People-centric energy management in office buildings

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ABSTRACT

Although office buildings consume a significant amount of energy to create comfortable spaces for people to work in, the current energy management systems do not assign sufficient importance to people's presence. To fill this gap, we propose an approach based on a scale-free metric that can help assess energy utilization efficiency by correlating occupancy and energy consumption along spatial, temporal and contextual dimensions. We evaluated this approach using data collected from a 7-month long pilot at an office building in Bangalore, and demonstrate this approach can address the needs of facility managers and occupants by spotting both energy-inefficient and uncomfortable zones. We further argue that HVAC systems must be tightly coupled with occupancy and energy prices, and present the preliminary design of a thermostat that considers these two factors. Through simulation results, we show that this thermostat can reduce energy consumption by 32% when energy prices are differentiated by a factor of 3.6.

Categories and Subject Descriptors

D.2.8 [**Metrics**]: Performance measures

General Terms

Design, Experimentation, Performance

Keywords

Buildings, Energy, Occupancy, Spatiotemporal Analysis, Thermostats, Energy utilization metric

1. INTRODUCTION

Office buildings around the world are major consumers of energy. For instance, in the U.S., office buildings are the most common type of commercial buildings and consumed more than 17 percent of the total energy used by the commercial buildings sector [37]. On an average, a U.S. building consumes 17.3 kWh [25] and an Indian office building, 16.25 kWh [18], per square foot annually. In a typical U.S. office building, lighting, heating, and cooling represent between 54 and 71 percent of total use depending on climate, making those systems the best targets for energy savings [26]. Since the primary objective of these systems is to support comfortable spaces for people to work in, their functioning must be tightly coupled with occupancy in the corresponding office spaces.

There are three main requirements for enabling such tightly coupled operations: detecting occupancy, metrics for correlating occupancy and energy consumption, and finally, occupancy based load controls. In this paper, we focus only on the latter two requirements since there are several well-studied approaches for detecting occupancy in addition to the passive infrared sensors (PIR) that are commonly used in modern buildings. In our past work, we had proposed an approach using only context sources that are commonly available in commercial buildings such as area access badges, Wi-Fi access points, etc [15, 34]. Researchers have proposed several methods based on different types of sensors - wireless presence sensors [1], cameras [33], sonar [32] and CO_2 sensors [38], etc.

Although there are several metrics [7, 11, 12] for assessing energy performance of commercial buildings, there is no simple normalization metric that correlates occupancy and energy consumption. We propose a metric, referred to as *Spatiotemporal Energy Metric* (STEM), that is a ratio of energy consumed in occupied areas of a building to the total energy consumed in that building. One of the primary advantages of this metric is that it can help balance user comfort (as it considers occupancy density recommended by local building codes) with energy efficiency. Furthermore, this metric can enable various types of performance assessments: comparing different areas of a building, comparing one building with another, analyzing the performance of buildings across different contexts (time of day, seasons, etc.).

Even though model-based methods are available that can correlate multiple factors, they are difficult to use as they require building sophisticated and accurate models. Also, such models cannot be reused as buildings (or even areas of a building) have certain characteristics unique to them (building materials, age, behaviors of occupants, etc). On the other hand, we believe our approach is simple and generalizable, as it requires only measuring electricity consumption and detecting occupancy. Moreover, there are established techniques for detecting and predicting occupancy, as explained above, and for profiling energy use, in office spaces [31] that can be leveraged by our approach.

Since occupancy can be detected and predicted, occu-

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pancy driven load control mechanisms can be realized. We propose such a thermostat, referred to as *FineTherm*, that can control variable air volume (VAV) systems using projected occupancy and energy prices, in order to perform efficient thermal management of zones in buildings. FineTherm, unlike the other occupancy-based HVAC controls such as ThermML [17], PreHeat [29] and Smart Thermostat [24] that take binary ON/OFF decisions, adjusts the air mass flow rates in a continuous manner. Moreover, none of them consider the energy prices while making control decisions.

