SENSOR-BASED OCCUPANCY BEHAVIORAL PATTERN RECOGNITION FOR ENERGY AND COMFORT MANAGEMENT IN INTELLIGENT BUILDINGS

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ABSTRACT

There has been extensive research focusing on developing smart environments by integrating data mining techniques into environments that are equipped with sensors and actuators. The ultimate goal is to reduce the energy consumption in buildings while maintaining a maximum comfort level for occupants. However, there are few studies successfully demonstrating energy savings from occupancy behavioural patterns that have been learned in a smart environment because of a lack of a formal connection to building energy management systems. In this study, the objective is to develop and implement algorithms for sensor-based modelling and prediction of user behaviour in intelligent buildings and connect the behavioural patterns to building energy and comfort management systems through simulation tools. The results are tested on data from a room equipped with a distributed set of sensors, and building simulations through EnergyPlus suggest potential energy savings of 30% while maintaining an indoor comfort level when compared with other basic energy savings HVAC control strategies.

INTRODUCTION

Occupant presence and behavior in buildings has been shown to have large impacts on space heating, cooling and ventilation demand, energy consumption of lighting and space appliances, and building controls (Page, 2007). Several stochastic models have been developed to model occupant presence and interactions with space appliances and equipment. Fritsch et al. (1990) proposed a model based on Markov chains to model the random opening of windows by occupants. Degelman (1999) developed a Monte Carlo modeling approach for space occupancy prediction based on survey statistics. Reinhart et al. (2004) determined occupant presence for lighting software by using a simplified stochastic model of arrival and departure. Wang et al. (2005) applied Poisson distributions to generate daily occupancy profile in a single-occupied office. Mahdavi et al. (2006) explored the possbilities of identifying general patterns of user control behavior as a function of indoor and outdoor environmental parameters such as illuminance and irradiance. Bourgeois et al. (2006) integrated an occupancy model based on Reinhart's algorithm into ESP-r to investigate lighting use. However, most of the previous occupancy presence models were either tested on a single person office or presented a specific application such as lighting control. Only recently, Page et al. (2008) targeted individual occupancy behavior by developing a generalized stochastic model for the simulation of occupant presence with derived probability distributions based on Markov chains. However, the occupancy behavior derived from stochastic model was based on the assumption that occuapncy will interact with different appliances in the space and the validation was conducted in single-occupied offices. Most of the previous works are based on supervised approaches, which require ground truth occupancy information. In addition, the latest models are all based only on motion sensors, which often fail to detect occupants that are sitting or standing still, and thus have been shown in some cases to provide insufficient accuracy for occupancy detection (Lam, et al., 2008). Because occupants generate heat, water vapour, CO_2 and odors, a richer sensor enviroment allows for a more robust means of detecting occupancy presence and behaviour than motion sensors alone.

Recently, there has been extensive research focusing on developing smart environments by integrating data mining techniques into environments that are equipped with rich sensors and actuators. A smart environment is defined as an environment able to acquire and apply knowledge about the resident and the physical surroundings to improve the resident's experience (Cook et al, 2004). Duong et al. (2006) used hidden semi-Markov models for modeling and detecting activities of daily living such as cooking, eating, etc., and Youngblood et al. (2007) introduced a new method of automatically constructing hierarchical hidden Markov models using the output of a sequential data mining algorithm to control a smart environment. Other work investigates HVAC preconditioning and device automation via mined location and device interaction patterns, and the energy savings potential is estimated through a relatively simple consumption model (Roy et al. 2007). The objective of this study is to develop and simulate unsupervised algorithms for ambient sensor-

