.g., application adaptation [24] or operating system adaptation [70]. Since the performance of the application or operating system is degraded, it is only applicable for mobile devices where power is critical and an extended battery life is desired. Users of stationary devices are typically not prepared to accept this performance degradation. For example, it is unlikely a user would choose to reduce the performance of their application because it will slightly reduce the building's energy consumption. They might however choose this policy if it means they can work on their laptop for longer before the battery goes dead.

Device-driver-level policies are the lowest level policies. They are either implemented in the device driver or the operating system and can make use of past device usage patterns to predict when next to power down the device. At this level the user of the device is seen as the device driver. There is no knowledge of the operating system, applications or human user that are indirectly causing the requests. Operating system-level policies have knowledge of operating system data such as the processes running on the machine and the size of caches and can make use of this extra information to improve the power management policy. Application-level policies can make use of known application patterns to predict future request arrival times and user-level policies can make use of information about the human user to predict future device requests.

2.2.1 Device-driver-level policies

For device-driver-level policies, the power management policy observes information from the device driver and uses this to make its down/up decisions. Most current power management policies are device-driver-level including the ubiquitous threshold policy and a range of predictive and stochastic (probabilistic) policies.

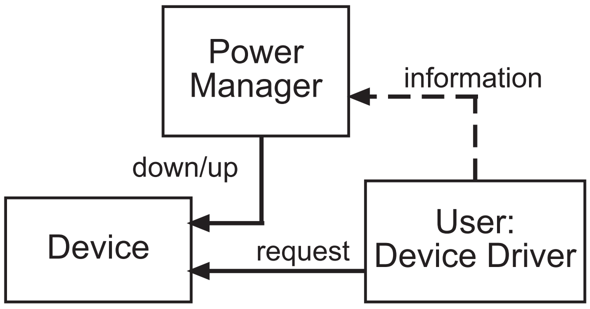


Figure 2.5: Device-level power management

The threshold policy defines an idle period T_{idle}after which the device is powered down to a lower power state. The device powers up on the next user request. This is the simplest policy to implement but has the drawback of consuming energy while waiting for T_{idle} to pass and it incurs performance degradation as the subsequent request response time is increased by the resume time. The threshold policy is based on the assumption that user requests are continuous and therefore the longer the idle time the less chance there is of receiving a request in the near future. Douglis [20] compared a threshold policy (with several T_{idle} values) to the optimal oracle policy using a four hour usage trace of the hard disk for a machine that was running Microsoft Word and Eudora mail. The manufacturers recommended T_{idle} before spinning the disk down was 5 minutes. The oracle policy could reduce the hard disk power consumption by 48% of the 5 minute threshold policy and the best threshold policy (with T_{idle} of 1 second) reduced power consumption by 45%. Equivalently, if we say the 5 minute policy consumes an average power of 10W, then the optimum policy would consume 5.2W and the 1 second policy would consume 5.5W, which is within 6% of the optimum. However, the performance degradation due to spin-up delays was very high. There was a total of 98 spin-up delays over the four hour period of the trace, one every couple of minutes. He also notes that the performance of the threshold policy varies significantly depending on the usage trace and the performance characteristics of the hard disk. For example, desktop computer hard disks have much slower spin-up times than those for laptops. So, the same policy on a desktop computer would incur even worse resume time delays. In conclusion he states that ultimately a better approach may be predictive policies but that these may remain elusive. The competitive algorithm (CA) is a special case of the threshold policy with T_{idle} set equal to the break-even time of the device. Karlin [32] states that this setting achieves a good balance between energy saving and performance.

More complex predictive policies use past request data to predict if the time to the next request will be greater than the break-even time T_{be}, if so the policy powers down the device immediately thereby saving on the idle time. It powers up again on the next user request incurring a response-time penalty. Predictive policies require more processing overhead than the threshold policy to determine their action and one key concern is whether there are significant power saving gains to justify this overhead. The main predictive policies are adaptive time-out, L-shape, exponential average (EA) and adaptive learning tree [39].

The adaptive time-out policy adjusts the T_{idle} value by considering the ratio of the previous actual idle period to the device resume time. When the ratio is small T_{idle} increases and when it is large T_{idle} decreases. The L-shape policy works well when short busy periods are frequently followed by a long idle period (i.e., their scatter plot forms an “L-shape”). The policy is formulated so the device is powered down after such short busy periods. The exponential average method uses the predicted and actual lengths of the previous idle periods to predict the length of the current idle period. The previous lengths are weighted exponentially and averaged to determine the current idle length. Finally, the adaptive learning tree algorithm stores each idle period as a discrete event in a tree node. It uses finite-state machines to select a path that resembles previous idle periods.

Stochastic policies model the arrival of requests and device state changes as stochastic processes [51, 60]. The stochastic process is optimised to give the optimal solution for the given request arrival rate. There are several varieties of stochastic policies the most basic being the discrete-time Markov decision process (MD). The algorithm assumes a stationary geometric distribution of request arrivals and does not cope well with varying device usage. This algorithm is extended to handle non-stationary request arrivals by using a sliding-window technique (SW). The main disadvantage of this discrete time approach is that the power-down decision has to be reevaluated for each period even when the device is in the sleeping state thus causing unnecessary energy consumption in the CPU. The continuous-time Markov process (CM) is an improvement as it makes decisions only at the occurrence of an event and therefore does not incur computational overhead when the device is already sleeping. Both discrete and continuous-time approaches model request arrivals and power state transitions as memoryless distributions. The time-indexed semi-Markov model (SM) improves on this by using a Pareto distribution.

Lu et al. [39] have done a quantitative comparison of 11 different policies from the simple threshold policy to the more advanced stochastic policies. These polices were implemented for the hard disk of a desktop PC and compared against the optimal oracle policy and the worst case scenario of the disk being always on. Two eleven-hour usage traces are used in the experiment, one from developing C programs and the other from making presentation slides. The algorithms are compared on power consumption, number of power downs, number of false power downs, average time sleeping and average time before power down. The comparison showed that SM, SW and CA are the best in terms of power consumption saving nearly 50% of power compared to the always-on case and coming within 18% of the oracle policy. The three policies are similar in power consumption but SW has less than half the number of false power downs at 28 compared to 76 for SM and 64 for CA. The number of power downs that occurred in the eleven-hour trace for SW was 191, which corresponds to one every three minutes. We believe that this number of power downs would severely degrade the user-perceived performance of the hard disk.

All device-driver-level policies have no knowledge of the entities above causing the device requests and therefore cannot imply future request patterns from knowledge of an entity's behaviour. Typically the future request predictions hold true only for the near future (order of seconds) so the policies only suit transitions to device power states where the break-even time is small. Also, none of these policies are effective in predicting future device power up so a response-time delay is always experienced with these policies. For example, a policy of powering down the hard disk for every predicted idle period of 10 seconds would significantly degrade its performance and would typically not suit the user of a stationary device. In order to predict request arrivals in the far future, we believe that policies need to observe higher-level information.

2.2.2 Operating system-level policies

Operating system-level policies observe the state of the operating system and use this information to make decisions for powering down/up a device. Here the user of the device is viewed as the operating system, which indirectly causes the device requests. A policy at this level can make use of higher-level operating system information to make more intelligent power management decisions.

Lu's [38] task-based power management (TBPM) policy uses the state of processes running in the operating system to find idle periods more accurately. For each device in the system the policy keeps a list of all processes using the device and their associated device utilisation. The device utilisation is measured as the reciprocal of the average time between device requests. How soon the policy powers the device down is a function of the total utilisation of the device. When a process terminates it is deleted from the list and when there are no more processes using the device it is powered down

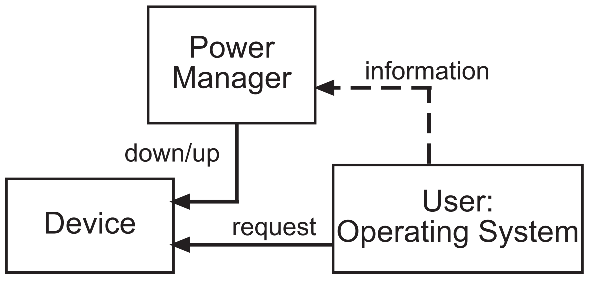


Figure 2.6: Operating system-level power management

immediately. The policy includes a performance rule that ensures that no more than two consecutive power downs are issued within time period T_W. Lu compares the TBPM policy with four device-level policies, EA, SM, CA and threshold with T_{idle} of one and two minutes. The experiment was conducted on real usage traces for a desktop computer hard disk. The results show that the average power used for TBPM was 0.435 W, SM was 0.507 W and CA was 0.499 W. These are the policies that perform best in terms of power consumption but the TBPM policy has far fewer power downs due to the performance rule (181 compared to 477 for CA and 581 for SM). If we assume that the SM and CA policies are within 18% of the oracle policy (see Section 2.2.1) then we can deduce that in this case the TBPM policy is within 2%. Lu claims that the additional operating system-level information enables the policy to find idle periods more accurately and hence can implement the performance rule without reducing the power efficiency. However, the device performance degradation is still large, 181 power downs in the 10 hour usage period, on average one power down every 3 minutes.

The TBPM policy is a good example of using higher-level information to infer knowledge of future user requests. For example, we know a priori that a process causes requests therefore when the last process associated with a device terminates, this device can be powered down immediately. It performs better than previous policies but still has a high performance penalty.

Steinbach's [62] adaptive mid-level power management policy monitors application and transport layer data from a network stack to optimise the power management of a wireless network card. He states that the drawback of device-driver-level policies is that no extra knowledge of future requests can be inferred from monitoring the device-driver-level packets. His technique monitors the packets for each application protocol (e.g., SSH, HTTP) and uses a machine learning technique called reinforcement learning to learn an optimal policy for each application protocol. The policies are trained from past trace data and he believes that these policies will out perform device-driver-level policies by "learning" patterns in each of the application protocols to more accurately predict when to power down. He states,

> "We also note that our approach is supported by the end-to-end argument [57], which holds that system functions such as power management, implemented at a low level, are likely to be of little value in comparison to those same functions implemented at a higher level."

However, unfortunately this policy has not been compared experimentally to the other policies.

It is worth noting here the work of Ellis et al. [22] who have stated the case for moving power management from the device-driver-level to the operating system. They have implemented an operating system wide energy accounting framework which allocates energy tokens to tasks and then charges the tasks for the energy they consume through use of the system devices. The initial applications of this framework have been to throttle the tasks (processes) when system energy is low in order to extend the battery lifetime. Further work [69], has investigated using this framework to implement "power management policies". However, these are not power management policies but rather techniques to optimise usage of the device. Examples are delaying disk access to create more bursty patterns which will complement the disk power management policy and delaying writes to disk when it is not spinning. They also use similar techniques to modify some of the operating system tasks such as charging the disk-flush daemon extra for writing to the disk when it would require a spin-up. So far, the framework does not help in making policy decisions as to when to power down the device and hence is out of scope of the analysis in this paper.

Similarly Flinn [24] devised an operating system-level framework for monitoring system energy and making up-calls to applications to reduce their "fidelity" (quality or performance) when system energy is low. Again this work is out of scope of our analysis as the typical users of stationary devices would not implement this application adaptation strategy.

2.2.3 Application-level policies

Application-level policies communicate with the applications running on a system and make use of this information in making power down/up decisions.

Lu et al. [37] describe an application-level power management architecture. The power manager provides an API for application programs to communicate their future device needs. The example scenario is of a browser application that presents real-time news from the Internet. The application requires use of the network card, graphics adapter, and hard disk, and communicates this information to the power manager, which ensures that these devices will not be powered down for the browser's duration. Future request information from applications could also enable predictive power up of devices eliminating the response time overhead associated with most power management policies.

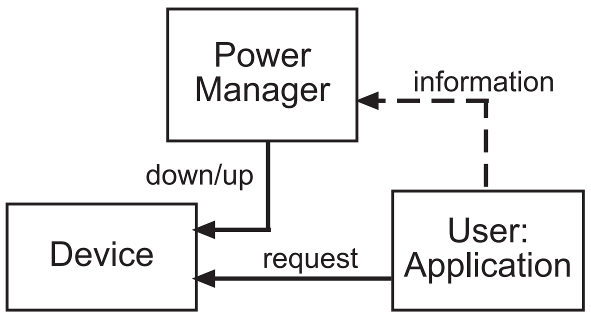


Figure 2.7: Application-level power management

This predictive power up will not however work at the user-level as the application does not know when or what the user will do next. Lu states that “accurate prediction is difficult for operating systems because they do not have enough knowledge about the future behaviour of applications”. To date these application-level policies have not been implemented so we have no real data in order to compare their effectiveness against the previous policies.

The main drawback to this general approach is that applications have to be programmed to take advantage of the power management API. This approach may be used for mobile devices but is unlikely to be used for stationary devices. Another possible problem is how would the power manager know when the user is finished viewing the browser application? The user could have left the office with the application still running and the power manager still ensuring that the devices do not power down.

Kravets et al. [36] have implemented a software power manager residing at the transport layer of a network protocol stack to dynamically power manage the network card. Power management is built into the network protocol as the mobile device communicates to the base station when it is going to sleep and when it has woken up again. This enables the mobile device to save energy by periodically switching off the network card. They cite the key problem to solve as the policy that decides when is the best time to power down and up the mobile network card. Their first approach is to use a simple threshold policy for detecting idle periods to power down. The second approach is for the power manager to provide an API for applications to communicate their future communication needs. Future work is stated as the development of an appropriate API that will cater for the needs of all applications using the network card. Again no data was available for comparison purposes.

Flinn et al. [23] extended their power management middleware (Puppeteer) to manage the power consumption of Windows component-based applications such as PowerPoint. The middleware can access an external API allowing it to both query application data and modify application behaviour without needing to modify the application's source code. Again, the primary function of the middleware is to reduce the application's "fidelity" (quality) when system energy is running low in order to extend battery life. However, another function of the middleware is to communicate relevant information to the power manager about the application behaviour. The example used is the timing of the auto-save function. The power management policy can use this information to (i) prevent untimely power downs of the hard disk and (ii) to predict wake-up for the hard disk to eliminate response time delays. Flinn estimates a saving of 4% in the energy consumption of the auto-save operation if the power management policy knows when the auto-save occurs. There is not enough information in the paper to derive how close this policy is to the oracle.

Puppeteer is a specific technique for closed source applications that have rich APIs enabling the middleware to gain access to data relevant to the power management policies. More interesting work could be to define a general power management API for applications to program to. This standard power management API would enable applications to communicate information on their device usage to the power manager.

2.2.4 User-level policies

In the area of dynamic power management there has been little research into user-level policies that use information about the state of the user to make their power down/up decisions.

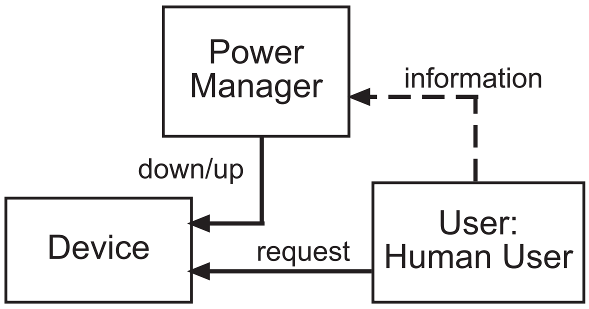


Figure 2.8: User-level power management

Current user-level policies implemented are simple threshold policies that observe user activity from the keyboard and mouse input devices. Reasoning about the user's activity by monitoring incoming keyboard and mouse events is very limited. The presence of events tells us that the user is using the device, possibly editing a document or browsing the web but an absence of events does not tell us that the user is not using the device. The user could be reading from the screen or presenting a slide show to an audience. For this reason threshold policies are set to very long idle periods such as 20 to 30 minutes to avoid false power down of the device. A user-level policy can control the power state of any sub-devices such as the hard disk or display, but also the state of the entire device. Relative to a sub-device, putting the entire device into standby has large power savings but also a considerable performance penalty as typically the whole device response time is large. To date, in the area of dynamic power management, we have not found research into more sophisticated user-level policies where more context is known about the user's activities. However, in the area of context-aware computing there are several projects exploring user-level, context-aware power management, which are described later in Section 2.4.

2.2.5 Discussion

Current state-of-the-art dynamic power management policies are suited to managing sub-devices that have short break-even and resume times. Furthermore, they are aimed at management of mobile devices where performance degradation is tolerated for increased battery life. In contrast, stationary devices typically have power states with longer break-even and resume times, and since they have no battery life problems, the user is unlikely to accept much device performance degradation.

Table 2.2 gives the measured power consumption, break-even time, and resume time for the power states of a DELL Optiplex GX270 (desktop tower computer) running Windows XP. A power monitor was used to measure the active power of the computer in its range of power states. To achieve an accurate measurement of power, the power monitor is set to measure the energy consumption in Watt hours over a several hour period. The power is then estimated as the total energy consumed divided by the measurement time period in hours.

Power State	Power Consumed	Break-even time *(energy)*	Resume time
$\mathrm{on}_{\mathrm{max}}$	120.5W	-	-
$\mathrm{on}_{\mathrm{idle}}$	60.0W	-	-
hard disk off	54.0W	14.9s	2.5s
standby	2.8W	24.8s	7s
hibernate	1.5W	60s	23s
soft off	1.5W	60s	25s

Table 2.2: Measured power consumption of DELL Optiplex GX270

The table highlights the large difference in power consumption between $\mathrm{on}_{\mathrm{idle}}$ and $\mathrm{on}_{\mathrm{max}}$, which is the power measured for the machine at maximum load (i.e., CPU 100% and reading from the hard disk). The hard disk off state is just on_{idle} with the hard disk powered down, whereas standby powers off all sub-devices except the random access memory (RAM) and the network card. The state of the system is stored in RAM so it can be resumed in a reasonable amount of time (~7 seconds). Hibernate is a slightly lower power state where the state is saved to hard disk and soft off is the state where the PC is physically shut down, no system state is saved, but it is still connected to the mains. Both of these states have very long resume times as the operating system needs to be rebooted, making them impractical for dynamic power management.

Typically, a desktop computer will spend most of its operating time in the on_{idle} state. Switching the hard disk off gives a modest saving of 6W (10% of the base on_{idle} consumption), whereas switching the PC to standby gives a very significant saving of 57.2W (95% of the base on_{idle} consumption). Modern PCs are designed to achieve these very low power standby states by use of dual mode power supplies, which provide trickle power when the PC is in standby, enough to power the network card and refresh the RAM [34]. Making this state change to system standby has significant savings over putting individual components into standby but also significant performance penalties. The system standby state has a significantly longer resume time than the hard disk. Furthermore, putting the system into standby affects the visible state of the system as the display will also be powered off.

As an example, using a threshold policy with T_{idle} of 10 seconds at the user-level to power the system to standby is clearly unrealistic. It would cause unworkable performance degradation through frequent false power downs and manual power ups. This being due to an inability to predict relatively long idle periods and an inability to predict when next to power up the device. Thus, the limitations of current dynamic policies for management of stationary devices are:

1. They are not capable of accurately and quickly predicting when the user will not be using the device for a relatively long period of time (e.g., 1 minute, 5 minutes, 10 minutes).

2. They always incur some degree of performance degradation as they cannot predict when the next user request may arrive.

To achieve the large savings of system standby and not incur large performance penalties we must develop policies that can (a) accurately and quickly predict long idle periods (order of minutes) and (b) predict when the user will make the next request. The first requirement brings us close to the oracle policy in terms of power efficiency and the second requirement enables us to minimise performance degradation. We believe that users of stationary devices will not tolerate significant performance degradation as energy is not critical. Also, we believe a realistic solution will require a relatively low cost of implementation. Finding a power management solution that is transparent to the user with little additional overhead is key.

2.3 Context-aware computing

Dey [17] gives one of the most cited definitions for *context* and *context-aware computing.*

> "Context is any information that can be used to characterise the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and application themselves."

The definition is user-centered, focusing on users' interactions with computing devices. In particular, it envisions the main applications being for mobile devices where the users' and applications' context may change often. While context can be used for power management of mobile devices, this research only explores its application to stationary devices. Dey's definition of context is still relevant to the application of power management for stationary devices as a user's context will change often with respect to the stationary devices in the environment. Dey goes on to define the primary types of context to be *location*, *identity*, *activity* and *time*[2], and gives a general definition for a *context-aware* system.

> "A system is context-aware if it uses context to provide relevant information and/or services to the user, where relevancy depends on the user's task."

An example model for context-aware computing suited to CAPM is detailed next.

2.3.1 Context-aware computing model

Biegel et al. [4] describe a context-aware computing middleware, based on the *sentient object model*, to ease the development of context-aware applications. They state that the pervasive computing function should necessarily be autonomous and proactive and give a definition of context that is less centered in user interaction.

> "Context is environmental information that an application may use to autonomously and proactively fulfill its goals."

At the core of the model is the *sentient object* abstraction (see Figure 2.9). The model uses an event-based programming paradigm for communication between sentient objects. The solid arrows

[2]This can also be defined as the where, who, when and what (i.e., what is the user doing).

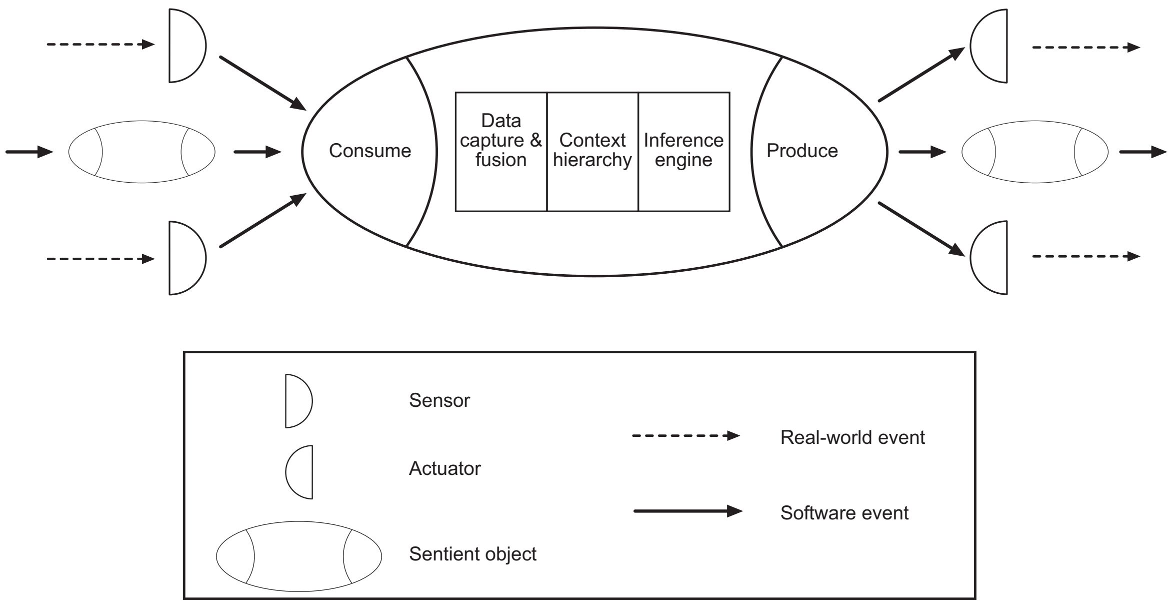


Figure 2.9: Sentient object model

show software events and the dashed arrows show physical events. The sentient object consumes events from either physical sensors or other sentient objects, and produces events that are either consumed by other sentient objects or actuators for control of the physical environment. A sentient object provides support for data capture and fusion, a context hierarchy and an inference engine for intelligent processing of sensor events.

The data capture and fusion component uses a filtering mechanism so that only relevant events are passed to the sentient object and the fusion mechanism is based on an inference technique called Bayesian networks, which uses probability to derive high-level contexts from noisy, low-level, multi-modal sensor data. The context hierarchy is structured into three layers. The top-level *mission context* defines inputs that are of interest to the sentient object and rules that are always valid; several *major contexts* define distinct strategic objectives of the sentient object and, finally, *sub-contexts* define operational actions carried out in fulfillment of a major context. The inference engine uses a production rule-based system which fires actions when the object is in a particular context. The rules provide a natural approach to representing knowledge within the system and the context information derived from the sensor inputs is stored as facts in the rule engine.

The CAPM framework is loosely based on this sentient object model. For this thesis, the framework implementation has focused on the core components of data capture, fusion and inference. To enable more distributed operation it could be plugged into the sentient object middleware with each power manager being implemented as a sentient object.

2.3.2 Properties of sensors and multi-sensory information

Gassmann et al. [25] state key properties of physical sensors are sensor accuracy, reliability and cost. It is important to consider the accuracy of measurement required by an application. For example, is location required to +/-5m or to +/-5cm. Secondly, the reliability of the sensor is important, i.e., how long will it last without maintenance and/or replacement. Finally, for practical applications, the financial cost of the sensor needs to be considered.

The raw data from the physical sensors are combined/fused to provide multi-sensory information. Luo [40] states that there are four fundamental properties of multi-sensory information: redundancy, complementarity, timeliness and cost. Redundancy occurs when multiple sensors perceive the same feature in the environment, which can reduce the overall uncertainty of the information. Complementary information from multiple sensors allows features in the environment to be perceived that are impossible to perceive using just the information from each individual sensor operating separately. Information may be more timely using multiple sensors by parallelising the information processing. Information from multiple cheaper sensors may be less costly than using one more expensive sensor to provide the same quality of information. For his analysis Luo defines cost in purely financial terms. Other costs can be consumption of computing resources (e.g., CPU cycles) and consequently energy consumption. Multiple cheap sensors might be less expensive to purchase but a multi-sensor system may consume more computing resources and more energy.

Luo draws a distinction between multi-sensor fusion and integration. Multi-sensor integration refers to the complementary use of information provided by multiple sensors, whereas multi-sensor fusion is the actual combination of different sources of sensor information into one representational format. Redundant information is usually fused at a lower level of representation compared to complementary information, which is usually either fused at a higher level or provided directly to different parts of the system without being fused. The advantage of more redundancy is increased certainty, of more complementarity is increased number of perceived features, and of increased timeliness is increased ability to react in time to a particular situation.

2.3.3 Granularity versus cost

Intuitively, finer-grained context can be obtained by adding more, different types, and more accurate types of sensor into a space. Observing additional features enables detection of more distinct patterns/cues for finer-grained context. This more certain, more accurate, complementary, and timely information enables applications to make better and more timely decisions. However, also intuitively, the more sensors there are and the more feature processing, the more the resource and energy cost of the information.

For example, coarse-grained location/presence information can be a good cue for a person ABOUT TO USE their PC, if for example, their behaviour is that they always check their email when they re-enter the office. For other users it may not be a good cue, they may often pop in and out of their office without checking their email and without using the PC[3]. Adding additional sensors to the scene may help us do better. For example, knowing the time of day could help in determining whether they are ABOUT TO USE their PC (e.g., they always check their email first thing in the morning, after lunch and at the end of the day). Time of day is cheap to obtain but does depend on the user being very regular in their behaviour. How well this works depends on the user's usage pattern. Adding other physical sensors could improve the situation, for example, to detect whether the user is alone or with others, where the user is in the space, or whether the user is moving towards the PC. These observations could possibly be made with additional sensors such as acoustic, video, object ranging, and more accurate location, to try to establish finer-grained context. Example user context, from coarse to finer grained, could include PRESENT, NOT PRESENT, ALONE, WITH OTHERS, TAKING A BREAK, READING, WRITING, TALKING, ON TELEPHONE, IN MEETING, SLEEPING, USING COMPUTER, NOT USING COMPUTER. Some activities can be interleaved and also, there can be dependencies between activities. For example, if READING was detected we could infer NOT USING COMPUTER, although we would still be uncertain for how long the person will remain reading and not using the PC.

As the primary objective of CAPM is to minimise overall energy consumption, there is a bound on the granularity of context that is appropriate. Overstepping this bound and the system will start consuming more sensor energy than the device energy it is saving due to the additional context. The additional complicating factor is that user-perceived device performance must also be added to the cost equation. To date we have not found any work that explores this boundary, i.e., the balance between granularity of context and its cost (energy and device performance) for context-aware power management.

The following section reviews the current state-of-the-art context-aware power management applications. The applications are loosely ordered by their increasing use of sensors and sophistication in the techniques used to determine finer-grained user context.

[3]These users may check their email with a hand-held device.

2.4 Context-aware power management review

A few projects have explored context-aware power management. In the following sections we provide an overview and analysis of these projects.

2.4.1 A context-aware approach to saving energy in wireless sensor networks

Chong et al. [11] present a framework for power management of sensors in a sensor network, the objective being to minimise the energy consumed by the sensors, which are battery powered[4]. They state that current work in this area has focused on improving energy-efficiency of the hardware, tailoring sensor designs to be efficient for specific applications, and improving the efficiency of communication protocols. Their context-aware power management framework addresses power management at the application level and is not application specific. The central idea is to use changes in the sensed context to adapt the operating (power) states of the sensors, thereby saving energy when the sensors are not being fully utilised by the particular application. An example they give is of a pig farm where pig sties are monitored for temperature, light and sound. Detection of no (or minimal) sound for a long period is a pattern in the data that relates to a context of PIGS TEMPORARILY OUT OF STY. The application developer manually maps this context to a power management function that reduces sensing frequency for the sensors in the sties. When the pigs come back the sensing frequency is returned to normal.

The framework consists of three main components, context discovery, context trigger engine and communication. These components correspond loosely to the sentient object model described in Section 2.3.1. Context discovery is responsible for data capture and fusion of raw sensor data into context. Currently this fusion of raw data is done by manually configured if-then rules. A future version will use a data mining service to automatically discover new contexts (i.e., frequently occurring patterns in the data). The context trigger engine maps sensed contexts to power management functions that change the operating (power) states of the sensors. Again, these are manually configured rules, as in the example above, **if** PIGS TEMPORARILY OUT OF STY **then** reduce sensing.

The evaluation of the framework is based on a twenty-minute simulation of the pig sty scenario. They compare the energy consumption of their context-aware power managed network with a network with no CAPM. The context-aware power manager modifies the sensing frequency of the sensor nodes between 1-second, 10-second and 100-second sampling frequencies depending on what context the

[4]This reduces the frequency of battery replacement.

application is in. They report an estimated power saving of 33% compared to the control experiment, which keeps the sensing interval fixed at 1 second.

2.4.1.1 Analysis

To summarise, the sensors used were temperature, light and sound to infer when pigs were NOT PRESENT in their stie. The inference technique was a simple if-then rule-based approach. The work is currently at quite a formative stage with few real results for proper evaluation. Data would need to be collected from a real pig sty to properly evaluate the actual usage patterns and subsequently the actual potential savings. Furthermore, they do not evaluate what impact the power management may have on the performance of the pig sty monitoring application. For example, when the pigs re-enter the sty, what effect does the delay in resuming the frequency from 100 seconds to 1 second have on the monitoring application. Is there a loss of valuable data? Another point to evaluate would be the time required by the operator to manually code the mappings from contexts to power management functions.

Finally, the scenario is a simplified study of CAPM as the power management is based solely on occupancy, which is detected using a simple acoustic sensor. The logic reduces to, when the pigs leave the sty, reduce the sensing and when they return increase it again. The simulated scenario does not give any real insight into the issues of CAPM. However, the paper does show that there is interest in the area of context-aware power management.

2.4.2 Location aware resource management in smart homes

The MavHome project's goal is the creation of an intelligent home environment [16]. Roy [55] focuses on resource (power) management of the electrical devices in a home environment based solely on user location and predicted future location. The MavHome floor plan (see Figure 2.10) is divided into 15 zones containing 11 RFID[5] readers and 9 pressure mats. Zone connectivity is represented as a simple graph with each edge of the graph being annotated with a list of the sensors a user would pass to get from one zone to the next. These are termed paths and there may be more than one path between zones.

Zones and sensors are labelled alphabetically. The user's symbolic location is determined by sampling the 20 sensors and user mobility is captured as a string of characters, for example, *ajlloojh-haajlloojaajlloojaajlm*, signifying the user passed from sensor a to j to l to l and so on. The sensors

[5]Radio frequency identification.

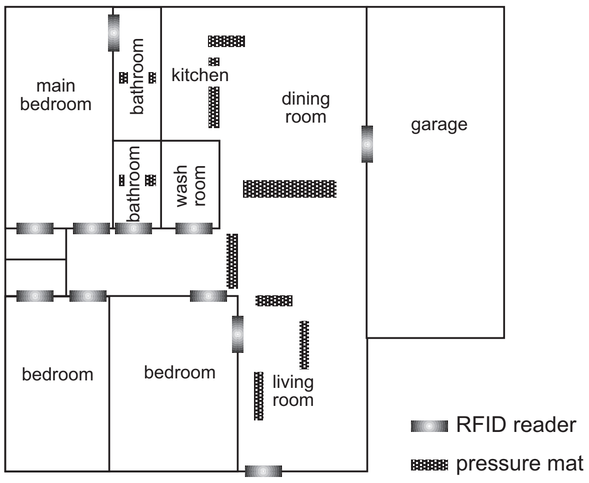


Figure 2.10: MavHome floor plan

give room-level location granularity with the use of pressure mats to divide up the large open plan kitchen, dining, and living rooms. There are two parts to the CAPM algorithm:

1. When the user leaves a zone, predict the path to the next zone based on their current zone and the user's mobility history.

2. Switch on all devices along the path. (Presumably all devices in the previous zone are switched off after a short timeout period.)

Emphasis is given to the user mobility prediction part of the algorithm. The Lempel-Ziv text compression scheme is used to compress user mobility strings, which are subsequently sent to a server and stored in a search trie. The compression technique finds regularly occurring patterns in the data and also reduces the cost of data acquisition as the data strings are compressed. The mobility prediction scheme makes its decisions based solely on the history of the room-level user mobility patterns and does not take into account other valuable data such as the time of day or day of week to aid its prediction.

2.4.2.1 Analysis

To summarise, the sensors used were RFID readers and pressure mats to obtain room-granularity location. A compression technique was used to discover user mobility patterns, which drove the power management policy of switching devices on before the user reached the predicted next zone. The policy to switch on all devices in the user's predicted path from one zone to the next is naive.

First, they do not categorise the devices into continuous and intermittent devices. Continuous devices experience no idle periods during their operation and typically they are devices that carry out a well-defined task such as making coffee, cooking food, washing clothes etc. Only intermittent devices (i.e., devices that experience idle periods) are suitable for context-aware power management. Intermittent devices include lighting, sound, video display, heating, cooling and ventilation. Second, a user will typically not require all intermittent devices all the time. Switching on all of these devices all of the time will potentially frustrate the user and waste energy.

User-perceived performance of power management algorithms is sensitive to even small delays in response and subtle changes from the normal operation of the device. Mozer cites even a 700ms delay in his system as enough to annoy the user [43]. Since the predictive policy was not actually implemented in reality it is hard to estimate what the real user-perceived performance of the policy is. Our first concern, however, is the delay in actuation caused by the compression approach withholding sensor data from the policy. They also assume negligible transfer time from sensor to policy and back to actuator, which is not the case. Second, the path prediction success is 85% meaning 15% of the time the predictive policy will switch on the wrong set of devices and the user will be left to manually switch these off and the desired ones on. For the system to be workable we believe the predictive success has to be close to 100% to avoid user annoyance.

Finally, there is no evaluation of potential energy saved nor energy consumed by the system. Probably the most fundamental flaw in the system is assuming that the user will want all devices in their future path switched on. There is no mechanism for capturing the user's preferences or behaviour. A possible improvement to the system is reviewed next.

2.4.3 Improving home automation by discovering regularly occurring device usage patterns

Also part of the MavHome project, Heierman [27] developed a data mining technique, termed episode discovery (ED), to discover significant patterns in a user's device interactions to improve home automation. ED could be applied to Roy's location-aware power management policy above to improve its effectiveness by discovering which devices are used at given times of the day. So, a device would only be switched on when the user enters its vicinity and they regularly switch this device on at this time of the day. He states the main challenge in discovering regularly occurring device usage patterns is the excessive noise in the data. For example, it would not be desirable to automate appliance interactions for random and frequent trips to the kitchen to get a drink of water.

Their data mining technique, ED, is influenced by several characteristics of device usage, (i) there is no explicit start and end points to sequences of device interactions (episodes), (ii) the ordering of interactions within the pattern must be discovered, (iii) the discovery needs to balance frequency with pattern length, and (iv) the dataset is of moderate size allowing use of techniques not suitable for large datasets. The technique mines the device activity stream to discover episodes that are closely related in time. This enables the algorithm to discover events that occur on a daily basis and weekly basis. An example they give is the sequence of devices the user switches on and off after they get out of bed in the morning {alarm on, alarm off, bedroom light on, coffee maker on, bathroom light on, bathroom video on, shower on}. An example weekly event occurrence is the water sprinkler being turned on and off.

The ED algorithm uses a 15 minute sliding window to generate a complete set of candidate significant patterns. This is achieved by incrementally processing the event stream. Each window of events is a maximal candidate pattern. Within each maximal pattern there are the possible set of "child" sub-patterns, which are pruned to prevent exponential explosion of the candidate set. ED evaluates each of the candidate patterns using the minimum description length (MDL) principle. The fundamental idea behind the MDL principle [54] is to view pattern learning (finding regularity in the data) as compression. The more the data can be compressed the more we have learned about the data. The MDL compression technique balances the length of patterns with their frequency, which Heierman states is a good property for finding significant device interactions. The amount of compression equates to the pattern's significance and because a high level of confidence is required, a minimum compression level of 80% was chosen to determine device interactions that are worth automating. The algorithm is used to (i) improve a prediction algorithm's accuracy by removing noise from its training data and (ii) recognise regularly occurring device interactions that should be automated. The algorithm is evaluated using synthetic data for two prediction algorithms, Incremental Probabilistic Action Modelling (IPAM) and a Back Propagation Neural Network (BPNN). IPAM is a frequency based prediction algorithm that maintains a probability distribution for the next event given the current state. The synthetic data contains 5 randomly generated scenarios that cover typical device interactions over a 6 month period. There were 14 regularly occurring daily and weekly patterns and 68 noisy patterns. The results (see Table 2.3) show that the ED algorithm significantly improves the performance of the prediction algorithms for the synthetic data sets.

Table 2.3: Average Scenario Prediction Results [27]

IPAM	IPAM+ED	BPNN	BPNN+ED
41.0%	73.6%	63.6%	85.6%

As a final analysis, they collected one month of real device interaction data from 6 participants in the MavHome environment laboratory. The dataset consists of 618 device interactions contained in it patterns which occur once a week, multiple times a week and randomly. From this data, ED was able to correctly identify the patterns of three of the six inhabitants as significant episodes that occur weekly, it was unable to discover the patterns that occurred multiple times in a week. Heierman stated that further work was needed to discover the weekly patterns.

2.4.3.1 Analysis

This is an interesting paper as it demonstrates the discovery and use of device interaction patterns over time. The sensors used are "device interaction" sensors (i.e., power on switches), time of day, and the day of week. The ED algorithm uses a compression technique to discover the device interaction patterns. The results show that the algorithm performs well for smoothing synthetic data to be used by prediction algorithms (IPAM, BPNN). However, the discovery of significant device usage patterns from real usage data is poor, only discovering weekly patterns for three of the six users (i.e., 50%). This suggests that possibly there is not much regularity in users' actual device usage or there is more work to be done to improve the algorithms.

The technique could be added to Roy's system with little additional energy cost and potentially improve the performance. Unfortunately, there is no evaluation of this.

2.4.4 An adaptive fuzzy learning mechanism for intelligent agents in ubiquitous computing environments

The iDorm project [10] has instrumented a real student dormitory for use as a test bed for pervasive computing experiments. Doctor et al. [19] present a novel system for learning and adapting fuzzy logic controllers to automate a user's devices within the single-bed dormitory room. Their adaptive on-line fuzzy inference system (AOFIS) uses an unsupervised, one-pass algorithm to extract fuzzy membership functions and fuzzy rules from the data. The learned rules are applied to a fuzzy logic controller that models the user's behaviour. The rules map the sensor inputs to actuator outputs, which in turn control the environment. Figure 2.11 shows the five phases of their architecture.

The system was run for a five-day period, monitoring the user for the first three days and then automating the system for the final two days. The sensors used were internal light level, external light level, internal temperature, external temperature, chair pressure, bed pressure and time measured on an hourly scale. The actuators controlled four spot lights, a bed lamp, a desk lamp, a window blind, the heater and two PC applications, a word processing program and a media playing program.