The main contributions of this paper are:

- A scale-independent spatiotemporal energy metric for assessing the energy performance of office buildings.
- The design of a thermostat that can control VAV systems based on occupancy and energy prices.
- Evaluation of these technologies using a real-world pilot and simulation studies.

The rest of the paper in organized as follows. Section 2 presents the Spatiotemporal Energy Metric (STEM). Section 3 describes FineTherm and Section 4 presents the evaluation results of STEM and FineTherm. Section 5 reviews the related work and finally, Section 6 concludes with a discussion about future work.

2. SPATIOTEMPORAL ENERGY PROFILING

2.1 Motivation

Several factors drive energy consumption in buildings including but not limited to building size, building type, outside weather conditions, thermal and lighting comfort requirements, and occupancy. Among these factors, occupancy is an important determinant of consumption in the following ways:

1. Cooling: Occupants contribute to the thermal load in a building, because of metabolic heat generation. The thermal load contributed by an occupant depends on her activity level. For instance, it is estimated that on an average, the heat gain per occupant is approximately 130 W in an office environment, when occupants are doing sedentary work [10]. Each such contribution translates into additional air-conditioning load on the building's HVAC system.

2. Ventilation: Ventilation requirements in buildings are often expressed in terms of occupancy. For example, the ASHRAE Standard 62, which governs ventilation for acceptable indoor air quality, specifies an outdoor airflow rate requirement per person. Hence, the number of occupants determines the outdoor air flow rate, which in turn drives energy requirements for ventilation.

3. Lighting: Lighting in most commercial buildings in controlled based on occupancy. Passive Infrared (PIR) sensors are often deployed which detect the presence or absence of occupants to turn the lights in a given area ON or OFF. Hence occupancy density and patterns determine the lighting energy consumption in a building.

4. Plug loads: The operation of several plug loads in buildings is occupancy dependent. Examples of such loads include computers, phones, printers and coffee makers in a commercial setting, and televisions, cloth washers and treadmills in a residential setting. These appliances directly contribute to the electrical load in the building, when in use. Additionally, they can also indirectly contribute to energy consumption by emitting heat which adds to the thermal load. For example, it has been estimated that desktop and laptop computers can emit upto 250 W and 40 W of heat, respectively, when in use [35].

Occupancy and other contributing factors driving energy consumption are often functions of space and time. Different areas in an office building such as printer rooms, meeting rooms, cubicles and pantry rooms can have different occupant densities. Therefore, we expect the energy consumption across different regions in the same building to be non-uniform. Hence, spatial profiling of energy is important to correctly identify the portions of a building which are using energy less efficiently or which provide a lower degree of occupant comfort than other spaces.

An example of temporal variation in occupancy could be a situation where most people in an office prefer to work from home on a particular day in the week (e.g. Friday), when compared to other days. At a more granular resolution, occupancy in a commercial environment can vary over the course of the day, exhibiting potentially low occupancy during lunch time. Hence, using arguments similar to ones made for spatial profiling, we identify the need for temporal profiling of energy to isolate time periods - e.g. hours in a day, days in a week, seasons in a year, etc. - when a building or one or more of its zones/sections are operating unsatisfactorily.

Profiling across space and time can lead to identification of target sections and time periods in a building, for application of appropriate remedial actions for performance improvement. Examples of such measures can be software retrofits such as augmentation of algorithms for HVAC control to include occupancy, or changes to building usage patterns such as incorporation of a dynamic seat allocation methodology based on time of day. In this work, our focus is on the development of an occupancy centric profiling methodology, enabled by metrics described in the next section. Remedial actions to address the issues identified from the profiling exercise are not included in this paper, since their choice depends on several factors such as technical feasibility of an action, budget constraints for maintenance, etc. and therefore merits a broader discussion.