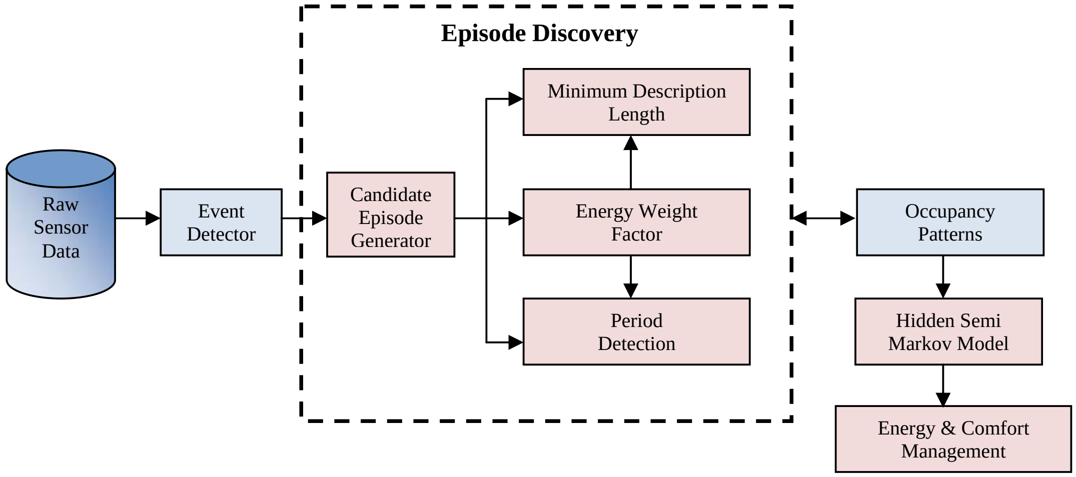

Figure 1 A holistic view of this study

based modelling and prediction of user behaviour within the context of intelligent buildings and connect the derived user behavioural patterns to building energy and comfort management. We base our approach on the work of Youngblood et al. (2007) in that a behavioral pattern model is constructed by mining sensor events for significant patterns (Episode Discovery), and then a Markov model is generated from the resulting patterns. Our contributions lie first in the integration of a rich environmental sensor network using acoustics, temperature, relative humidity etc. into the data-driven model of occupancy behavioural patterns. Sensor event definitions account for significant behavioral changes and energy events, and the resulting (semi-)Markov models incorporate duration to capture behavioral transitions over larger time scales. Second, we develop a formal method to connect the discovered patterns with energy and comfort management in buildings and demonstrate through simulation the energy-savings potential on real data from a conference room in an office building. In particular, we propose a dynamic occupancy schedule for use in both EnergyPlus (Crawley, 1999) simulations as well as more commonly used energy management strategies, thus providing a first step to truly integrating smart building concepts into the building management community.

An overview of the approach used in this study is shown in Figure 1. The outline of the paper is as follows. Section II describes sensor event detection. Section III presents the approach for frequent pattern detection using Episode Discovery, minimum description length (MDL), period detection (PD) and energy weight factors. Section IV introduces a semi-Markov model for occupancy duration models. Section V discusses the connection of these frequent patterns with building and energy comfort management, and Section VI presents conclusions and possibilities for future work.

OCCUPANCY PATTERN RECOGNITION

Event Detector

We first discuss the detection of events from a variety of different sensors. We denote each single event with a symbol and an episode as a sequence of symbols. Table 1 shows symbol assignments; an example of an episode is "*agghkjhk*…". A detailed explanation of the event definitions for each sensor is discussed below. All parameter values used in the definitions are determined empirically for the testing environment used in this work; however, variations in these values are possible while still producing meaningful sensor events.

Table 1
Definition of important events from sensors

Sensors	**State Transitions**	**Code**	**Sensors**	**State Transitions**	**Code**
Acoustics	1. Low acoust.	a	CO_2	1. Increasing	g
	2. Loud acoust.	b		2. Decreasing	h
Illumination	1. Off-On	c	Temperature	1. Increasing	i
	2. On-off	d		2. Decreasing	j
Motion	1. Off-on (motion)	e	Relative Humidity	1. Increasing	k
	2. On-off (no motion)	f		2. Decreasing	l

a. Acoustics

The acoustics sensor outputs a calibrated percentage of the acoustics level in the space. Figure 2 shows an example acoustics profile for a typical day in a conference room. The acoustic events are categorized into two types: (1) ventilation noise or background noise, defined as an acoustics level between 15% and 20% that is accompanied by at least a 5% increase from the previous level (event '*a*'); (2) human activity (e.g., voice or door opening/closing), defined as an acoustics level above 20% accompanied by at least a 10% increase from the previous level (event '*b*'). A smoothing method based on a root mean square approach is implemented to reduce noise (Smaton and McHugh, 2006).