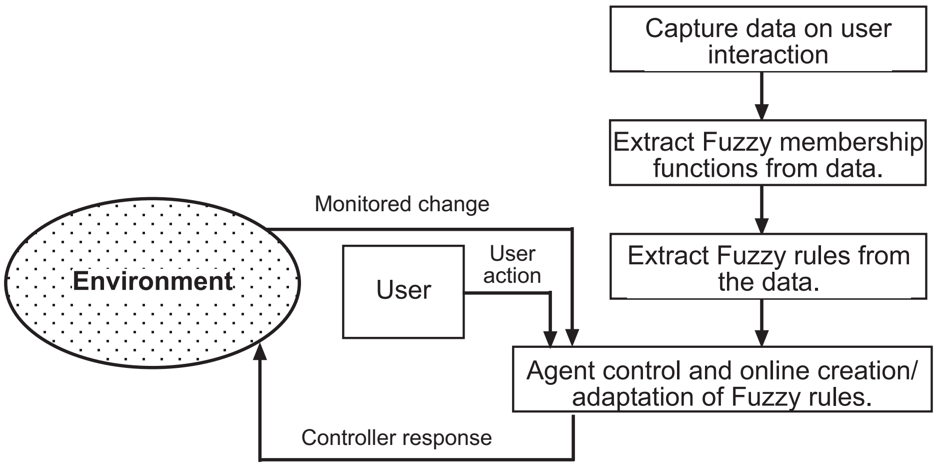

Capture data on user interaction
Extract Fuzzy membership functions from data.
Extract Fuzzy rules from the data.
Agent control and online creation/ adaptation of Fuzzy rules.
Monitored change
Environment
User
User action
Controller response

Figure 2.11: Five phases of AOFIS [19]

In the initial monitoring phase the device usage data was captured. Whenever the user interacted with a device a snapshot of the sensor readings and the actuator changes were recorded. This generated a set of multi-input multi-output data pairs. In the next phase the data was categorised into a set of fuzzy membership functions that map the raw sensor data into symbolic labels or predicates (e.g., cold, warm, hot). These membership functions are extracted from the raw data using a statistical clustering technique. An example membership function is ChairPressure{weight, noWeight}, which categorises the chair pressure sensor readings into two categories weight and noWeight. Once the membership functions are learned, they are fed to the fuzzy rule extraction phase.

The fuzzy rule extraction phase extracts multi-input multi-output rules to describe the relationship between the membership functions, and take the following form: $if\, ChairPressure = weight\, then\, DeskLight = on$[6]. Once the membership functions and set of rules are extracted from the data, the fuzzy logic controller can start automating the device interactions on behalf of the user. The agent is designed to continually learn new or modified rules, as the system may need to be tuned and will need to adapt to the user's behavioural changes. This is done by taking a snapshot of the sensors, whenever the user makes a manual adjustment to the actuators.

Data captured in the three-day monitoring phase of the experiment was used to compare with three other learning algorithms, genetic programming (GP), adaptive-neuro fuzzy inference system (ANFIS), and a multi-layer perceptron neural network (MLP). The algorithms were trained on two thirds of the data and tested on the other third. The AOFIS algorithm generated 155 rules from the 272 training instances. Performance was based on the average scaled root mean squared error

[6]This is our example to illustrate the author's system.

in the algorithms' predictions (i.e., the difference between what device interaction was predicted by the algorithm and what device interaction actually happened). The results show that AOFIS (0.12) performed marginally worse than the GP algorithm (0.11) and marginally better than the ANFIS (0.14) and MLP (0.16) algorithms.

2.4.4.1 Analysis

To summarise, the sensors used were light, temperature, and pressure sensors to infer whether the user was ABOUT TO USE a device (lighting, heating, media application). The technique they used was a fuzzy logic controller, which includes learning and updating of its rules from past device usage data.

The evaluation was only done for one user of the system, therefore it is not possible to tell if the results are significant or not. The results show only marginal differences between the algorithms' performance suggesting that there may not be any difference. Having more users do the experiment would begin to indicate what variance exists in the system for different types of user. The on-line performance was evaluated by running the fuzzy logic controller for a further two days. Its performance was measured by monitoring the total number of rule adaptations over time. The controller started with 186 rules from the 3 days and learnt another 120 rules in the subsequent two days.

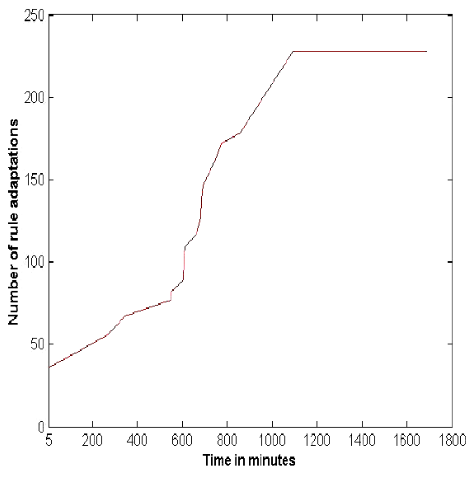


Figure 2.12: Rule modifications [19]

Figure 2.12 shows the number of rule modifications the system undertook over the two-day control period. This equates to the number of times the user had to manually adjust a device because the fuzzy logic controller failed to adjust it or adjust it correctly. The graph shows that on average there was one modification every five minutes. One possible reason for this poor performance could be the sparse number and type of sensors used (7 sensors in total) to control the 10 devices. The authors explain the levelling off of adaptation on the afternoon of the second day as the system suddenly performing better. This might also be explained by the user either having fallen asleep or having left the room for this period.

Again, there is no evaluation of energy saved by the system and the results suggest the user-perceived performance is poor, with many manual adjustments being required.

2.4.5 Lessons from an Adaptive House

The Adaptive House project [42] has a similar floor plan to the MavHome project but has a more sophisticated CAPM framework that has been developed from eight years of actual implementation and experimentation. The real-life experience from this project highlights the subtle requirements for effective power management. Here user mobility prediction is only one component of the CAPM framework and it utilises dozens of environment and user context variables in making the power management decisions. Also, the project focuses only on home comfort devices, namely air temperature, water temperature and lighting devices. These devices fall into the category of intermittent use.

The system is composed of 75 sensors monitoring room temperature, ambient light, motion, sound level, door and window positions, and outside weather and insolation. Actuators control a central heating furnace, electric space heaters, water heating, lighting and ventilation. [43] concentrates on the issue of lighting control, the objective being to automate the setting of lighting levels within the house to maximise inhabitant comfort and minimise energy consumption. The main challenges are:

1. There are several lights in each room, each with 16 settings. The user prefers different lighting moods depending on the task s/he is doing.

2. Motion sensors have a time lag in detecting user occupancy and there is delay in the X10 communications of 700ms causing a delay in system response.

3. Motion sensors do not detect the presence of a person very well. For example, a person could be present in a room and reading but not moving.

4. The policy must satisfy two often opposing constraints, user comfort and energy consumption.

The lighting control system architecture, ACHE, is shown in Figure 2.13 below.

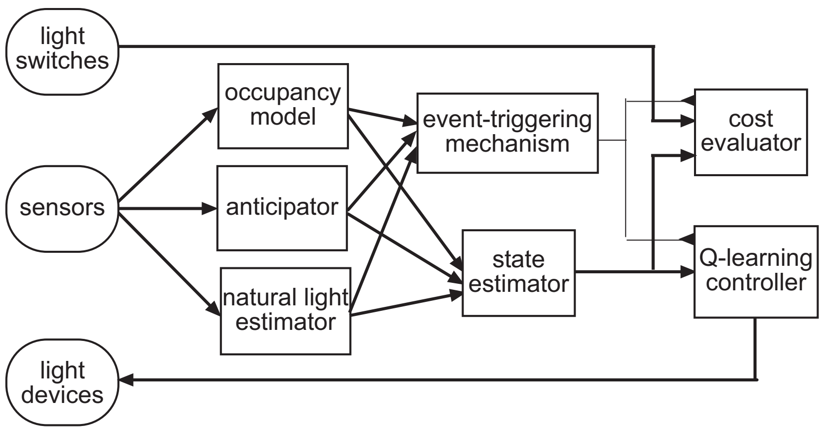


Figure 2.13: Adaptive House Architecture (ACHE)[43]

It has two levels of abstraction that filter noisy sensors and provide higher-level information to the Q-learning controller. This reinforcement learning technique models user discomfort and energy costs and uses trial and error learning to minimise the total average cost. In classical decision theory, each decision leads to a state s, which has a well defined reward $R(s)$. There is a complete prior model of the reward function, which can be used to learn an optimal policy. In reinforcement learning, there is no prior knowledge of the reward function for each state and the algorithm attempts to learn an optimal policy based on receiving infrequent reward signals. The ACHE Q-learning controller has a partial model of the reward function. It can learn about other bad decisions in lighting level based on the setting the user selects. If the decision was A and user corrected up to C, then any B lower than A would also have been a bad decision.

The natural light estimator estimates natural daylight from raw sensors (as if the lighting was turned off). The anticipator is a single-hidden-layer neural network that predicts if a zone will be entered in the next 2 seconds. It runs every 250ms and its inputs are motion, door status, sound level, zone occupancy and time of day. This component has been identified as not predicting sufficiently accurately due to sparse sensor representation. This caused user annoyance when lights would go on in an unoccupied zone. The occupancy model predicts whether a zone is occupied or not and the inputs are motion sensed in zone, number of people in the house and motion in adjacent zones. The state estimator forms a high-level state representation for decision-making with the most important inputs being estimated user activity and natural light level. The user's activity is estimated by zone change frequency.

2.4.5.1 Analysis

The Q-learning policy costed energy (\$0.072 per kWh) and user discomfort (\$0.01 per manual adjustment, \$0.01 per failed anticipation and \$0.01 per false turn on) in dollar units and graphed these costs over time. Figure 2.14 shows the energy cost per event dropped over time from 0.5 cent to 0.05 cent. However, it is not clear how this cost relates to the actual energy cost of the lighting.

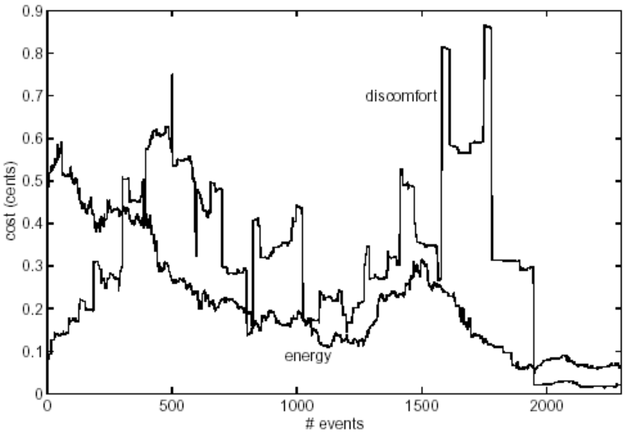


Figure 2.14: Energy versus user discomfort [43]

The graph also shows the user discomfort cost starting at 0.1 cent per event rising to 0.8 and decreasing again to 0.01 cent per event (after an error in the system code was fixed). These figures do not really give a good idea of the actual user-perceived performance. The two main discomforts the author experienced were the slow response of the system (due mainly to X10 communication delay) and the occasional false anticipation of zone entry. This caused switching of lights on in unoccupied zones. Surprisingly, there is no specific evaluation of the control of lighting level based on user activity prediction. User activity is based only on recent user mobility patterns. For example, the user being still for 5 minutes equating to the user READING and frequent zone change equating to CLEANING HOUSE. Mozer notes user activity classification as an interesting area for future research.

> "ACHE, however, has no explicit representation of user activities, e.g., whether the inhabitants are preparing dinner, relaxing, studying, etc. Such an intermediate level representation could serve a valuable purpose, particularly in integrating sensor information over time and increasing coherence of control decisions over time."

Mozer states that the set of activities sufficient to characterise the typical behaviour of the inhabitants is finite and could be inferred from sensor data. Being able to infer these activities could increase the performance of the control decisions over time.

In summary, ACHE is the most advanced CAPM application that we know of, employing in total 75 sensors monitoring temperature, light, motion, sound, door and window positions, and weather to infer NOT USING and ABOUT TO USE of lighting devices. The techniques used are a neural network for mobility prediction, and a reinforcement learning technique for the decision policy. However, there is no evaluation of the potential energy savings of the system nor its energy cost. Adding further "activity classification" context can potentially improve system performance but it will also add to the energy cost.

The following section gives an overview and analysis of the current state of the art in user activity monitoring. Some of these techniques could potentially be used to improve CAPM.

2.5 User activity monitoring review

This section presents an overview and analysis of several projects in user activity monitoring, which highlights how finer-grained user activity may be obtained but also the significant potential energy cost of obtaining this context. This provides clear evidence of the need to evaluate the balance between energy saving and energy consumed by obtaining finer-grained context. For CAPM it is not simply a solution to obtain more context to solve the power management problem.

2.5.1 Inferring Activities from Interactions with Objects

Philipose et al. [52] propose that the sequence of objects a person uses while performing an activity robustly characterises the activity's identity. Their Proact system is applied to the area of elder care where it is necessary to monitor whether people with early-stage cognitive decline are performing their activities of daily living (ADLs) and how well they are performing them. They state the key challenges are that (i) users can perform ADLs in various ways, so models of activities and recognition software must adapt to this variety, (ii) the underlying sensors must report the features required robustly across varying environments (such as light levels, sound levels, and locations), and (iii) there are a large number of ADLs (20-30 classes with 1000s of instances). They further state that a system should model each activity with minimum human effort. A subset of example ADL classes that were used in the experiment are listed in Table 2.4.

The Proact system consists of three components, RFID sensors to detect object interactions, a probabilistic inference engine to infer activities given the sensor observations, and a model creator to generate the probabilistic activity models. Objects of interest are tagged with postage stamp sized

Table 2.4: Activities of daily living [52]

	ADL		ADL
1	Personal appearance	8	Caring for clothes and linen
2	Oral hygiene	9	Preparing simple snack
3	Toileting	10	Preparing simple drink
4	Washing	11	Telephone use
5	Housework	12	Leisure activity
6	Use of appliance	13	Infant care
7	Heating control	14	Taking medication

RFID tags. The user must wear a glove, which has a small RFID reader attached, to sense when the user touches a tagged object. The main advantages of this system are that it robustly reports data at object-level granularity and it is modular allowing more tags to be added to objects if extra detail is needed for a particular activity. They note that the RFID information could be augmented with other sensor streams to fill in any information gaps, but for the experiment they just used RFID. The reader samples the environment twice a second and broadcasts any detected objects to a wearable iPaq that forwards this data wirelessly to a workstation running the inference engine. The glove's batteries last for two hours at this duty cycle.

Activities are modelled as linear sequences of activity stages. For example, making tea is a three-stage activity of boiling water, steeping tea in water, and flavouring tea with lemon, sugar, or milk. Each stage is annotated with the objects involved and the probability of their involvement. The probability combines three sources of ambiguity: sensor error, model error and modelling generality (an object is sufficient but not necessary). Each stage may optionally have a time to completion modelled as a Gaussian probability distribution. The models are converted into dynamic Bayesian networks (DBNs) where the sub-activity is the query variable and the set of objects seen and time elapsed are observed variables. The network probabilistically estimates the sub-activities from the sensor data. Activity models are generated from a pseudo English description of the activity similar to that used in recipe books. Once the objects involved in the activity are specified, the involvement probabilities are mined from the Internet using word counts via the Google API.

The experiment chose 14 ADLs for evaluation (see Table 2.4) and tested the system using 14 subjects performing the ADLs in the author's instrumented house (108 objects were tagged within a few hours). Each user spent on average 45 minutes in the house to perform the 14 ADLs. When the user touched something they heard a beep to confirm it was recorded. Because the experiment was not meant to test the efficacy of the glove, the users were asked to retouch the object if they did not hear the beep. While performing the tasks the subjects wrote down on a sheet of paper which task they were doing. After the experiments were completed the sensor data streams were fed to the inference engine to predict the most probable ADL at any given time. This was compared with the activity sequence the subjects previously wrote down. When Proact correctly claimed an activity occurred it scored a True Positive (TP), an incorrect claim scored a False Positive (FP), and no claim when the activity actually occurred scored a False Negative (FN). Proact correctly inferred that an activity occurred 88% of the time and of the activity instances that actually happened, Proact detected 73% correctly.

Issues included, (i) the RFID not performing well near water (e.g., washing hands), (ii) ADLs with few observations such as adjusting the thermostat were not easily distinguishable from noise, and (iii) overlapping activities with the same starting point were not possible to detect. For instance, when Proact detects someone entering the bathroom, there are four possible activities that are equally likely. If they then pick up their toothbrush, the system infers ORAL HYGIENE, however if they then use the toilet the system misses this activity as there was no starting point of entering the bathroom. They state that they need to reconsider their activity model to solve this issue. Another possible improvement is to include unsupervised learning of model parameters, such as the duration of sub-activities to improve model accuracy. In future work they want to integrate other sensors, particularly location sensors. Where a person is located can be a good discriminator of performing a certain task. They also want to integrate the time of day into their inference model as the time of day influences the probability of performing a certain task. Key challenges include modelling overlapping activities, multi person activities, and more complicated temporal models.

2.5.1.1 Analysis

To summarise, the sensors used are device-interaction sensors and the technique of dynamic Bayesian networks is used to infer activity from the sensor data. This is interesting work that could in theory be applied to an office environment. Possible objects that could be tagged are the telephone handle, writing pen, and tea cups, which could be used to infer activities such as ON TELEPHONE, WRITING, TAKING A BREAK. However, in an office environment there does not appear to be as many activities that can be detected by object interaction as compared with the typical activities of a person in the home. Furthermore, the practical barriers of needing to tag objects and getting users to wear RFID readers makes the approach not viable for power management in an office environment.

2.5.2 Discovery and Segmentation of Activities in Video

Brand et al. [7] state that hidden Markov models (HMMs) are the standard technique employed for visual event classification. They are used widely in spoken word and visual gesture recognition but they fall down when applied to more complicated systems, as it becomes non-trivial to manually construct and train the HMM. An example more complicated system is the classification of significant user activities in a video stream for an office environment. They propose an unsupervised approach whereby entropy minimisation of the HMM does away with the need for careful hand-crafting of the model.

A HMM consists of a dataset X and a hidden-variable probabilistic model whose parameters and structure are specified by the vector Θ. The normal method for training the model is that one guesses the structure of Θ in advance and then re-estimates non-zero parameters to maximise the likelihood $P(X|\Theta)$. This becomes very labour intensive for more complex models. They state that related models such as dynamic Bayesian networks, also require careful hand-crafting. In entropic estimation the size of Θ, its structure, and its parameter values are learned simultaneously in an unsupervised manner. Minimising entropy is in practice similar to maximising the regularity of the data (i.e., its compressibility). They state that their technique is similar to the MDL technique described in Section 2.4.3.

Their first example application is to learn a model of office activity. They state the main challenge being that office activities have a range of time spans from just half a second to pick up a phone to several hours for writing. The HMM represents the image as a set of ellipse parameters fitting the single largest connected set of active pixels in the image. Active pixels are the pixels that move in the scene, as distinct from the stationary background. A statistical model of the background is acquired to separate the foreground active pixels from the background. The HMM was trained using 30 minutes of data acquired when the user was active in the office space. The unsupervised entropic training yields a set of significant office activity states/patterns (see Figure 2.15) that occurred during the 30 minutes of activity.

By comparing the learned states with the actual video frames, the states were manually labelled as to what activity they represent. Once labelled, the HMM can annotate the video stream with the current user activity. They have shown that by using entropy minimisation, the HMM can learn observed activity into highly interpretable hidden states. The discovered hidden states are not guaranteed to coincide with events that are of interest, but they state in their experience they have always been interpretable and useful. The example application they give is of detecting anomalous behaviour in the office, such as the user sleeping in their chair and the office being occupied by a

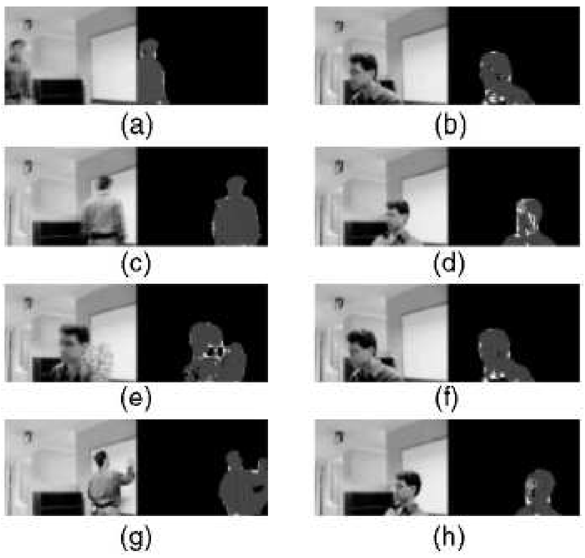


Figure 2.15: Several learned states in the trained HMM model. (a) ENTERING ROOM, (b) AT COMPUTER, (c) AT WHITE BOARD, (d) SITTING, (e) ON TELEPHONE, (f) LOOKING FOR A KEY, (g) WRITING, and (h) SWIVELING RIGHT. [7]

worker with different habits.

2.5.2.1 Analysis

To summarise, the sensor used is a web camera positioned beside the user's PC to infer user activities in an office environment. They use an unsupervised entropy minimisation technique to learn the set of distinct user activity patterns and these activities are manually labelled after training. This technique of using video to infer user activity gets over the practical problems of object tagging and wearable readers from the previous technique. However, it is difficult to get a sense of how well the unsupervised learning of activities works as they do not test the trained model against a hand labelled video sequence. They only show that the technique does discover significant patterns in the video and that these patterns are manually interpretable. In particular, activities (b) AT COMPUTER and (f) LOOKING FOR A KEY look visually very similar, and also (d) SITTING and (h) SWIVELLING RIGHT appear quite similar.

It would be interesting to apply this system to the problem of CAPM to see empirically how well the technique works. The next section reviews a more advanced system including more sensors for activity recognition and gives evidence for the concern of resource/energy consumption.

2.5.3 Layered Representations for Human Activity Recognition

Oliver et al. [48] present a layered hidden Makov model technique for performing sensing, learning and inferencing at multiple levels of temporal granularity. They apply the model to a system named SEER that infers user activity from real-time streams of video, acoustic, and computer interactions in an office environment. They state that much of the previous work on leveraging video and acoustic information to recognise human activities has centered on identification of a specific type of activity in a particular scenario, for example, hand gesture recognition [12]. This work applies to recognising more complex patterns of specific human behaviour, extending over longer periods in time.

They developed a formulation of layered hidden Markov models (LHMMs) and explored the challenge of fusing the readings from binaural microphones, a USB web camera, and a keyboard and mouse, to infer the activities, PHONE CONVERSATION (PC), FACE TO FACE CONVERSATION (FFC), ONGOING PRESENTATION (P), DISTANT CONVERSATION (DC), NOBODY IN THE OFFICE (NP), and USER PRESENT ENGAGED IN SOME OTHER ACTIVITY (O). They initially experimented with a single-layered HMM, which generated a large parameter space, requiring large amounts of training data and resulting in low classification accuracies. They state that standard HMMs suffer from a lack of structure, an excess of parameters, and an associated over fitting of data when they are applied to reasoning about long and complex temporal sequences with limited training data. Also, when the system moved to a new office, copious retraining was typically necessary to adapt the model to the specifics of the signals and user in the new setting. The layered formulation of LHMMs makes it feasible to decouple different levels of analysis for training and inference. The system employs a two-layer HMM architecture. The raw sensor signals are processed within a time window of 100 milliseconds to obtain feature vectors for the first layer of HMMs. Example features for the video are motion density, face density, foreground density, and skin colour density. Example audio features are the signal energy, the mean and variance of the fundamental frequency over a time window, and the source location of sound. A history of the last 1, 5, and 60 seconds of mouse and keyboard activities is also used. The first layer of HMMs classify these features with a time granularity of 1 second and in the final stage, the second layer of HMMs represents the typical office activities associated with a time granularity of 5 to 10 seconds.

They tested SEER in multiple offices and collected data from a range of users and environments. The high-level layer is relatively robust to changes in environment. Only some of the lower-layer HMMs needed to be retrained to tune their parameters to new conditions such as different ambient noise, background images and illumination. The number of parameters to estimate is much lower than the single-layered HMM implementation. Encoding prior knowledge about the problem in the structure of the models decomposes the problem into a set of simpler sub-problems and reduces the dimensionality of the overall model. They trained and tested the performance of the single-layered HMM and LHMMs on 60 minutes of recorded office activity data (10 minutes per activity, 6 activities and 3 users). They used 5 minutes of data for training and the other 5 minutes for testing. The average accuracies on the testing data were 72.68% (standard deviation (STD) 8.15%) with the single-layered HMM and 99.7% (STD 0.95%) with LHMMs. In summary, the accuracy of the LHMMs is significantly higher than the single-layered HMM for the same amount of training data and LHMMs are more robust to changes in environment requiring retraining of only the higher layer.

A further paper [49] presents an extension to SEER, S-SEER, which attempts to address the significant CPU usage of the feature vector extraction algorithms. They say that, although the methods have performed well, a great deal of video and acoustic feature processing has been required by the system, consuming most of the resources available in a PC. They develop an approach, expected value of information (EVI), which uses the principle of maximum expected utility to determine dynamically which features to extract from the sensors in different contexts. The EVI of computing a feature combination $\mathrm{f_k}$ (e.g., motion density and face density and audio energy) is the difference between the expected utility of the system's best action when observing the features in $\mathrm{f_k}$ and not observing them, minus the cost of sensing and computing such features. If the net expected value is positive then it is worth computing the features. The additional computational overhead to carry out the EVI analysis is $O(M * F * N^2 * J)$, where M is the maximum cardinality of the features, F is the number of feature combinations, N is the maximum number of states in the HMMs, and J is the number of HMMs.

They performed a comparative evaluation of the S-SEER system when executing the EVI selective perception policy against two baseline policies, random selection and rate-based. Random selection is a simple policy that selects the features at random on a frame by frame basis. Rate-based is a heuristic policy that defines an observational frequency and duty cycle (i.e., period during which the feature is computed) for each feature f. The observation frequency and duty cycle are determined by processing a validation set of real-time data. In the experiment the selection policies select any combination of the four possible sensors, vision, audio, keyboard and mouse activities and sound localisation. The results are shown in Table 2.5.

The results show that the EVI algorithm performs very well across the set of activities, reducing the accuracy only slightly and manages to reduce the average computational cost from 54.3% to 33.4%, out performing the baseline policies. Further observations they make from the experiment are that at times, the system does not use any features at all when it is confident enough about

Table 2.5: Average accuracies and computational costs for S-SEER [49]

Recognition Accuracy				
	No policy	EVI	Rate-based	Random
PC	100	100	29.7	78
FFC	100	100	86.9	90.2
P	100	97.8	100	91.2
O	100	100	100	96.7
NP	100	98.9	100	100
DC	100	100	100	100
Average	100	99.5	86.1	92.7

Computational cost (% CPU time)				
	No policy	EVI	Rate-based	Random
PC	61.22	44.5	37.7	47.5
FFC	67.07	56.5	38.5	53.4
P	49.8	20.88	35.9	53.3
O	59	19.6	37.8	48.9
NP	44.33	35.7	39.4	41.9
DC	44.54	23.27	33.9	46.1
Average	54.3	33.4	37.2	48.5

the situation but also that the system guided by EVI tends to have longer switching time (i.e., to realise when a new activity is taking place) than when using all the features all the time. In most of the experiments the sound localisation was never turned on due to its high cost and relatively low informational value.

Finally, in [50] they compare use of a HMM at the highest level to the use of a dynamic Bayesian network for inferring high-level user activities. HMMs can be viewed as a specific case of the more general class of dynamic Bayesian models. They state that DBNs present several advantages to the problem of user modelling from multi-modal sensory information, DBNs can handle incomplete data as well as uncertainty, they are trainable, they encode causality in a natural way, algorithms exist for learning the structure of the networks and doing predictive inference, they offer a framework for combining prior knowledge and data, and finally, they are modular and parallelisable. One disadvantage they state is that they cannot handle continuous data very well.

Figure 2.16 shows the DBN model for inferring the user activity from the video, audio, sound location (SL), and keyboard/mouse (KM) sensors. The experiments compare the accuracy of HMMs versus DBNs and evaluate any practical advantages and disadvantages. They collected 90 minutes of activity data (15 minutes per activity). Table 2.6 shows the recognition accuracy for HMMs and DBNs with and without the selective perception.

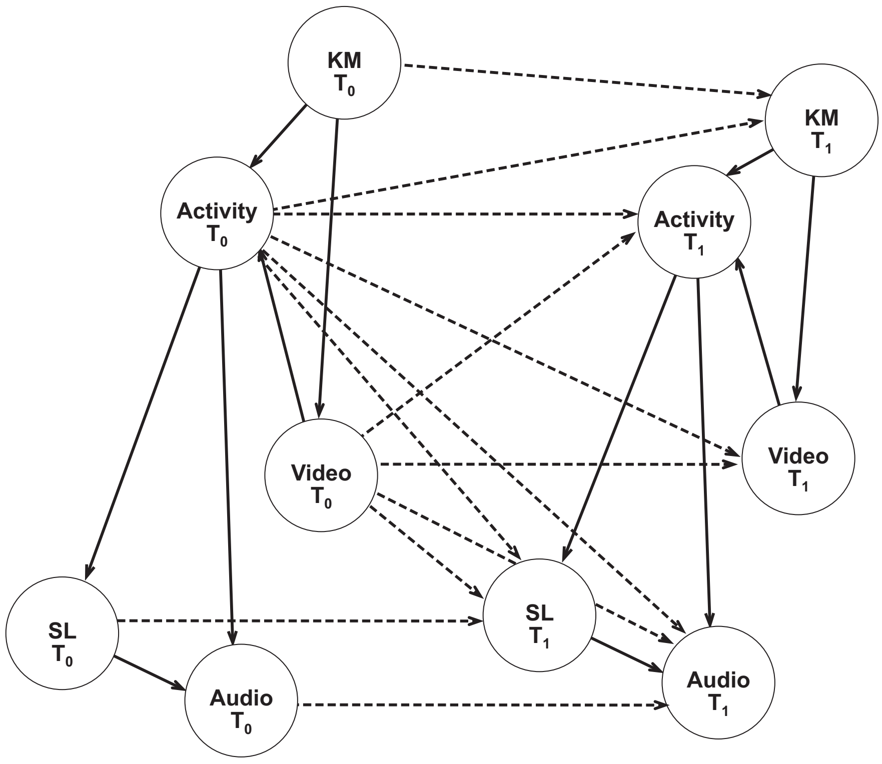


Figure 2.16: S-SEER dynamic Bayesian network [50]

The results show that DBNs have better recognition accuracy for this problem and employing the EVI selective perception policy incurs less loss of accuracy for the DBN. They state an important difference for selective perception is that the HMMs marginalise over the unobserved variables, whereas with the DBN the previous time slice (T_0) influences inference about the unobserved variables, improving the accuracy.

2.5.3.1 Analysis

This is possibly the closest work to our research in the sense it uses similar sensors (video, audio, keyboard/mouse) in a similar office environment. They appear to achieve very good results for activity recognition but at a very high computational cost. Even with their EVI sensor selection

Table 2.6: Recognition accuracy [50]

	HMMs	DBNs
PC	97/98	95/90
FCC	99/97	97/97
P	86/88	99/99
O	93/100	99/99
NP	100/100	100/99
DC	91/70	96/96
Average	94.3/92.2	97.7/96.7

policy their activity recognition algorithm consumes 33.4% of CPU time (on average). From the figures for desktop PC power consumption given in Section 2.2.5, this equates to an average power consumption of 20.2 W which is 33.6% more than CPU idle consumption. This gives clear evidence that there is a boundary of granularity for context-aware power management. Another concern with S-SEER is the need for retraining of the lower layer of HMMs for different environmental conditions. In practice it would be desirable for the system to require no initial training stage. It would however be interesting to see S-SEER applied to CAPM to evaluate how well it performs in terms of energy saving and user-perceived performance.

2.6 Summary

This chapter has introduced the two areas of dynamic power management and context-aware computing and reviewed the current state of the art in dynamic power management and CAPM. The field of user activity monitoring was also reviewed.

The review shows that current state-of-the-art dynamic power management policies are not suitable for power management of stationary devices. There is a need to develop policies that can (i) accurately and quickly predict long idle periods (order of minutes), and (ii) predict when the user will make the next request (order of seconds beforehand). To achieve this we need to obtain context from the user of the device. In particular, about when the user is NOT USING and when the user is ABOUT TO USE a device.

Current state-of-the-art CAPM has focused on developing inference techniques for inferring such high-level context from low-level, noisy, and incomplete sensor data. There has been some work in the area of CAPM that points towards the need for finer-grained context to do better.

At the same time, there has been work done in the area of user activity monitoring for fine-grained activity recognition. A range of techniques have been developed, including discovering patterns of device interactions, video processing, and acoustic processing. There has been reasonable success with recognition of user activities, the main challenges left being recognition of interleaved/overlapping activities and the cost (CPU/energy consumption) of recognition.

This review has provided evidence that there is a bound to the granularity of context appropriate for CAPM. In particular there is a need to explore the potential energy savings and energy costs of such CAPM systems. To our knowledge there has been no research into what are the potential savings of context-aware power management and what granularity of context is appropriate.

Chapter 3

CAPM Framework Design

In this chapter we identify the key requirements for CAPM and present the design of the CAPM framework. At the core of the framework is a Bayesian network, which performs the context inference. We justify the selection of Bayesian networks for context inference and go on to give a detailed explanation of Bayesian networks and parameter learning of the networks. Finally, we show the evolution of the Bayesian models that were developed for the CAPM framework. We begin the chapter by presenting initial experimental results, which give an insight into the main issues that need to be addressed by a CAPM system.

3.1 Initial experimental results

To explore the requirements of context-aware power management and gain insight into user behaviour patterns, we first examined in detail the the use of location as a key piece of context for power management of users' stationary desktop PCs in an office environment. The objective was to minimise overall electricity consumption of the system while maintaining acceptable desktop PC performance. We were interested in the relation between the user's location and their user behaviour (i.e., whether they were using the device or not when in it's vicinity). We implemented two simple location-aware policies and performed 6 user trials, each over a period of a week. The trace data collected from the trials was analysed to gain insight into the energy consumption and user-perceived performance of the location-aware policies. The office spaces included personal and shared spaces, and there was only one user per desktop PC. The two simple location-aware policies use the location context derived from detecting users' Bluetooth-enabled mobile phones. The policies execute on each desktop PC and continuously poll to discover the presence of their owner's Bluetooth phone in the area. The two location-aware policies were:

1. Standby On Bluetooth (SOB). When the PC is on, the policy polls for the user's phone via the Bluetooth discovery mechanism. If the phone is not found the PC powers down to standby. The user manually wakes up the PC when s/he next needs to use it.

2. Standby/Wake-up On Bluetooth (SWOB). When the PC powers down to standby the policy passes control to a nearby server. When the server detects the phone again it sends a wake up message to the user's PC. (We used a server to implement wake up because as yet we do not know of a Bluetooth device that can wake up the PC from standby).

Using the Windows power management API we recorded all power state change events for the PC during each user trial. This included recording when the PC was powered down to system standby, when it resumed to the on state, both automatically and manually, and when the PC was on but idle for the last minute. The on-idle time enables us to estimate how much energy the policy wasted by the machine being on but (potentially) not being used. Knowing the idle times enables us to generate the oracle policy trace (see Section 2.1) and the range of threshold policy traces (see Section 2.2.1). The range of the Bluetooth connection was 10 metres and its latency was approximately 10 seconds (i.e., it could take up to 10 seconds for the Bluetooth inquiry to find the phone). We also noted during implementation that sometimes the inquiry would not find the phone even though it was there. To overcome this source of error it was necessary to duplicate the number of inquiries. This polling process took approximately 90 seconds to complete so there was a significant delay before the machine was powered down. Policy traces were collected from 6 separate user trials, 4 of which used the SOB policy and 2 of which used the SWOB policy. Software was written for analysing the traces in terms of energy consumption and user-perceived performance (i.e., number of manual resumes and short standby periods). For each trace collected, the oracle policy trace and a range of threshold policy traces were generated. For the SWOB traces, corresponding SOB policy traces were generated by removing the automated resume events of the SWOB policy. We estimated the mobile phone consumed an extra 6 Wh of energy over the 4-day trial due to extra recharging necessary because the Bluetooth discover mode was on all the time. The extra energy consumed on the PC by the power manager was not measurable and we considered it negligible. Also, for the SWOB policy we did not take into account the energy consumed by the wake-up server, as we assume this functionality would eventually be provided within the USB Bluetooth adapter. The 6 Wh has been added to the energy cost of the location-aware policies.

3.1.1 SOB policy energy performance

Figure 3.1 below graphs the energy consumption in Watt hours for each policy for each trace. The SOB policy values are the actual estimated consumption from the real trace (except for A-SWOB and D-SWOB) and the other values are calculated from the generated policy traces. The traces are all for 4 days, Tuesday to Friday. Previous monitoring of traces and actual measurement of PC power consumption show that, on average, the estimated power consumption (from a trace) correlates well with the measured power consumption (within 7.2% over a period of a week).

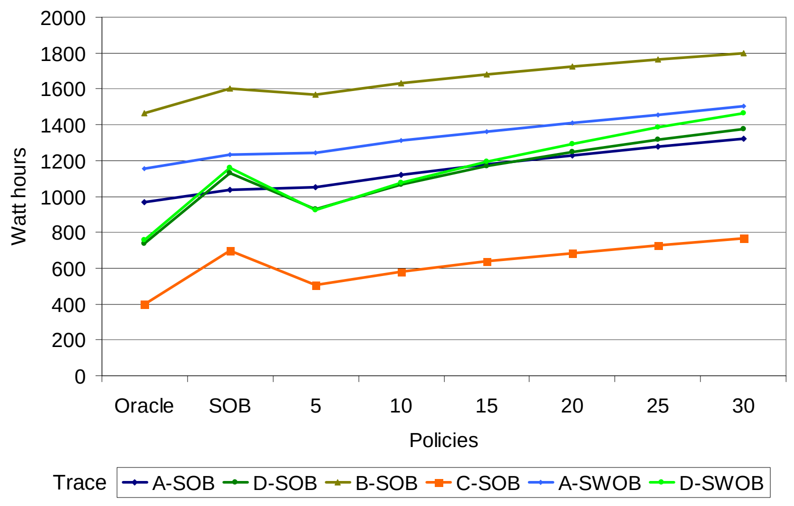


Figure 3.1: SOB energy consumption

Each user has different user behaviour, which affects the performance of the policies. From the graph, it seems that there are two distinct user behaviour patterns emerging. The SOB policy performs quite well for the A-SOB, A-SWOB and B-SOB traces (HeavyUsePattern). In these cases the SOB policy is close to the oracle policy (approximately 8% from oracle) and similar in consumption to the 5 minute threshold policy. The reason for the good performance is that A and B are heavy users of their PC while in its vicinity (i.e., the usage traces have a relatively small amount of idle time when the user is in the 10-metre vicinity). The SOB policy performs similarly badly for the C-SOB, D-SOB, and D-SWOB traces (LightUsePattern). In these cases the SOB policy is far from the oracle (> %50) and the traces have a significant amount of idle time when the user is in the 10-metre vicinity. We can state as a general rule, the SOB policy will perform well for devices that are heavily used when the user is in their vicinity. Another pattern to note within the traces is the slope of the threshold policy graphs. The A-SOB, A-SWOB, B-SOB and C-SOB traces threshold slopes are very similar (10.8, 9.3, 10.3, 10.5) (LowFrequencyUsePattern) compared to the slope of the D-SOB and D-SWOB threshold consumptions (18.0, 21.6) (HighFrequencyUsePattern). This indicates another distinct user behaviour pattern in the traces that affects the performance of the threshold policies. Intuitively, the higher the frequency of idle periods the worse the threshold policy performs from oracle as it consumes extra power waiting to timeout, each time there is an idle period. So while the SOB policy performs badly for all three LightUse user traces, due to the large number of idle periods, the threshold policies perform worse for D-SOB and D-SWOB than C-SOB as user D has a high frequency of idle periods (41 and 47 periods) compared to user C (24).

3.1.2 SOB policy user-perceived performance

We evaluated the quantitative user-perceived performance of the SOB policy by counting the maximum number of times (over the 4-day trace) that the user had to resume the PC in a 10-minute, 30-minute, one-hour, four-hour and eight-hour period. Figure 3.2 graphs the performance values per user trace for the eight-hour period (The other periods have a similar pattern but with less resume events). The Threshold-5 policy shows the HeavyUse traces having (7, 8, 9) resumes in an eight-hour period compared to the LightUse traces (11, 12, 14). As would be expected the performance improves as the threshold increases, with 20 minutes appearing to reach saturation (i.e., after this threshold there is little improvement in performance). What is interesting to note is that for the HeavyUse traces, the SOB policy performs similarly to the Threshold-5 policy but for the LightUse traces, the SOB performs considerably better (7, 7, 7 resumes compared to 11, 12, 14). This intuitively makes sense, as the HeavyUse users do not allow the Threshold-5 policy to power down while in the office, whereas the LightUse users would. So, another general rule is that the SOB policy keeps the user-perceived performance acceptable for LightUse users.