2.2 Methodology

Consider a region of space in a building denoted by by the set $S := \{1, 2, ..., N_S\}$, which is decomposed into N_S discrete sub-regions. Similarly, consider a time window $T := \{1, 2, ..., N_T\}$, which consists of N_T discrete time slots. In order to enable the aforementioned objectives of energy profiling - namely (i) profiling that is occupancy centric, and (ii) spatial and temporal profiling, we propose a metric, referred to as *Spatiotemporal Energy Metric* (STEM), defined in (1). In an office building, the space S can represent a cubicle, a meeting room, a floor or the entire building. Similarly, examples of the time duration T are an hour, a day, a month, a season or a year.

$$\text{STEM}_{S,T} = \frac{\sum_{i \in N_S} \sum_{j \in N_T} \frac{\rho_{i,j}^{meas}}{\rho_{i,j}^{bc}} E_{i,j}}{\sum_{i \in N_S} \sum_{j \in N_T} E_{i,j}}. \quad (1)$$

In the above definition, $\rho_{i,j}^{meas}$ refers to the occupancy density (number of occupants per m^2 of floor area) observed in space i during time slot j. Here, $i \in \{1, 2, ..., N_S\}$ and $j \in \{1, 2, ..., N_T\}$. The variable $\rho_{i,j}^{bc}$ denotes the occupant density based on the relevant building code. $E_{i,j}$ refers to the energy consumed (in kWh) by space i during time slot j.

We make the following remarks with regard to the definition (1):

1. STEM represents a family of metrics as opposed to a unique metric, because it can be used to profile different categories of loads. For example, we can define *Spatiotemporal HVAC Metric* (STHM) as shown in (2), which represents a specific form of STEM that profiles energy consumption associated with HVAC. Similar metrics can be defined for other categories of loads such as lighting or plug loads.

$$\text{STHM}_{S,T} = \frac{\sum_{i \in N_S} \sum_{j \in N_T} \frac{\rho_{i,j}^{meas}}{\rho_{i,j}^{bc}} E_{i,j}^{HVAC}}{\sum_{i \in N_S} \sum_{j \in N_T} E_{i,j}^{HVAC}}. \quad (2)$$

   In the above equation, $E_{i,j}^{HVAC}$ represents the HVAC related power consumption for space i during time-slot j.

2. In order to perform a truly occupancy centric energy profiling, $E_{i,j}$ should only include energy consumption associated with occupants. For example, energy consumed by chillers employed in server rooms should be excluded from $E_{i,j}^{HVAC}$ while profiling using STHM, because it represents an essential or background load that is needed irrespective of whether a building is occupied or not.

We note that an alternative version of STEM can also be developed which makes use of information on expected energy consumption, if available through physics-based or data-driven models. We refer to this metric as STEM^{alt}, defined in (3).

$$\text{STEM}_{S,T}^{alt} = \frac{\sum_{i \in N_S} \sum_{j \in N_T} \frac{\rho_{i,j}^{meas}}{\rho_{i,j}^{bc}} E_{i,j}^{expected}}{\sum_{i \in N_S} \sum_{j \in N_T} E_{i,j}}. \quad (3)$$

In the above equation, $E_{i,j}^{expected}$ represents the expected energy consumption for space i during time-slot j obtained using an appropriate model. The use of STEM^{alt} allows a means to incorporate model-based energy profiling methodologies proposed in literature [7, 22]. This renders our proposed approach amenable to existing state of the art profiling methodologies. The results presented later (Section 4) are specifically for profiling using STHM, since AC accounts for majority of the consumption in Indian office buildings [18].