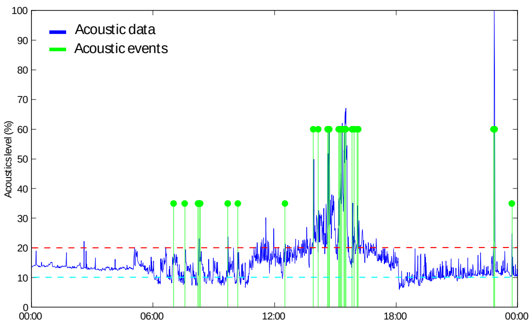

Figure 2 One day example of acoustic events

b. Lighting
Lighting events are defined as: (1) light turned on (event '*c*'); (2) light turned off (event '*d*').

c. Motion
Motion sensor events are defined in the obvious way for a binary motion sensor with an event each for motion switching (1) on (event '*e*') and (2) off (event '*f*'). However, to avoid capturing high frequency fluctuations that occur naturally when occupants are inside the room and to obtain a more informative signal, a 10 minute time window is used to smooth the signal. A motion off event must be followed by no motion activity within this window. Figure 3 shows an example motion profile and the accompanying events.

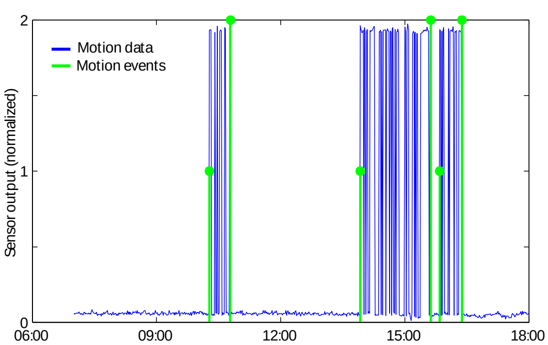

Figure 3 Example motion events

d. CO_2
According to the results from Lam et al. (2008), an increase of 50 ppm CO_2 level in 10 minutes is found to have high correlation with human presence. This, however, clearly depends on the location of the sensor; in this study, the CO_2 sensor is located above the conference table in the center of the room at roughly nose level. The events are then defined as: (1) CO_2 increase of 50 ppm in a 10 minute time window (event '*g*'); (2) CO_2 decrease of 50 ppm in 10 minutes (event '*h*').

e. Temperature and relative humidity
In a room without any windows, as is the conference room test-bed, individual human-based temperature fluctuations are minimal or on vary slow time scales. Large changes in temperature (1 ºC) in a short time frame (10 minutes) are more likely associated with high energy activities such as large group presence, the HVAC system being turned, or a projector. Hence, the events for temperature are defined as (1) 1 ºC increase in 10 minutes (event '*i*'); (2) 1 ºC decrease in 10 minutes (event '*j*'). Relative humidity fluctuates very little under the test-bed conditions unless there are occupants inside the space or the HVAC system brings in outside air. Hence RH events are defined as: (1) 10% increase in 10 minutes (event '*k*'); (2) 10% decrease in 10 minutes (event '*l*').