A qualitative survey of the users revealed that for 2 of the users the performance penalty of resuming the PC every time they came back to their office would not stop them implementing the SOB policy. The other 2 users thought it necessary that the PC would resume automatically to avoid the performance penalty. Clearly user-perceived performance is subjective and there is a balance for each user of how long the standby period should be to justify the subsequent performance penalty (i.e., a performance break-even time). Figure 3.3 shows the standby period frequency in minutes for the SOB and Threshold-5 policies for the D-SOB (LightUse) trace. The graph shows the Threshold-5 policy has many more short standby periods. Also, the total number of standbys for the SOB policy is 24 compared to 52 for the Threshold-5 policy. Therefore, 28 of the Threshold-5 policy standbys occurred when the user was in the vicinity. Clearly, these short standby periods when the user is in

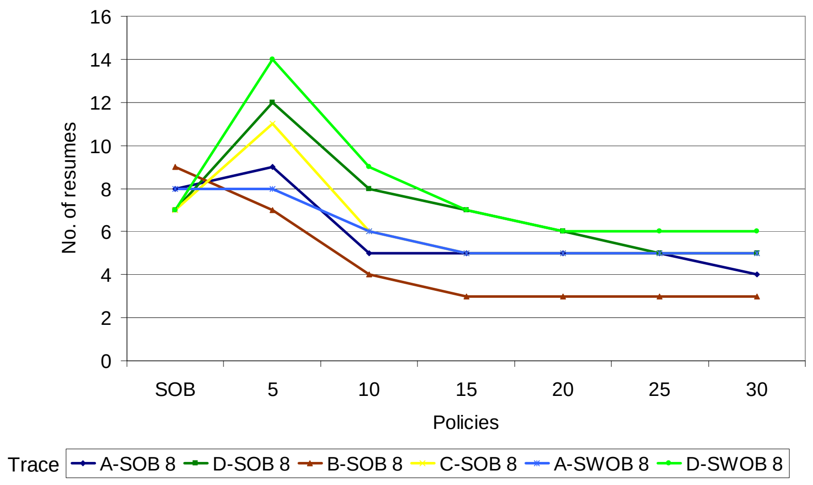


Figure 3.2: SOB user performance

the vicinity would severely degrade the user-perceived performance, making the Threshold-5 policy unlikely to be implemented by any user.

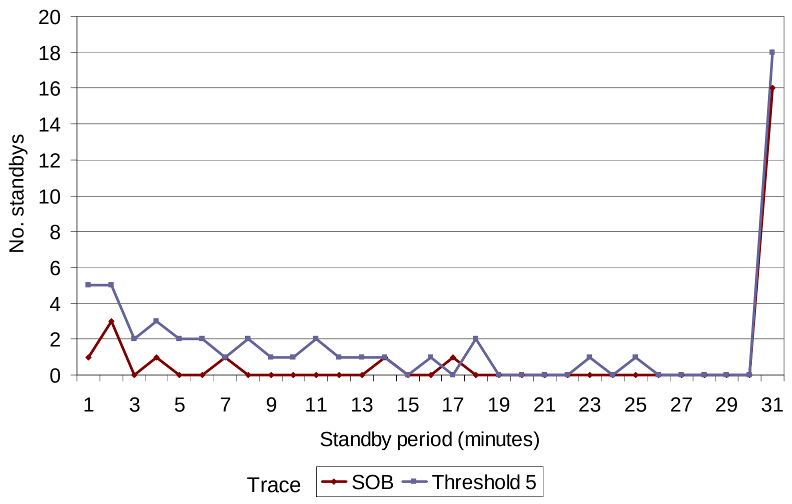


Figure 3.3: Standby period frequency

3.1.3 SWOB policy energy performance

The SWOB policy is an extension to the SOB policy where the PC powers up again when the mobile phone is next detected in the 10-metre vicinity. For this reason we chose to evaluate the policy with just two user trials. Figure 3.4 shows the policies' energy consumptions for the A-SWOB and D-SWOB traces. The graph compares the SWOB policy to the generated oracle, SOB and threshold policy traces. Again, the two users have similar performance to their original traces with A-SWOB performing well and D-SWOB performing badly compared to the oracle. Also, again the slope of the threshold performances is similar to the original user traces. For A-SWOB the SWOB policy energy performance is very similar to the SOB policy but for D-SWOB it is significantly worse. The increase in energy consumption is caused by the SWOB policy automatically resuming the PC when the user enters the vicinity. Hence, the PC can be on and idle before the user requests its use. The trace distinguishes between when the PC is resumed automatically (i.e., over the network) and when the user first pressed the keyboard after being in standby. So, we can measure the time from when the PC is resumed automatically until when the user first uses the PC. We call this period the auto-on-idle period. There are significantly more auto-on-idle periods for the D-SWOB trace (154 minutes in total) than the A-SWOB trace (5 minutes in total). Also, there were 14 occurrences in the D-SWOB trace where the PC was resumed and later went back to standby without being used by the user. In interview after the experiment, user D stated that he would nearly always use the PC immediately after entering the room. If this is true, it suggests that the PC was automatically resumed when the user passed by the room.

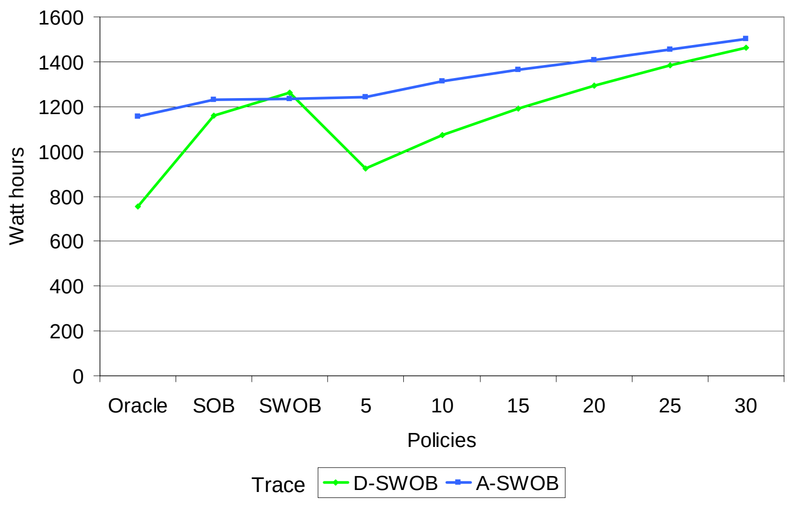


Figure 3.4: SWOB energy consumption

3.1.4 SWOB user-perceived performance

On average the Bluetooth discovery took approximately 10 seconds to discover the mobile phone and the desktop PC takes approximately 7 seconds to fully resume from standby. Therefore, under the SWOB policy it took approximately 17 seconds from the time the user enters the 10-metre vicinity until the PC resumes fully, ready for use. To evaluate the user-perceived performance of the SWOB policy we have to determine whether the PC was resumed in time for the user. Figure 3.5 shows the graph of auto-on-idle period frequency in seconds for both traces.

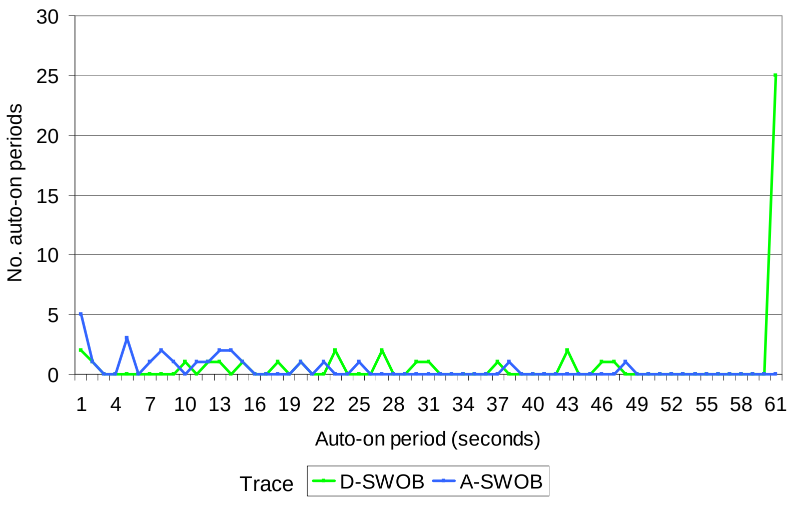


Figure 3.5: Auto-on-idle period frequency in seconds

The graph shows the D-SWOB trace to have few short periods (3 periods $<$ 8 seconds) compared to the number of longer periods (25 periods $>$ 60 seconds). On the other hand the A-SWOB trace has relatively many short idle periods (10 periods $<$ 8 seconds) compared to number of periods greater than 60 seconds. The auto-on-idle period is measured from when the PC starts to resume and it takes approximately 7 seconds before it resumes fully and can be used. Therefore the data suggests that user A experienced 10 delays in waiting for the PC to fully resume and user D experienced 3 delays. The length of the delay is partly dependent on the geographical layout of the user's return path and how long it takes the user to return to their PC after they have entered the 10-metre vicinity. In general, the current Bluetooth discovery time makes the auto wake up of the PC borderline functional and very dependent on the user's return path and their time to reach the PC. A more responsive sensor could improve the SWOB policy's user-perceived performance and be less dependent on geographical layout.

3.1.5 Conclusions

The experimental user trials and subsequent policy trace analysis has highlighted several user behaviour patterns that affect the performance of the power management policies. The location aware SOB and SWOB policies perform well energy-wise for HeavyUse users where the device is used a lot when the user is in the 10-metre Bluetooth vicinity. For LightUse users they begin to deteriorate, consuming energy when the user is in the vicinity but not using the device. For FrequentUse users (i.e., the user uses the device many times during the day) the threshold policies deteriorate as energy is wasted every time the policy waits for the timeout period. The SOB and SWOB policies are less affected by this FrequentUse pattern, as the timeout period is less (90 seconds).

The user-perceived performance of the SOB policy appears to be acceptable to some users but not others. The performance remains constant for both HeavyUse and LightUse users while the Threshold-5 policy performance deteriorates significantly for LightUse users. The SWOB policy user-perceived performance is dependent on the geographical layout of the users return path and how long it takes for the user to return to their PC after entering the 10-metre Bluetooth vicinity. This makes it suitable for only some cases. Furthermore, the SWOB policy comes at a price in increased energy consumption, particularly in the case of LightUse users and unsuitable geographical layouts (e.g., where the user passes by the office within the 10-metre range).

A further concern of implementing these policies is that of device lifetime. For many devices, switching them on and off affects their expected lifetime. We have estimated the break-even due to lifetime for a desktop PC to be around 2 minutes. The estimate assumes that the hard disk is the first component to fail in the PC and is based on the lifetime figures for a given Sea Gate 80Gb Barracuda ATA V hard disk and a typical usage trace taken from the experiment. The reliable lifetime is estimated to be 600,000 power-on hours and 50,000 start-stop cycles. The lifetime of the disk is fixed at 10 years and we assume 250 working days in each year. For the given usage trace and lifetime of 10 years, the number of the number of allowable start-stop cycles per day is 19 and the power-on hours is 4. The next smallest idle period in the trace is 2 minutes, hence it is not worth powering down for this 2 minute period. Other devices have longer lifetime break-even times such as fluorescent lighting (5 to 10 minutes)[63]. Figure 3.6 shows the total number of standby periods for all traces, of which there are a significant number of short standby periods occurring. Policies may have to take device lifetime into consideration when making their power off decisions.

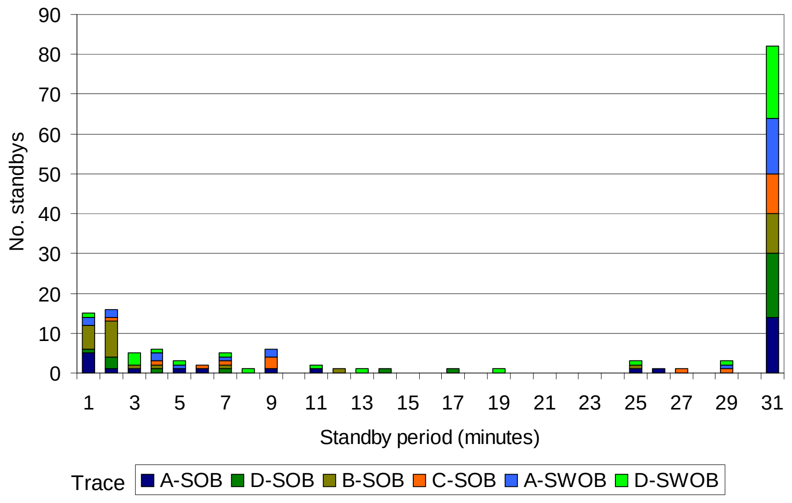


Figure 3.6: Standby period frequencies (minutes)

3.2 CAPM requirements

From the experimental trials we have identified several requirements for CAPM.

- **R1: Required context** - CAPM requires the prediction of the context NOT USING for at least the given break-even period and ABOUT TO USE at least the resume time beforehand.
- **R2: Context granularity** - The most important result from the initial experiments is that coarse-grained location alone is not sufficient to determine the detailed user behaviour necessary for effective CAPM. Finer-grained context is needed to predict (i) the user in the vicinity but NOT USING the device and (ii) the user in the vicinity and ABOUT TO USE the device. Passing by the device but not ABOUT TO USE it is a special case of scenario (i). The second scenario is difficult to achieve, as one key advantage of coarse-grained location is that it is a distant sensing device, i.e., it senses the user at a distance thereby enabling time for the device to resume before the user requests its use. Saving energy by switching off devices in the near vicinity of the user is difficult to achieve transparently.
- **R3: Distant prediction** - The second result is that there is a need for distant (time wise) prediction to offset delay in sensor response and long device resume times. For example, some form of mobility prediction might overcome the problem of the latent Bluetooth sensing.
- **R4: Distributed sensing** - The third result is that there is a need for distributed sensing of users and possibly recognition of user plans to predict longer future idle periods (for cases

where the device break-even time is an order of minutes). For example, given the results it would not be sensible to switch off fluorescent lighting every time the user leaves the room as this would cause premature failure. We define distributed sensing as the ability for sensor data to be communicated amongst distributed sensing devices. For example, a sensing node in the office bathroom could communicate the user's presence with the power manager of the user's desktop PC in the office.

- **R5: Decision under uncertainty** - The initial experimental location-aware polices used a simple rule-based design where, observed sensor states are matched to power management actions. There is no representation of uncertainty, which is required in most real-world decision applications to account for incomplete and noisy data [35]. Given a level of certainty in whether the user is NOT USING or ABOUT TO USE the device, a decision can be made as to which power management action to take.

- **R6: Adaptation** - The simple rule-based design has no learning of new rules based on usage. This design would not scale well to accommodate more sensors, as the rules would become increasingly complex making it successively harder to configure for each individual user. Some form of learning technique is needed, which can continually learn from device usage history and adapt to the user.

The CAPM framework addresses these requirements and its design is detailed next.

3.3 CAPM framework design

The design of the CAPM framework is loosely based on the sentient object model (see Section 2.3.1). A sentient object encapsulates the CAPM power manager for a device. Each power manager can execute a number of policies, one power-down policy for each device state and one power-up policy for when the device is in a reduced power state. Communication is event-based, enabling sensing of distant sensors (fulfilling R3 and R4). Filtering of sensors enables the power manager to consider only information relevant to it. In our implementation, filtering is configured manually but some "intelligent" mechanism could automate the selection of sensors most relevant to the device's power manager. Sensors can include any physical sensing devices, power state changes of other devices, and "software sensors", such as time of day, or day of week. The power manager controls the power-down and power-up of the device through the device's power management API. Currently power management of computing devices is non-standard with each operating system having their own

API[1]. Development of a standard API would be advantageous for power management of heterogeneous devices. Until this is achieved wrappers are needed for the various operating system APIs.

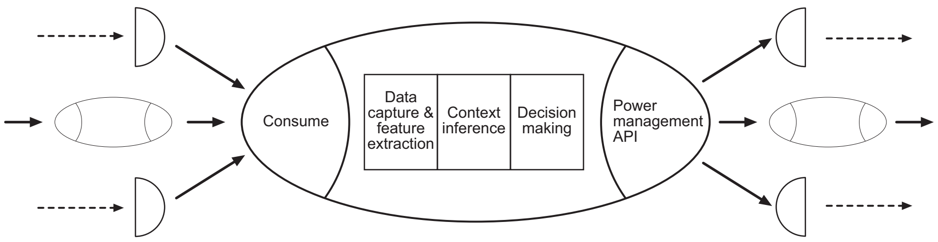


Figure 3.7: CAPM framework

At the centre of the framework are the data capture and feature extraction, context inference, and decision components. Our research has concentrated on the development, realisation, and evaluation of these core components.

3.3.1 Data capture and feature extraction

This is the first layer of data processing. Raw sensor events are captured and in most cases preprocessed to obtain relevant features. For example, a video signal could be captured and preprocessed to obtain features such as density of foreground pixels, density of motion, density of face pixels, and density of skin colour [48]. A Bluetooth detection event could be preprocessed using a counter to count the number of times a Bluetooth tag has not been detected. This gives a history of when the tag was last seen, for example, a count of 10 means the tag has not been detected in the last ten polls. A value of 0 means the tag was detected in the previous poll. It is also possible that for some sensors, their data can be passed onto the next layer unprocessed. For example, the prediction from a mobility prediction service that a user is going to enter the room in the next 10 seconds.

Sensor events received via event messaging are more likely to be already preprocessed (to reduce bandwidth), whereas events from sensors that are directly connected to the sentient object are more likely to require preprocessing (feature extraction), e.g., a video signal from a web cam or an audio signal from a microphone. The output from data capture and feature extraction is made available to the context inference layer.

[1]The ACPI standard currently only defines interfaces between hardware devices and the operating system, not applications and operating system.

3.3.2 Context inference

The context inference layer is responsible for inferring more certain, higher-level context from the low-level sensor and feature data (inference can also be termed sensor fusion). The inference can involve combining redundant data to achieve more certainty and multi-modal data to infer context based on a combination of the multiple sensor modes. This is the most challenging part of the data processing as it is trying to infer high-level notions from low-level, noisy, and incomplete sensor data and/or their features. In the framework, probability theory is used to deal with this uncertainty in the data (fulfillment R5). This gives a level of confidence in the proposition of a certain context being true. This probabilistic inference of the contexts NOT USING and ABOUT TO USE is carried out using Bayesian networks (fulfillment of R1). This context is made available for use by the decision layer. The Bayesian network is trained based on observation of the user USING and NOT USING the device (fulfillment of R6).

3.3.3 Decision

The decision layer is responsible for taking the power-management actions. The possible actions depend on the current state of the device. When the device is on the possible actions are either to remain on or to power down to a lower-power state. When the device is in a lower-power state the possible actions are either to remain in the lower-power state or to power up the device. For the initial version of the CAPM framework the decision layer was designed as a simple threshold rule. If the probability of NOT USING exceeded the given threshold (80%) then the action to power down was taken. Likewise, if the probability of ABOUT TO USE exceeded the given threshold (60%) the action to power up was taken.

The design could be extended by the use of utility theory. Utility theory estimates the expected utility of an action based on the level of certainty it has in the state of the world, the potential benefit of the action and the potential cost. Given these inputs, the decision is then simply a matter of choosing the action with the highest expected utility. Expected utilities can be implemented using decision nodes, which are an extension to standard Bayesian networks. This extended Bayesian network is called a Decision network.

3.4 Selection of inference technique

We have identified that the key challenge for CAPM is inferring the user's context correctly, which is carried out by the context inference component. The job of this component is to infer from low-level data the contexts NOT USING and ABOUT TO USE given uncertainty in the data, i.e., noisy and incomplete sensor data. Korb et al. [35] state there are at least three distinct forms of uncertainty:

1. Ignorance. This refers to either a lack of information or a lack of understanding of how the system fully operates. Ignorance relates to the incompleteness of sensor data. It may not be practical to observe every possible event in the event space.

2. Physical randomness or indeterminism. Even if everything was known about the system, there would still be some degree of randomness or indeterminism in the sensors that would cause uncertainty. Indeterminism relates to noisy sensor data. Sometimes sensors report erroneous values through either faulty hardware or indeterminate protocols. For example, the Bluetooth discovery protocol's frequency hopping sequence may fail to discover a device that is actually in the vicinity.

3. Vagueness. Assertions are sometimes not clearly defined or vague. For example, it is often unclear whether to classify a human as brave or not, or a dog as a spaniel or not. For CAPM, it can be unclear as to when a person is NOT USING a device. For example, some people might like the television on in the dining area when they are preparing food in the kitchen and some people might like their PC display on when they are reading at their desk, in case an email comes in. The notion of NOT USING is subjective to the individual.

We now briefly highlight some of the inference techniques employed by the state of the art in context-aware computing and provide a justification for our use of Bayesian networks. A Bayesian network is a graphical model that represents causal relationships between entities and models the uncertainty in the state of a system. The technique is based on probability theory, which provides the foundation for reasoning under uncertainty. The specification of dependencies between variables leads to an efficient, tractable method for calculating the probabilities.

Chong et al. (see Section 2.4.1) use a rule-based approach to inference in the implementation of their sensor fusion component. Russell and Norvig [56] give a good overview of rule-based inference and the reasons why it is no longer used. They state that rule-based inference systems have three desirable properties:

1. Locality. Given a rule of the form $A \Rightarrow B$ (fact A implies proposition B), then B can be concluded given fact A. It is not necessary to consider any other rules.

2. Detachment. Once a logical proof is found for a proposition B, the proposition can be used regardless of how it was derived.

3. Truth-functionality. In logic, the truth of complex sentences can be computed from the truth of the components.

There were several attempts to represent uncertainty in a rule-based inference system that retained these desirable properties. The central idea was to attach degrees of belief (probability) to propositions and rules and to devise purely local schemes for combining and propagating those degrees of belief. The belief in the rule is assumed constant and specified by the knowledge engineer. For example, $A \mapsto_{0.9} B$ is read as fact A implies B with 90% probability. However, [56] states that the properties of locality, detachment and truth-functionality are not appropriate for uncertain reasoning. Problems begin to occur when rules interact. The example they give is

$$Rain \mapsto_{0.99} WetGrass$$

$$WetGrass \mapsto_{0.5} Rain$$

The two rules allow for both causal and diagnostic reasoning, i.e., given that it is raining the probability of wet grass is 99% (causal), but also given that there is wet grass the probability that it is raining is 50% (diagnostic). This forms an undesirable feedback loop, the belief in rain increases the belief in wet grass, which in turn increases the belief in rain. Inter causal reasoning (explaining away) is also difficult to model. Given two rules

$$Sprinkler \mapsto_{0.99} WetGrass$$

$$WetGrass \mapsto_{0.5} Rain$$

The fact that the sprinkler is on increases the belief that the grass is wet, which in turn increase the belief that it is raining. This clearly does not make sense. This rule-based inference technique was developed for the MYCIN medical diagnosis system [9]. The modelling involved extremely careful engineering of the rules to avoid undesirable interactions. Most applications used either causal reasoning or diagnostic reasoning and rule sets were carefully designed to avoid interactions. Because of the difficulty in avoiding undesirable rule interactions, research into rule-based inference under uncertainty has been discontinued.

Both Roy and Heierman employ pattern recognition techniques (see sections 2.4.2 and 2.4.3). Both techniques are based on compression algorithms that compress a single mode event stream, location in Roy's case and device interaction in Heierman's. The level of compression is the measure of how significant a pattern is in the data. For example, Heierman uses a threshold of 80% compression to determine significant device interaction patterns. Although important, these techniques only deal with single mode streams and cannot infer context from multi-modal sensors.

The iDorm project (see Section 2.4.4) employs a fuzzy rule engine for inference and learning. Fuzzy set theory introduces the notion of vagueness, or how well an object satisfies a vague categorisation. The example that Russell [56] gives addresses the proposition of whether "Nate is TALL". Is this proposition true if Nate is 5' 10"? This is not a question of uncertainty in the world (we know that Nate is 5' 10"). The issue is that there are degrees of tallness. Fuzzy set theory treats TALL as a fuzzy predicate and says that the truth value of TALL(Nate) is a number between 0 and 1, rather than just being true or false. Fuzzy logic is the method for performing logical inference with fuzzy member sets. For example, the complex sentence $tall(Nate) \wedge heavy(Nate)$ is evaluated as $min(tall(Nate), heavy(Nate))$ (The symbol $\wedge$ is logical and[2] and the symbol $\vee$ is logical or). Fuzzy control is the method for constructing control systems in which the mapping between real-valued input and output parameters is represented by fuzzy rules. Again this rule-based approach suffers from the difficulty in avoiding undesirable rule interactions.

Brand (see Section 2.5.2) uses a Hidden Markov Model (HMM) for estimating user activities from video streams. HMMs are a specialised form of dynamic Bayesian network. They model the world as a set of states with transition probabilities between these states. The HMM models the user's activities as a set of states and the HMM transitions from state to state over time. Oliver [50] demonstrates that dynamic Bayesian networks have several advantages over HMMs. They encode causality in a natural way through the graphical modelling of relationships between variables. They represent uncertainty through the use of probability theory. The networks can be trained and can handle incomplete data (i.e., where the full set of variable values is unknown). There are algorithms for learning the structure of the networks (i.e., the relationships between variables). The network can be configured with prior knowledge and data before training. This can help the network make good inferences from the start. Finally, they are modular and can be parallelised.

Both Philipose and Oliver employ the use of Bayesian networks (see sections 2.5.1 and 2.5.3). Other researchers have also found Bayesian networks to be a good approach [41]. The sentient object model, on which the CAPM framework is loosely based, uses Bayesian networks for its inference (sensor fusion). From this evidence we selected Bayesian networks as the context inference component for the CAPM framework.

At the time of making our choice the advantages of Bayesian networks for CAPM we perceived were [26]:

1. The graphical programming model is simple to understand and modify by non-technical users.

2. The model naturally represents the causal modelling of the inferred data NOT USING and ABOUT

[2]This can be easily remembered as the $\wedge$ looks like the A of And.

TO USE.

3. The Decision network extension could be used to extend the decision component of the CAPM design.

4. The model can be configured with prior probability distributions so it can make intelligent (conservative) decisions from the start.

5. The learning process is relatively simple and should continually improve with more data.

6. Bayesian networks can solve up to 36 nodes with a tractable/lightweight algorithm.

We perceived one possible disadvantage of Bayesian networks being that if the prior distributions are incorrect, they can adversely affect the learning of an optimal policy.

Section 3.8 describes the actual evolution of the Bayesian models for CAPM. It shows that a significant amount of hand-crafting (trial and error) was needed in constructing the networks. Furthermore, at the evaluation stage some issues arose with learning in the Bayesian networks. Chapter 5 gives an evaluation of Bayesian networks for implementing CAPM.

3.5 Probability and Bayesian networks

Probability calculus was invented in the 17th century by Pierre Fermat and Blaise Pascal to deal with the problem of uncertainty in gambling. The basic element of the language is the *random variable*, which represents some entity or event in the world. Each random variable has a set of states. The type of a state can be either discrete[3] or continuous and the set of states must be mutually exclusive and exhaustive. An example of a discrete random variable is a coin C with states <heads, tails>. The two states are mutually exclusive, i.e., the coin can only be in one of the states at a time, and exhaustive, i.e., the set of states fully describe all possible events. We use the convention that names of random variables are capitalised and states are given in lower case. A proposition is a statement that a particular state will occur. For example, $C = heads$ is the proposition that the coin will land heads up. The probability of this proposition is $P(C = heads)$. A probability of $P(C = heads) = 0.5$ states either a belief or observed evidence that the coin will land heads up 50% of the time. Kolmogorov showed how to build all of probability theory from three fundamental axioms [1].

1. All probabilities are between 1 and 0. For any proposition x,

$$0 \leq P(x) \leq 1$$

[3]Boolean is a special type of discrete variable.

2. Necessarily true propositions have probability 1, and necessarily false propositions have probability 0.
$$P(true) = 1 \qquad P(false) = 0$$

3. The final axiom enables us to compute the probability of combined events. If the random variables are independent of each other then,
$$P(x \vee y) = P(x) + P(y)$$

Another form of axiom 3 is that $P(x \wedge y) = P(x) * P(y)$, this is the joint probability of both X and Y being true given that X and Y are independent. In the CAPM framework sensor observations are considered as events and are represented as random variables in the probability calculus. Example events might be the presence of a user in the vicinity of a device or of voice activity being detected in its vicinity. Axiom 3 gives us the basis to reason or infer probabilities about the occurrence of multiple events happening at the same time. Axiom 3 assumes that events are independent, which means the occurrence of one does not affect the probability of the other event occurring, i.e., one event does not cause or depend on the other event and vice versa. More formally, two events X and Y are independent if conditioning on (setting the value of) one variable leaves the probability of the other unchanged.
$$X \perp Y \Rightarrow P(X \mid Y) = P(X)$$
The previous equation reads as, if X and Y are independent, then the probability of X given the value of Y (conditioned on Y) is equivalent to the probability of X. Two rolls of dice are normally independent. Getting a 6 on the first roll does not influence the probability of getting a 6 again on the second roll. Given a fair dice, the probability of rolling a 6 is $1/6$. The probability of rolling two 6s in a row is $1/6^2$. However, independence between variables is a strong assumption that is often not the case. Consecutively picking 5 diamonds from a deck of cards is not simply $(1/4)^5$ as the probability of picking a second diamond is influenced by the fact there are less diamonds in the pack. The extension of axiom 3 for events that are dependent on each other gives the following equation.
$$P(X \vee Y) = P(X) + P(Y) - P(X \wedge Y)$$
This can be intuitively understood by considering the Venn diagram shown in Figure 3.8. $P(X)$ is equivalent to the area covered by the area of circle X and $P(Y)$ is equivalent to the area of the circle Y. $P(X \vee Y)$ can be visualised as the sum of both areas, $P(X) + P(Y)$, minus the intersection $P(X \wedge Y)$ so it is not counted twice.

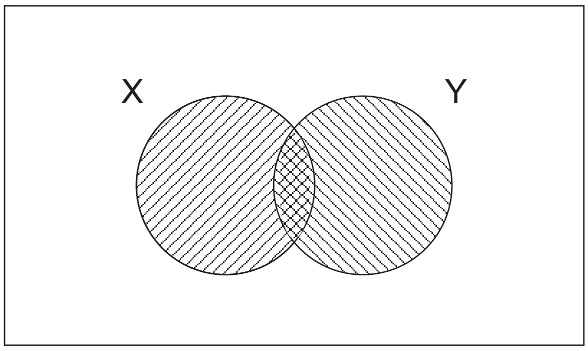


Figure 3.8: Venn diagram showing conditional probability

Conditional probability, $P(X \mid Y)$, can be defined in terms of unconditional probabilities by the following equation.

$$P(X \mid Y) = \frac{P(X \wedge Y)}{P(Y)}$$

Again, this can be seen intuitively from the Venn diagram, the probability of x occurring given that y has just occurred is the ratio of $P(X \wedge Y)$ (the intersection) to the whole of $P(Y)$. The product rule is derived from this equation.

$$P(X \wedge Y) = P(X \mid Y)P(Y)$$

The product rule gives us the joint probability for variables that are dependent. A joint probability distribution describes the probability of two or more events occurring. The full joint probability distribution specifies the probability of every combination of events and is therefore a complete specification of the uncertainty in the system. A particular value in the joint distribution is given as $P(X_1 = x_1 \wedge X_2 = x_2 \wedge ...X_n = x_n)$, which can be more compactly written as $P(x_1, x_2, ..., x_n)$. From the product rule, we can derive the chain rule, which allows us to express the full joint probability as a product of conditional probabilities.

$$P(x_1, x_2, ..., x_n) = P(x_1) * P(x_2 \mid x_1) * P(x_3 \mid x_1, x_2)..., *P(x_n \mid x_1, ..., x_{n-1})$$

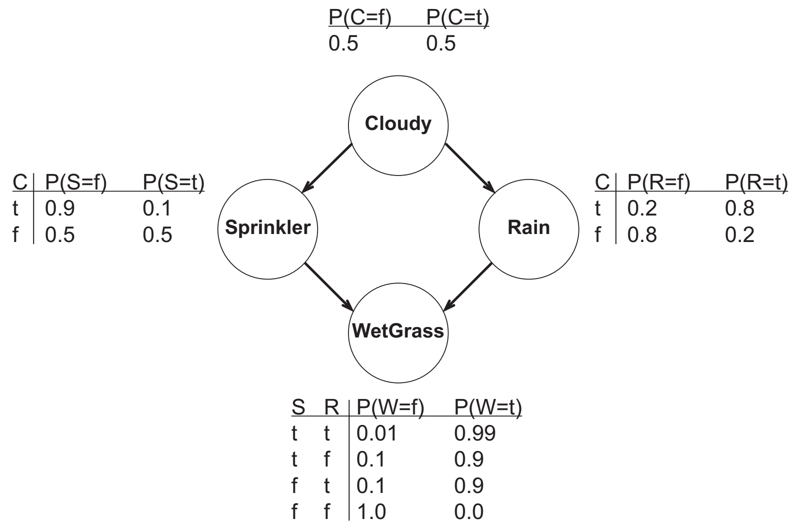
$$= \prod_i P(x_i \mid x_1, ..., x_{i-1})$$

However, this does not scale very well as the computation is exponential in the number of random variables to be solved for. For a domain described by n random variables, the size of the input table is $O(2^n)$ and the computation time is also $O(2^n)$.

3.5.1 Bayesian networks

Bayesian networks (BNs) are graphical models that represent the full joint probability distribution of a set of random variables in a tractable way. Nodes in the BN represent random variables (discrete or continuous) and arcs between nodes represent causal connections between variables, i.e., an arc from X to Y represents X causing Y, so they are dependent on each other. For discrete variables the strength of a causal dependence is modelled by a conditional probability table (CPT) associated with each node. There is one constraint on the arcs in that there can be no directed cycles, i.e., you cannot return to a node by following a sequence of directed arcs. Such graphs are called directed acyclic graphs (DAGs). Modelling with BNs requires the assumption of the Markov property. That is all direct dependencies (i.e., where one variable directly causes another) in the system must be explicitly shown via arcs. However, it is not necessary that there is a dependency for every arc modelled, as the CPT may be parametrised to nullify any dependency. This is done by setting all probabilities in the CPT as equal, so setting the value of the parent node does not influence the probabilities of the child node. A fully-connected BN can represent any joint probability distribution over the variables being modelled, although not in a very efficient manner. Given the Markov property, the value of a particular node is conditional only on its parent nodes, so the chain rule joint probability distribution can be reduced to

$$P(x_1, x_2, ..., x_n) = \prod_i P(x_i \mid Parents(X_i))$$



P(C=f)	P(C=t)
0.5	0.5

C	P(S=f)	P(S=t)
t	0.9	0.1
f	0.5	0.5

C	P(R=f)	P(R=t)
t	0.2	0.8
f	0.8	0.2

S	R	P(W=f)	P(W=t)
t	t	0.01	0.99
t	f	0.1	0.9
f	t	0.1	0.9
f	f	1.0	0.0

Figure 3.9: BN example

Table 3.1: Joint probability table

C	S	R	W	$P(C)$	$P(S \mid C)$	$P(R \mid C)$	$P(W \mid S \wedge R)$	$P(C \wedge S \wedge R \wedge W)$
1	1	1	1	0.5	0.1	0.8	0.99	0.0396
1	1	1	0	0.5	0.1	0.8	0.01	0.0004
1	1	0	1	0.5	0.1	0.2	0.9	0.009
1	1	0	0	0.5	0.1	0.2	0.1	0.001
1	0	1	1	0.5	0.9	0.8	0.9	0.324
1	0	1	0	0.5	0.9	0.8	0.1	0.036
1	0	0	1	0.5	0.9	0.2	0	0
1	0	0	0	0.5	0.9	0.2	1	0.09
0	1	1	1	0.5	0.5	0.2	0.99	0.0495
0	1	1	0	0.5	0.5	0.2	0.01	0.0005
0	1	0	1	0.5	0.5	0.8	0.9	0.18
0	1	0	0	0.5	0.5	0.8	0.1	0.02
0	0	1	1	0.5	0.5	0.2	0.9	0.045
0	0	1	0	0.5	0.5	0.2	0.1	0.005
0	0	0	1	0.5	0.5	0.8	0	0
0	0	0	0	0.5	0.5	0.8	1	0.2

This offers a significant reduction in computing to work out the full joint probability, especially for networks with few parents. An example BN is shown in Figure 3.9. It models four boolean random variables Cloudy, Sprinkler, Rain and WetGrass. Cloudy causally affects the probability of both the Sprinkler being on and it Raining, which in turn causally affects whether the grass is wet or not (WetGrass). We can use the BN to reason both causally and diagnostically.

The joint probability table for the network is shown in Table 3.1. Each conditional probability is simply read from the BN's CPTs and the joint probability distributions are simply the product of the conditional probabilities from the chain rule. It is interesting to note that the sum of the column of joint probabilities is 1. This concurs with the fact that all states are mutually exclusive and the sum of their probabilities is 1.

From the table we can derive the probability of any combination we are interested in. For example, we could calculate the probability of the grass being wet, $P(W = t)$ by simply summing all of the rows where $W = t$. This gives $P(W = t) = 0.647$, i.e., given no evidence the probability of the grass being wet is 64.7%. This is also known as the *prior* probability, as it is the probability before we observe any evidence. The posterior probability is the probability calculated after we observe something.

We can reason causally, for example, by observing that the weather is cloudy ($C = t$). What affect does this have on the probability of the grass being wet? We can use the table again to update our belief in the grass being wet given the information that it is cloudy, $P(W = t \mid C = t)$. This can be calculated by summing the columns where $C = t$ and $W = t$ and dividing by the sum of columns where $C = t$, $P(W = t \mid C = t) = \frac{P(W=t \wedge C=t)}{P(C=t)} = \frac{0.3726}{0.5} = 0.745$. Given that we know it is cloudy the probability of wet grass has increased to 74.5%.

To reason diagnostically (in the other direction) we need to apply Baye's rule, which can be derived from the product rule. The product rule, $P(X \wedge Y) = P(X \mid Y)P(Y)$ can also be written as $P(X \wedge Y) = P(Y \mid X)P(X)$. Equating both right hand sides and dividing by$P(X)$ gives

$$P(Y \mid X) = \frac{P(X \mid Y)P(Y)}{P(X)}$$

This is Baye's rule and is used to calculate a conditional probability given the conditional probability in the other direction and two unconditional probabilities. For example, we may wish to calculate the probability of Cloudy given the Sprinkler is on. Given Baye's rule, $P(C = t \mid S = t) = \frac{P(S=t|C=t)*P(C=t)}{P(S=t)}$. We can calculate $P(S = t \mid C = t) * P(C = t)$ and the unconditional probability $P(S = t)$ from the tables. From the product rule $P(S = t \wedge C = t) = P(S = t \mid C = t) * P(C = t)$, which is the sum of the columns where $S = t$ and $C = t$ (0.05), and $P(S = t)$ is the sum of columns where $S = t$ (0.3). So, $P(C = t \mid S = t) = \frac{0.05}{0.3} = 0.1666$. So, the probability of it being cloudy when the sprinkler is on is 16.7%. Hence, a Bayesian network can be used to efficiently calculate the probability of any particular event occurring given the set of observations that are available.

In a ubiquitous computing scenario, the goal is to estimate the current context based on input from the available set of sensors in the environment. The basic BN structure is shown in Figure 3.10, where the context we want to infer is the parent node of the sensors. This is known as a "naive Bayes" model and it assumes that the sensor variables are independent of each other given the context. This independence is shown by the lack of arcs between the sensor nodes. The states of the context variable is the list of all possible context values (e.g., USING, NOT USING). The reasoning is diagnostic whereby the given context value is perceived to cause the current sensor values. For example, given that the user is USING the PC causes the Bluetooth sensor to detect the presence of the user's Bluetooth tag. To query the most probable current context, the physical sensors are sampled and the sensor node values are set to the sampled values. Then an update of the probabilities for the context is performed given the new sensor values.

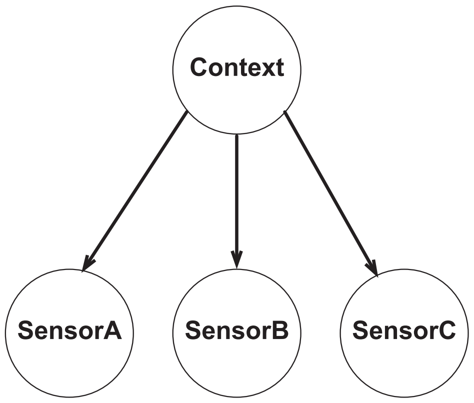


Figure 3.10: Example BN for ubiquitous computing

3.5.2 Dynamic Bayesian networks

Bayesian networks model probabilistic relationships between a set of variables at a particular point in time. They cannot explicitly model temporal relationships between a variable at different points in time. The only way to do this would be to add another variable with a different name representing the variable at a previous point in time. To model these temporal relationships, Bayesian networks can be extended to dynamic Bayesian networks, which model probabilistic relationships between variables that occur at different points in time [46].

Dynamic BNs assume that changes occur between discrete time points, indexed by non-negative integers and up to some finite time T. Let $\{X_1, X_2, ..., X_n\}$ be the set of random variables whose values change over time and $X_i[t]$ be a random variable representing the value of X_i at time t for $0 \leq t \leq T$. A simple dynamic Bayesian network is effectively a Bayesian network containing the variables that constitute the T random vectors $X[t]$ and which is determined by the following specifications:

1. An initial Bayesian network consisting of an initial DAG containing the variables $X[0]$ and an initial probability distribution for these variables.