We identify the following salient features for the class of metrics represented by (1):

1. *Explicit consideration of occupancy*: The form (1) of STEM allows the explicit consideration of occupancy in energy profiling in two ways. Firstly, it includes a ratio of observed occupant density to the required occupant density specified by the building codes. Therefore, it provides a means to assess the impact of under-utilization or over-utilization of space on energy consumption. Secondly, STEM excludes energy consumption on account of loads which are not related to occupancy, for example lighting of hallways or cooling of server rooms. The explicit use of occupancy differentiates STEM from other commonly used metrics for building energy profiling such as Energy Use Intensity (EUI) [11], which do not consider occupancy.

2. *Spatiotemporal profiling*: STEM enables spatiotemporal profiling, since space S and time T are design parameters that can be tailored for specific profiling requirements. Therefore, the same metrics are applicable for various choices of space and time.

3. *Scalability*: The use of space S and time T as tunable design parameters allow the profiling resolution to be scaled up or down, along both spatial and temporal dimensions. It should be noted, however, that the profiling resolution is constrained by the sensing infrastructure installed in a building. For example, if smart meters providing real time electrical consumption are installed, profiling can be performed at fine-grained temporal resolutions, say 15 minutes to an hour. However, if only conventional watt-hour meters are available, which require manual logging of data, profiling might be feasible only at coarse temporal resolutions such as a day, a week or a month.

4. *Normalization*: STEM provides a normalized measure of how efficiently energy is being used. A value smaller than 1 indicates over-utilization of energy because of under-utilization of space. This could be result of lights or air-conditioning left ON in unoccupied zones. Similarly, a value greater than 1 indicates under-utilization of energy due to over-utilization of space. This can result when occupant density in the profiled area is greater than the recommended values and hence could potential discomfort for occupants. While 1 represents an ideal target value for STEM, from a practical perspective it might be more appropriate for facility managers to target a value which is slightly less than 1. This allows the consideration of space which cannot be occupied due to factors such as the presence of furniture or other fixtures. This ability of STEM to provide a normalized measure of performance allows it to benchmark two buildings, even if they are located across context-boundaries. This feature differentiates it from metrics such as EUI which restrict benchmarking to buildings that are only of the 'same' type.

5. *Ease of use*: The form (1) of STEM is intuitive and reminiscent of popularly used metrics used in other energy related contexts such as Power Usage Effectiveness (PUE) in data centers, or coefficient of performance (COP) in air-conditioning plants. It can also be computed easily, without requiring in-depth expertise in a particular technical domain. Therefore, we believe it can be easily understood by facility managers

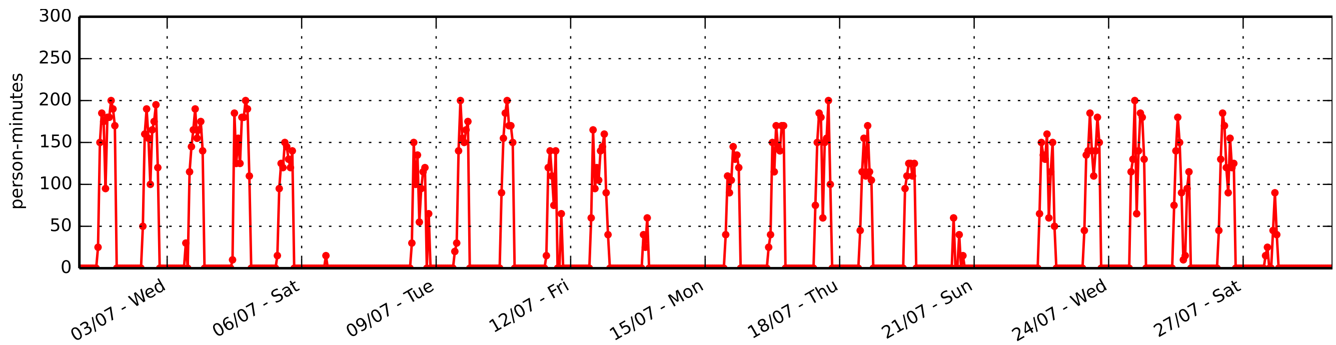

Figure 1: Observed occupancy values in a zone for 4 weeks

or operators who are involved in day to day system operation.