Episode Discovery

Episode Discovery (Heierman et al., 2004) is the process of discovering significant patterns in the data sequence by first generating candidate sequences and then pruning this set to obtain a final set of important sequences. Time series sensor event sequences generated according to our definitions in the previous section are mined for potentially significant candidate episodes using a sliding time window. Briefly, in every episode window, the event codes are ordered according to the time of occurrence. If the codes happen at the exact same time, they are ordered by alphabetical order for consistency. For each episode window, all possible subsets of the episode are generated. The generation of these subsets as additional candidates accounts for fluctuations in event order or the occurrence of spurious events. For example, if the episode pattern in a 3 minutes time window is {*c*,*e*,*f*,*g*,*d*}, then the candidate episode patterns are {null}, {*c*,*e*,*f*}, {*g*,*d*} and so on. However, to make this problem more tractable and avoid considering the superset of the episode as candidates, subsets are pruned using the following rule (Heierman et al., 2004). The subset candidates of a candidate episode that have the same episode occurrences as the parent episode do not need to be generated as candidates. An example resulting candidate episode is '*cef*', which, for our event definitions, corresponds to 'light on' followed by 'motion on' and 'motion off' and is most likely representative of someone entering a room.

After candidate episodes are generated, significant episodes to be included in the behavioural model are determined using the minimum description length (MDL) criteria and periodicity (PD) as described below. Additionally, because our focus is on energy consuming behaviour, we use a weighting factor in both the MDL and PD steps to increase the importance of episodes containing high energy impact events, namely lighting, temperature, and humidity events.

1. Minimum description length

The intent of MDL is to discover event patterns that best represent the original input stream. Event patterns may be thought of as a code table for encoding the original input sequence. The optimal code table is the one that minimizes both the size of the code table plus the length of the encoded original sequence. A brief algorithm is shown below (for a detailed algorithm, see Bathoorn, 2006):

```
Let candidate episodes Θ={P1, P2,.. Pn}, where Pn is the nth episode.
1. Ordering Θ according to
        a. Length; b.Frequency
2. Compress (Θ)
CodeTable = allSinglePatterns;
minSize  = computeSize(CodeTable)
for each Pi Є Θ
    CodeTable.add(Pi)
    newSize = computeSize(CodeTable)
    if newSize<minSize
      minSize = newSize;
    else
      CodeTable.remove(Pi)
return CodeTable
```

2. Periodicity detection

Often, behaviors with the most utility for smart building or building automation systems are those that exhibit some periodicity. In a time series data set D_{org}, a symbol s or an episode p is said to be periodic with a period l, if s or p exists every l time steps. We compute episode periodicity using a convolution-based approach, where the time series is shifted l positions and the shifted series D_{new} is compared with D_{org} (Mohamed et al., 2005). This amounts to conducting a frequency spectrum analysis using a Fourier transform. A detailed algorithm can be found in Elfeky et al. (2005).

Semi-Markov model generation

One of the most important inputs in designing an optimal room controller is the duration of occupancy in the room. To this end, we investigate an occupancy duration model from the discovered event patterns. Specifically, we employ a semi-Markov model that allows for duration in each state before transitioning to the next state (Murphy, 2002). Duong et al. (2006) applied HSMMs for pattern recognition of daily human activities. In this study, as in Youngblood et al. (2007), we treat each discovered important pattern as a state in the Markov model. We learn the semi-Markov model using a forward-backward algorithm (Yu and Kobayashi 2003). Note that in our current approach, states are not considered hidden and thus the typical HSMM framework is not needed. Hence, the model parameter estimation algorithm is greatly simplified.

EXPERIMENT IN A CONFERENCE ROOM

Sensor data collection

Six different types of wireless and wired sensors are installed in a conference room of a commercial building in Pittsburgh. Data is collected every one minute from May 1st to August 31th, 2008. Figure 4 shows a picture of the conference room and its installed sensors.