2. A transition Bayesian network that is a template consisting of a transition DAG containing the variables in $X[t]$ and $X[t+1]$, and a transition probability distribution that assigns a conditional probability to every value in $X[t+1]$ given every value of $X[t]$.

3. The dynamic Bayesian network containing the variables that constitute the T random vectors consists of the DAG composed of the DAG G_0 and for $0 \leq t \leq T-1$ the DAG G evaluated at

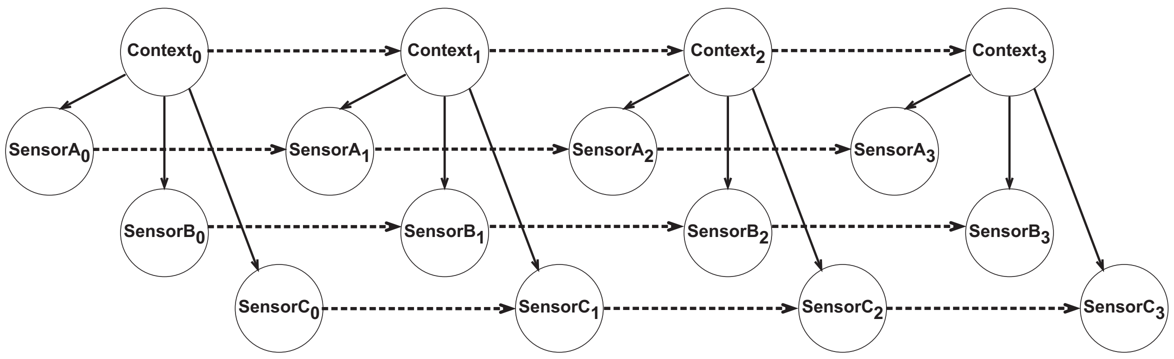


Figure 3.11: Example DBN rolled out to 3 time slices

t and the following joint probability distribution.

$$P(x[0], ..., x[T]) = P_0(x[0]) \prod_{t=0}^{T-1} P(x[t+1] \mid x[t])$$

All the information needed to predict a world state at time t is contained in the description of the world at time $t-1$. No information about earlier times is needed. Owing to this, we say the process has the Markov property.

So, in effect a DBN can be thought of as a BN that has been rolled out in time. An example is shown in Figure 3.11, which is an extension of the ubiquitous computing BN in Figure 3.10. The initial Bayesian network is the same structure as in Figure 3.10 but the nodes are subscripted with $t = 0$. The transition Bayesian network is shown by the dashed arrows, which contain the transition probability distributions for the nodes in one time step to the next time step. The DBN has been rolled out to 3 time slices. If the time step between slices is 20 seconds, then by querying the Context$_3$ variable, we are querying what will be the context 1 minute into the future. This could be useful for CAPM as it is necessary to know what the context of the user will be a break-even time into the future (i.e., will they be still NOT USING the PC in one minute's time).

3.6 Parameter learning for Bayesian networks

The values for the CPTs of a Bayesian network can either be set according to a domain expert's beliefs or they can be learned from past observed data. This learning of the network's CPTs is called parameter learning (i.e., learning the probability parameters of the CPT). The other type of learning, structure learning, deals with learning the dependency arcs (structure) of the network and is not dealt with here. Probabilities that are learned from data are termed relative frequencies. For a set of m

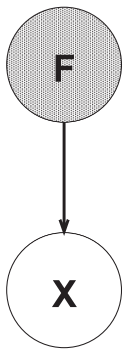


Figure 3.12: Augmented Bayesian network

identical repeatable experiments the relative frequency approaches a limit, which is the probability of the outcome [65].

$$p = lim_{m \to \infty} \frac{\sharp outcomes}{m}$$

As an example, consider tossing a thumbtack. If we tossed the thumbtack 10,000 times and it landed heads 3,373 times, the estimate for the probability of heads is about 0.3373.

3.6.1 Parameter learning for binary variables

We first consider learning the probability parameters for a single binary variable. Let X be a binary random variable with possible values 1 and 2. The technique for learning is to use another random variable F with values in the interval $[0, 1]$ to model the belief in the probability of X. This technique is called an augmented Bayesian network as it includes a node representing our belief about another node's probability distribution given evidence data (see Figure 3.12).

The probability distribution for F can be modelled as a Beta distribution ($beta(f)$) [46]. The Beta distribution having parameters $a, b, N = a + b$, where a and b are real numbers > 0, is defined in terms of the Gamma distribution Γ as

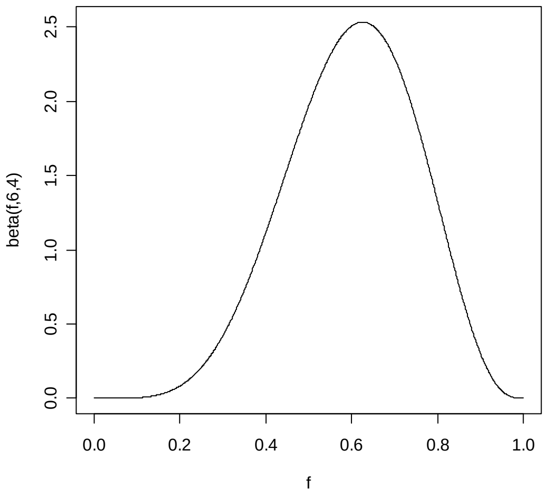
$$beta(f) = \frac{\Gamma(N)}{\Gamma(a)\Gamma(b)} f^{a-1}(1-f)^{b-1} \qquad\qquad 0 \le f \le 1$$

If F has a Beta distribution with parameters $a, b, N = a + b$, then the expected value for F, $E(F)$ is given as

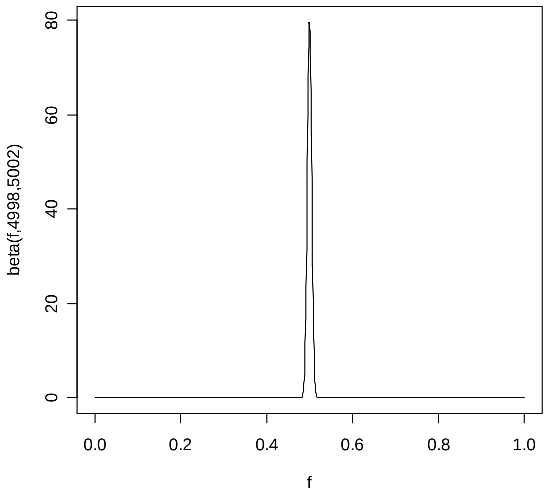
$$E(F) = \frac{a}{N}$$

We can think of a and b as the counts for each outcome 1 and 2, and N is the total count of both outcomes. As an example, we consider a coin toss C with two possible outcomes, heads and tails. So, if we observe 6 heads from 10 coin tosses, then the expected value $E(F)$ for the probability

$P(C = heads)$ is $\frac{a}{N} = \frac{6}{10} = 0.6$. The Beta distribution not only gives us the expected value for the probability $P(C = heads)$, it represents the strength of belief in this probability given the number of observations that have been made.



(a) Beta(6, 4)



(b) Beta(4998,5002)

Figure 3.13: Beta distributions

Figure 3.13 shows two Beta distributions, Figure (a) shows the belief in $P(C = heads) = 0.6$ after 10 observations and Figure (b) shows the belief in $P(C = heads) = 0.4998$ after 10,000 observations. The distribution is much more strongly focused in Figure (b), representing a stronger belief in the estimate. To continually learn from the observed data we simply need to keep updating F's Beta distribution given the newly observed data d. Given a sample, the probability distribution of F conditional on data d is called the updated density function of the parameters and is given by

$$beta(f \mid d) = beta(f; a + s, b + t)$$

Figure 3.14 shows an example Beta distribution with 3 observations for heads and 3 observations for tails. Subsequently, a further 8 observations for heads and 2 observations for tails are made. The new updated distribution, $beta(f; 11, 5)$, has an estimated probability for $P(C = heads) = 0.6875$ and the belief has grown in strength.

The theory for learning the parameters of a single binary random variable can be simply extended to all variables in a Bayesian network by generalising the augmented Bayesian network. From [46], an augmented Bayesian network (G, F, ρ) is a Bayesian network determined by the following:

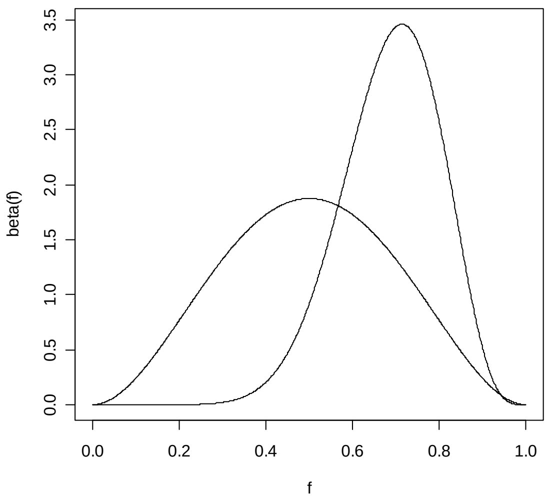


Figure 3.14: Updating the Beta distribution

1. A DAG $G = (V, E)$ where $V = \{X_1, X_2, ..., X_n\}$ and each X_i is a random variable.
2. For every i, an auxiliary parent variable F_i of X_i and a Beta distribution $beta_i$ of F_i. Each F_i is a root and has no edge to any variable except X_i. The set of all F_is is denoted by F.
3. For every i, for all values pa_i of the parents PA_i in V of X_i and all values f_i of F_i, a probability distribution of X_i conditional on pa_i and f_i.

The nodes in F represent the beliefs concerning the unknown conditional probabilities (parameters) needed for the DAG. Since the F_is are all root nodes, they are mutually independent, which simplifies the calculation of their joint probability distribution.

3.6.2 Learning multinomial variables

The theory developed for binary variables can be easily extended to multinomial discrete variables by use of the Dirichlet distribution, which generalises the Beta distribution. A multinomial variable is a variable with more than two values. The Dirichlet distribution with parameters $a_1, a_2, ..., a_r, N = \sum_{k=1}^{r} a_k$, where $a_1, a_2, ..., a_r$ are integers ≥ 1, is

$$dirichlet(f_1, f_2, ..., f_{r-1}) = \frac{\Gamma(N)}{\Gamma_{k=1}^{r}\Gamma(a_k)} f_1^{a_1-1}, f_2^{a_2-1}, ..., f_r^{a_r-1} \; 0 \leq f_k \leq 1, \; \sum_{k=1}^{r} f_k = 1$$

The random variables $f_1, f_2, ..., f_{r-1}$ represent the probabilities for r values of the node in question. The probability assessor's experience is equivalent to having seen the k^{th} value occur a_{k} times in N trials. We can think of a_{k} as representing the count of outcomes for the k^{th} value. The expected value for any F_k is given by

$$E(F_k) = \frac{a_k}{N}$$

Learning for all multinomial variables in a Bayesian network can again be extended by the augmented Bayesian network for multiple variables.

The Spiegelhalter Lauritzen algorithm [61] is a commonly used learning algorithm available in many of the BN tools. It uses the augmented Bayesian network technique as described above. The two main assumptions behind the algorithm are that all nodes are represented as Dirichlet distributions and the parameters of the CPTs are mutually independent. Since the nodes are Dirichlet distributions, the values of the nodes must be discrete. Therefore variables that are naturally continuous (such as time) must be discretised and given finite limits. The simplification of assuming mutual independence between the parameters only works well for networks with a significant amount of training data compared to the number of parents in the network. This is less of a problem for networks with few parents, such as in the case of the example ubiquitous computing BN.

3.7 Choice of sensors for CAPM

The sensors used in the initial experimental trial were user presence from the user's Bluetooth phone and idle time from the keyboard and mouse. For the final user study the Bluetooth phone was replaced by dedicated Bluetooth tags as not enough users had Bluetooth-enabled phones to conduct the study. The choice of additional sensors was motivated by the preference to use sensors that we believe will be part of future pervasive/ubiquitous computing environments.

It is likely that a web camera and microphone will become integrated in the PC display as the popularity of video communication applications increases. Therefore we chose to use both of these sensors to capture finer-grained context. Oliver et al. (see Section 2.5.3) also uses a web camera and microphone to infer user activities in an office environment. Their system, S-SEER, consumed a significant proportion of the CPU resources (on average 33.4%), primarily due to the large amount of video and acoustic feature processing. For our system we chose a standard face detection algorithm as the single feature to extract from the video stream and a basic voice activity detection algorithm for the acoustic stream. The face detection only detects a face that is looking straight at the camera and the voice activity gives a measure from 0% to 100% of the level of voice activity detected in the environment.

The final sensor chosen was an ultra-sonic object range sensor in order to detect near presence of the user. We do not envisage this sensor as being part of a standard pervasive computing environment and so it would need to be installed as part of a CAPM solution. The motivation for choosing it was that it could possibly give good information at low energy cost, as there is no need for expensive feature processing. Infra-red object range sensing could also have been used. A possible benefit of this would be the additional sensing as to whether the object was warm or cold. We chose the ultra-sonic sensor as the technology was already available within the research group.

3.8 Design of BNs for CAPM

We divided the problem into designing a distinct type of BN for each inference task, i.e., NOT USING for at least the break-even period and ABOUT TO USE at least the resume time beforehand. The structure of both types of BN is similar but they use different sensors and different sensor models. Development of the two types of BN was an iterative approach, starting with simple models and evolving the models to cope with issues that occurred. The models were evaluated through actual simulation on real usage traces. This section describes the evolution of the BN models, starting with the initial BN we developed, then describing the final-stage BN and finally the dynamic BN model. The learning of the BN models' parameters is also described.

3.8.1 Initial models

The initial model is based on the naive Bayes structure, which is a standard approach for inference of context based on a set of observed features [56].

3.8.1.1 Not using

Figure 3.15 details the initial BN for the NOT USING (NU) context. The IsNotUsing node is the query node, we are asking what is the probability that the user is NOT USING the device for at least the given break-even time. This node has causal connections to each of the sensor nodes. This represents the fact that the user USING (U) or NOT USING the device is causing the observed sensor readings. The initial model did not include the object range detection sensor and the CPTs were manually estimated, i.e., not learnt from the data. To estimate the CPTs we must estimate what the sensor values are likely to be given that the user is USING and NOT USING the device. For example, given the user is USING the device we estimated the probability of IdleTime=0-1 minute is 0.7, Bluetooth

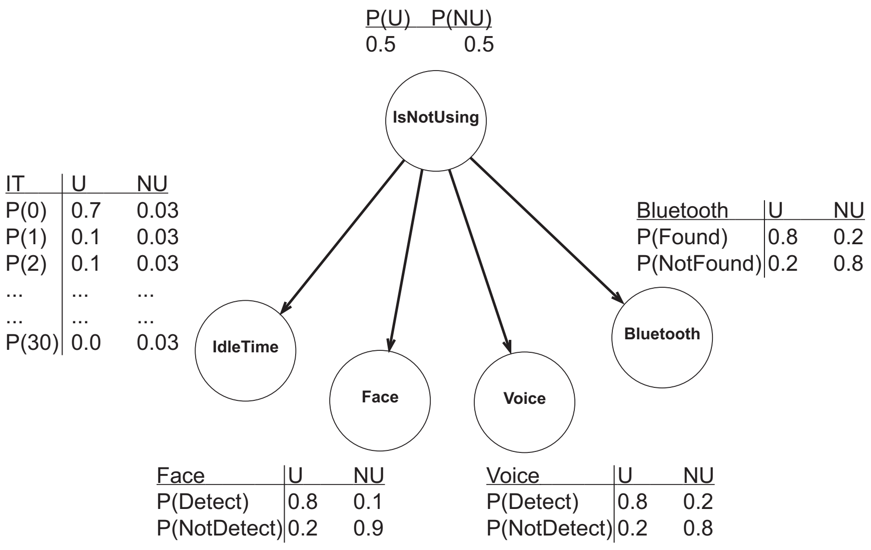


Figure 3.15: Initial NOT USING model

found is 0.8, Voice detected is 0.8, and Face detected is 0.8. Given the user is NOT USING the device, the probability of IdleTime=0-1 minute is 0.03, Bluetooth found is 0.2, Voice detected is 0.2, and Face detected is 0.1. Given the full set of CPTs the model can reason diagnostically from the sensor values to give the probability of the user NOT USING the device. The power-down decision threshold was set at a probability of NOT USING greater than or equal to 0.8 (80%). This threshold figure was derived from trial and error experimentation with the model.

The main drawback associated with the model was its absence of recent history for sensor readings. For example, the Bluetooth node either recorded the Bluetooth tag as found or not found. There is no representation of whether in the previous scan the tag was found or not. Given that making a Bluetooth connection can be unreliable, i.e., the scan may not detect the tag even though it is there, it was desirable to record the history of when the tag was last found. If it was found one scan ago, it may be that the tag is still there and the scan just missed it. This would be much less likely if the tag had not been found for the last 10 scans. The history was recorded by using a simple counter and is explained in the next section. Again, the same problem was found for the Face detection node and a counter was used to record its recent history. The initial Voice node was modelled as whether there was voice detected in the last 5 second recording, i.e., whether the percentage of voice activity was greater than 10%, or not. This did not work well as during a conversation voice can vary considerably with significant silent periods. The IdleTime node was discretised into one minute intervals, 0 to < 1

minute, 1 to < 2 minutes, 2 to < 3 minutes, up to 30 minutes and greater. The 0 to 30 minute range for the IdleTime node was found to be too long and was shortened for the final BN model.

3.8.1.2 About to use

The ABOUT TO USE model is similar in structure to the NOT USING model but does not include the IdleTime sensor as it is not a good indicator of when a user is ABOUT TO USE the device, (see Figure 3.16).

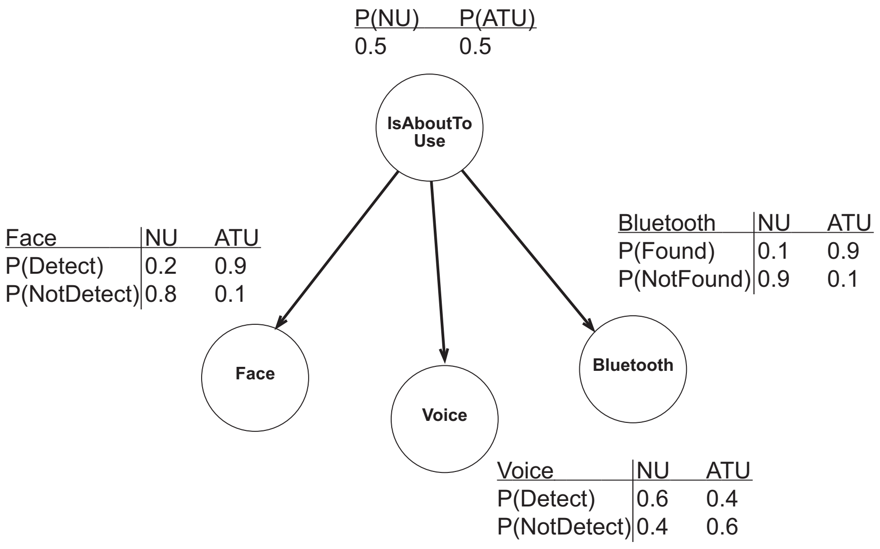
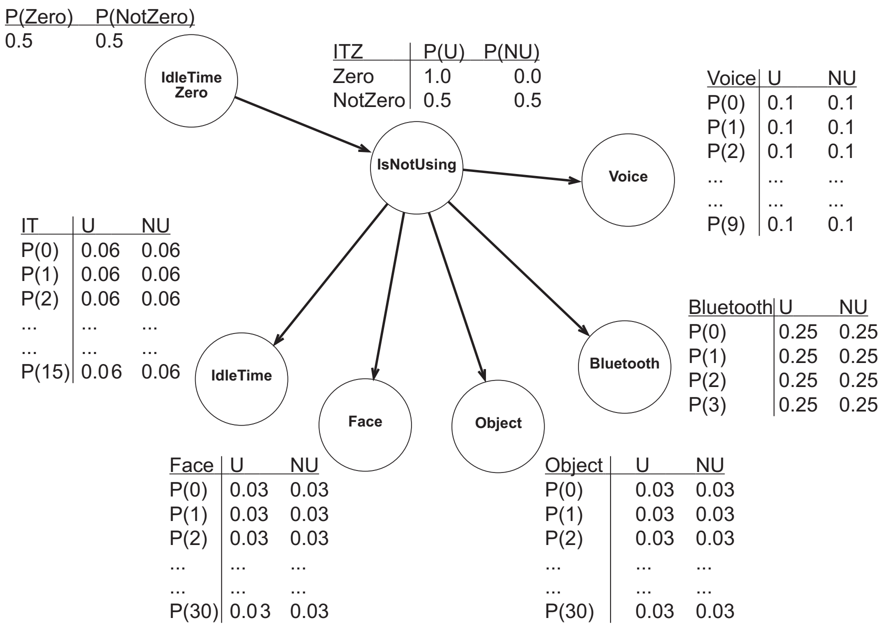


Figure 3.16: Initial ABOUT TO USE model

The CPTs for this model were set so that detecting either the Bluetooth tag or the Face would increase the belief in ABOUT TO USE past the power-up threshold (60%) and hence power up the device. The main issue with this model was that it did not handle the case where the device is powered down and the user is still there. Because the Bluetooth tag is still being detected this model causes the device to be powered back up again straight away. The final BN model provides a solution to this issue.

3.8.2 Final BN models

The final BN models accounted for the issues that occurred in the initial models.



P(Zero)	P(NotZero)
0.5	0.5

ITZ	P(U)	P(NU)
Zero	1.0	0.0
NotZero	0.5	0.5

Voice	U	NU
P(0)	0.1	0.1
P(1)	0.1	0.1
P(2)	0.1	0.1
...	...	...
...	...	...
P(9)	0.1	0.1

IT	U	NU
P(0)	0.06	0.06
P(1)	0.06	0.06
P(2)	0.06	0.06
...	...	...
...	...	...
P(15)	0.06	0.06

Bluetooth	U	NU
P(0)	0.25	0.25
P(1)	0.25	0.25
P(2)	0.25	0.25
P(3)	0.25	0.25

Face	U	NU
P(0)	0.03	0.03
P(1)	0.03	0.03
P(2)	0.03	0.03
...	...	...
...	...	...
P(30)	0.03	0.03

Object	U	NU
P(0)	0.03	0.03
P(1)	0.03	0.03
P(2)	0.03	0.03
...	...	...
...	...	...
P(30)	0.03	0.03

Figure 3.17: Final BN NOT USING model

3.8.2.1 Not using

The Bluetooth node is modelled with four states, 0 to 3. A counter is used to count the number of times the Bluetooth tag is not found. A value of 0 represents the tag found, 1 represents not found once, 2 represents not found twice, etc. The value of three counts was chosen by analysing test connection data for the Bluetooth tag; we did not observe the Bluetooth scan missing the tag more than three times in a row, when it was actually in the vicinity. The Bluetooth scan occurs about every 10 seconds so it takes approximately 30 seconds to reach a value of 3 (i.e., the tag is almost definitely not in the vicinity).

The Face detection node is modelled with 31 states. The face counter counts from 0 to 30, with 0 representing the face detected, 1 represents not detected once, and so on. The sensor is sampled every 5 seconds, so the time it takes to reach the value 30 is about $2\frac{1}{2}$ minutes. We used this longer count as not looking at the display is not as good a cue for NOT USING as the person not being present. This is because it takes longer for a person to return from not being present than for them to turn around and face the display again.

The Object range node was also added to this network. The object range sensor reports the distance of the nearest object in centimeters. In order to model this sensor in a similar way to the

Face detection node it is necessary to establish the range in centimeters where the user is USING and NOT USING the device. For example, a user may use the device in the range 30cm to 90cm and when they are not using the device the range sensor reports from 110cm to 150cm. The range values whereby the user is USING and NOT USING the device are determined first by analysing the measured usage of the device. Then, similar to the Face detection, a counter is used to count when the user is detected in the NOT USING range (e.g., 110cm to 150cm). A higher count means the sensor has been detecting range values in the NOT USING range for longer. The counter is reset to zero when the user is detected in the USING range or in neither of these ranges. Again, the Object range node is modelled with 31 states for the same reason as the Face node.

Voice was recorded in 5 second samples and processed to extract the percentage of voice in the 5 second sample. As conversations can have silent periods within them the voice recognition percentage can fluctuate considerably throughout a conversation. To cope with this we averaged over the 5 past values (about 25 seconds) to achieve a smoothed representation of the detection of voice in the environment. Based on observed traces of voice activity, this seems of be a reasonable period, smoothing out the voice prediction to take into account typical conversation. The Voice sensor is modelled with 10 states representing 0% to $< 10\%$ voice activity, 10% to $< 20\%$ voice activity, up to 100% voice activity. This more detailed resolution than the simple detected/not detected model was chosen as the CPTs for the final BN are trained from the data. It was thought that potentially different levels of voice activity would relate to USING and NOT USING cues.

We reduced the IdleTime node's number of states from 31 to 16. The reason for this was the idle time values for when the user was USING the device rarely went past 15 minutes and so the values past 15 minutes did not have sufficient data for proper training of the CPT.

Finally, the IdleTimeZero node is used to set the probability of USING to 1 if the idle time is between zero and one minute. It was necessary to implement this rule to avoid a large number of false power downs caused by the NOT USING threshold being reached too quickly.

The CPTs for all of the sensor nodes are initially set to an even distribution as they are learnt from the measured usage trace collected for each user in the user study. Table 3.2 shows an example of the supervised data (training cases) used as input to the Speigelhalter-Lauritzen learning algorithm. The cases are sampled at 10 second intervals from the start to end of one day of the user study. Each case contains the values of the observed sensor nodes and the measured context, USING or NOT USING. Any short NOT USING period, which is less than the device's break-even time is also considered to be a USING training case. The set of cases shows a transition from USING the PC to NOT USING the PC. The Bluetooth values go from 0 to 3 and the FaceDetect and ObjectRange values begin to increase.

Table 3.2: Example BN training cases

No.	IdleTime	Bluetooth	FaceDetect	VoiceActivity	ObjectRange	IsNotUsing
1	*	0	2	*	1	Using
2	*	0	1	*	0	Using
3	*	0	1	*	0	Using
4	*	0	1	*	0	Using
5	*	0	0	*	0	Using
6	*	0	2	*	2	Using
7	*	1	4	*	4	*
8	*	2	6	*	5	*
9	*	3	8	*	7	*
10	*	3	10	*	9	*
11	*	3	12	*	11	*
12	1	3	14	*	12	*
13	1	3	16	*	14	NotUsing
14	1	3	18	*	16	NotUsing
15	1	3	20	*	18	NotUsing
16	1	3	22	*	19	NotUsing
17	1	3	24	*	21	NotUsing
18	2	0	25	*	0	NotUsing
19	2	0	27	*	1	NotUsing
20	2	0	29	*	3	NotUsing

The asterisks (*) represent values that are not to be included in the learning. These include idle time values less than one minute, voice activity values of 0% and any cases where the value of USING/NOT USING is not known. Given this supervised training data the expected probabilities of the CPTs are estimated.

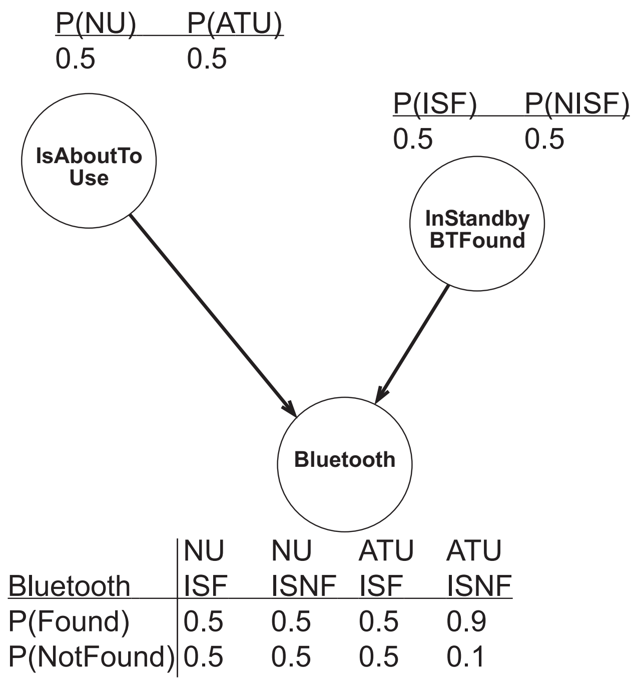
To give a concrete example of the learning theory explained in Section 3.6, we consider learning of the CPTs for the Bluetooth node based on the set of cases given in Table 3.2. The Bluetooth node is a multinomial variable with four values 0, 1, 2 and 3. For each state of the parent node IsNotUsing, there is a Dirichilet distribution, F, that represents the expected probability of each of the Bluetooth values, given the parent state. For example, given the user is USING the PC we expect the probability of the Bluetooth value 0 (i.e., detected) to be high. The distribution has four parameters a_1, a_2, a_3 and a_4 to represent the number of times each Bluetooth value is observed in the given parent state, and the parameter N, which keeps a total count of the number of cases observed. The expected probability for any of the Bluetooth values is given as $E(F_k) = \frac{a_k}{N}$. Initially the expected probability for all values in the Bluetooth node's CPTs are evenly distributed with value $\frac{1}{4}$. In the first training case, the parent state is USING and the Bluetooth value is 0. Therefore the expected probability for Bluetooth value 0 given USING rises to $\frac{2}{5}$ and the expected probabilites for the other values reduce to $\frac{1}{5}$. By the sixth case the expected probability for Bluetooth value 0 given USING rises to $\frac{7}{10}$ and the probability for the other values reduce to $\frac{1}{10}$. For the following six cases, the state of IsNotUsing is not known and hence these cases cannot be learnt. The thirteenth training case is the first case where the parent state is NOT USING. Therefore the expected probability for Bluetooth value 3 given NOT USING rises to $\frac{2}{5}$. By the seventeenth case, this probability has risen to $\frac{6}{9}$. In the eighteenth case the Bluetooth tag is detected again (value 0) but the user is still not using the device. Therefore the expected probability for Bluetooth value 0 given NOT USING rises to $\frac{2}{10}$. By the final case the expected probabilities for Bluetooth values 0, 1, 2, 3 given NOT USING are $\frac{4}{12}$, $\frac{1}{12}$, $\frac{1}{12}$ and $\frac{6}{12}$ respectively.

This has given a concrete example of how the case data is used for learning the CPTs. Example CPTs for each of the sensor nodes, which have been trained on a full day of case data are described in Section 4.1.

3.8.2.2 About to use

In the initial ABOUT TO USE model the device is powered up anytime the Bluetooth tag is detected. This causes a problem when the device is put into standby and the Bluetooth tag is still being found in the vicinity. The model was extended by adding the InStandbyBTFound node to model this InStandbyFound (ISF) state. When in the ISF state the influence of the Bluetooth tag being found is nullified (the probability of Bluetooth being found is 0.5 for both the NOT USING (NU) and ABOUT TO USE (ATU) cases). This prevents the presence of the Bluetooth tag causing the device to be immediately powered up again. Only when the device powers down to standby and the tag is not found (ISNF), will the device power up due to the Bluetooth tag being found again.

The ABOUT TO USE model needs to power up the device as quickly as possibly to avoid the user experiencing any resume-time delay. Therefore it is not necessary to extend the Bluetooth node to record recent history as it needs to power up the first time the Bluetooth tag is detected. This requirement to power up quickly causes a problem for the Face and Object range sensors, as they are more prone to reporting false detections. When either of the sensors falsely detected a face or object,



P(NU)	P(ATU)
0.5	0.5

P(ISF)	P(NISF)
0.5	0.5

	NU	NU	ATU	ATU
Bluetooth	ISF	ISNF	ISF	ISNF
P(Found)	0.5	0.5	0.5	0.9
P(NotFound)	0.5	0.5	0.5	0.1

Figure 3.18: Final BN ABOUT TO USE model

the device was powered up. Therefore, in the final version of the ABOUT TO USE model the Face and Object range sensors were not used as they caused too many false power ups. The Voice sensor was not used either as it is not a good indicator of ABOUT TO USE. The CPTs for the ABOUT TO USE model are fixed (i.e., not learnt from the data) as shown in Figure 3.18.

3.8.3 DBN models

Finally, a dynamic Bayesian model was designed to investigate if this technique could improve on the performance of the final Bayesian model, in particular, for devices with relatively long break-even times.

3.8.3.1 Not using

The DBN NOT USING model is a simple extension of the final BN model to include a number of time slices in the future. The structure of the nodes is the same within a time slice and the transition arcs link a node in the previous time slice to the corresponding node in the next time slice (see Figure 3.19). This rolled out network is effectively a standard Bayesian network and the techniques for inference updating and learning are the same. The IdleTimeZero node is only needed at the final IsNotUsing$_6$ node to implement the rule of USING if the idle time is less than one minute. The size of the time step between time slices is calculated as the break-even time of the device divided by the number of time slices (6). Therefore, if the break-even time is one minute, the time step is 10 seconds; if the break-even is 6 minutes, the time step is one minute. This gives the prediction of the NOT USING probability for the IsNotUsing$_6$ query node to be the break-even time in the future for the device.

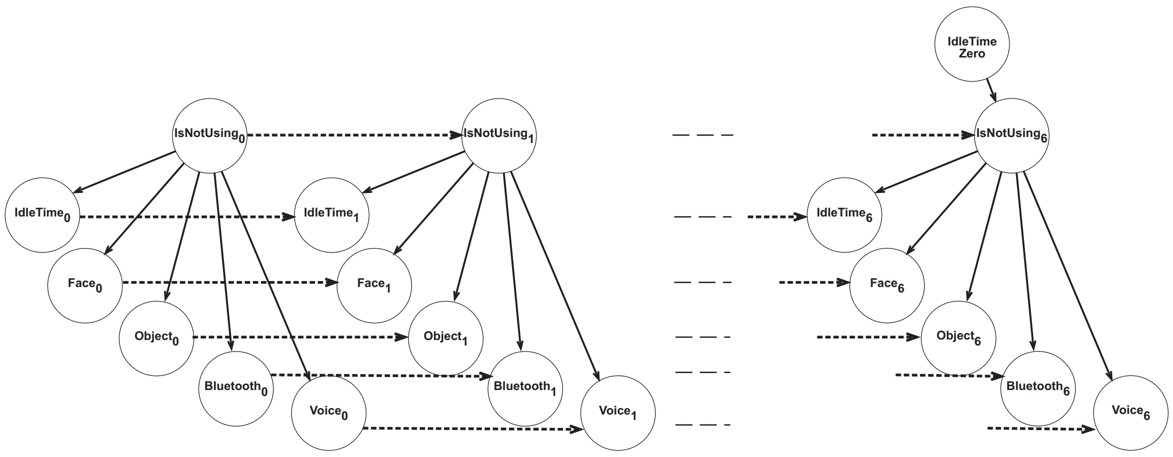


Figure 3.19: DBN NOT USING model

Again, as for the learning of the BN model, the CPTs for all sensor nodes are initially set to an even distribution. The training cases are sampled at the given DBN time step (e.g., 10 seconds, 1 minute) from the start to end of one day of the user study. The training cases for the DBN are much wider as a value is needed for each sensor node in the each of the time slices. Table 3.3 shows an example set of training cases for the six time slices of the Bluetooth nodes and the IsNotUsing$_6$ node. A complete case would include all of the nodes in each of the time slices. The example set of cases shows the Bluetooth nodes values changing from detected (0) to not detected (3) as the IsNotUsing$_6$ node transitions from USING to NOT USING the PC. Training the DBN model with the complete case data learns both the conditional probabilities of the nodes (e.g., the probable values of BT6 given the IsNotUsing$_6$ state) and the transition probabilities between nodes in the subsequent time slice (e.g., the probable values of BT6 given the value of BT5).

Table 3.3: Example training cases for the DBN model

BT0	BT1	BT2	BT3	BT4	BT5	BT6	INU6
0	0	0	0	0	0	0	Using
0	0	0	0	0	0	0	Using
0	0	0	0	0	0	0	*
0	0	0	0	0	0	1	*
0	0	0	0	0	1	2	*
0	0	0	0	1	2	3	*
0	0	0	1	2	3	3	*
0	0	1	2	3	3	3	*
0	1	2	3	3	3	3	NotUsing
1	2	3	3	3	3	3	NotUsing

3.8.3.2 About to use

It was decided to use the final BN ABOUT TO USE model for the power-up policy. This was because the policy does not need to predict far into the future and needs to react quickly in order to power up the device in time.

3.9 Summary

The initial experimental results for simple location-aware power management policies helped in identifying several key requirements for CAPM. These are the requirement for prediction of the contexts NOT USING and ABOUT TO USE, the need for finer-grained context other than coarse-grained location, the need for distant prediction to overcome long resume times and delays in sensors, the need for distributed sensing for prediction of longer idle periods, the need for a robust algorithm to cope with decisions under uncertainty, and finally the need for adaptation to adjust power management to suit the individual.

The design of the CAPM framework is loosely based on the sentient object model, which enables distributed sensing and subsequently distant prediction such as mobility prediction. The main focus was on the core parts of the framework, namely the data capture and feature extraction, context inference and decision components. A number of inference techniques were considered and from these, Bayesian networks were selected to implement the context inference component. Based on probability theory, they enable inference based on uncertain data and provide mechanisms for learning to adapt to users' behaviours. The set of sensors selected for CAPM of desktop PCs were a Bluetooth tag, web camera, microphone, ultra-sonic object range sensor and idle time from the mouse and keyboard input events. The design of the networks involved substantial trial and error modelling until a final BN model was settled on. The evolution of the design of the Bayesian networks is detailed. Finally, a dynamic Bayesian model was also designed so its performance could be compared to the BN model's performance.

The next chapter details the implementation of the CAPM framework for power management of desktop PCs and their displays.

Chapter 4

Implementation

This chapter describes the implementation of the CAPM framework for power management of desktop PCs and their display units in an office environment. Figure 4.1 shows the structure of the implementation.

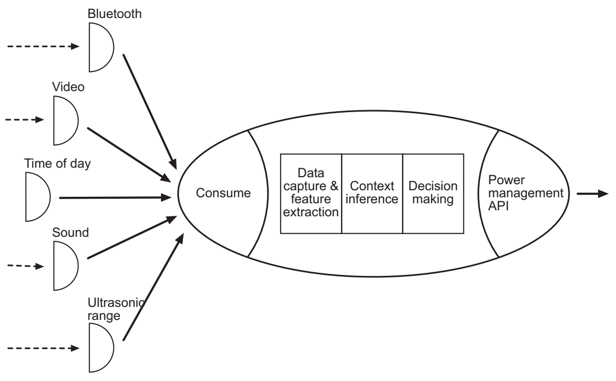


Figure 4.1: Software structure

We first describe the sensor hardware and software used for data capture and feature extraction. Significant characteristics of each of the sensors are also highlighted. We then go on to describe the choice of Bayesian software used for implementing the Bayesian inference and learning, which is the core of the CAPM framework. The CAPM implementation is divided into two parts, (a) the runtime (on-line) CAPM implementation, and (b) the off-line CAPM evaluation software. The runtime CAPM software provides the actual implementation of the BN policies, whereas the off-line CAPM software is used for the evaluation of the user study. It records the sensor data and user's usage of the PC, and subsequently simulates the range of BN policies for evaluation purposes. The runtime CAPM implementation is first described, including the Windows power management functionality. Finally, the CAPM evaluation software is described.

4.1 Sensors

The hardware and software implementation of the sensors is detailed in the following sections. The development platform used was the Microsoft platform SDK, Windows server 2003 family, and the code was compiled for Windows XP. The Bluetooth sensor required the use of service pack 2. As described in Chapter 3 the sensors used in the CAPM implementation were system idle time, Bluetooth presence, face detection, voice activity detection, and object range detection.

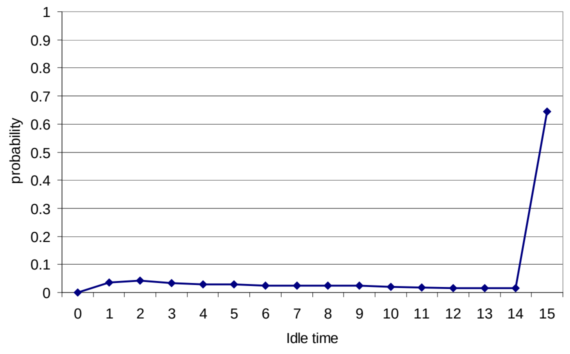
4.1.1 System idle time

System idle time is the amount of time since the user last caused an input event (e.g., moved the mouse or touched the keyboard). The Windows GetTickCount() method returns the amount of time, in milliseconds, that has passed since the last time the computer was started. This is called the *tick count* of the computer and represents how long the computer has been running. The GetLastInputInfo() method retrieves the tick count of the last input event into the LASTINPUTINFO structure. The IdleTimeGetState() method simply subtracts this value from the current tick count to get the idle time in seconds (see Listing 4.1). The tick count loops every 49.7 days, which is not an issue for this experiment. The energy cost of this sensor information is not measurable and is assumed to be zero.