Despite these benefits, since STEM is a product of two independent parameters, in some cases, the metric value can be same for two very different situations - high energy consumption with low occupancy and low energy consumption with high occupancy or vice versa. It is important to note that any metric that mathematically combines two independent parameters into a single scalar value will have the same issue.

3. OCCUPANCY DRIVEN THERMOSTAT - FINETHERM

3.1 Motivation

Although occupancy in a given section of a residential or commercial building can vary with time, similar patterns are expected for a given context. For example, as illustrated in Figure 1, weekly occupancy patterns recorded for a zone in an Indian office were observed to be similar. Data driven modeling tools can therefore be employed to predict occupancy in such cases. In this section, we propose an occupancy driven thermostat that can be used in situations where occupancy can be predicted in advance, for instance using regression based methods. The objective of this thermostat is to make more informed control decisions for variable air volume (VAV) systems, using projected occupancy and power costs (if predictable), in order to perform efficient and cost effective thermal management of zones in buildings. The proposed thermostat is different from a conventional thermostat in the sense that the latter does not explicitly include occupancy in decision making and controls VAV systems based on measured zone temperature alone.

Occupancy modeling methodology is presented below, followed by a specific formulation of an occupancy driven thermostat for zone-level thermal management, which is based on an optimization framework. The proposed methodology applies to the case of cooling, but can also be easily adapted for heating. It should be noted that although this formulation prescribes a specific methodology, several variations are possible, discussions of which are beyond the scope of this work.

3.2 Methodology

3.2.1 Occupancy modeling

Occupancy patterns in most commercial establishments are a function of the time of the day and the day of the week. Therefore, we propose the following regression based occupancy model:

$$\hat{n}_o(t, d) = a_0 + a_1 t + a_2 d \tag{4}$$

Here t represents the time of day and d represents the day of the week. We assume that a day is divided into T (e.g. 24) time slots, and therefore $t \in \{1, 2, ..., T\}$. The day $d \in \{M, T, W, R, F, SA, SU\}$. The parameters a_0, a_1 and a_2 are coefficients to be determined from training data through the use of an appropriate learning algorithm such as KNN.

3.2.2 Occupancy based thermostat control

Before a formal presentation of the optimization framework, we first define the underlying nomenclature. We use a discrete time set up, where sampling is performed every ΔT seconds, and a time instant is denoted by t. The mass flow rate and temperature of conditioned air supplied to the zone at time t are denoted by $\dot{m}_a(t)$ and $T_{supp}(t)$, respectively. The zone temperature at time t is denoted by $T_z(t)$. The look-ahead time window for optimization consists of N time samples, and is therefore of length $N\Delta T$ seconds. The lower comfort bound on zone temperature is represented by $T_L(t)$. The upper comfort bound is reprented by $T_{U,1}(t)$ when no occupants are present in the zone, and by $T_{U,2}(t)$ when the zone is occupied. Note that, $T_{U,1}(t) > T_{U,2}(t)$. The ambient temperature forecast for time t is denoted by $\hat{T}_{amb}(t)$, which governs thermal interactions between the ambient and the zone. The predicted price of electricity at time t is denoted by $\eta(t)$, and the coefficient of performance of the air-conditioner (a measure of chiller efficiency) is represented by COP. The number of occupants predicted inside the zone at time t is denoted by $\hat{n}_o(t)$, and the internal heat generation in the zone due to sources other than occupants is forecasted as $\hat{Q}_{int}(t)$. Other parameters used in the formulation are UA, c_p, Q_o and C_z, which represent the overall heat transfer coefficient between the zone and ambient, the specific heat capacity of conditioned air, the estimated heat gain per occupant (metabolic rate), and the thermal capacity of the zone, respectively.