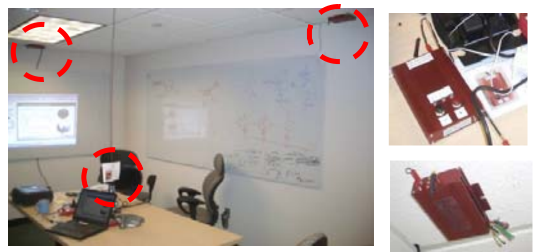

Figure 4 Test-bed in a conference room, wireless mote and occupancy counting input device

Results of event detection

Figure 5 illustrates an example day of sensor events generated according to the definitions described earlier. Event numbers on the y axis indicate which event occurred for the given sensor according to the codes in Table 1. For example, at 5:40am, the temperature decrease event (Event_2 for the temperature decrease event) occurred when the air conditioning system turned on. As is typical with most days in the conference room, numerous motion and acoustic events occur from 10:00am to 11:00am when the room is active with meetings. At 11:00 pm, a custodian enters the room, generating lighting and acoustics (vacuum cleaner) events.

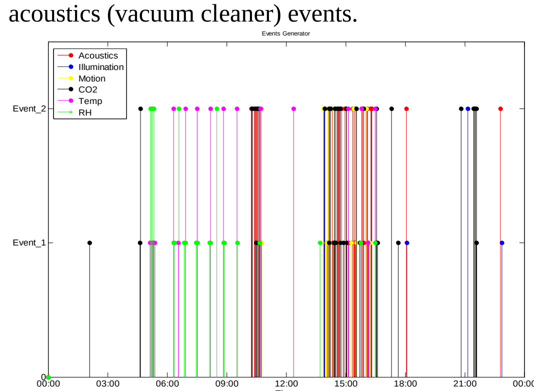

Figure 5 A one day example results of event detection

Results of MDL and PD

Based on a time window of 10 minutes, a summary of important patterns resulting from the MDL and PD selection criteria are shown in Table 2. It is noted here that the MDL component discards some very long patterns due to highly infrequent occurrence (once every week or every few days). The final set of important patterns are those resulting from both MDL and PD.

Table 2
Results of Patterns from MDL and PD

	# of Patterns	Longest Pattern	Most Compressed Pattern	Other Patterns
MDL	9	*bebdf (22)*	*cedf (19)*	*dfcedf, bebdf, ebbdf, fefe, aa, ghg,gge*
PD	8	*ebbfe(24)*	*bg (84)*	*bgfb, feg, hbe, aec, fhd*

Results of semi-Markov model

The exponential family of distribution functions were found to best model the durations associated with the discovered patterns. This is consistent with other work in speech recognition (Russell, 1985) and occupancy of single-person offices (Wang et al., 2005). Figures 6 and 7 show the resulting semi-Markov model of important patterns. Event code letters are as defined in Table 1. Figure 6 shows a standard Markov model with numbers on the arcs indicating the transition probability between states, Transitions with relatively low probabilities (less than 15%) are not shown. Parentheses indicate number of occurrences of the pattern in the training period. As an example, state "*ecf*" has a 25% transition probability to state "*eb*" and a 24% probability to state "*def*", with "*ecf*" occurring 22 times, "*eb*" 37 times and "*def*" 15 times during the month. Figure 7 shows the results of including duration in the model. Each duration distribution is denoted as X~(*time*), where *time* is the expected duration for the exponential model. For example, "*ecf*" has an expected duration of 30 minutes before it transitions to state "*eb*" and 10 minutes before transiting to state "*def*". The red-dotted line indicates a typical 75 minute meeting scenario where an occupant enters the room, triggers the motion sensor "*e*", turns on the light "*c*", and sits down, triggering the motion off "*f*". The occupant continues to stay in the room, generating acoustics "*b*" and moving around generating motion "*e*". Upon leaving, the occupant turns off the light "*e*", moves towards the door "*e*" and finally departs "*f*". Another possible duration path is on average 138 minutes, representing a longer meeting.