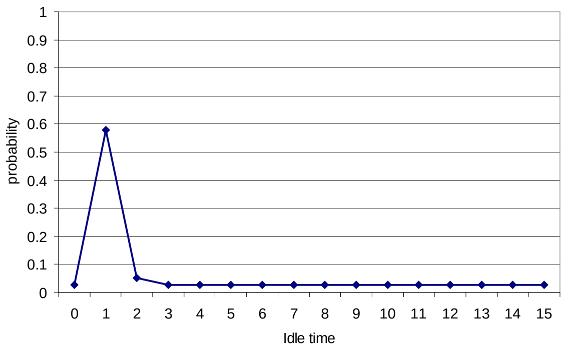
Listing 4.1: System idle time

```
int IdleTimeGetState() {
    LASTINPUTINFO lpi;
    lpi.cbSize = sizeof(lpi);
    // Get the TickCount (time) of the last user input
    GetLastInputInfo(&lpi);
    // Return the current TickCount - last user input TickCount
    return (GetTickCount() - lpi.dwTime) / (1000);
}
```

In the designed Bayesian network, the idle time node represents the idle time in one minute bins from 0 to 1 minute, up to 15 minutes and greater. Figure 4.2 shows an example of the learned conditional probability tables (CPTs) for the idle time node. Figure (a) shows the probability of an



(a) Probability given Not Using



(b) Probability given Using

Figure 4.2: Idle time CPTs

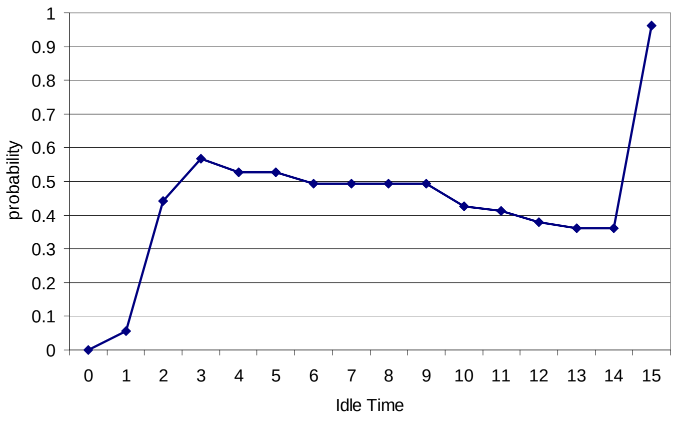


Figure 4.3: Inferred probability of NOT USING

idle time given the user is NOT USING the device and Figure (b) gives the probability of an idle time given the user is USING the device. The 0 to 1 minute period has been excluded from the learning as for this value the probability of USING is explicitly set to one. (The IdleTimeZero node ensures that USING = 1 when the idle time is less than 1 minute.)

Figure 4.3 shows the inferred probability of NOT USING for the given idle times. The probability of NOT USING rises sharply after the 1 to 2 minute period (from 0.06 to 0.44) and then stabilises around 0.5. It drops off again after the 9 to 10 minute period and finally rises sharply to 0.96 in the 15-minute-and-greater period. The fluctuation of the probability is due to the lack of cases for learning in the higher idle time periods and the sharp rise at the end is because the 15-minute-and-greater period encompasses all cases greater than 15 minutes.

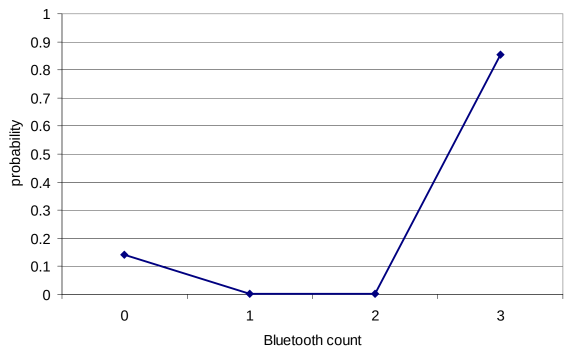
Sparsity of data for learning is a common issue for learning of parameters. Also, the discretisation of continuous values (e.g., idle time) cause problems when upper bound limits are set. Applying a smoothing function to the idle time CPTs could reduce the fluctuation in the graph of NOT USING probability versus idle time and may be more appropriate. For example, an exponential function could possibly be used to ensure the idle time CPTs transition smoothly from the 0 to 1 minute to the 15-minute-and-greater period. This would need to be explored further as future work.

4.1.2 Bluetooth presence

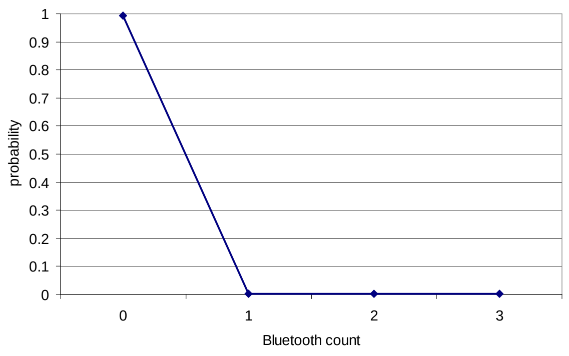
The initial experimental trials used Bluetooth-enabled mobile phones as location/presence tags. For the larger user study we purchased dedicated Bluetooth tags as not enough of the population currently have Bluetooth-enabled phones. The tags we choose were Bluelon BodyTags 002 [5], which have a Class I (100mW) radio with a range of up to 100m. For the experiment, the power was tuned down to 2.5mW (giving a range of 10m), which is the range of the Class II radios found in mobile phones.

All Bluetooth devices have a unique device address, and a clock to enable frequency hopping. A network (piconet) of Bluetooth devices can be established with one device as the master and the rest as slave devices. There are two possible methods of determining whether a Bluetooth device is present, either by using device discovery to attempt to discover the device or, if the device's address is known, a faster direct attempt to connect to that device can be made. Both of these protocols are implemented in the link controller layer. In an error-free environment the worst case time to discover a device is around 10s [8]. Device discovery is the method we used in the initial experimental trial for detecting the presence of the mobile phone.

We improved on this time by using the connection protocol to detect whether the device is present or not. To initiate a connection the master device enters the paging mode, whereby it transmits the slave device's address on a 32 channel frequency hop sequence. This paging device hops at a fast rate, one hop every 312.5μs. Meanwhile, the slave device should be in the page scan mode, listening for connections. This scanning device hops over the same channels at a slow rate of one hop every 40ms. When the paging device catches up with the scanning device, the slave hears its address being broadcast and then replies to the master. Once this handshaking has been achieved, the connection is established. For the experiment, the desktop PC acts as the master device continually attempting to connect to the PC owner's slave Bluetooth tag. The Windows Winsock API was used to implement the connection with the tag. The WSALookupServiceBegin function attempts to connect to the given Bluetooth tag address. If the connection succeeds then we determine the Bluetooth tag is present. If the connection fails then either the Bluetooth tag is not there or the connection protocol failed to



(a) Probability given Not Using



(b) Probability given Using

Figure 4.4: Bluetooth CPTs

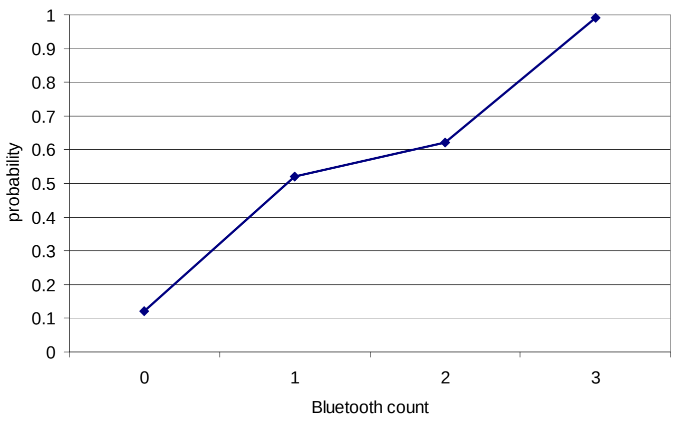


Figure 4.5: Inferred probability of NOT USING

connect to the tag, which sometimes happens.

A series of experiments were conducted for the Bluetooth connection. The average time to make a new connection to a Bluetooth tag was measured to be between 1 and 2 seconds. When the Bluetooth tag was not there the time it took for the connection to timeout was measured to be between 5 to 6 seconds. The connection error rate is the percentage of times the connection fails to connect with the tag when the tag is present. This was measured by leaving a tag in close proximity (20cm) for a 4 hour period. The error rate for not detecting the tag once was 14.05%; not detecting twice in a row was 0.73%; not detecting three times in a row was 0.17% and there were no cases of not detecting four times in a row. Based on this connection error rate the Bluetooth node was modelled to have three not detected states.

Figure 4.4 shows the Bluetooth CPTs for a typical user. When they are not using the PC (Figure (a)), the tag is detected with probability 0.14 and not detected (value 3) with probability 0.85. When they are using the PC (Figure (b)) the Bluetooth tag is nearly always detected (value 0). Figure 4.5 shows the inferred probability of NOT USING rising as the Bluetooth count goes from 0 to 3. All values of the Bluetooth count are well sampled and the smooth transition of the NOT USING probability models well the increasing certainty that the user is not there and therefore NOT USING the PC.

4.1.3 Face detection

A web camera (initially a Creative USB 2.0 camera) was used to capture video at 30 frames per second (fps) and 640x480 resolution. The general-purpose face detection algorithm is a Haar-like training classifier, which is implemented by the open computer vision library (OpenCV). This open source library is a collection of algorithms for basic computer vision problems and was originally developed by Intel [30].

Face detection is a relatively difficult object detection task due to the large variety of possible face instances, e.g., faces may be slightly rotated or tilted, some people wear glasses, some have beards or moustaches, and often part of the face may be in shadow. Statistical model-based training can be used to cope with this large variety. The Haar-training classifier used by OpenCV was originally developed by Viola and Jones [64] and is described in [6]. The method uses simple geometric features (the features are computed in a similar way to coefficients in Haar wavelet transforms) and a cascade of boosted tree classfiers as the statistical model. Face detection is done by sliding a fixed size window across the image and classifying whether the candidate image in the window looks like a face or not. To detect faces of different sizes, the image is scaled. In the algorithm, fourteen Haar-like features are used (see Figure 4.6).

Each feature is described by its black and white template, its relative coordinate in the window, and its size. For example, in many faces eyes are darker than the surrounding regions so feature 3 (a) centered at one of the eyes and properly scaled will likely give a large feature value. The computed feature value x_i is fed into a very simple classfier $f_i = \begin{cases} +1, x \geq t \\ -1, x < t \end{cases}$, where t is a given threshold value, +1 means face detected, and -1 means not detected. A more robust "boosted" classifier is then built from the set of "weak" classfiers as a weighted sum of the weak classifiers: $F = sign(c_1 f_1 + c_2 f_2 + ... + c_n f_n)$. The more classifiers included in the sum the better the prediction of the boosted classifier. To manage the computational complexity, Viola suggested using a set of boosted classifiers F_k with increasing complexity. The image is then sequentially applied to the set of classifiers in increasing order. In

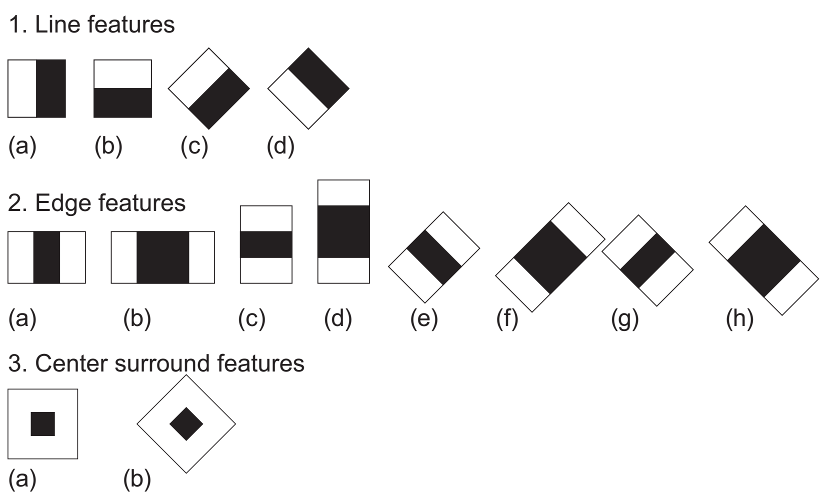


Figure 4.6: The Haar-like features

experiments, 70-80% of candidate images get rejected in the first two stages, leaving the final more complex stages to handle candidate images that could be faces. The initial window size for detecting faces was set to 100x100 pixels to avoid detecting small scale faces, (i.e., in the distance). A nice property of this algorithm is that there is no need to train the classifier to a specific user's face.

The positioning of the camera was either on top of the user's monitor or below it, depending on the monitor's height. In one case the face detection did not work as the particular user had their head very close to the monitor, so it was not possible to get a front on image of the face for recognition. Figure 4.7 shows 4 sample images of the face detection (where a red box means the face is detected). It shows that the face needs to be looking straight at the screen for it to be detected. Sometimes a false detection of a face in the background can occur.

The CPU consumption of the Creative camera was very high for image capture, at around 30% of the CPU. We found a cheaper Trust USB 2.0 camera, which consumed much fewer CPU resources (8% CPU) to run the user trials. To estimate the potential error rate of the camera we conducted a simple experiment, whereby a user constantly looked at the screen for an hour (i.e., their face position was fixed for this period). From this, the error rate of the face detection was estimated to be 1.58%, (i.e., the face was not detected once in every 63 samples). This error rate increases in circumstances of poor lighting or when the camera positioning is not suited to the user's position.

Figure 4.8 shows typical learned CPTs for the face detection node. Given the user is NOT USING the PC, the most probable face detection value is 30-and-greater (Figure (a)). If the user is USING the PC the most probable values are between 0 to 4 face detect counts (Figure (b)). This models the

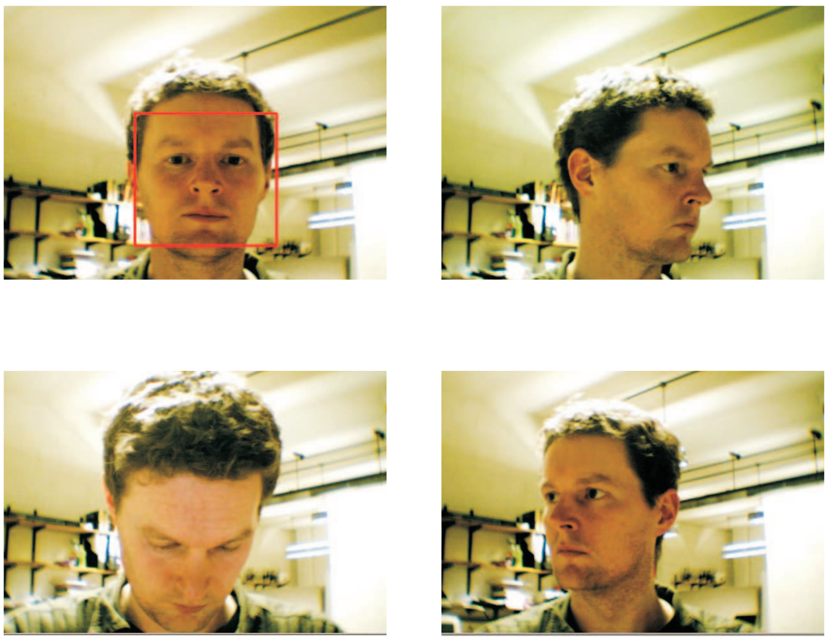
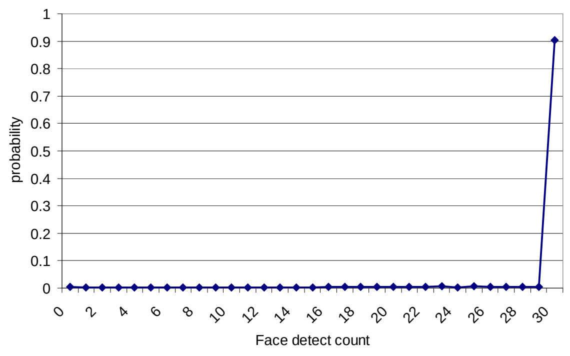


Figure 4.7: Face detection

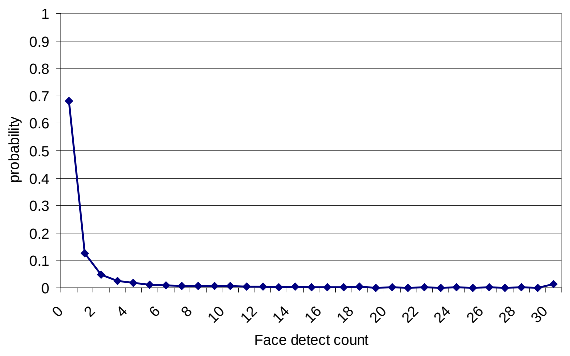
fact that the face is not always detected during the use of the PC.

4.1.4 Voice activity detection

A standard, cheap PC microphone (LabTec AM-22) and standard PC sound card were used for the sound recording. The voice activity detection (speech detection) algorithm is a simple energy and periodicity algorithm commonly used for *end pointing* in speech recognition algorithms [53]. End pointing is used to seperate acoustic events of interest (i.e., speech) from the background signal. Rabiner states there are three factors that make the task of speech detection difficult [53]. The first is the extra sound made by a speaker such as lip smacks, heavy breathing, mouth clicks, and pops. The second is due to difficult environmental conditions such as noisy backgrounds (e.g., due to fans, machinery running), non-stationary environments (e.g., door slams, trains passing by, car horns), and in hostile circumstances when the speaker is stressed (e.g., when navigating an airplane). Rabiner states that some of these interfering signals produce as much speech like quality as the desired speech signal itself, making accurate speech detection quite difficult. The final source of difficulty is the



(a) Probability given Not Using



(b) Probability given Using

Figure 4.8: Face detection CPTs

distortion introduced by the transmission medium itself. For signals with a stationary and low noise background, a straight-forward energy-level algorithm produces reasonably good accuracy.

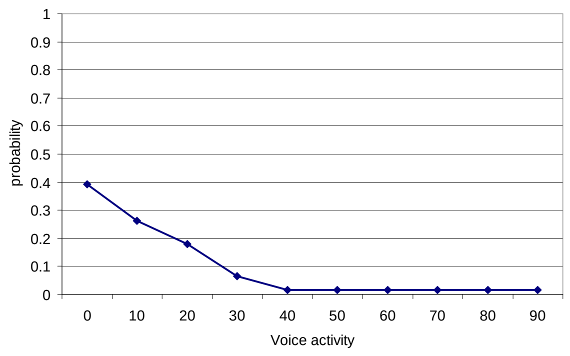
The algorithm we selected is from Intel's integrated performance primitives (IPP) toolkit [29]. The toolkit provides a library of optimised functions for audio, video, speech, computer vision, image and signal processing[1]. The approach involves measuring the short-time energy level of the sound sample and the periodicity of the sample to filter unwanted noise in the background. Speech signals are periodic in nature, which distinguishes them from the background noise.

The voice activity detection code records the sound from the microphone every 5 seconds as a pulse code modulated (PCM) file. The PCM file is processed by the IPP speech detection algorithm and it returns the percentage of active sample windows in the sound recording. This gives the percentage of voice activity that occurred in the last 5 seconds of recording.

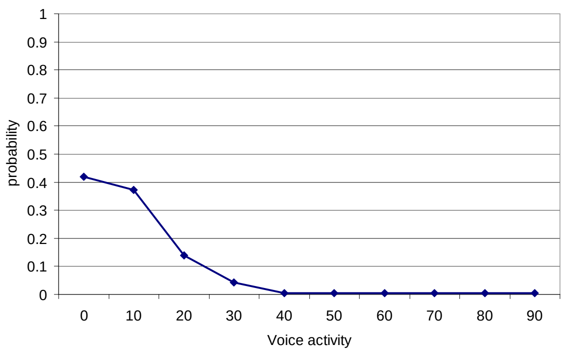
The voice activity detection was initially tested with a user speaking directly into the microphone. For the experiment, the microphone was positioned hanging above the user's work station. This reduced the performance of the algorithm as the microphone was further from the speech. A possible solution to this could have been to use better quality microphones, which are more sensitive.

Figure 4.9 shows typical CPTs for the voice activity. There is no significant difference between the NOT USING and USING CPTs, which means that in both contexts the voice activity is quite similar. This suggests that the voice activity information was not a good indicator for inferring the contexts USING and NOT USING.

[1]Intel's OpenCV library can use IPP for optimised performance.



(a) Probability given Not Using



(b) Probability given Using

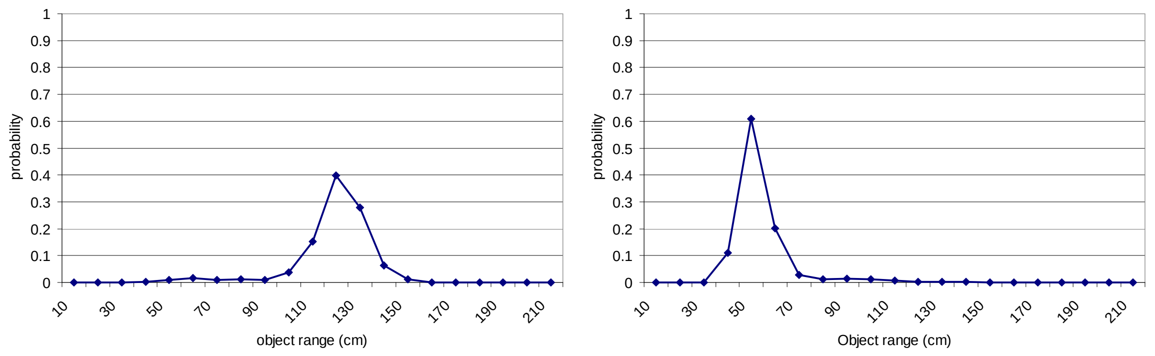
Figure 4.9: Voice activity CPTs

4.1.5 Object range detection

An ultrasonic range-finding sensor was used to determine the distance to the nearest object in front of the PC. The sensor works by transmitting a short burst of high-frequency (ultrasonic) sound into the environment and measuring the time taken for the reflected echo to return to the receiver. The distance is calculated by simply dividing the echo time by the speed of sound. The accuracy of an ultrasonic sensor varies as the speed of sound changes depending on environmental factors such as temperature, air pressure, humididty, and acoustic interference [59].

We used an SRF08 ultrasonic sensor, which has a range of about 6 metres. The sensor is connected to an OOPIC-R micro-controller via an IC2 bus. The micro-controller sends the sensor a signal to transmit, which causes the sensor to transmit the ultrasonic beam. The sensor then listens for an echo for a period up to 65ms (i.e., corresponding to the maximum range of 6m). Once ranging is complete, the measured range can be read from the sensor. The micro-controller then outputs this range reading to its serial port, from which it can be read by the PC.

In the experiment the sensor was positioned at the top of the monitor and its beam angled to pick up the head of the user when they were sitting at the PC and facing the monitor. This required a certain amount of calibration and in some cases it was difficult to pick up the user's head without picking up the back of a high office chair when the user was not there. Another difficult case was when the user was turned around 180 degrees talking to a colleague as the back of their head was being picked up at a similar distance to when they were using the PC. A possible improvement could be to use an infra-red sensor, which can also distinguish body heat. This would eliminate the more common problem of picking up the back of a high chair. Infra-red sensors are not as accurate as ultrasonic



(a) Probability given Not Using (b) Probability given Using

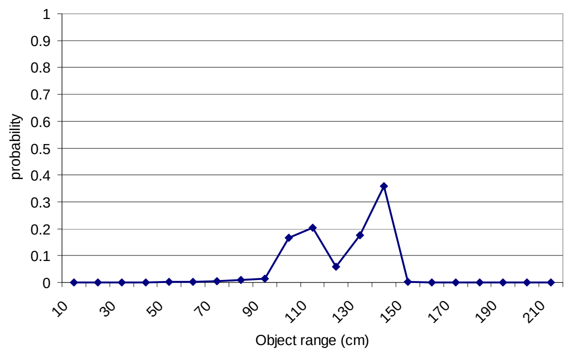
Figure 4.10: Typical USING/NOT USING object ranges

ones, so a possibility might be to use both sensors [25]. The reliability of the range detection was estimated by placing an object 6cm in front of the sensor and recording the measurements over an hour. The measurements' median and standard deviation were 5.88cm +/- 0.80cm for the 6cm object. The sensor more commonly over-estimated the distance with the largest reading being 12cm.

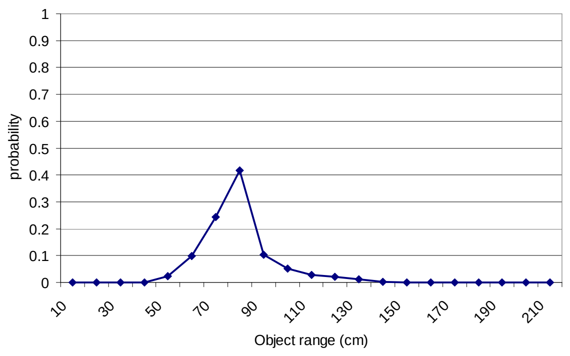
The object range detection node was designed to count when the user was last detected in the USING object range. The USING/NOT USING ranges were different for each user and were determined based on the object range values and the measured usage trace. Figure 4.10 shows typical object range values given the user is NOT USING (Figure (a)) and USING (Figure (b)) the PC. The ranges are well seperated with the USING range from 30cm to 80cm and the NOT USING range from 90cm to 160cm.

However, for some users the separation of ranges was not so clean and the USING and NOT USING ranges coincided. Figure 4.11 shows the USING range coinciding with the first part of the NOT USING range from 90cm to 120cm. In these cases where there is some overlap, the USING range is given precedence (e.g., 40cm to 120cm) and the NOT USING range is reduced to exclude any overlap (e.g., 130cm to 150cm). This means that in the overlap range it is not possible to classify whether the user is in the USING or NOT USING range and the safest option is to assume they are USING to avoid a false prediction of NOT USING the device.

Once the USING/NOT USING ranges are known the object range values can be converted into object detection counts. The counter is incremented if the object range is in the NOT USING range and reset to 0 if it is in the USING range. This gives a history of when an object was last detected in the USING range. Figure 4.12 shows typical CPTs for the object detection count. Given the user is NOT USING

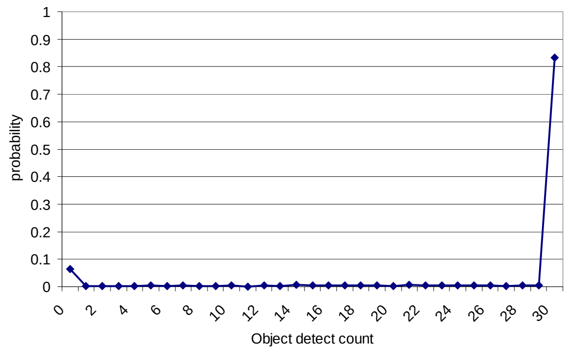


(a) Probability given Not Using

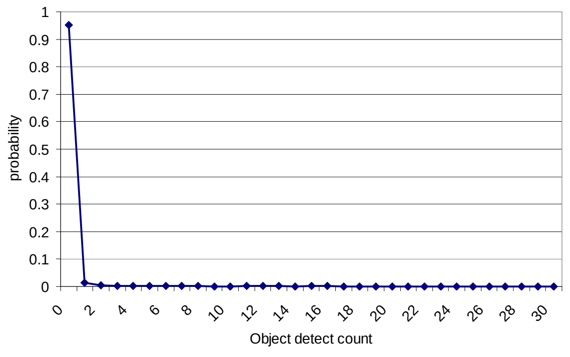


(b) Probability given Using

Figure 4.11: Coinciding USING/NOT USING object ranges



(a) Probability given Not Using



(b) Probability given Using

Figure 4.12: Object detection CPTs

the PC the most probable object detection count is 30-and-greater (Figure (a)). If the user is USING the PC the most probable object detection count is 0 (Figure (b)).

4.1.6 Sensor power consumption

The power consumption of each sensor was measured to be the difference between the power consumption of the base PC and the power consumed when the individual sensor was operating. A power monitor was used to accurately measure the energy consumption in Watt hours (Wh) over a 12 hour period for the base PC and the PC with each of the individual sensors. The measurements were each repeated 7 times to estimate the possible variance in the energy consumption. The base PC had a freshly installed operating system with no applications or anti-virus software installed. It included a

Bluetooth radio, web camera, and microphone hardware as it is assumed this hardware will become standard for a PC. Figure 4.13 shows the average power of each of the sensors (i.e., the difference of power consumed when the sensor was operating and the power of the base PC).

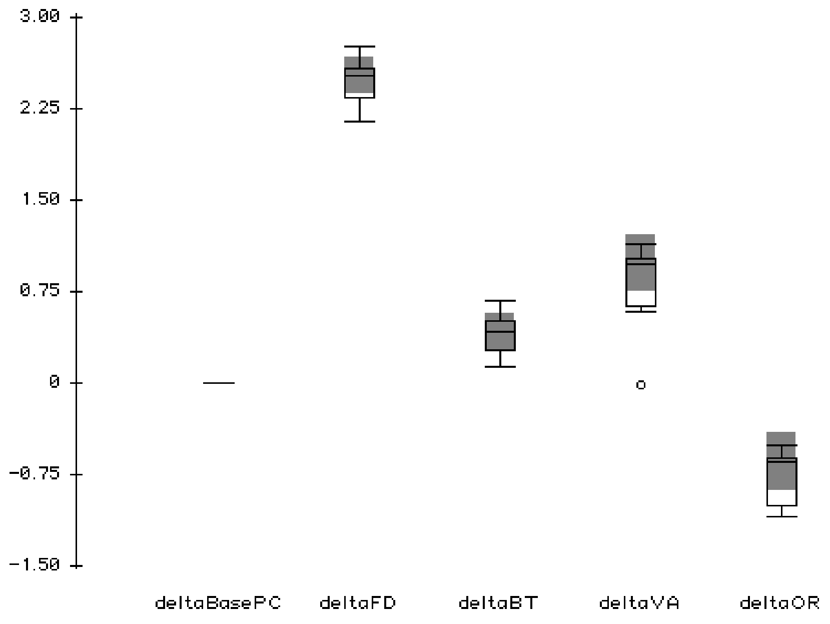


Figure 4.13: Energy consumption of sensors

The average power of the Bluetooth presence detection is estimated at 0.41W +/- 0.19W. This is based on a sample rate of attempting to connect once every 5 seconds and the tag being present during normal office usage (i.e., for several periods during the day the tag was not present). It was also necessary to estimate the energy consumed by recharging the Bluetooth tag. The power of the charger is 1.03W and it was estimated that 3 hours of charging was necessary for the tag to last the 5 day trial period. Therefore the estimated energy consumption of recharging the Bluetooth tag is 0.62Wh per day, which is added to the energy cost of the Bluetooth presence detection.

The average power of the face detection was estimated at 2.47W +/- 0.22W above the base PC. This is based on a sample rate of face detection once every 5 seconds. The power of the face detection is significantly higher than the other sensors and is due to the large amount of processing needed to perform the face detection algorithm. The average power of the voice activity detection is estimated at 0.78W +/- 0.40 W. Again, the sample rate is once every 5 seconds but the data processing required is less than the face detection.

The average power of the object range detection was divided into the power consumed by polling the sensor for readings and the power consumed by the sensor itself. The measurements in Figure 4.13 show the power consumed by polling the sensor to be slightly less than that of the base PC, which was unusual. We re-measured the base PC and found its power to be the same. We concluded that the wall-powered OOPIC micro-controller might influence the base PC energy reading and that the power consumed by reading the RS232 port once every 5 seconds is negligible. The average power of the SRF08 sensor was measured by measuring the energy consumption of the power supply and OOPIC micro-controller (over a one hour period) and comparing this with the energy consumption when the SRF08 sensor was connected. The power difference was measured to be 0.10W +/- 0.03W (i.e., from 0.07W to 0.13W) for the sensor. A technical specification of the sensor is given by Robot Electronics [21]. Their measurements state the average current of the sensor in ranging is 12mA and in standby is 3mA. The sensor ranges for 65ms and is in standby for 1s (the polling frequency was set to 1s). These figures give the total average power to be 0.02W for the sensor. We took the figure of 0.07W, which is at the lower end of the measured power, as the estimated average power of the object range sensor.

4.2 BN software selection

This section defines the general requirements for a Bayesian network tool for CAPM. Most of the information presented derives from Kevin Murphy's web page [44] and Appendix B of [35].

4.2.1 Requirements

The general requirements were listed as:

Must

1. support continuous nodes (i.e., continuous-valued variables such as time).
2. support parameter learning (or allow it to be provided).
3. support dynamic BNs.
4. be executable on Windows, Unix, Mac OSX and also other non-standard embedded processors (for CAPM of other office devices).
5. have an API.
6. support decision networks (or allow it to be provided).

Should

1. have good documentation.
2. have source code available and preferably in C, enabling pruning of code. This enables the code base to be reduced in size for embedded platforms.
3. have a graphical interface for creating networks.

Could

1. support structure learning (i.e., the dependency arcs between nodes in a network).

The main driver behind this set of requirements was the need for a tool that could be used to build a runtime CAPM implementation that could be executed on users' PCs.

4.2.2 Tool selection

Based on the above requirements a set of seven possible tools was evaluated. Table 4.1 details the name, authors, availability of source code, availability of an application programming interface, and the set of execution environments supported (Windows, Unix, Macintosh, Embedded).

Table 4.1: Comparison of BN tools

Name	Authors	Source	API	Execution
Hugin Expert	U. Aarhus	None	Yes	Win
Netica	Norsys	None	Yes	Win, Unix, Mac, Embed
Genie (SMILE)	U. Pittsburgh	None	Yes	Win, Unix
Probabilistic Networks Library (PNL)	Intel Research	C++	Yes	Win, Unix
Bayes Net Toolbox (BNT)	Murphy	Matlab, C	Yes	Win, Unix, Mac
Java Bayes	Cozman (CMU)	Java	Yes	Win, Unix, Mac
Bayesian Filtering Library (BFL)	Klaas Gadeyne	C++	Yes	Win, Unix, Mac, Embed

The closed source tools Hugin Expert, Netica and Genie (SMILE), have a wide range of functionality and comprehensive documentation. Hugin and Genie have the advantage of being closely connected to BN research groups and implement more advanced inference algorithms. However, Genie (being non-commercial) has less functionality, for example, parameter learning is currently being implemented, whereas, Hugin has structure learning. Genie can read both Hugin and Netica file formats. Netica is a lighter weight implementation, which uses the standard junction tree inference algorithm and a number of parameter learning algorithms. It is robust, capable of being embedded (using only the standard C library) and provides for real-time requirements (i.e., all functions take a predictable amount of time to complete). The open source tools PNL, BNT, Java Bayes and BFL may lack finish, but make the source code available. Of these tools BFL is out of scope as it only supports dynamic BNs and BNT is out of scope as it requires MatLab for execution. PNL has more functionality than Java Bayes and is implemented in C++. We compared Netica and PNL by writing a simple WaterSprinkler example for both. Netica has quite a simple well-documented API which was easy to use but potentially less flexible. PNL development is a bit more complex but also possibly more flexible. We decided to go with Netica and if further functionality was needed through access to the code base, we could progress to PNL.

4.2.3 Netica

Netica is oriented towards commercial use. Versions of the Netica API are available for Microsoft Windows (95/NT4 to XP), Linux, Sun Sparc, Macintosh (OS 6 to OS-X), Silicon Graphics and DOS. Each of these has an identical interface, so code can be moved easily between platforms. They also provide a service for building custom APIs to suit embedded platforms. There are two versions of the API. The Java API gives the full functionality of Netica in an easy-to-program object-oriented style. The C API is compact and fast, and is suitable for embedded systems. Each API comes with good documentation including example programs and detailed descriptions of each function. The C API does not require any library other than the Standard C library. The Java API does not require any Java packages other than those that come with a standard Java 2 environment.

The network supports continuous nodes by allowing controlled discretisation. This is a simple solution to handling continuous data (e.g., time) but does cause some modelling problems. For example, a limit on the range of the data needs to be selected (see Section 4.1.1). The parameter learning algorithms include the Spiegelhalter and Lauritzen parametrisation algorithm, and the expectation maximization algorithm, which are sufficient for our current requirements. Structure learning is not supported but this functionality could be provided by another tool dedicated to structure learning.

The latest version of Netica provides support for dynamic Bayesian networks through their "time-delay" links. This allows the programmer to build a BN with time-delay links and then "roll out" the network to include the required time slices. Decision networks are provided for and can support multiple decision nodes. This enables multi-stage decision problems, where later decisions depend on the outcomes of earlier ones.

The Netica inference engine has been optimised for speed for real-time performance. The network is compiled into a junction tree of cliques for fast probabilistic reasoning. Programs that use the API completely control the inference engine. They state that "no API function will ever take any action until called. The API will not do any I/O unless requested to, and all functions take a predictable amount of time before returning. Also, a limit may be set on the maximum amount of memory that Netica will use."

The graphical inteface is invaluable for making quick prototypes and experimenting with different structures, learning and inference. The source code is not available as it is a commercial product. A free version has the entire set of functionality as the licensed version but is limited in the size of net that can be constructed.

4.3 Runtime (on-line) CAPM implementation

Two versions of the CAPM framework were implemented. The first runtime (on-line) implementation was used for executing the CAPM policies during the runtime operation of a user's PC. The second off-line implementation was used for evaluation of the set of power management policies and is discussed in Section 4.4.

The runtime version of CAPM was implemented as a background Windows service and uses Netica's C API to perform the inference using the Bayesian networks. This implementation was only used for power management of the PC's display as the power-up part of CAPM could not execute if the PC itself was in standby. Additional hardware would be needed to implement automated power up for the PC, or, as was the case with the SWOB policy, a remote server could be used.

The program sits in a loop continually polling the set of sensors for their current value. The polling loop is divided into the two policies, power-down and power-up. If the PC's display is on, the power-down policy operates and the NOT USING network is used to infer the probability of the user NOT USING the display. If the display is in standby, the power-up policy operates and the ABOUT TO USE network is used to infer the probability of the user ABOUT TO USE the display. The Bayesian networks use predefined CPTs and there is no on-line learning of the CPTs. On-line learning of the CPTs is a possible area for future work. The decision making policy is a simple threshold decision. If the probability of the given context is above the threshold then the appropriate power management action (i.e., power down or power up) is performed.

We needed to determine whether the Bayesian inference consumed a significant amount of energy or not. The energy consumption of the base PC was measured with the CAPM service executing the full BN policy (i.e., Idle time, Bluetooth, Object range, Face detect, Voice activity). The actual sensors were not polled for data so the service was just executing the inference of the Bayesian network, once every 5 seconds. The energy consumption data was measured over a 12 hour period and compared to the base PC consumption. The average power was estimated at -0.26W +/- 0.56W, (0.30W, -0.82W), which is not significantly above zero. We therefore regard the energy consumption of the CAPM inference to be negligible.

The Windows user interface API provides the functionality to switch the display to standby and back on again. Listing 4.2 details the display (monitor) power management code. The SendMessage function simply broadcasts a SC_MONITORPOWER message to power off and on the display. The function's final parameter is set to 2 for powering off and -1 for powering on the display. The energy consumption of transitioning the display is assumed to be negligible.

Listing 4.2: CAPM

```
void MonitorSuspend(void) {
    SendMessage(HWND_BROADCAST, WM_SYSCOMMAND, (WPARAM)SC_MONITORPOWER, 2);
}

void MonitorOn(void) {
    SendMessage(HWND_BROADCAST, WM_SYSCOMMAND, (WPARAM)SC_MONITORPOWER, -1);
}
```

The Windows power management API provides the means to switch the PC to standby. The SetSystemPowerState function attempts to place the PC into the standby state. When the fForce parameter is set to FALSE, the function broadcasts a PBT_APMQUERYSUSPEND event to each application to request permission to suspend operation. As long as no application denies the request to suspend, the PC is put into standby.

The transition energy consumption T_e of switching the PC to standby and back on was measured by switching the PC to standby 10 times in a one hour period. The steady state on (O_p) and standby (S_p) power was measured independently and the on (O_s) and standby state (S_s) times were measured through the event API. The actual measured energy consumption of 22.78Wh is the sum of the transition energy plus the energy consumed in the on state and the energy consumed in the standby state (i.e., 22.78Wh = $10xT_e + O_pxO_s + S_pxS_s$). From this equation, the transition energy was estimated at 0.19Wh per transition. This energy is added to the energy consumption of the evaluation policies.

4.4 Evaluation (off-line) CAPM implementation

The evaluation of the CAPM policies required another set of software for the purpose of data collection and off-line simulation of the set of policy traces. Figure 4.14 shows the structure of the evaluation software.

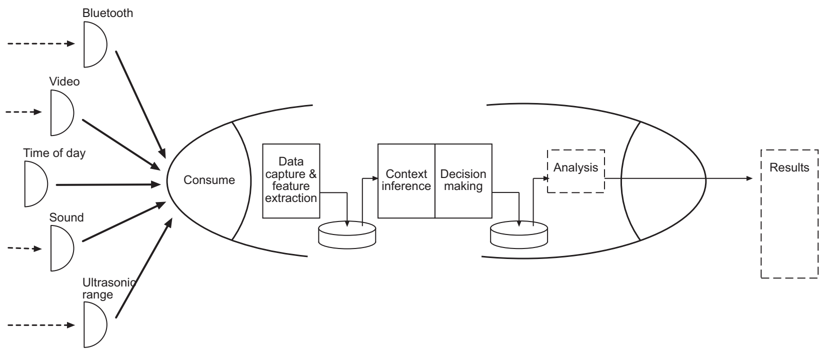


Figure 4.14: Evaluation software structure

The physical sensor hardware and software providing the data capture and feature extraction is the same as for the on-line implementation. The evaluation software is divided into the data-collection stage, which collects all of the data during the running of the user trial, the simulation of the policies based on the data collected, and finally, the analysis of the simulated policy traces.

4.4.1 Data collection

A set of Windows services were implemented for polling the sensors and writing the time-stamped values to disk for subsequent processing. These services reused the sensor code from the CAPM implementation above. The Bluetooth, FaceDetect, ObjectDetect and VoiceActivity services polled their respective sensor once every 5 seconds and wrote the sensor value to disk. Furthermore, the Bluetooth service displayed a warning message box to the user if they were detected using the PC when the Bluetooth tag had not been found for 10 periods or more. This warning ensured that the users had their Bluetooth tag with them and that it was switched on. The IdleTime service recorded every idle period greater than 30 seconds to the Windows event log. The PowerEvent service reported all power event changes (standby, resume, shut down, start up) to the event log.

Finally, in order to evaluate the policies it was necessary to determine when the user was actually using and not using the PC, (i.e., the device usage). This was achieved by implementing the NotUsing service that monitored the idle time and for any idle period greater than 60 seconds, it would display a message box asking the user if they were still using the PC. If the user saw this message box and determined they were still using the PC then they could simply move the mouse to make the box disappear. If they were involved in some other activity and did not see the message box, then the display was powered off, establishing that the user was NOT USING the PC for this period. The display off and display on events were recorded to the event log. This is a sensitive part of the evaluation as the measurement has the potential to change the user's normal behaviour. To further minimise the potential for modifying the user behaviour, an additional rule was added, whereby if the face was detected looking at the display the policy would not attempt to power off the display. This is discussed further in Section 5.3.

4.4.2 Simulation of policies

A *device model* framework was designed and implemented to simulate the set of evaluation policies based on the recorded set of sensor data and the recorded device usage. This framework was implemented in Java and used Netica's Java API to interact with the same Bayesian networks used for the on-line CAPM. The code was divided into three packages, Device Model, Capm, and Capm Analysis. The Device Model class structure is detailed in Figure 4.15.

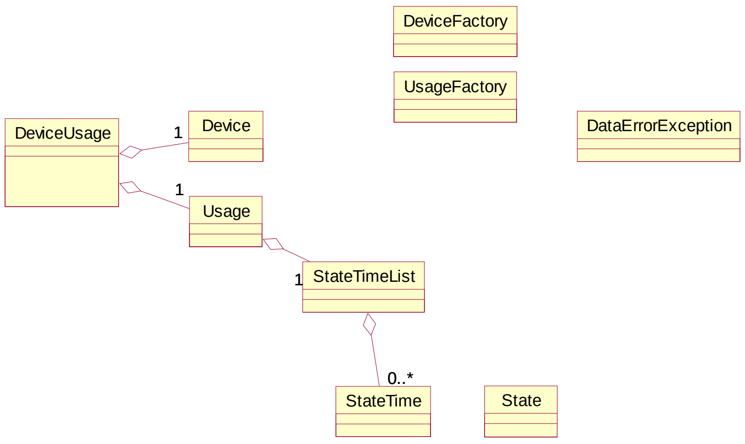


Figure 4.15: Device Model

The Device class models the power states of a device and the Usage class contains the complete list of power-state transitions for a particular usage trace. The DeviceUsage class combines a particular device and usage trace together. The DeviceUsage is then used to provide information on the trace, such as its energy consumption, the number of false power downs, and the number of manual power ups. There are two types of trace. The measured usage trace is the measured record of when the user was using and not using the PC. All other traces are policy traces which record when the device was powered down and up by a particular policy.

The Capm classes are detailed in Figure 4.16. The Monitor class contains the measured usage trace and reports to the particular Simulation class if the device can be powered down or not. The Simulation classes use the Monitor and the recorded sensor data to run through the trace from start to finish and generate the simulated policy trace. The InferenceEngine class provides the interface to the Netica inference engine and the LearnCases class, implements the learning of the Bayesian network CPTs based on the training cases. The SimulationEnv class generates these training cases from the sensor data and the measured usage trace.

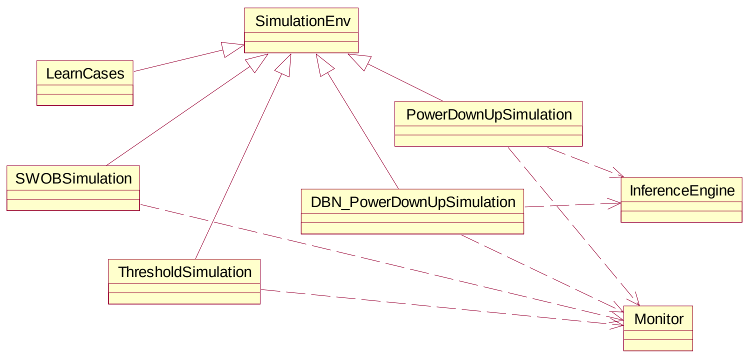


Figure 4.16: CAPM simluation

The Capm Analysis package processes the simulated policy traces. All of the required evaluation metrics (e.g., energy consumption, false power downs) are queried from the DeviceUsage class and printed to a .csv file. The .csv file format enables the results to be imported into a statistical package for further analysis and presentation.

4.5 Summary

This chapter described the sensors used for CAPM of desktop PCs in an office environment. It highlights the issues with each of the sensors and their estimated energy consumption. The selection of the BN tool was then described and the implementation of the on-line CAPM and off-line CAPM evaluation software were described. The next chapter describes the user study and presents the full evaluation of the CAPM policies.

Chapter 5

Evaluation

This chapter begins by outlining the objectives of the CAPM user study, i.e., the research questions we are trying to answer. We then describe how the user study was designed to ensure that the analysis of its results answered the research questions. The data collection and processing of the measured usage trace is then discussed and the simulation of the policies is described in detail. Finally, the evaluation metrics are described and the results from the simulation are presented and evaluated.

5.1 Objectives

The first objective of the user study is to evaluate the potential of context-aware power management for devices in an office environment. The initial experiments highlighted the failing of a simple location-aware policy (SWOB) for LightUse users (see Section 3.1.5). Adding further types of sensor can potentially do better but there is a limit as sensors themselves consume energy. The evaluation objectives were to establish:

1. What is the potential extra energy that can be saved beyond the simple SWOB policy?
2. How much extra energy do policies with additional sensors save?
3. What is the estimated energy cost of operating the sensors?
4. What is the estimated user-perceived performance for each policy?

Overall, we are trying to establish what granularity and what types of context are appropriate for CAPM of office devices. The sensors explored are user presence based on Bluetooth detection (BT), near presence based on ultrasonic object range detection (OR), face detection (FD), and voice activity detection (VA). The devices we consider are desktop PCs and their display units. These devices account for a significant proportion of the energy consumed by office devices [33] and they are possible to analyse within a single user study. Also, the break-even times of the devices (1 and 5 minutes) enable evaluation of policy performance over a range of break-even times.

The second objective is to evaluate whether dynamic Bayesian networks are better for implementing context-aware power management than standard Bayesian networks. Also, several general issues regarding the use of Bayesian networks for CAPM are highlighted.

5.2 Design of the CAPM user study

In order to make some general statements about power management of devices in an office environment we performed the study on a representative sample of the office population. We defined the population of the study to be all workers in an office environment that use a desktop PC.

The initial experimental trial (see Section 3.1.5) highlighted the variability of usage patterns and hence performance of the policies across a small sample of users (4 in total). From this four user types were identified: HeavyUse, LightUse, FrequentUse and InfrequentUse. The trial also showed that the performance of the SWOB policy depends primarily on whether the user is LightUse or HeavyUse. Hence, the study is focused on these two user types. The sample selection for the trial was designed to choose as diverse a range of users as possible from the set of potential candidates, in order to capture as broad a range of device usage and office environments as possible. This was done by generating a list of office users that could feasibly be approached to conduct the trial. The list included the academic, administrative and postgraduate staff of Trinity College and several office users from outside the college. There were four sets of hardware available to enable running the user trials in parallel. However, each user trial took one hour to setup, normally 9 days to collect 5 days of data and there were invariably problems encountered along the way. Due to the time constraints and effort needed for conducting the trials, the sample size was set at 20 users. The criteria used for selection from the list of potential users were:

1. Random, even spread from different job functions.
2. Random, even spread from different office environments.
3. Random, even spread from single office users and open plan office users.

The constraining requirements were that the potential candidates had to have a relatively new PC (less than 5 years old) running Windows XP, a single display unit, and they had to be the sole user

Table 5.1: Sample selection

User	Job	Office type	Location
A	lecturer	single	O'Reilly
B	lecturer	single	Lloyd
C	administration	open-plan	O'Reilly
D	postgrad	open-plan	O'Reilly
E	manager	open-plan	Westland row
F	technician	open-plan	Lloyd
G	technician	open-plan	Lloyd
H	administration	single	O'Reilly
I	lecturer	single	O'Reilly
J	administration	single	O'Reilly
K	postgrad	open-plan	Lloyd
L	lecturer	single	O'Reilly
M	administration	open-plan	O'Reilly
N	system admin	single	O'Reilly
O	postgrad	open-plan	Lloyd
P	lecturer	single	Lloyd
Q	programmer	open-plan	Digital hub
R	lecturer	single	Parson's building
S	administration	open-plan	Merrion square
T	postgrad	single	Westland row

of the PC. From the list of 33 candidates approached, 13 of them were rejected because they did not meet the requirement; 5 did not have Windows XP, 2 used laptops, 2 were not comfortable with being monitored, one was busy moving office and 3 of the PCs had software conflicts with the monitoring services[1]. Table 5.1 details the spread of people that were selected for the trial based on job function, office type and location.

The trial length was set to run for 5 working days. Based on initial results, we believed this would give enough data for training and simulation of the policies. Idle period data was collected for several weeks after each trial to enable evaluation of any side affects from the trial.

[1]The PCs' remotely-managed anti-virus detection software shutdown the monitoring services when it started its daily execution.

In order to compare a range of sensors and policies for each user's usage trace it was necessary to collect all sensor data simultaneously as the user was using the PC during the trial and subsequently run policy simulations on the real usage data. Hence, the trial is broken into a data collection and processing phase, and a subsequent simulation phase.

5.3 Data collection and processing

As described in Section 4.4.1 the data was collected for all sensors every 5 seconds; each value was date stamped and stored to file. Furthermore, all idle periods of 30 seconds or more and all power events were logged to the Windows event log. The most difficult data to collect was the actual usage of the display and PC, i.e., when the user was actually USING or NOT USING these devices. To measure the actual usage, the NOT USING service attempts to power off the user's display if the PC has been idle for greater than 60 seconds. The 60-second period of time attempts to balance accuracy against the experiment causing excessive user disruption. A message box appears asking the user if they are still using the PC; if they are the message box disappears by simply moving the mouse. This short mouse input will be removed in the data processing as it would not have happened during normal deivce usage. To reduce disruption further the service checks if a face is detected before displaying the message box. If a face is detected consistently during this period we assume the user is using the PC and the idle period extends until the face is not detected (i.e., no message box will be displayed until the face is not detected). It is possible that the face detection is identifying some object other than a face, but this is unlikely as, (i) the reliability of the face detection was estimated at 1.58%, (ii) the PCs are single user, and (iii) the user had been inputting 60 seconds before.

We imagined the affect that the NOT USING service may have on the users' behaviour was that they would tend to make more inputs than normal to stop the monitor being powered off. This would lead to a higher frequency of short idle periods than usual occurring in the usage trace. For this reason, idle period data was collected for several weeks after each trial. The evaluation of this affect is detailed in Section 5.7.

The event logs are processed to create the measured device-usage trace, of when the user was USING and NOT USING the display or PC. Such a trace is graphed in Figure 5.1 where the line at level 8 represents USING and level 1 represents NOT USING the PC. The line at level 7 represents idle periods that occurred when USING the PC. There are periods in every trace where we don't know whether the user was using the PC or not. These are the idle periods before the service attempts to power down the monitor. The user may or may not be using the device at this time. These idle

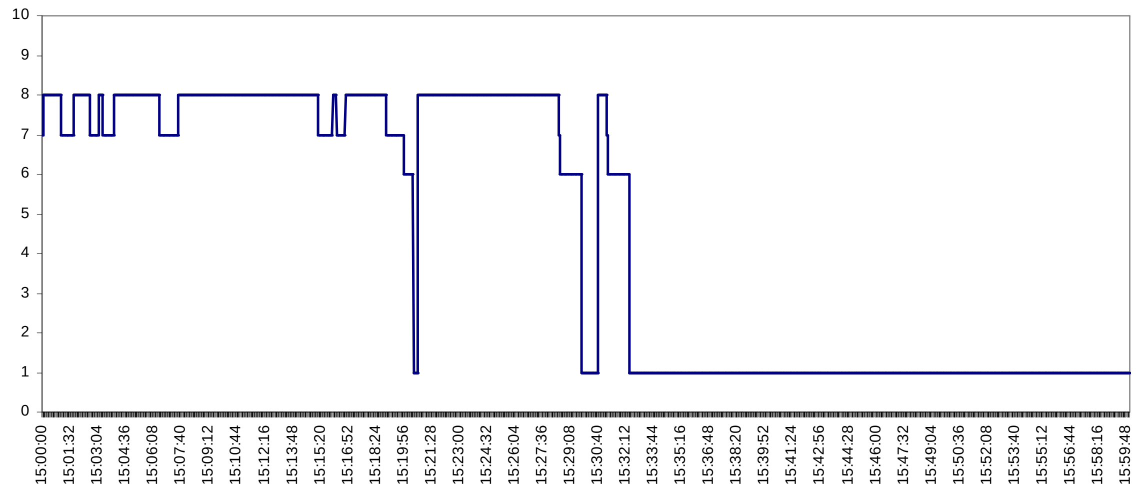


Figure 5.1: Measured device usage

periods are scanned for face detection events. If a face is detected, we assume the state is USING (i.e., the user was looking at the display during this idle period). If a face is not detected, a DON'T KNOW state is inserted to indicate that we don't know whether the user was using the PC or not at this time. This DON'T KNOW state is represented by a line at level 6.

5.4 Simulation of policy traces

All of the policy traces are generated from the measured usage trace. We assume the behaviour of all the users is good in that they power down their PC when leaving the office for the evening. So, for all traces the device is switched to off for the night time period. For all policies, the policy is allowed to power down in the DON'T KNOW and NOT USING states; attempting to power down when the user is still USING represents a false power down.

From the measured trace, it is straightforward to generate the estimated Oracle policy trace and the AlwaysOn trace. The Oracle policy trace is generated by placing the device in its standby state for all NOT USING periods that are greater than the device break-even time. The solid line in Figure 5.2 represents the power downs and power ups of the Oracle policy and the dashed line is the measured device usage. The AlwaysOn trace is generated by leaving the device on for the duration of the day.

The SWOB policy was generated by running through the measured trace at a 5 second time step. The policy attempts to power down if the Bluetooth tag is not detected more than 5 times and the

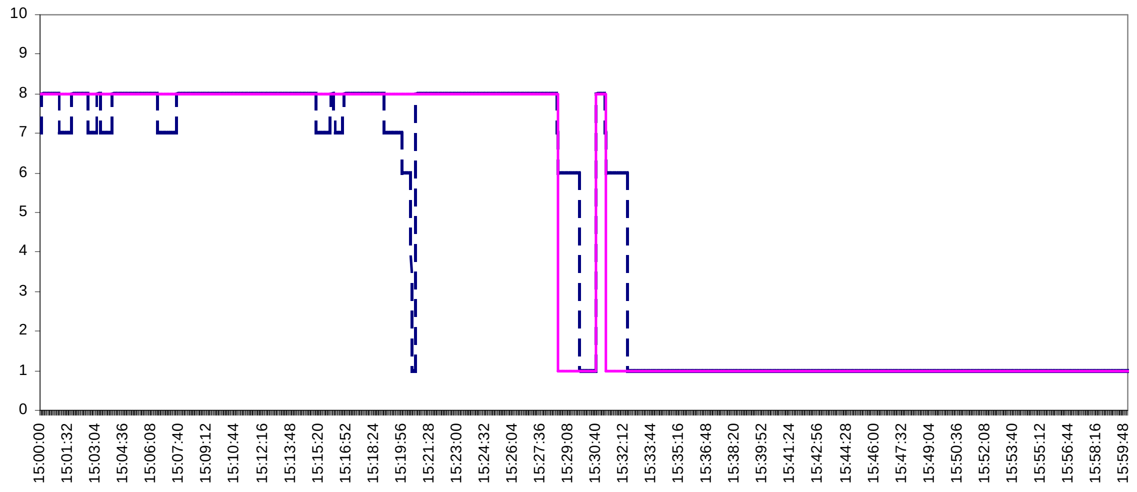


Figure 5.2: Oracle versus Measured

current idle time is greater than 60 seconds. If the measured usage is still in the USING state a false power down is reported, otherwise the policy powers down the device. The policy powers up when it detects the Bluetooth tag (see Figure 5.3).

The range of Threshold policy traces were generated by running through the measured trace at a 5 second time step. If the current idle time was greater than the given threshold, then the policy attempts to power down. There is no automated power up for the Threshold policies. Figure 5.4 shows the Threshold 5 policy powering down 5 minutes after an idle period begins.

The Bayesian policies require a learning stage and a simulation stage. To be rigorous, we employed a five-fold cross-validation strategy to the learning and simulation of the policies [18]. This involves training the model on one day of data and simulating for the other four days, and repeating this five times, training on each of the days. The resulting values are then estimated as the average of the five simulation results, giving a more robust analysis of the policies. It also enables us to look at variability of performance across training days and simulation days.

The Bayesian models we chose to compare, were idle time (IT), IT-Bluetooth (IT-BT), IT-object range (IT-OR), IT-BT-OR, IT-BT-face detect (IT-BT-FD), IT-BT-OR-FD and IT-BT-OR-FD-voice activity (IT-BT-OR-FD-VA). This selection of models gives an increasing order of sensor granularity to enable comparison of each sensor's affect on the CAPM policy. Idle time was included in every model as it is also used in the SWOB and Threshold policies, and Bluetooth was included in all but one model as it gives the coarse-grained user presence, which is the basis of the SWOB policy. We

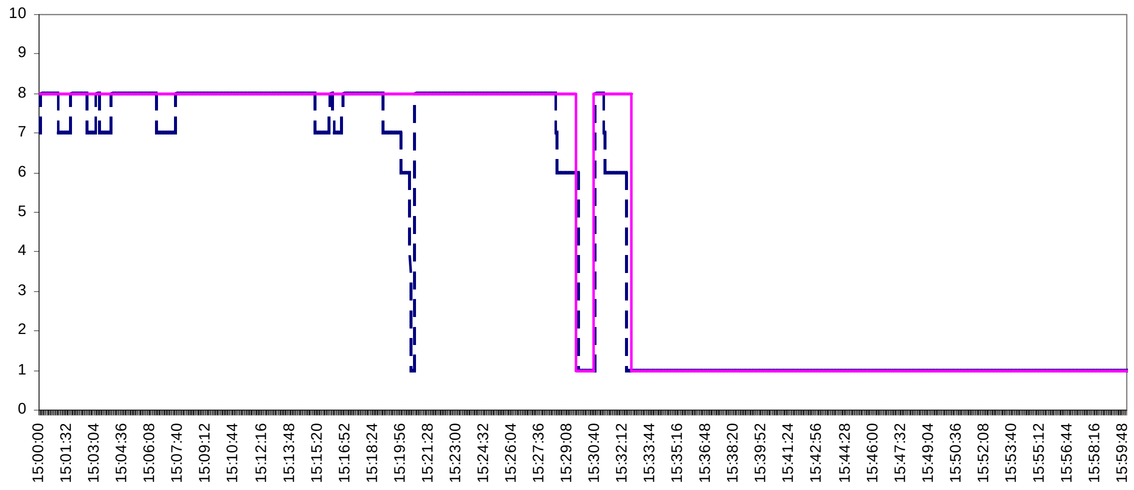


Figure 5.3: SWOB versus Measured

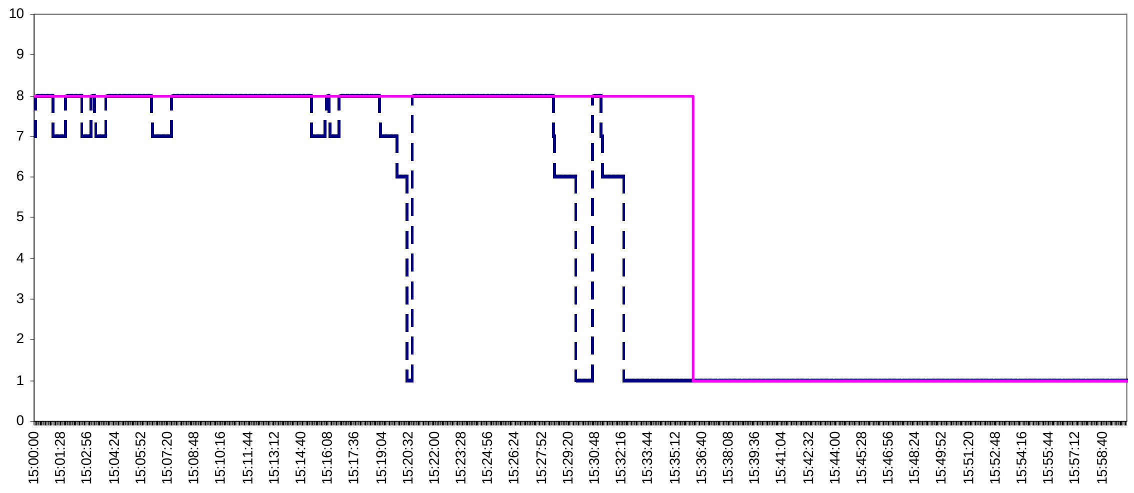


Figure 5.4: Threshold 5 versus Measured

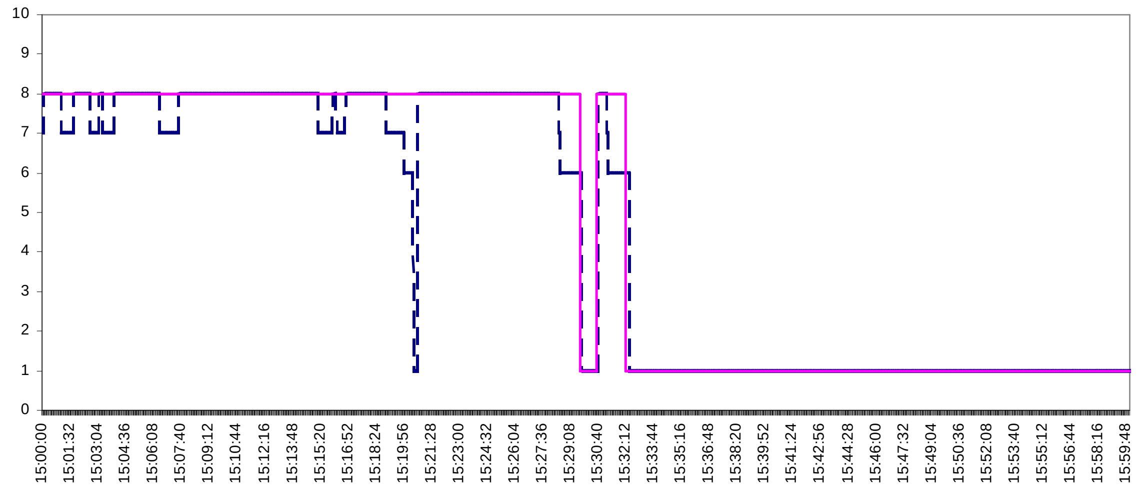


Figure 5.5: BN IT-BT versus Measured

selected IT-OR as a special case to investigate the affect of only having the near presence information. Within the Bayesian models, there are two variations, normal Bayesian network (BN) and dynamic BN (DBN). Parameter learning of the models was carried out using the standard Spiegelhalter Lauritzen algorithm [61].

The set of BN policy traces were generated by running through the measured usage at a 10-second time step in the power-down cycle and a 5-second time step for the power-up cycle. The power-down cycle operates when the device is on waiting to be powered down and the power-up cycle operates when the device is in standby. The shorter 5-second time step is used as the device needs to be powered up as quickly as possible (this is the limit as the sensor data were recorded at 5-second intervals). At each time step sensor values from the sensor records are applied to the BN power-down or power-up model and the model is updated to give the new probability of NOT USING or ABOUT TO USE. If the probability exceeds the threshold the policy attempts to power down or power up the device. Figure 5.5 shows the IT-BT BN policy powering down soon after the idle period begins.

The time step for each DBN simulation depends on the break-even time of the device. For the display with break-even time of 1 minute the time step is 10 seconds (i.e., 6 time slices x 10 seconds), and for the PC with break-even time of 5 minutes the time step is 50 seconds (i.e., 6 time slices x 50 seconds).

The 14 Bayesian models plus the Oracle, SWOB, six Threshold policies and AlwaysOn policy resulted in 23 different policies to compare in total for each of the devices.

5.5 Evaluation metrics

For each user trial the set of simulated policy traces were analysed according to a set of evaluation metrics. The metrics chosen were the total energy consumption, delta energy consumption from Oracle per day, percentage from Oracle per day, number of false power downs (FPDs) per day, number of manual power ups (MPUs) per day and the number of standby periods less than the break-even time (SBEs) per day.

The total energy consumption gives the total energy consumed by a particular policy for a particular user trace. Total energy consumption of a policy cannot be compared across different users as it is affected by how long each user used the device over the period. In order to compare the performance of policies across user traces we use the delta energy consumption from Oracle metric. This is the difference in energy consumption of a particular policy from the Oracle policy for that user trial.

User-perceived performance is estimated by the number of false power downs the user experienced in a day and the number of times the user had to manually power up the device. The SBE metric counts the number of standby periods that were less than the device's break-even time. It is a measure of how often a policy powers down for periods that are not worth powering down for. A high number of SBEs is a concern if the device's lifetime degrades significantly with many power state transitions.

5.6 Results

The 20 user trials were labelled from A to T, of which 18 were selected for analysis. Both user trial A and N were omitted due to problems with the face detection data. In case A the camera failed to detect the face as the angle from the camera to the user's face was too acute to get a front elevation image of the face when it was looking at the display. In case N the face detection failed due to difficult lighting conditions in the office; the user's face was in shadow with light coming from the window behind. This is a significant issue for face detection as many computer users work with the lights switched off in their office.

The 18 users were divided into the two types LightUse and HeavyUse by calculating the percentage of time they were NOT USING the PC when the Bluetooth tag was detected. A small percentage indicates the user is a heavy user of the PC when they are in the vicinity and a large percentage indicates they are a light user. We note here that if a user left their BT tag in the office for an extended period while absent, they could be misclassified as LightUse. To avoid this users were asked to attach the tag to something they always take with them such as keys or a mobile phone. A figure

User	% Not Using	User	% Not Using
Q	1.3	K	16.9
S	5.8	L	18.3
D	7.4	M	19.3
T	8.9	F	19.4
I	10.6	C	24.5
O	11.1	E	26.2
G	13.1	H	26.7
		P	28.2
		B	29.0
		J	39.9
		R	42.9

Table 5.2: LightUse and HeavyUse users

of 15% was chosen as the cut-off giving 7 HeavyUse and 11 LightUse users. 15% was chosen as there is a significant gap of 3.8% between users G and K and it gives a reasonably balanced number of users in each type. Table 5.2 below shows this split of LightUse and HeavyUse users.

Results for the Oracle, SWOB, Always On and Threshold policies for the display are presented first and compared with the results from the initial experimental trial. This larger set of results verify the conclusions that were made from the initial experimental trial. The potential extra energy that could be saved from the SWOB policy is then presented and also the estimated energy consumption of the sensors. Next the results for the BN policies for the display and PC are presented. Finally, results for the DBN policies for the display and PC are presented.

5.6.1 Oracle, SWOB, Always On and Threshold policies

To compare the results with the initial experimental trials we look at the pattern of total energy consumption for the LightUse and HeavyUse users and their percentage from the Oracle. Figure 5.6 shows the same pattern for the Oracle, SWOB and Threshold policies as we saw in the initial trial (the Always On policy is included for completeness). Again, it shows the SWOB policy doing well for HeavyUse users coming close to Oracle (average 12.2%) and poorly for LightUse users (average 40.6% from Oracle). The initial trials reported around 8% for HeavyUse and greater than 50% for LightUse users. The standard deviation for HeavyUse is small at 3.7% but quite large for LightUse users at 16.9%, showing there is a large range of usage within the LightUse users.

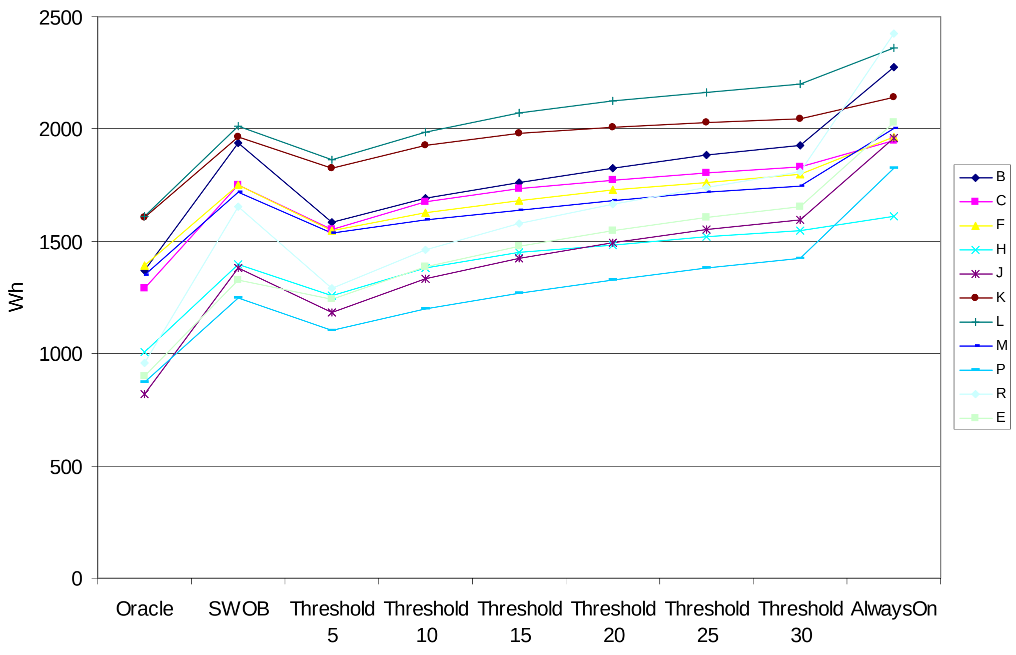
Figure 5.6 also shows the variability of energy consumption between the users. For example, user I consumes much less energy (around 500Wh) than user Q (around 2100Wh) because user I spent less time per day in their office. This variance is why we use the delta energy from Oracle metric when comparing the energy performance of policies across a set of users.

The user-perceived performance of the policies is estimated by the number of FPDs per day and the number of MPUs per day. The number of FPDs per day for both LightUse and HeavyUse is shown in Figure 5.7. The box plots show the median, inter quartile range, range and any outliers in the data. Some outliers exist in the data as the NotUsing service, which recorded when the user was using and not using the PC did not work perfectly for all PCs. In a small number of cases the service appears to have hung for a period of minutes thereby marking small parts of a trace as USING when the person may well not have being using the PC. These small number of outliers are accounted for in the box plots and do not affect the overall results.

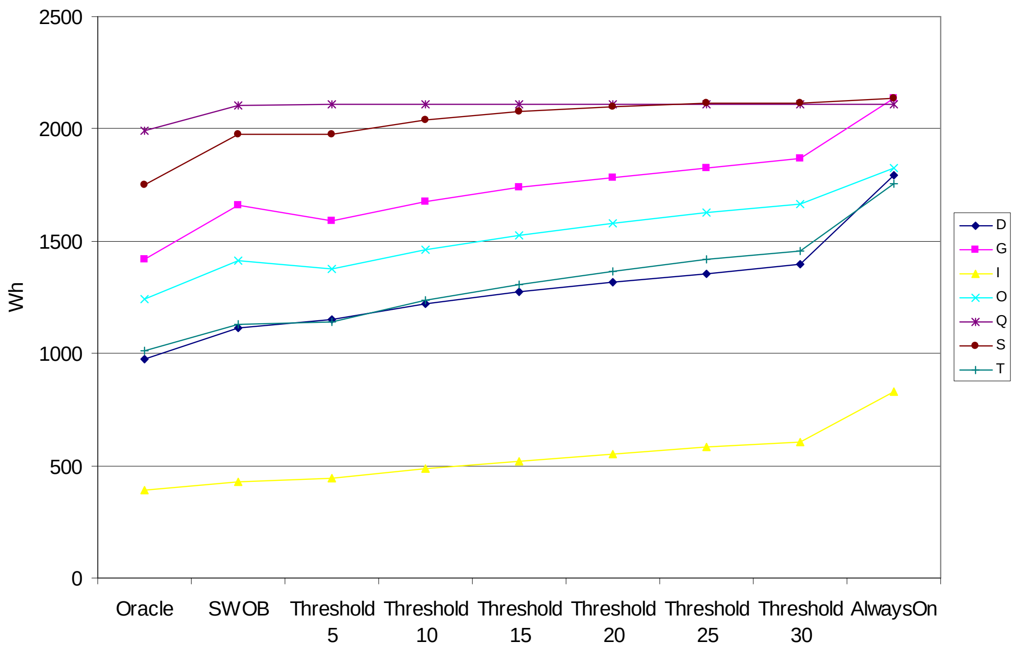
The SWOB policy has no FPDs for both LightUse and HeavyUse, which is sensible as the policy only powers down when the user is not in the vicinity. We were surprised by the results of FPDs for the Threshold policies, as the Threshold 5 has very few FPDs (median 0, range 0 to 2). We also graphed FPDs for Thresholds 1, 2, 3 and 4, which show a steep decline from median 20 per day to the Threshold 5 median of 0 per day. We are confident that the usage was recorded and analysed correctly and it suggests that when a user is using their PC there are very few idle periods of greater than 5 minutes. One possible side effect from the experiment was that the NotUsing service caused the user's to make more frequent inputs. This is evaluated in Section 5.7, which indicates that there was no significant affect to the users' behaviours.

The number of MPUs per day are shown in Figure 5.8. The SWOB policy has very few MPUs for both LightUse and HeavyUse (median 0, range 0 to 2), whereas the Threshold policies show more MPUs for LightUse users than for HeavyUse users, median 8 compared to median 5 for the Threshold 5 policy. Both results intuitively make sense. The SWOB policy only powers down when the user leaves the vicinity and will power up again when they return. A manual power up will only occur if the power-up policy does not sense the BT tag in time. For the Threshold policies, there is no power-up policy and LightUse users will allow the device to power down more often, hence incurring more MPUs.

We next estimate the extra energy that can potentially be saved by using a more sophisticated policy than the SWOB policy.

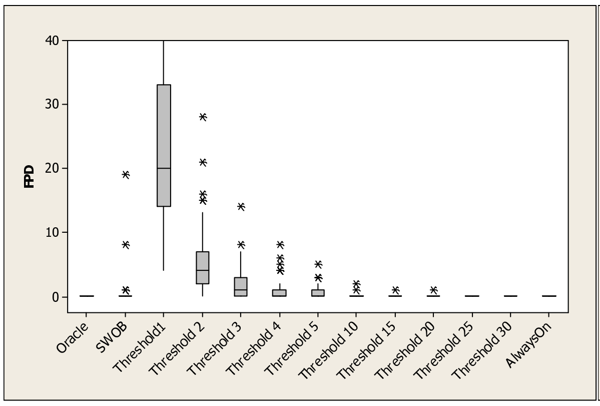


(a) Light Use

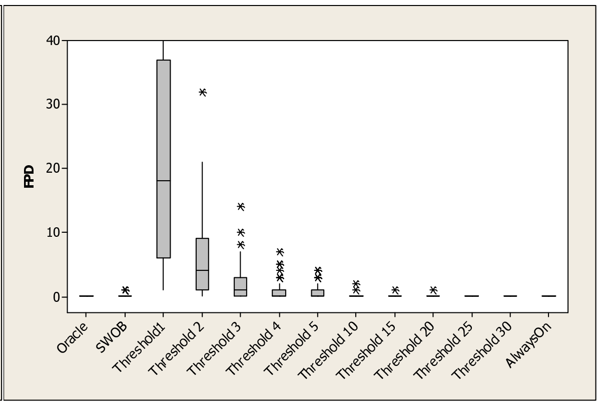


(b) Heavy Use

Figure 5.6: SWOB total energy comparison

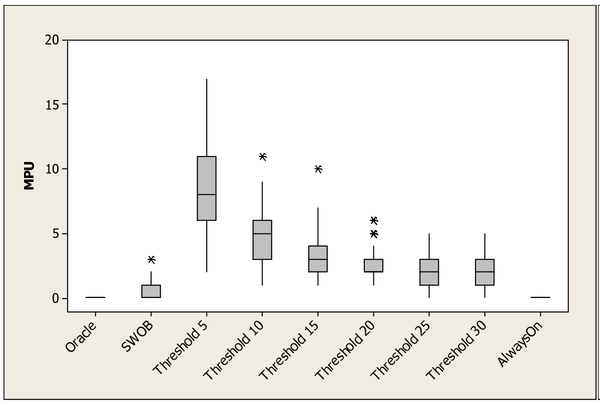


(a) LightUse

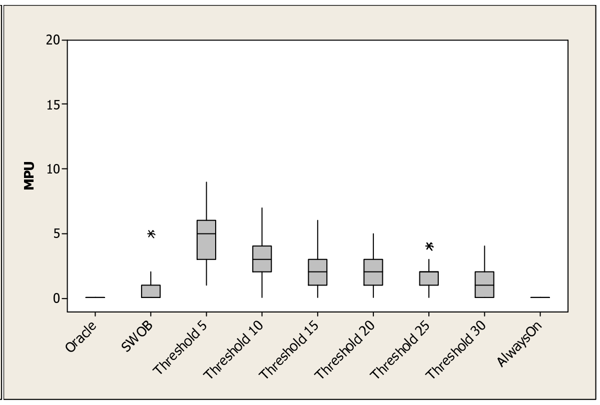


(b) Heavy Use

Figure 5.7: False power downs per day



(a) Light Use



(b) Heavy Use

Figure 5.8: Manual power ups

5.6.2 Potential extra energy from SWOB

The potential extra energy that can be saved if we can do better than the SWOB policy is simply the delta energy consumption of the SWOB policy from the Oracle policy. Figure 5.9 shows box plots of delta energy consumption per day for both LightUse and HeavyUse users of the display and PC.

The box plots show there is significantly more energy to be saved for LightUse users and also there is a larger variance in their energy consumption. For LightUse of the display, the median potential energy to be saved is 78Wh, range 20Wh to 185Wh. The equivalent median percentage from Oracle is 31.1%, standard deviation 28.5%. Similarly, for LightUse of the PC, the median potential energy to be saved is 59Wh, range 5Wh to 150Wh (22.1% from Oracle, standard deviation 21.6%). Furthermore,

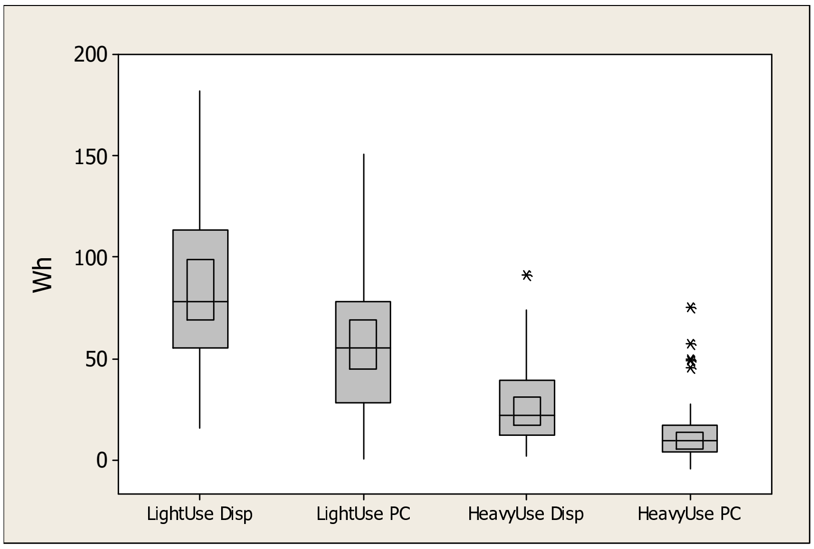


Figure 5.9: Potential extra energy from SWOB

the potential energy is less for the PC as its break-even time is relatively long compared to the display (5 minutes compared to 1 minute). This effectively means there are less opportunities for saving energy for the PC as the NOT USING period must be greater than 5 minutes.