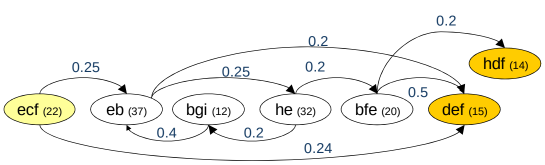

Figure 6 Markov model of discovered patterns on 10 minutes maximal window

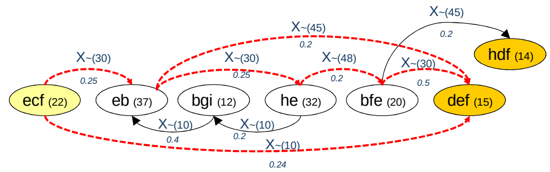

Figure 7 Semi-Markov model of discovered patterns on 10 minutes maximal window

Additional models representing longer time scales may be generated by considering a pattern such as '*ecf*' as a new event '*G*' and repeating the pattern discovery process (Youngblood et al., 2007). Results are shown in Figures 8 to 9 for the resulting model of this approach using a maximal window of two hours.

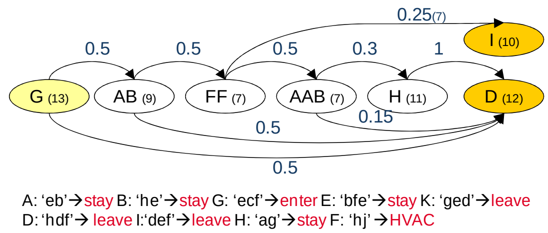

Figure 8 Markov model of discovery patterns on patterns

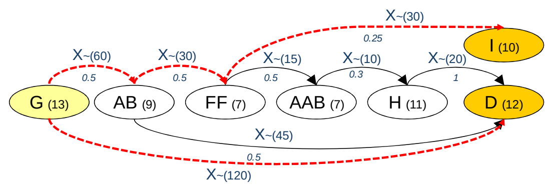

Figure 9 Semi-Markov model of discovery patterns on patterns

ENERGY AND COMFORT MANAGEMENT

A dynamic occupancy schedule with expected durations was developed from the behavioural pattern recognition results. This dynamic schedule, as described below, can be connected with a building energy and comfort management system (BECMS) through dynamic real-time temperature and ventilation set point inputs. The BECMS can then make decisions according to the dynamic schedule. In order to test the practicality of this approach, we coupled the dynamic schedule with EnegyPlus, a widely used energy simulation tool.

There are several current approaches in the literature for modelling occupancy within the context of energy simulation. Claridge et al. (2001) suggested that occupancy diversity profiles might be derived from lighting diversity profiles through establishing a strong correlation between observed occupancy levels. However, other studies suggested diversity profiles generate misleading information when occupancy-sensing lighting controls are used (Degelman ,1999). Bourgeois et al. (2006) developed a sub-hourly occupancy-based control (SHOCC) coupled with the ESP-r simulation program. SHOCC tracks individual instances of occupants and occupancy-controlled objects such as blinds. However, its application is limited with lighting controls.

In this study, the dynamic schedule was used toward lighting and HVAC controls. The control strategy utilizes the learned Markov model of behaviour and takes advantage of the fact that some patterns such as '*ecfdef*' only last briefly, corresponding to commonly found scenarios where users step into the conference room to, for example, make a cell phone call. In situations such as this, the HVAC system does not need to meet the temperature set point and ventilation rate. Figure 10 illustrates the coupling of an HVAC control strategy with occupancy pattern recognition. The term "dynamic schedule" refers to the time and state-dependent use of the Markov model in the HVAC and lighting control strategy. The system monitors sensor events to determine the current state of the environment as given by the Markov model. If an entry state (e.g., one involving lights turning on) is identified, the system computes the most probable duration of occupancy based on the model and responds accordingly. The control strategy is updated as the detected state changes. Because our emphasis here is on illustrating the utility of data-driven behavioural modelling for energy management rather than on controller design, we implement a simple occupancy-dependent on/off control; however, more advanced controllers can achieve better performance by utilizing the duration information contained in the model. For our simulation, a software link between the dynamic schedule and EnergyPlus is used so that the time dependent schedule can be generated automatically from pattern recognition.