For HeavyUse of the display, the median potential energy to be saved is 22Wh, range 5Wh to 80Wh (9.0% from Oracle, 10.0% standard deviation). For HeavyUse of the PC, the median potential energy is 13Wh, range 0 to 30Wh (5.7% from Oracle, standard deviation 8.4%). Trying to do better than the SWOB policy for HeavyUse users is therfore difficult.

We next estimate the energy consumption of the sensors used by the CAPM policies.

5.6.3 Energy consumption of sensors

Figure 5.10 shows the estimated energy consumption per day for each of the sensors. The assumption made is that the sensors run constantly for the duration of the user's working day at the 5 second sensor sample rate. So, the sensor energy consumption is calculated as the estimated power of the sensor (at the sample rate) times the number of hours for the user day. The median energy consumption per day for the sensors is BT 3.4Wh, OR 0.6Wh, FD 20.2Wh and VA 6.4Wh.

FD and VA consume a significant amount compared to the potential savings from the SWOB policy for the PC and display (LightUse - 59Wh and 78Wh, HeavyUse - 13Wh and 22Wh). The energy consumption of OR is significantly lower as there is no data processing needed. The most significant part of sensor energy consumption is due to the increased CPU cycles for processing the

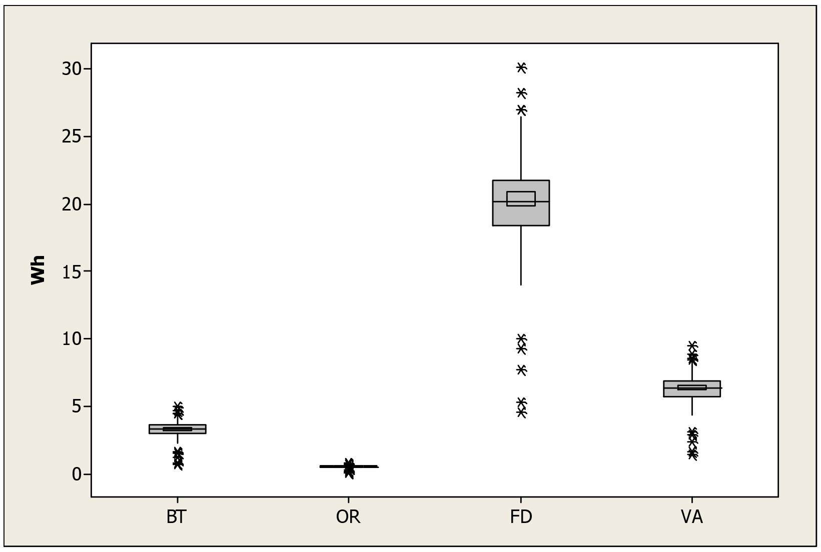


Figure 5.10: Estimated sensor energy consumption per day

face detection and voice activity data. It may be possible to decrease the sensor energy consumption by employing some form of power management for the sensors, but this is not explored in the thesis.

We next examine how the more sophisticated Bayesian CAPM policies compare to the SWOB and Threshold policies for both LightUse and HeavyUse users.

5.6.4 BN models for power management of the display

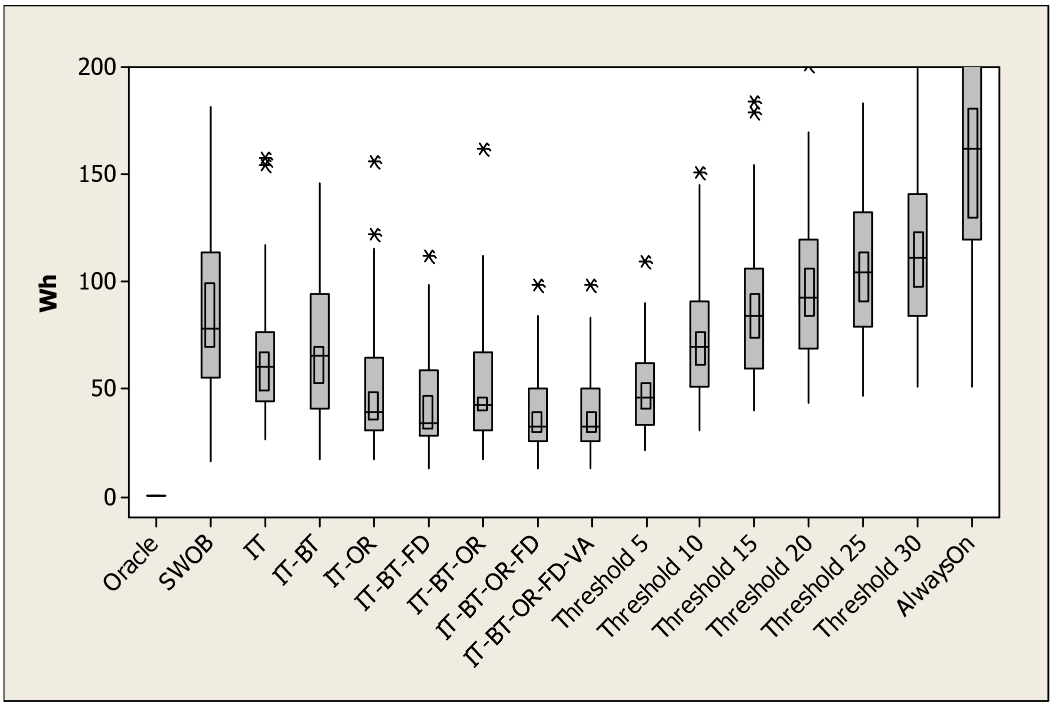
The energy consumption of the display unit is 45.8W when on and 1.8W in standby. The transition energy is assumed to be negligible. Its estimated break-even period is 1 minute and its resume time is 2 seconds. Figure 5.11 shows a box plot of the delta energy from Oracle per day of each policy for LightUse and HeavyUse users (the estimated sensor energy is not included). The LightUse SWOB policy's median energy consumption is 78Wh above the Oracle and ranges from 20Wh to 185Wh depending on the particular user and day. The equivalent median percentage from Oracle is 31.1% with standard deviation 28.5%. The inner box of the box plot, which covers the median shows the 95% confidence interval for the median. This signifies the true median lies within this range with 95% probability. Policies where the confidence interval boxes do not overlap have a significant difference in their medians. Therefore we can conclude that the BN policies IT-OR, IT-BT-FD, IT-BT-OR, IT-BT-OR-FD and IT-BT-OR-FD-VA do similarly well energy wise for LightUse users. They do better energy wise than SWOB with their medians between 32Wh to 42Wh and range from about 15Wh to 120Wh. The equivalent median percentages from Oracle are 13.4% to 17.5% from Oracle and standard deviation 12.7% to 18.6%. They are similar in energy consumption to the Threshold 5 policy with median 46Wh and range 25Wh to 90Wh (median 19.5% from Oracle, standard deviation 13.9%).

The energy consumption for HeavyUse users contrasts dramatically with the LightUse users. Overall the policies are closer to the Oracle and they have less variance. The SWOB policy performs similarly well energy wise (median 22Wh, range 5Wh to 80Wh, median 9.0 % from Oracle, standard deviation 10.0%) to the BN policies IT-BT, IT-OR, IT-BT-FD, IT-BT-OR, IT-BT-OR-FD and IT-BT-OR-FD-VA. Their medians are between 16Wh to 22Wh and their range is from 5Wh to 65Wh. The equivalent median percentages from Oracle are 7.2% to 9.0% from Oracle with standard deviation 4.1% to 6.0%. The Threshold 5 policy is also similar with median 29Wh (13.1% from Oracle, standard deviation 4.8%).

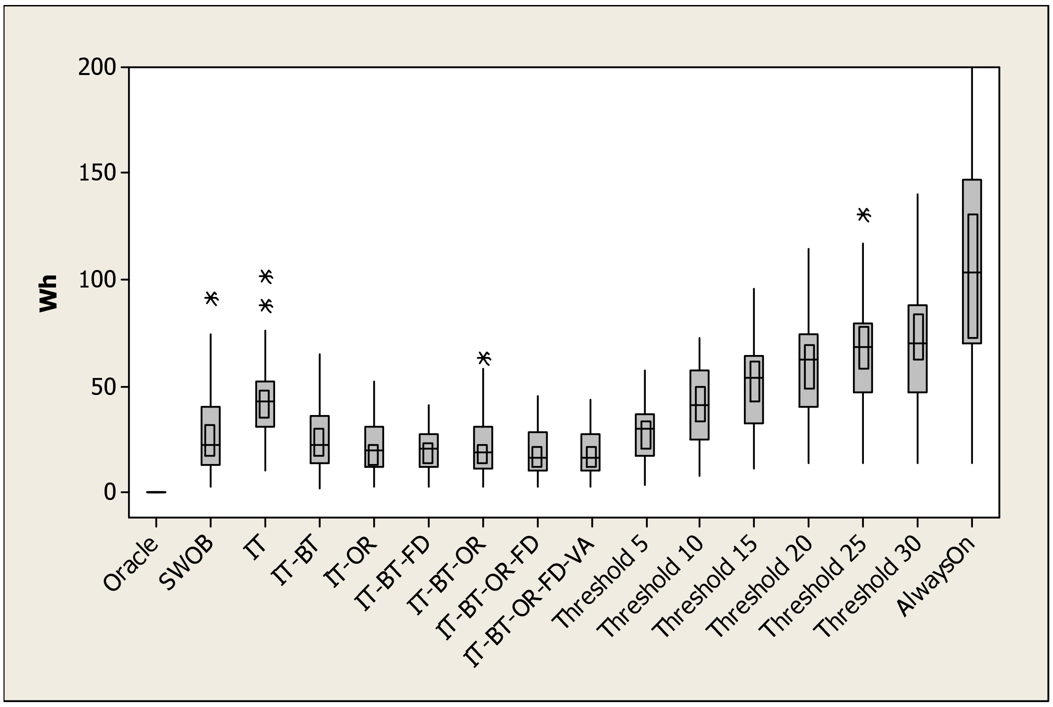
However, when the estimated sensor energy consumption is included there appears a bigger difference between the BN policies. Figure 5.12 shows the delta energy consumption including the estimated energy consumption of the sensors for LightUse and HeavyUse. It highlights the energy consumption of the face detection sensor as being very significant compared to the amount of energy that can be saved. After taking sensor energy into consideration the lowest consuming policies for LightUse are IT-OR 40Wh, IT-BT-OR 46Wh and Threshold 5 46Wh (median 17.3% to 19.5% from Oracle, standard deviation (STD) 13.9% to 18.6%). For HeavyUse the lowest consuming policies are IT-OR 21Wh, IT-BT-OR 21Wh, SWOB 25Wh, IT-BT 25Wh and Threshold 5 30Wh (median 8.9% to 13.1% from Oracle, STD 4.7% to 10.1%).

The number of false power downs is shown in Figure 5.13. The SWOB is the best of the CAPM policies with no false power downs for both LightUse and HeavyUse users. The BN policies for LightUse are similar with median of 0.5 to 1.25 per day and range of 0 to 3 FPDs per day. There is no significant difference for HeavyUse users with median 0.25 to 0.75 and range of 0 to 5. One possible reason why the BN policies perform slightly worse than the Threshold 5 policy (median 0, range 0 to 2) is because the learning of the idle time parameters for the BN models is too aggressive and perhaps a fixed, more conservative set of parameters would reduce the FPDs to near zero. Further experimentation would need to be done to achieve close to zero FPDs.

Figure 5.14 shows the number of manual power ups for each policy per day. The best CAPM policy for LightUse users is SWOB with median 0, then IT-BT (median 2) and IT-BT-OR (median 4.75) next. Since the power-up policy for all BN policies was limited to only powering up on BT, the more times the device was powered down when the user was in the vicinity, the more MPUs were incurred.

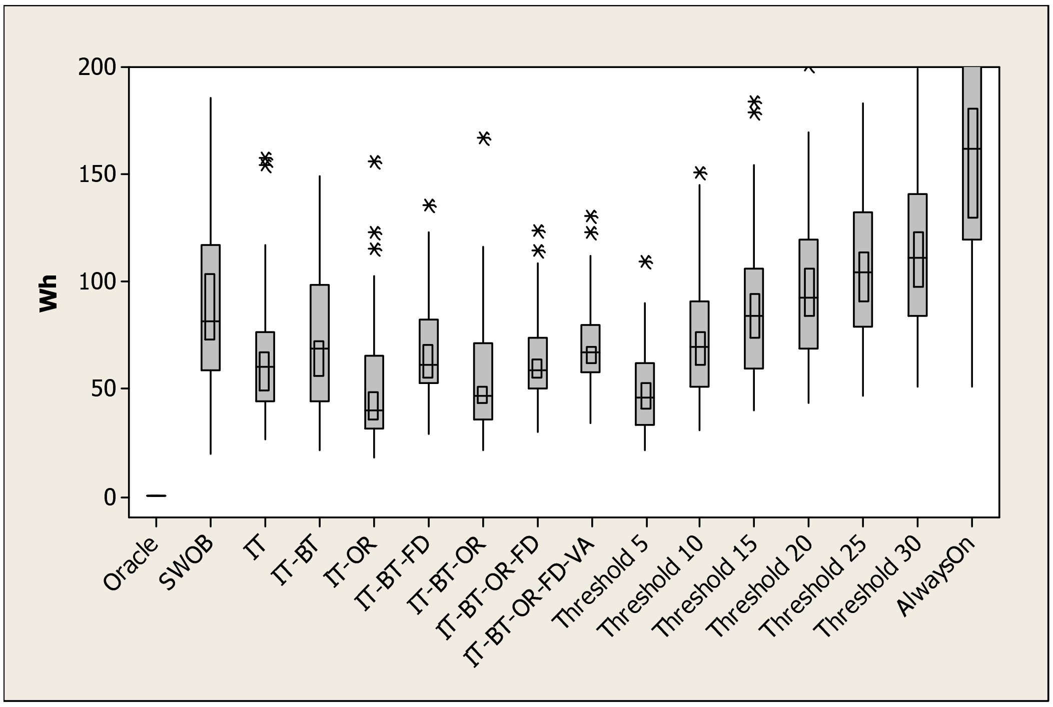


(a) Light Use

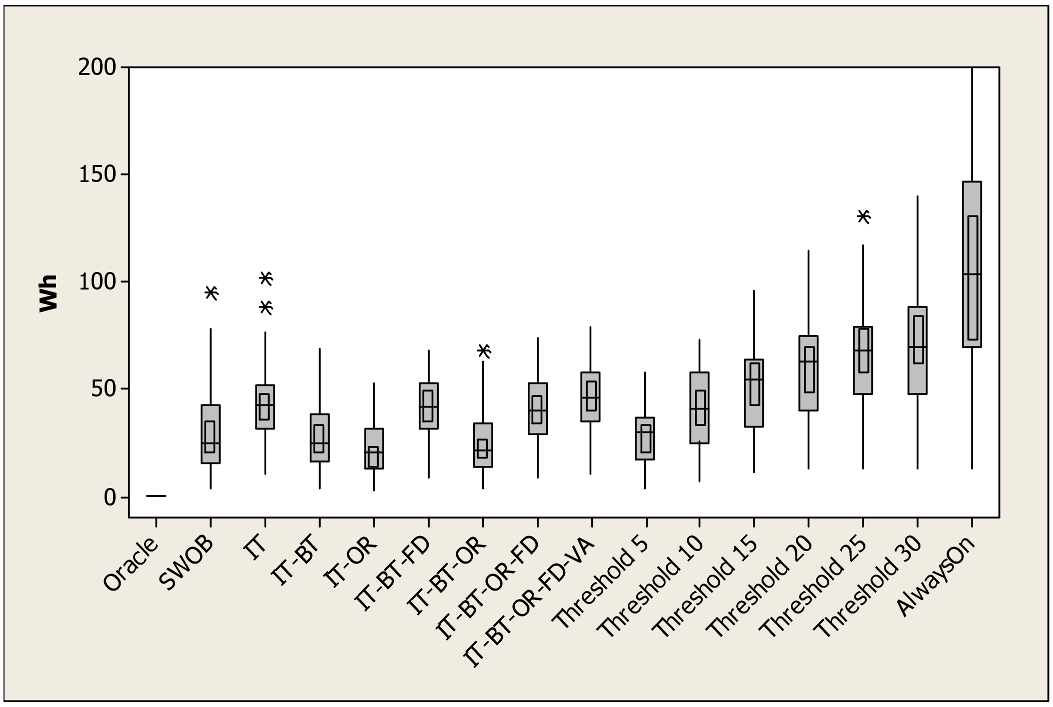


(b) Heavy Use

Figure 5.11: Delta energy

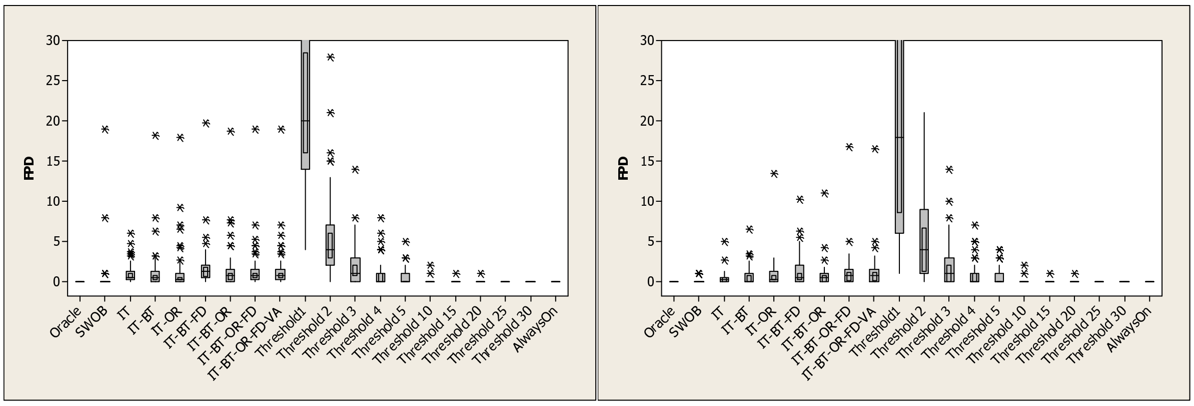


(a) Light Use



(b) Heavy Use

Figure 5.12: Delta energy including sensor energy



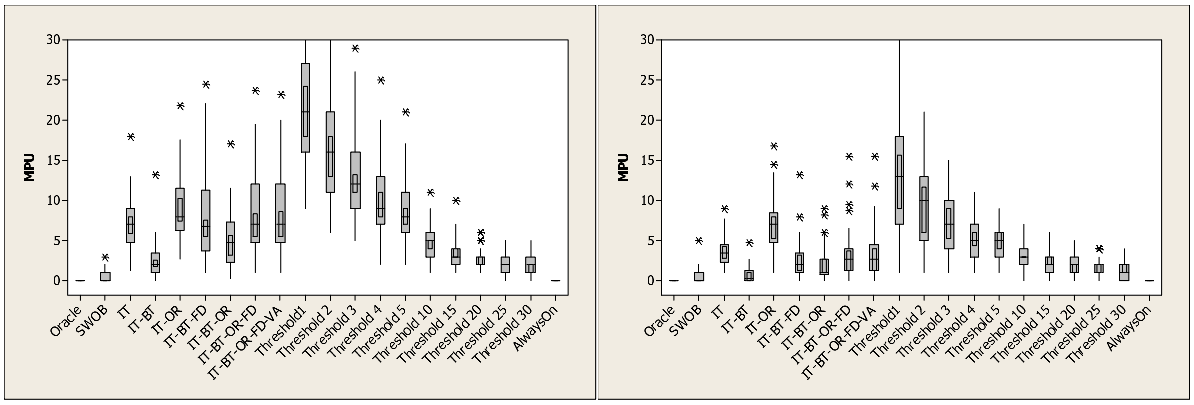
(a) Light Use

(b) Heavy Use

Figure 5.13: False power downs

The simple power-up policy was adopted because powering up based on OR and FD caused many false power ups. The power-up policy cannot use the same counting technique for its sensors as the power down, as it needs to power the device up on time (it cannot wait around to become more certain of the reading). Therefore a false object detection or face detection will cause the device to falsely power up. This caused particularly poor results if the object range values for USING and NOT USING were close or mixed (see Section 4.1.5).

The MPUs are less for HeavyUse users. This intuitively makes sense as HeavyUse users do not allow the device to power down as often, therefore requiring less power ups (SWOB median 0, IT-BT median 0.25, IT-BT-OR median 1).

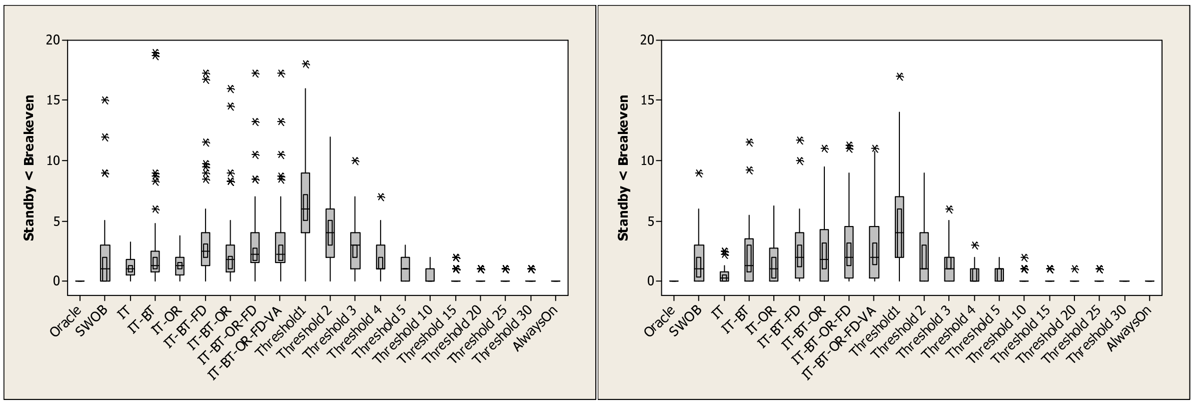


(a) Light Use

(b) Heavy Use

Figure 5.14: Manual power ups

Figure 5.15 shows the number of standby periods that were less than the break-even time for LightUse and HeavyUse users. The SWOB is similar for both (LightUse - median 1, range 0 to 5; HeavyUse - median 1, range 0 to 6) and the BN policies have similar medians (LightUse - 1 to 2.25; HeavyUse - 0.25 to 2.0) and similar range 0 to 7, 0 to 9. The HeavyUse Threshold policies have slightly less SBEs than for LightUse (LightUse - Threshold1 6, Threshold5 1; HeavyUse - Threshold1 4, Threshold5 1).



(a) Light Use

(b) Heavy Use

Figure 5.15: Standby break-even periods

From these results it is clear that the best policy for HeavyUse users is the SWOB policy performing well both energy wise and user-perceived performance wise. On average the energy consumption is 9.0% from the Oracle per day, there are median 0 FPDs and median 0 MPUs, resulting in very good user-perceived performance. The BN CAPM policies did not save significantly more energy and caused additional FPDs and MPUs. The median 1 standby break-even is relatively small.

For LightUse users the SWOB energy consumption is not as good and varies considerably across the users. It is equivalent to the Threshold 15 to 20 policies and on average within 31.1% of Oracle. To do better energy wise, it seems we must accept some performance penalties in terms of false power downs and manual power ups. Of the BN policies, the IT-BT-OR policy is one of the lowest energy policies with the least MPUs and FPDs. The IT-OR policy has similar low energy but worse user-perceived performance as it does not have the BT sensor for automated power ups. We believe that with further experimentation with the BN model parameters the number of FPDs could be reduced to the Threshold 5 level. This is important for the display device as FPDs are more annoying than MPUs as the resume time is relatively quick.

5.6.5 BN models for power management of the PC

The next set of results show the performance of the BN policies for power managing the PC, which has a longer break-even period of 5 minutes and a resume time of 7 seconds. This break-even time is difficult to measure and was estimated from the given lifetime on-hours and start-stop cycles for a standard PC hard disk, which was calculated at 2 minutes (see Section 3.1.5). We multiplied this by 2.5 to give an estimated upper bound for break-even time due to lifetime decay. The BN models have the same structure as before but the parameters are trained differently as periods where the user was NOT USING for less than 5 minutes are considered as USING cases. The energy consumption of the PC is 63.0W on_{idle}, 60.0W on and 2.8W in standby. The transition energy was measured to be 0.19Wh per transition.

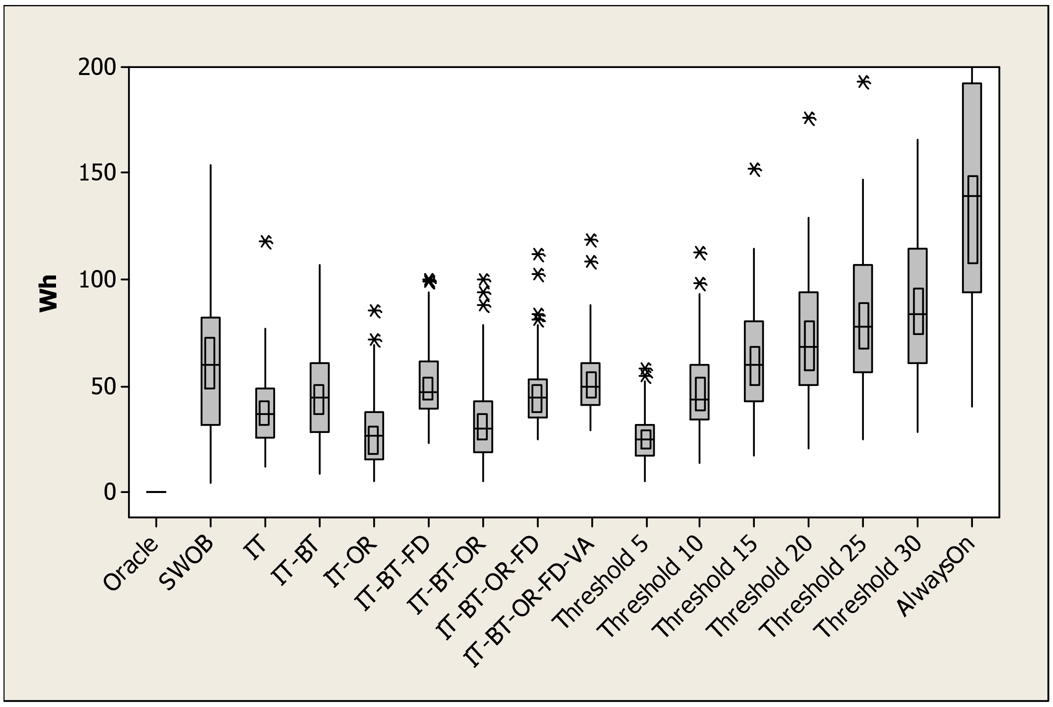
Figure 5.16 shows the delta energy consumption including sensor energy consumption. Again, the pattern is similar to the display device with large variance in the LightUse SWOB policy, which consumes median 59Wh, range 5Wh to 150Wh (22.1% from Oracle, standard deviation 21.6%), and Threshold 5 24Wh, IT-OR 27Wh and IT-BT-OR 30Wh consuming the least energy (9.4% to 12.0% from Oracle, standard deviation 6.6% to 10.9%). In general, all policies are closer to the Oracle than for the display device because the Oracle does not power down the PC for as many periods.

Similarly, the delta energy consumption for HeavyUse of the PC has a similar pattern to the energy consumption for the display. The SWOB policy consumes median 13.3Wh, range 0 to 30Wh (5.7% from Oracle, standard deviation 8.4%) and performs similarly well to the IT-OR 10Wh, IT-BT-OR 14Wh, Threshold 5 14Wh and IT-BT 18Wh policies, range 0 to 40Wh (5.5% to 7.9% from Oracle, standard deviation 3.8% to 5.7%).

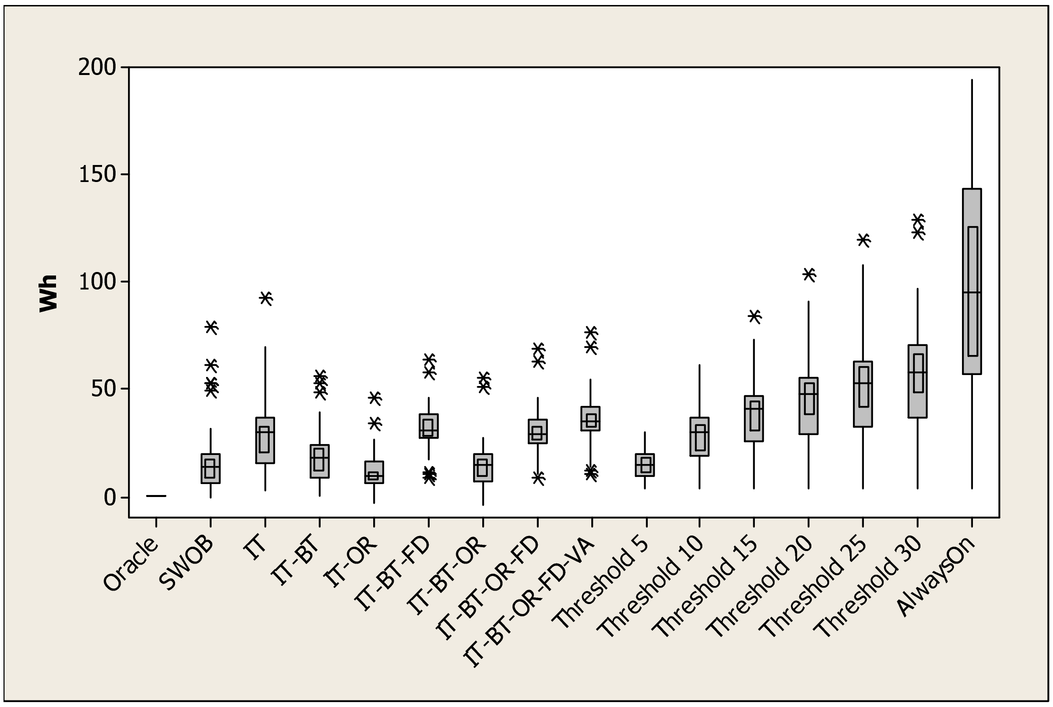
The number of false power downs for LightUse and HeavyUse of the PC are not significantly different to that of the display (see Figure 5.17). The SWOB policy has no FPDs for both LightUse and HeavyUse. The BN policy medians for LightUse are 0.25 to 0.5 and HeavyUse are 0.25 to 0.5 compared to LightUse 0.5 to 1.25 and HeavyUse 0.25 to 0.75 FPDs per day for the display.

Again, the MPUs for the PC are not significantly different to the display device. For LightUse the median MPUs are SWOB 0, IT-BT 2, IT-BT-OR 3.75 and IT-BT-FD 4.0. For HeavyUse the MPUs are less with SWOB 0, IT-BT 0.25, IT-BT-OR 1.0 and IT-BT-FD 1.0. Though the number of MPUs are similar to the display, the resume time for the PC is significantly longer so less MPUs will be tolerated by the user.

It was expected that the PC would have significantly more standby break-even periods than the display due to the break-even being 5 minutes. The LightUse SWOB (median 2, range 0 to 11) compares with the display values of (median 1, range 0 to 5) where the medians are similar but the

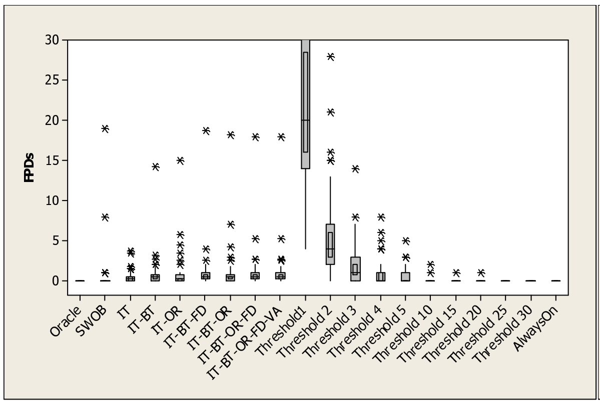


(a) Light Use

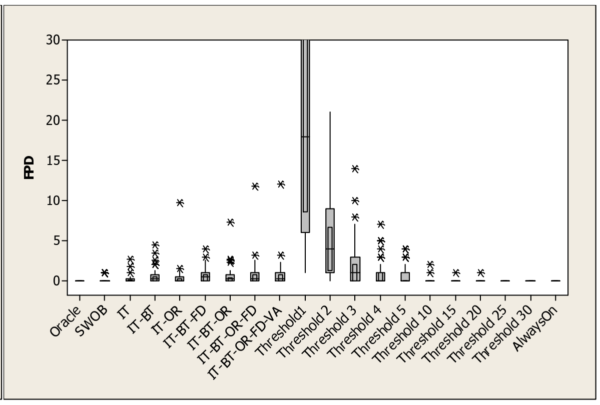


(b) Heavy Use

Figure 5.16: Delta energy including sensor energy

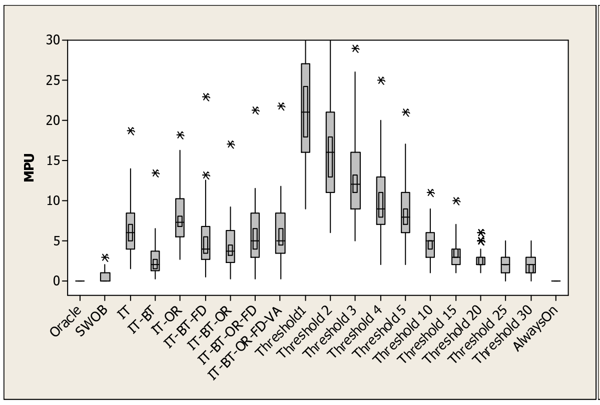


(a) Light Use

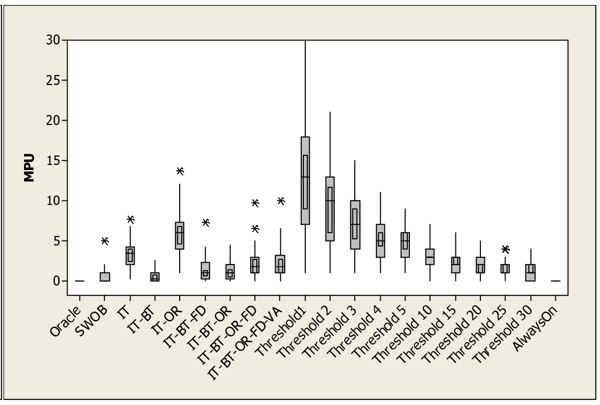


(b) Heavy Use

Figure 5.17: False power downs

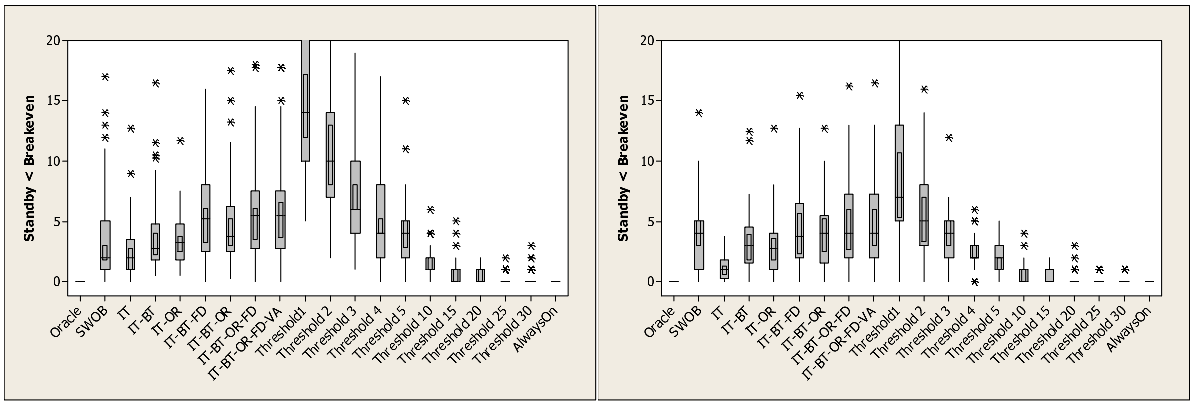


(a) Light Use



(b) Heavy Use

Figure 5.18: Manual power ups



(a) Light Use (b) Heavy Use

Figure 5.19: Standby break-evens

range is significantly larger for the PC. The HeavyUse SWOB (median 4, range 0 to 10) compares with the display values of median 1, range 0 to 6, where both the median and range are significantly larger (see Figure 5.19). The BN policies for LightUse and HeavyUse have similar medians (LightUse 2 to 5.5, HeavyUse 1.0 to 4.0) but the range is slightly more for LightUse. Also, for the Threshold policies the LightUse have slightly more standby break-even periods than for HeavyUse (LightUse - Threshold1 14, Threshold5 4; HeavyUse - Threshold1 7, Threshold5 1).

To summarise, the overall pattern of results for power management of the PC are similar to that of the display. For HeavyUse the SWOB policy is again the clear choice with both low delta energy consumption 13Wh (5.7% from Oracle) and no FPDs and few MPUs. The fact that the break-even time is longer means the policies achieve percentages closer to the Oracle policy. The number of standby break-even periods would be a concern for the lifetime decay of this PC with median 4 standbys per day less than the 5 minute break-even period.

For LightUse the IT-BT-OR policy has one of the lowest delta energy consumptions 30Wh (12% from Oracle) with the least FPDs and MPUs (FPDs median 0.5, MPUs median 3.75 per day). The number of MPUs is significant as the resume time of 7 seconds will cause significant user annoyance. The SWOB policy delta energy consumption for LightUse is 59Wh (22.1% from Oracle), which appears to be the best overall policy due to it having no false power downs and very few manual power ups (median 0).

5.6.6 DBN models for power management of the display

We experimented with dynamic Bayesian models to see if they could improve the predictive accuracy of the policies, in particular, reduce the number of FPDs, MPUs and SBEs for the Bayesian policies. The DBN for the display consists of six time slices with a 10 second interval between time slices. This gives a prediction for NOT USING that is 1 minute in the future.

Overall the performance of the DBN for power management of the display was very similar to the standard BN. Figure 5.20 shows the delta energy consumption to be very similar to the standard BN with the same policies performing the best. For LightUse IT-OR and IT-BT-OR are the best energy-wise with medians 42Wh and 52Wh compared to 40Wh and 46Wh for the BN versions. For HeavyUse the best DBN policies are IT-OR, IT-BT-OR and IT-BT with medians 16Wh, 25Wh, 26Wh compared with 21Wh, 21Wh, 25Wh for the BN versions.

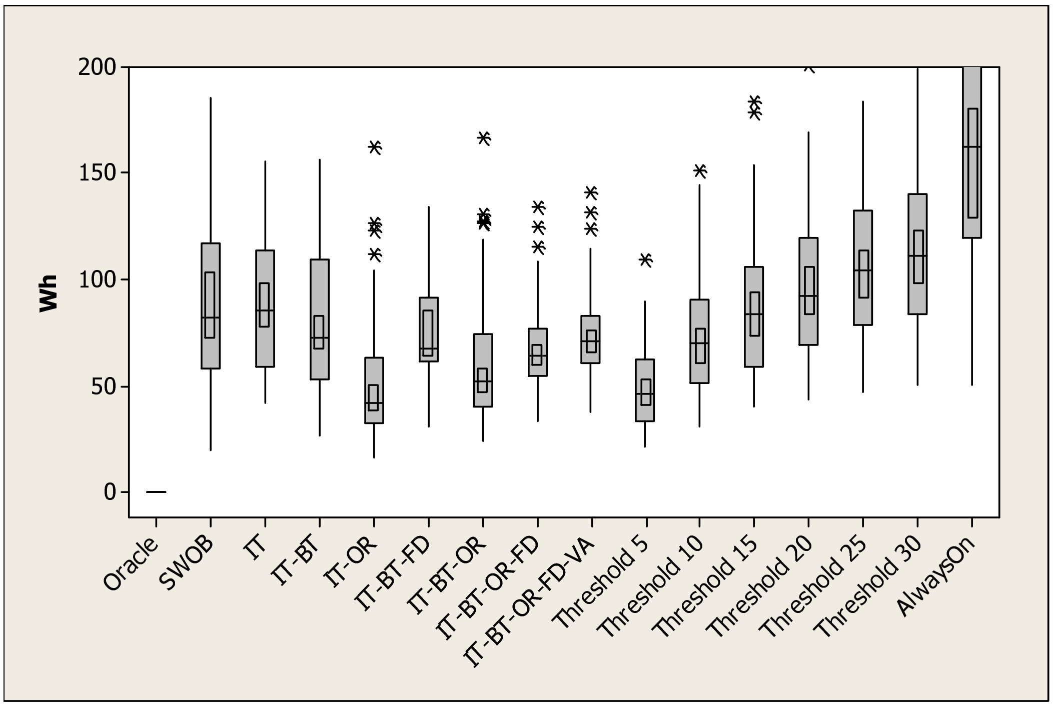
The user-perceived performance figures are shown in Appendix A. The FPDs for the DBN policies are in fact slightly worse than the BN policies with LightUse IT-BT-OR having median 0.75, range 0 to 5 and HeavyUse median 0.75, range 0 to 4. This compares to LightUse for the IT-BT-OR BN having median 0.75, range 0 to 3 and HeavyUse median 0.5, range 0 to 2. The MPUs are similar to the BN policies for the display, which is expected as the power-up policies for both are the same. The SBE periods are also similar to the BN policies with LightUse medians from 1 to 2.5 and HeavyUse from 1 to 1.5. The BN policies for the display have medians LightUse 1 to 2.25 and HeavyUse 0.25 to 2.0.

Overall there is no significant difference between the BN and DBN models for power management of the display.

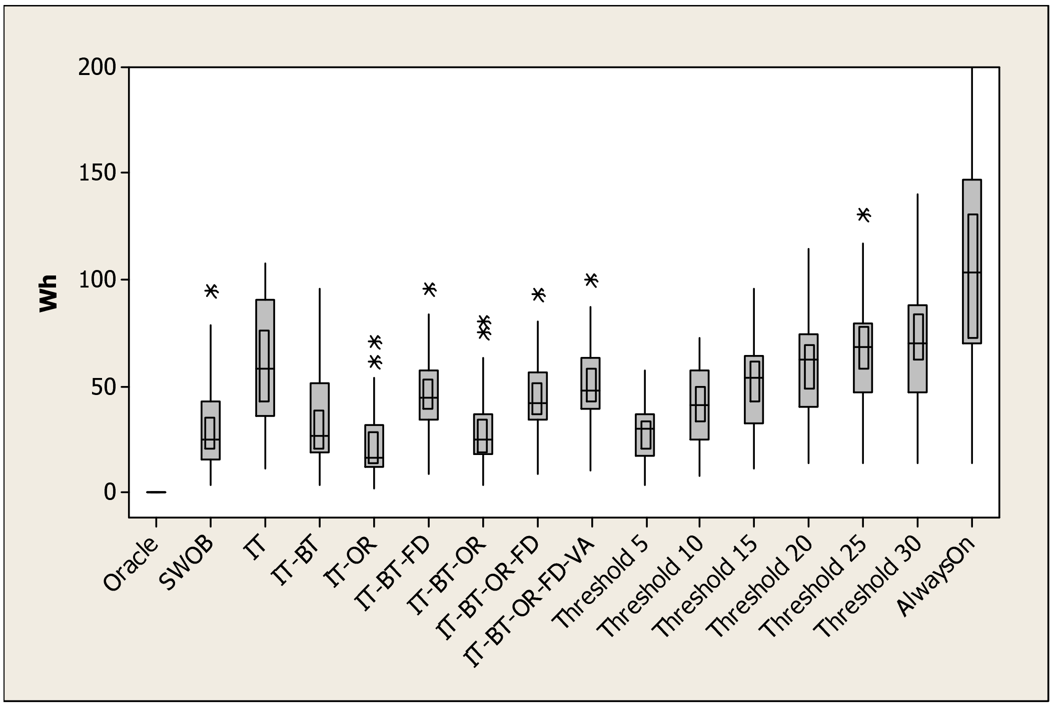
5.6.7 DBN models for power management of the PC

The DBN model for power management of the PC has 6 time slices with 50 second time intervals, giving a prediction of NOT USING that is 5 minutes into the future. Figure 5.21 shows the energy consumption of the DBN policies to be significantly higher than the SWOB policy for both LightUse and HeavyUse users. The user-perceived performance is an improvement on the BN polices (see Figures in Appendix A).

The reason for the significant increase in energy consumption and improvement in user-perceived performance is that the DBN policies take a long time for the NOT USING probability to reach the threshold and power down. Figure 5.22 shows the DBN IT-BT policy powering down 15 minutes from the point of NOT USING. From these results, it seems that the DBN models give no better performance than the BN models.

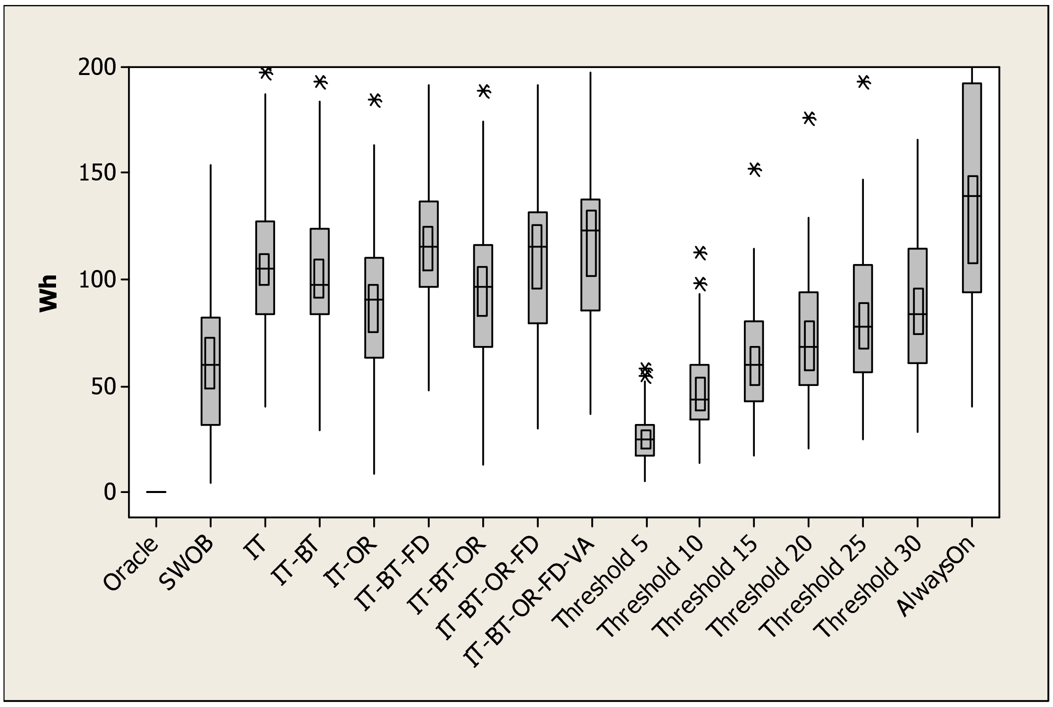


(a) Light Use

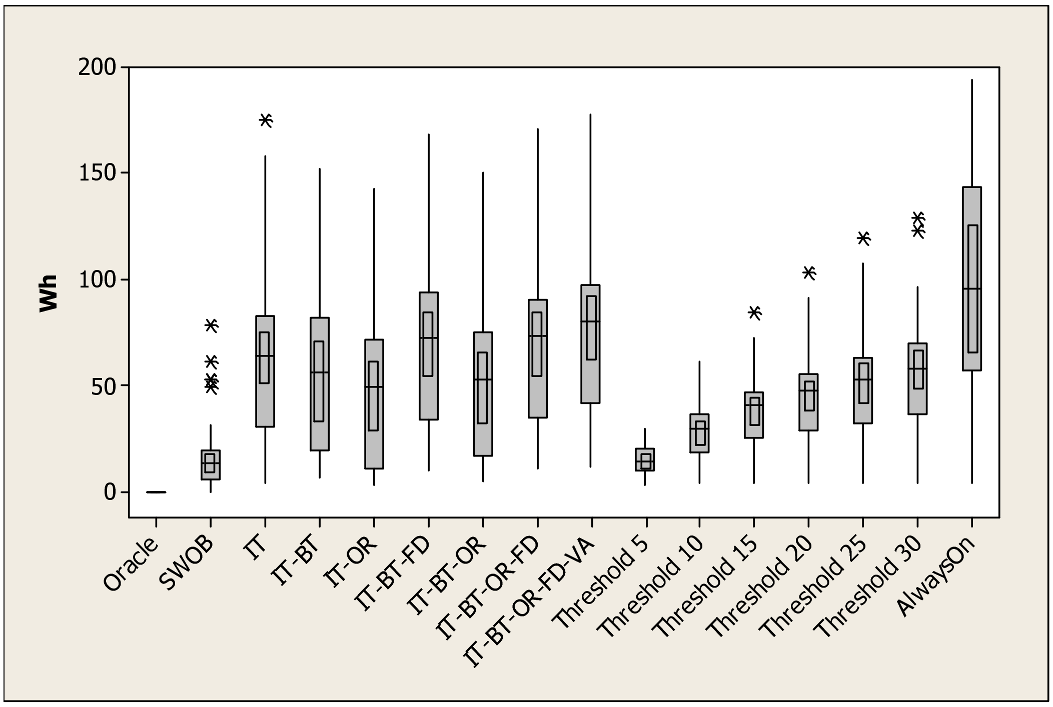


(b) Heavy Use

Figure 5.20: DBN display delta energy including sensor energy



(a) Light Use



(b) Heavy Use

Figure 5.21: DBN PC delta energy including sensor energy

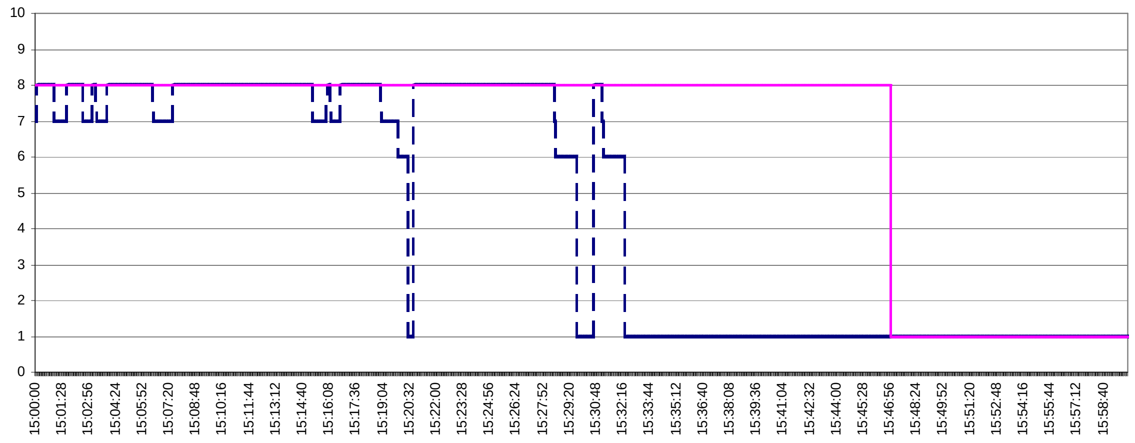


Figure 5.22: Example DBN policy trace

5.7 Evaluation of the affect of monitoring on users

It was necessary to evaluate if the user's behaviour was affected by the monitoring of the USING and NOT USING periods during the trial. We assumed that if there was an affect it would be that the users would make more frequent inputs due to the message box popping up. For example, when the user was prompted to confirm they were using the PC, they would change from what they were doing to use the mouse or keyboard and hence create a short idle period of less than 1 minute. If they just tipped the mouse to signify they were using the PC and continue their activity (for example reading from the display), the measured idle period is longer. This is because the short mouse input is removed from the measured trace during the data processing. So, if the monitoring affected the user's behaviour there would be significantly more short idle periods of duration 30 seconds to 1 minute.

To evaluate this we compared the frequency of idle periods in 1 minute bins (from 0 to $<$ 1 minutes to $>=$ 30 minutes) for the trial week and 5 normal weeks when just the idle periods were recorded. The measured trace for the trial week was processed to leave just the idle periods, so it could be compared with the traces of the 5 normal weeks. The analysis was done for a random sample of 8 of the users.

Figure 5.23 shows graphs of idle period frequencies for 6 of these users for the trial week and the 5 normal weeks. The trial week is the thicker line with the circle markers. The graphs show that the idle period frequencies for the trial week do not vary significantly outside of the normal weekly variability for each user. This suggests that the monitoring of the trial week did not have a significant effect on the users' frequency of input.

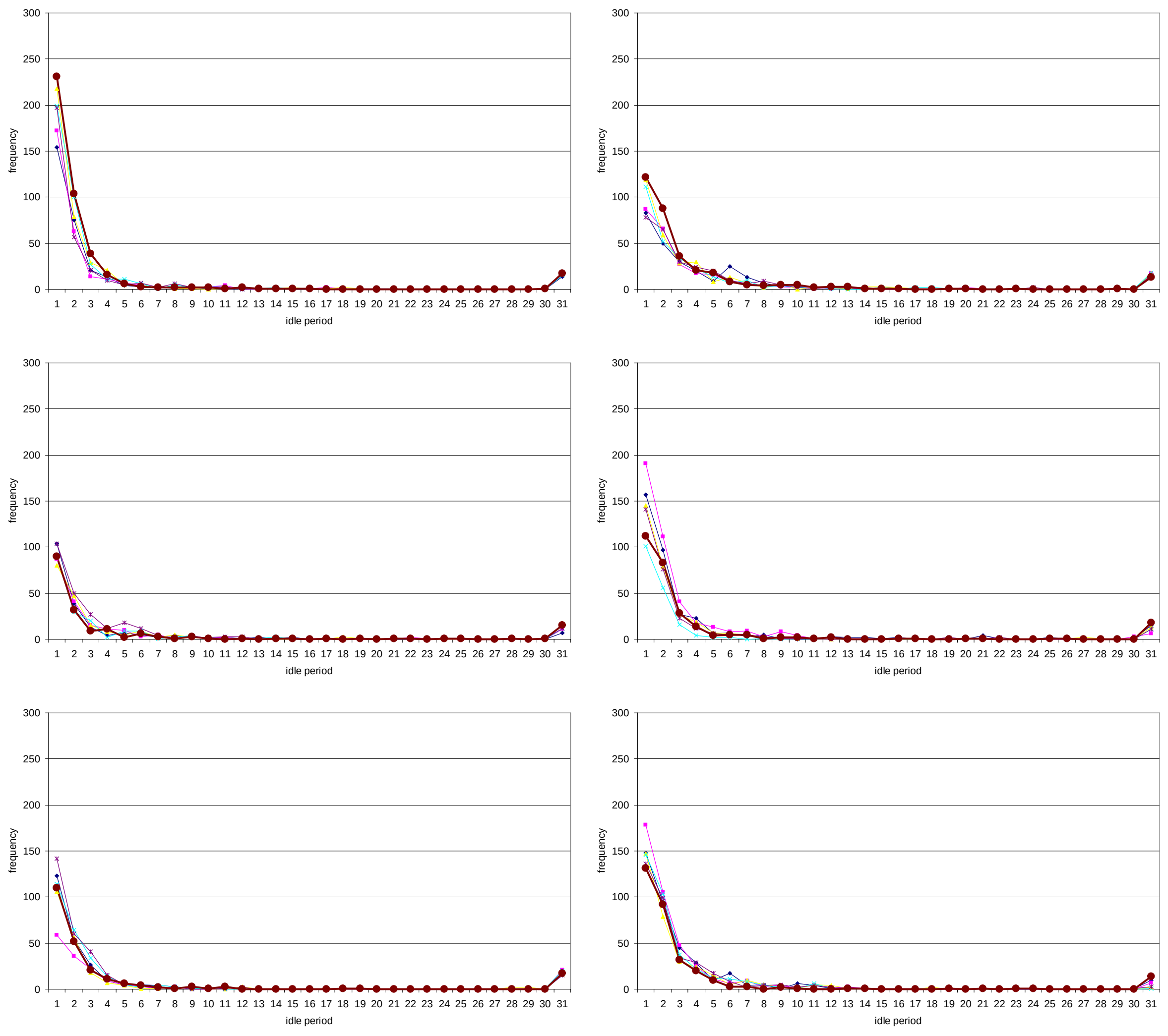
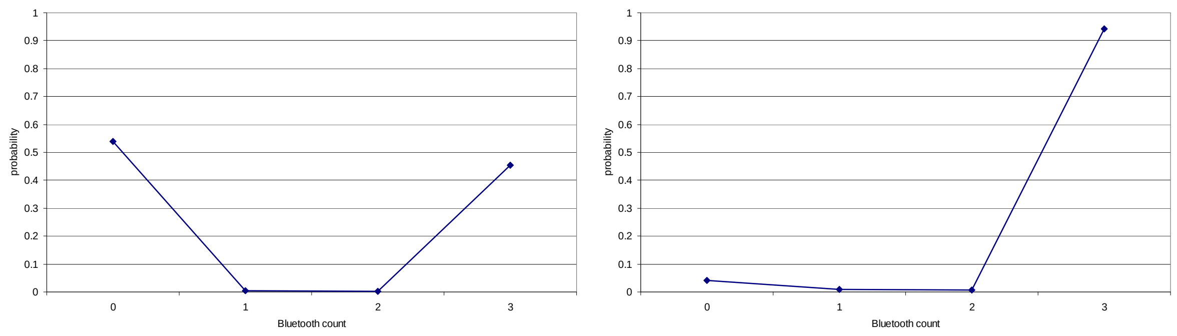


Figure 5.23: Idle traces for 6 of the users



(a) Light Use

(b) HeavyUse

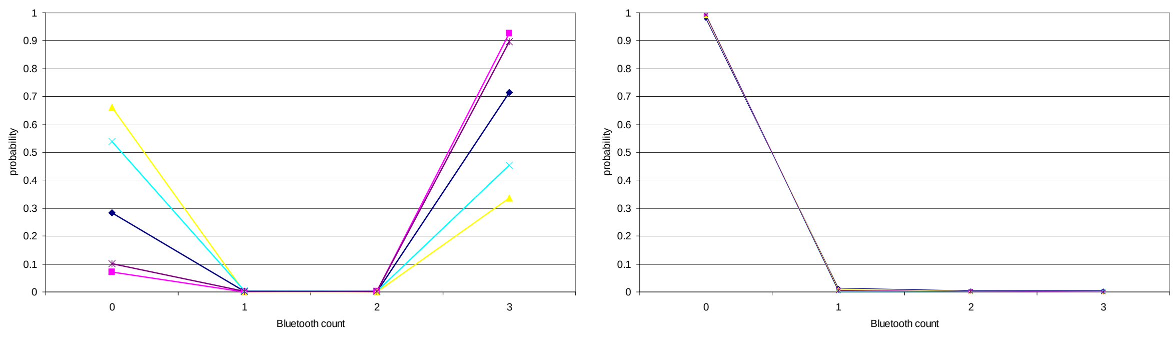
Figure 5.24: Bluetooth parameters given the user is NOT USING

5.8 Evaluation of BNs for device power management

Bayesian networks were used to implement the CAPM power-down policies. The supervised parameter learning captured the probability of each sensor value inferring NOT USING and the network combined these to give an overall NOT USING probability. Figure 5.24 shows the learned BT parameters given the user is NOT USING, for a LightUse and HeavyUse user. For the LightUse user, the presence of the BT tag has a greater probability of NOT USING than for the HeavyUse user. Therefore for a LightUse user in the vicinity of the PC, the probability of NOT USING will be reached more quickly as their presence is not a good indication of them using the PC.

However, there were some issues with the BN models. A rule had to be put into the model (the IdleTimeZero node) to infer USING if the idle time was less than 1 minute. This avoided a significant number of false power downs as the BN models could infer NOT USING too quickly. This would occur when the learned sensor parameters were stronger than the learned IdleTime parameter for 0 to 1 minute idle time and hence were too quick to predict a high probability of NOT USING.

The parameter learning for sensor values can be irregular if some of the sensor values are only lightly sampled. The parameter learning algorithm needs sufficient samples of a parameter value to give an accurate probability estimate for that value. This was in particular a problem for the IdleTime sensor where in most cases the probability of NOT USING fluctuated when the idle time became greater than about 9 minutes, as there were few samples for idle times greater than this. One possible solution discussed in Section 4.1.1 is to apply a smoothing function to the idle time CPTs to reduce the fluctuation in the NOT USING probability. Another possible solution could be to use a more conservative fixed parameter for the IdleTime to avoid the false power downs suffered by the



(a) Bluetooth given Not Using (b) Bluetooth given Using

Figure 5.25: Variance in BT parameters for the 5 training days

BN policies.

The learning of the power-down policy parameters was based on supervised data as we fully measured when the user was USING and NOT USING the PC using the pop-up message box. It would not be practical to do this in a deployment CAPM situation as it causes user annoyance to ask the user if they are using the PC or not after every minute of idleness. So, a semi-supervised method of learning the parameters would have to be developed. This method would only detect the user NOT USING the PC when it is powered down and USING the PC when the idle time is close to zero, say less than ten seconds. The other intervening cases would not be known.

Also, by looking at the parameter learning for each of the cross-fold training days, some of the LightUse users show significant variability in the parameter learning depending on which day was chosen (see Figure 5.25). This can significantly affect the outcome performance of the policies. Figure 5.26 shows the corresponding variability in policy energy consumption depending on the day it was trained on. The IT, IT-BT and IT-BT-FD policies have large variability for this LightUse user. For these variable use users, parameter learning over a longer period will produce an average parameter but the user's usage will vary significantly from this average.

Finally, the learning of the power-up policies was not successful as the learned ABOUT TO USE probabilities were very variable across the users. For example, with the simple IT-BT model, the probability of ABOUT TO USE when the BT tag was detected varied from around 40% to 80% for each of the users. A simple rule-based policy was more appropriate where the device always powered up when the BT tag was detected.

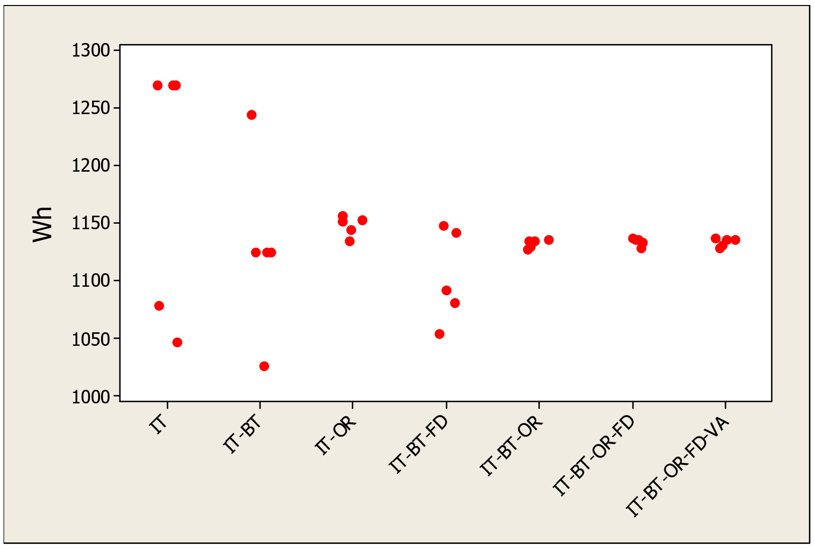


Figure 5.26: Variance in energy consumption per training day

5.9 Summary

The results show clearly that for HeavyUse (<= 15% NOT USING when in the vicinity) users of the display and PC, the SWOB policy does as well as the BN policies energy-wise, 22Wh (9%) from Oracle per day for the display and 13Wh (6%) from Oracle per day for the PC. Furthermore, the user-perceived performance of the SWOB policy is better with no FPDs and median 0, range 0 to 2 MPUs. The BN policies incur a number of FPDs (median 0.25 to 0.75, range 0 to 5) and on average one MPU per day. The Threshold 5 policy performs similarly well energy-wise and has median 0 FPDs, however has significant MPUs (median 5 per day). Therefore, we can conclude that for HeavyUse users the SWOB policy is the most appropriate for power management of the display and PC.

For LightUse (> 15% NOT USING when in the vicinity) users there is potential to do better than the SWOB policy. On average the potential extra energy that can be saved beyond the simple SWOB policy for LightUse users of the display is 78Wh (31%) from Oracle per day and for the PC is 59Wh (22%) from Oracle per day. However, the results show that it is difficult to do significantly better energy-wise than the SWOB policy without incurring performance penalties of false power downs and manual power ups.

For LightUse users of the display the best BN policy is IT-BT-OR with energy consumption of 46Wh (19%) from Oracle and from 0 to 3 FPDs (median 0.75) per day and on average 4.75 MPUs per day. The Threshold 5 policy does similarly energy-wise (46Wh) and has less FPDs (median 0, range 0 to 2) but more MPUs (median 8). We believe that with further tuning of the BN model, the FPDs could be improved for IT-BT-OR. Therefore we recommend the IT-BT-OR policy as the most suitable policy for power management of LightUse usage of the display.

For LightUse users of the PC, the best BN policy is again IT-BT-OR with energy consumption of 30Wh (12%) from Oracle and 0 to 2 FPDs (median 0.5) per day and on average 3.75 MPUs. The Threshold 5 policy does similarly energy-wise (24Wh), has fewer FPDs (median 0, range 0 to 2) but again more MPUs (median 8). While the performance of the IT-BT-OR policy might be acceptable for power management of the display, as the resume time is quick, we believe it would be unacceptable for the PC and hence the SWOB policy should also be recommended for power management of LightUse usage of the PC.

In all cases the face detection sensor consumes significantly more energy than the object range detection sensor and does not provide significantly better information. The voice activity sensor information does not improve the IT-BT-OR-FD policy at all as the quality of its information for determining NOT USING is very weak.

For the recommended policies for power management of the display (LightUse - IT-BT-OR; HeavyUse - SWOB) the SBE periods are relatively low (median 2, range 0 to 5; median 1, range 0 to 5) per day. However, for the PC the recommended SWOB policy incurs a significant number of SBEs (LightUse - median 2, range 0 to 11; HeavyUse - median 4, range 0 to 10). This would be a concern for power management of devices that incur a significant lifetime decay from switching on and off frequently. Possibly the inclusion of time of day information may help to reduce the number of short standby periods, or failing this knowledge of the user's distributed location may be needed to predict longer break-even periods. For example, if the user has gone to the bathroom they may be back soon but if they have left the building it is likely they will be back later.

The DBN policies did not perform better than the BN policies and in the case of the PC performed significantly worse energy wise due to the long delay before powering down.

It is possible that more tailor made rule-based policies could do better than the BN policies, achieving similar energy consumption but reducing the number of FPDs. However, we believe the number of manual power ups will remain similar due to the difficulty of automatically powering up in time when the user is in the vicinity. Therefore, the conclusions would still remain the same for the power management policies. For HeavyUse users, user presence (BT tag) is sufficient, whereas for LightUse users, user presence and near presence (OR detection) do better for the display, but incur too many MPUs for the PC which has a long resume time.

Chapter 6

Conclusions

This thesis began by outlining the motivation for device power management in buildings. There is a pressing need to reduce overall energy consumption, however, in spite of this there has been a steady rise in the energy consumed by electrical devices in buildings. Pervasive computing could further exacerbate the building energy problem, but on the other hand it could provide a solution by enabling more intelligent context-aware power management of devices.

Chapter 2 reviewed the current state of the art in dynamic power management and context-aware power management. The review concluded that current dynamic power management techniques are primarily focused on management of mobile, battery-powered devices and are not suitable for power management of stationary devices, which have longer break-even and resume times. Furthermore, it is necessary to obtain context from the user-level (e.g., user location) for effective power management of stationary devices. There have been several research projects in this area of CAPM, which have focused on developing techniques for inferring context from sensors. However, there has been no detailed study into what are the potential energy savings of CAPM and what granularity of context is appropriate.

6.1 Contribution

The initial experimental trial explored the use of location as a key piece of context for power management of desktop PCs in an office environment. The resulting SWOB policy powers down the PC when the user's presence (Bluetooth phone) is not detected and powers up again when the phone is detected again. The trial demonstrated that user behaviour is the key factor to the SWOB policy's performance. For heavy users, the SWOB policy performs well both in terms of energy and user-perceived performance and for light users it performs badly energy-wise but maintains good user-perceived performance.

A large user study was carried out to evaluate whether additional, finer-grained context could do better than the SWOB policy and at what extra cost. The sensors explored were idle time (IT), Bluetooth presence (BT), face detection (FD), object range detection (OR), and voice activity (VA). A Bayesian network was used to combine the multi-modal data to infer the contexts NOT USING and ABOUT TO USE.

The user study revealed the potential extra energy that could be saved beyond that of the SWOB policy was relatively small for heavy users (6-9% from Oracle). The BN policies with additional sensors did no better energy-wise and had worse user-perceived performance (median 1 MPU per day) because these policies power down when the user is still in the vicinity of the device. Therefore, the SWOB policy is recommended for heavy users of displays and PCs. For light users the SWOB policy does not perform as well energy-wise (22-31% from Oracle) and the best performing CAPM policy is IT-BT-OR (12-19% from Oracle). However, there are a significant number of manual power ups (median 4 to 5 per day) for IT-BT-OR. Therefore, we believe this policy would only be suitable for power management of displays, which have a short resume time.

The energy consumption of the face detection and voice activity sensors was found to be significant (FD 20.2Wh, VA 6.4Wh median per day) compared to the potential extra energy that can be saved for light users (PC 59Wh and display 78Wh median per day). The large energy consumption is due to the significant amount of CPU processing of the video and audio data. Furthermore, we found the voice activity sensor did not provide a good cue of the contexts NOT USING and ABOUT TO USE. Although, the face detection sensor provided valuable information, the energy cost of the sensor resulted in it performing worse overall than the coarser-grained object-range sensor.

The technique of Bayesian networks did not perform as well as we expected with the BN policies having a significant number of false power downs, more than the Threshold 5 policy. We believe that some hand-crafting of the BN parameters would be needed to reduce the number of FPDs to an acceptable level. Furthermore, the dynamic Bayesian network was not an improvement over the standard BN. Given the IT-BT-OR policy has relatively few sensors, it is possible that a simple rule-based policy could do as well, if not better than the BN technique.

6.2 Future work

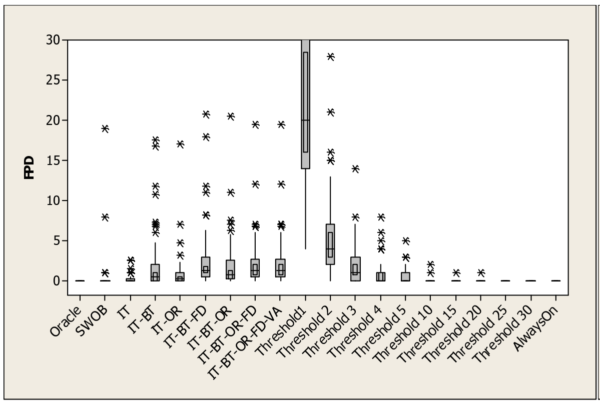
This thesis focused on the off-line evaluation of the BN policies. These policies were trained with supervised data gathered from the measurement of the users' usage. Currently the runtime CAPM framework does not incorporate on-line learning of the CPTs. In the on-line case it is not practical to fully measure when the user is USING and NOT USING the device, as this would cause significant user annoyance. Therefore, there is a need to develop a semi-supervised approach to learning of the CPTs, where it is possible to learn the CPTs based on a partial set of observed USING and NOT USING cases. Furthermore, given the results from the evaluation, it would also be necessary to explore techniques to avoid false power downs occurring.

Another finding from the evaluation is that user behaviour could vary significantly. For some of the light users, their behaviour changed from day to day, with some days being light use and others more heavy use. Therefore, another issue to deal with is learning for users with variable behaviour.

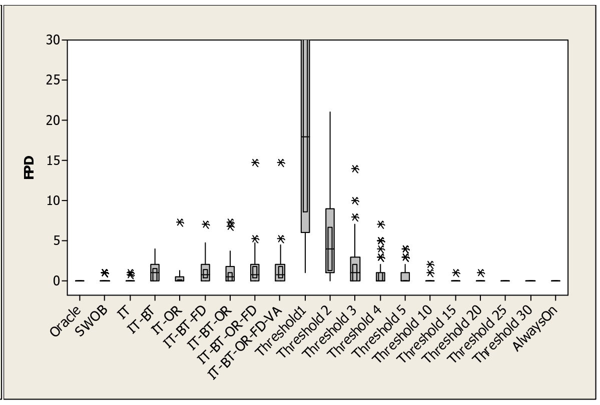
Finally, the requirements of distant prediction and distributed sensing were not implemented in the CAPM framework. These requirements could be addressed by inclusion of CAPM into the sentient object model. This would enable inclusion of data from distributed sensors, for example, the location of a user in other parts of the building. This could enable the prediction of longer idle periods necessary to reduce the number of standbys that are less than the break-even time for devices with long break-even times (5 minutes and greater). In addition, mobility prediction could be used for distant prediction to offset delays in sensor response and long device resume times.

Appendix A

Additional Evaluation Figures

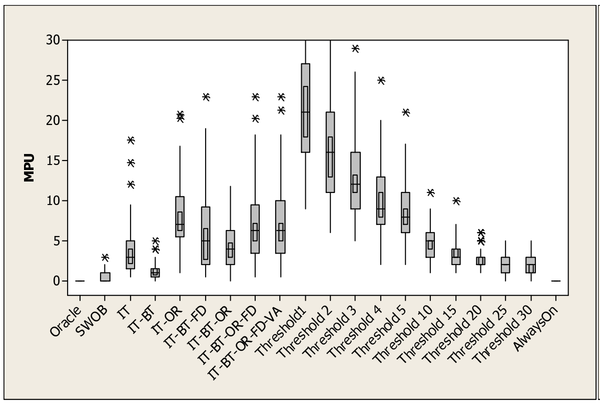


(a) Light Use

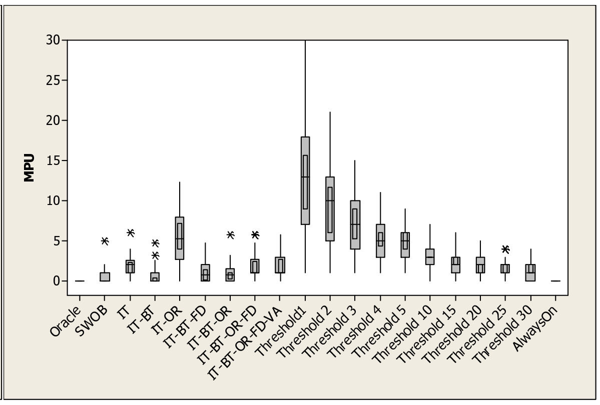


(b) Heavy Use

Figure A.1: DBN display false power downs

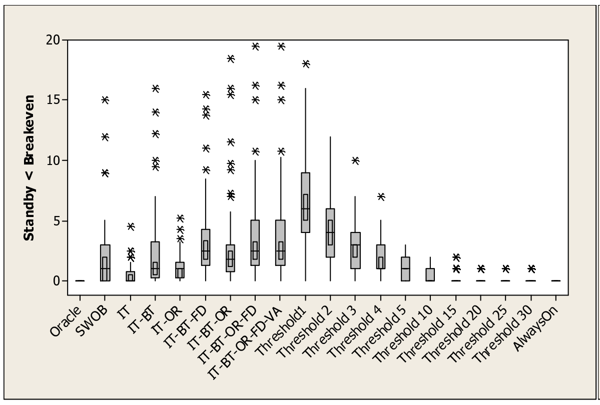


(a) Light Use

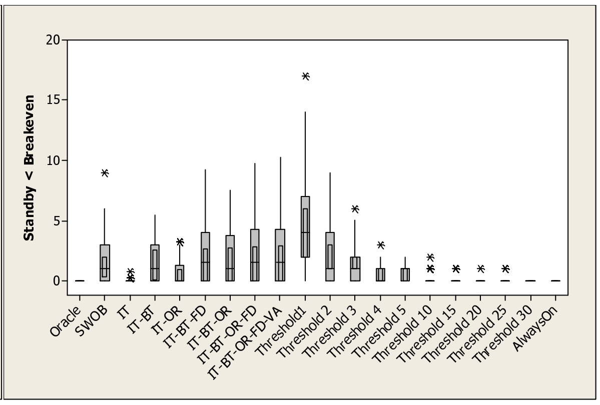


(b) Heavy Use

Figure A.2: DBN display manual power ups

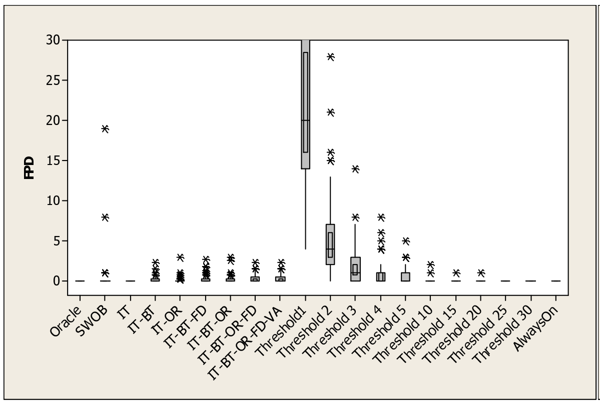


(a) Light Use

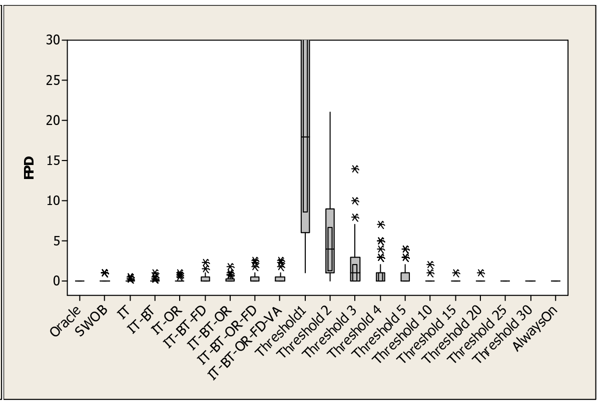


(b) Heavy Use

Figure A.3: DBN display standby break-evens

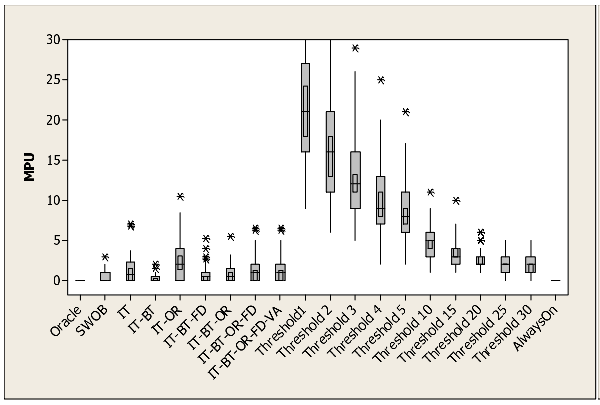


(a) Light Use

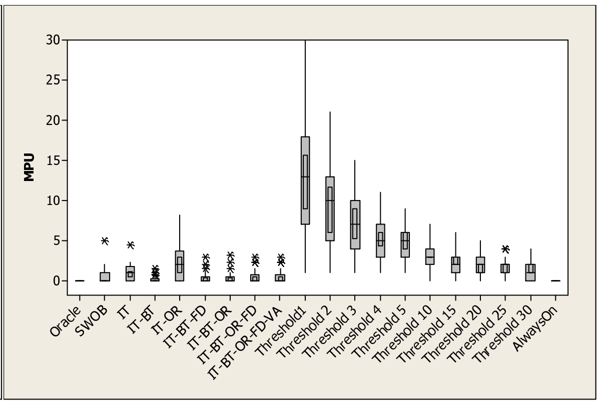


(b) Heavy Use

Figure A.4: DBN PC false power downs

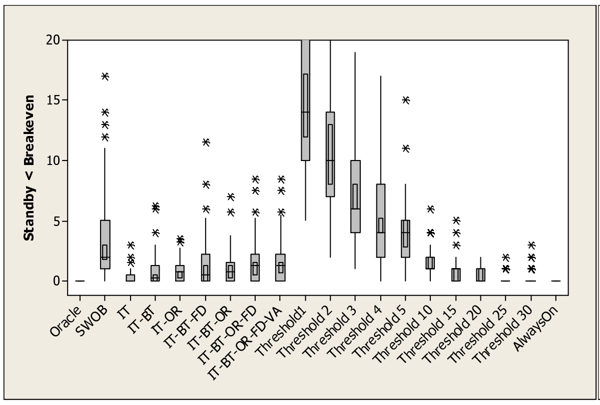


(a) Light Use

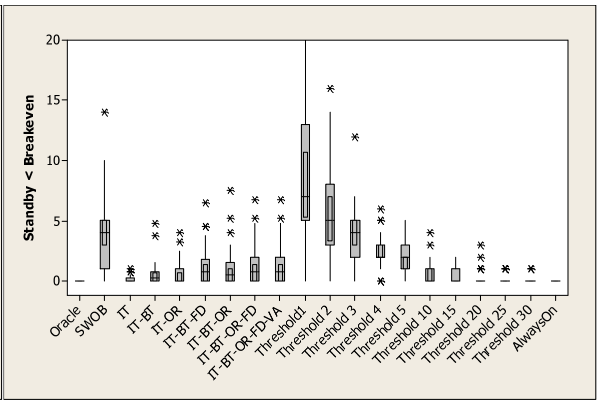


(b) Heavy Use

Figure A.5: DBN PC manual power ups



(a) Light Use



(b) Heavy Use

Figure A.6: DBN PC standby break-evens

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