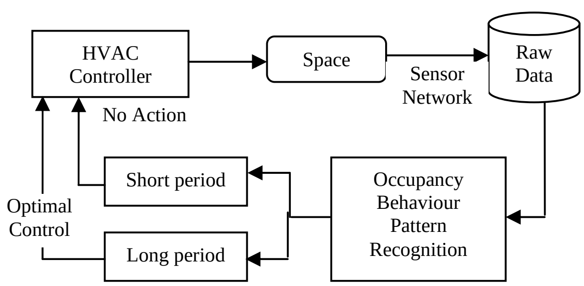

Figure10 HVAC controls based on pattern recognition

Comparison among current set point strategies

In order to evaluate the energy saving effects and thermal comfort conditions based on dynamic scheduling strategies from the occupancy behavioural patterns, the energy usage of four different set point strategies are compared. These four possible HVAC set point schedules, and their advantages and disadvantages are:

1. *Fixed system schedule set point at 24 C° from 7:00am to 6:00pm.*
   Advantage: simplicity for facility manager
   Disadvantage: High Energy Cost. No need to maintain 24 C° when there are no people present
2. *Outlook schedule based on company outlook* (Barney and Lynne, 2007)
   Advantage: exact meeting schedule and possible meeting duration
   Disadvantage: Many meetings occur spontaneously with no pre-scheduling in Outlook
3. *Occupancy (Motion) sensor based*
   Advantage: Simplicity
   Disadvantage: No motion occurs if occupants are relatively still in the room. Also, motion is triggered if an occupant enters the room in the middle of the meeting, generating spurious events.
4. *Dynamic occupancy schedule*
   Advantage: Dynamic temperature set point; An explicit meeting duration model; Automatic lighting control when zero occupancy; Save energy and maintain comfort
   Disadvantage: Need for additional sensors

All schedules have a night setback temperature of 30 C°, and, aside from the fixed-point schedule, all have a daily setback of 27 C° at 7:00 am. A lower temperature setpoint of 24 C° during the day is set as determined by the approach when the room is considered occupied.

EnergyPlus simulations with three zones were conducted: a simple conference zone of size 3m by 6m faces east, a "Resistive" zone before the conference zone, and a North zone. We focus on evaluating controller performance in the conference zone (the other zones are kept at fixed standard operation schedules). The building simulation is conducted from June 1st to August 31st, 2008, with TMY-3 Pittsburgh weather data, and the predicted occupancy profile used for the controller is based on training data from May 1st to May 30th, 2008. The true occupancy profile used for the simulation is taken from an "occupancy counter box" (see Figure 4) deployed in the conference room that allows occupants to keep track of the number of people in the room at all times by pushing up or down buttons. Table 3 shows the results from EnergyPlus in terms of total building loads for the three months.

Table 3

Building loads and comfort based on different HVAC set point schedules in the conference room

	Fixed	Outlook	Motion	Dynamic
Total Cooling Loads (kWh)	5483	4050	3794	3833
Total Lighting (kWh)	1150	880	872	872
Total (kWh)	6633	4930	4666	4705
Time Comfort Not Met (ASHRAE-55) (hour/day)	0.63	3.26	2.38	1

Table 3 shows that while the fixed schedule achieves very good comfort conditions (with very little time when comfort is not met), it is very energy inefficient. The Outlook schedule does not perform well because meetings are often either shorter than scheduled or even cancelled, leaving the HVAC system running with no one present. The largest total savings are from the motion–based approach; however, this comes with a sacrifice in occupant comfort because of times when occupants are present with little or no motion, causing the HVAC system to revert to the higher, less comfortable daily setback temperature. The dynamic schedule, which is derived from the data-driven pattern model, achieves energy savings comparable to that of the motion-based approach, but with a less amount of time when comfort is not achieved. The one hour per day of uncomfort arises mostly from short visits to the meeting room (approximately 10 minutes) that are not worth the cooling effort.

Figure 11 shows a daily indoor temperature profile from these four different set point schedules. The outlook schedule for the given day is: 9:15am~10:30am and 1:45pm~3:30pm. All three non-fixed set point schedules reach the daily setback temperature at 7:00am as scheduled. Beginning at 7:00am, the temperature profiles behave differently according to the different set point strategies. Interestingly, during lunch time, the motioned-based schedule still tried to meet the set point despite only short visits to the conference room during that time.

CONCLUSION

In this study, we demonstrate through simulation the energy-saving utility of using a data-driven model of occupant behaviour for energy management. Ambient sensing data such as lighting, acoustics, CO_2, temperature, and relative humidity are incorporated into an event-based pattern detection algorithm used for modelling occupant behaviour toward HVAC system control. Our aim is for an unsupervised approach that does not require extensive training or modelling of the environment at hand. The pattern discovery and model generation approaches are based on the work of Youngblood et. al (2007) with extensions for integrating ambient sensor events with a focus on energy-related activities and the use of semi-Markov models that allow for pattern or state durations. Additionally, we illustrate a connection of the learned behavioural model with energy control systems through the generation of a dynamic occupancy schedule. Such a dynamic schedule was generated from a conference room environment equipped with a wireless sensor network and tested as an input to an HVAC control system in an EnergyPlus simulation. Compared with other alternative occupancy-based control strategies, the results of the dynamic schedule show significant energy savings with minimal comfort sacrifice.

Possibilities for future work include investigations into data mining techniques for increased computational efficiency in generating learned patterns as well as the use of the Markov model for prediction-based control of energy management systems. Additionally, future studies may investigate more advanced control designs for exploiting learned behaviour for different HVAC systems (e.g., VAV).

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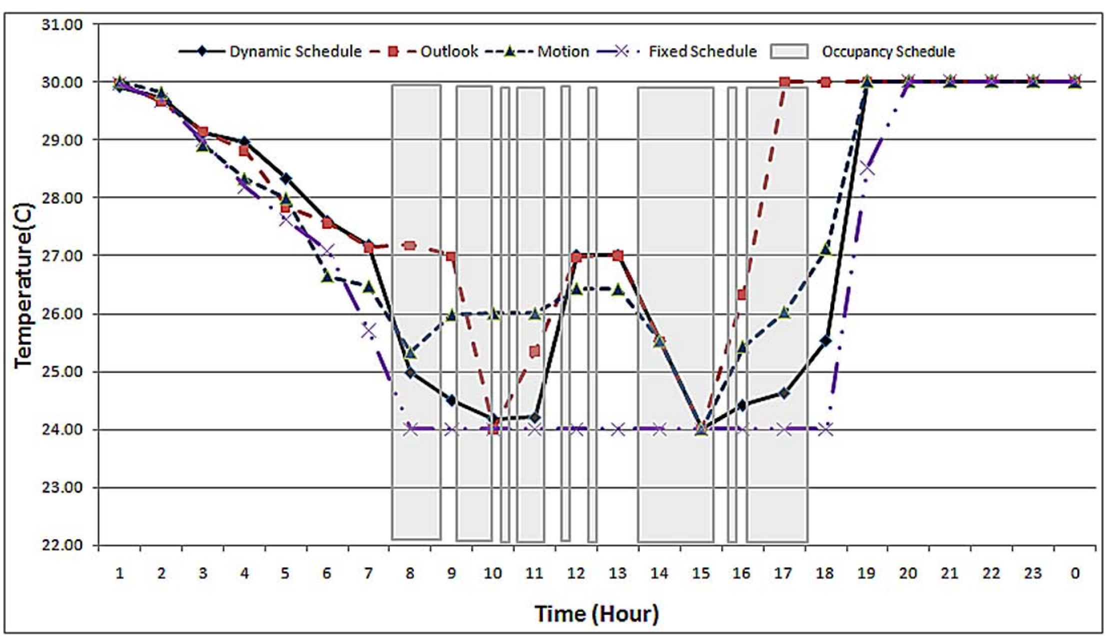

Figure 11 Temperature profile on Summer Design Day (July 21) based on different set points

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