Next, the following optimization problem is solved at each time instant t:

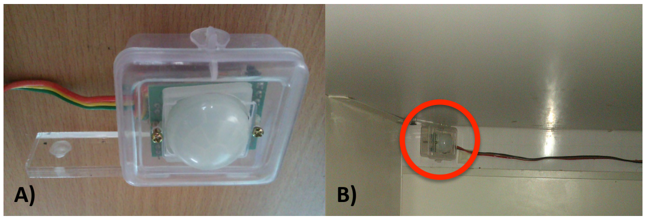

Figure 2: (a) A passive infra-red (PIR) based motion sensor, (b) placement of a PIR sensor under a seat.

$$\text{Minimize} \;\; J_t := \sum_{k=t}^{t+N-1} c_p COP \eta(t) \Delta T \dot{m}_a(k) \left(T_z(t) - T_{supp}(k)\right), \tag{5}$$

subject to the following constraints for all $k \in \{t, t+1, .., t+N\}$:

$$T_z(k) \in [T_L(t), T_{U,1}(t)], \;\; \text{if } \hat{n}_o(k) = 0, \tag{6}$$

$$T_z(k) \in [T_L(t), T_{U,2}(t)], \;\; \text{if } \hat{n}_o(k) > 0, \tag{7}$$

and the following constraints for all $k \in \{t, t+1, .., t+N-1\}$:

$$\dot{m}_a(k) \geq 0, \tag{8}$$

$$\frac{C_z}{\Delta T}\left(T_z(k+1) - T_z(k)\right) = \dot{m}_a(k)\left(T_{supp}(k) - T_z(k)\right) + UA\left(\hat{T}_{amb} - T_z(k)\right) + Q_o \hat{n}_o(k) + \hat{Q}_{int}(k). \tag{9}$$

The objective function J_t in (5) represents the cost of energy associated with cooling the zone during the time window $[t, t+N-1]$. Different upper bounds on thermal comfort, as shown in (6) and (7), are imposed to reflect the fact that if the zone is expected to be unoccupied during certain time periods, the thermal comfort requirements during such periods can be relaxed to drive energy and cost savings. The constraint (9) represents the zone thermal dynamics obtained using the first law of thermodynamics (energy balance). At each time instant t, the solution of the above optimization problem provides the optimal set of supply mass flow rates $\{\dot{m}_a^*(t), \dot{m}_a^*(t+1), ..., \dot{m}_a^*(t+N-1)\}$, the first element of which $\dot{m}_a^*(t)$ is applied. The optimization is then repeated at all future time instants in the same manner, which is reminiscent of model predictive control [5].

4. EXPERIMENTS

In this section, we present an evaluation of the proposed methods through pilot and simulation studies. We first provide a brief overview of the pilot and the collected data, then we present the evaluation performance results on the metric, energy usage profiling, and occupancy prediction in offices. The insights on energy savings obtained via FineTherm are based on simulated controls.

4.1 Data Collection

We conducted a 7-month long pilot in an office floor of a commercial building in Bangalore, India. An office floor of 29,200 ft^2 area with a seating capacity of 300 employees was instrumented with seat-level PIR sensors and zone-level temperature sensors to gather data about occupancy and indoor temperature respectively. Outdoor temperature data was collected from external weather websites. Figure 2 shows a PIR sensor with its placement at the pilot location. The PIR sensors were installed under the seats to ensure minimal inconvenience to employees, and they detected occupancy by monitoring movements of the lower halves of the bodies of employees. The temperature sensors were physically connected to the gateways that transported the data from sensors to a central server. Figure 3 depicts the placement of total 230 PIR sensors, 81 temperature sensors and 37 gateway nodes. Some sections of the floor, marked as empty boxes, were not covered due to infrastructure (power socket and/or ethernet port) unavailability. The shaded region at the bottom-left is exemplifies a section of the floor consisting of at least 4 seats, an HVAC vent and a temperature sensor. Such a section is termed as a ***zone*** hereafter.

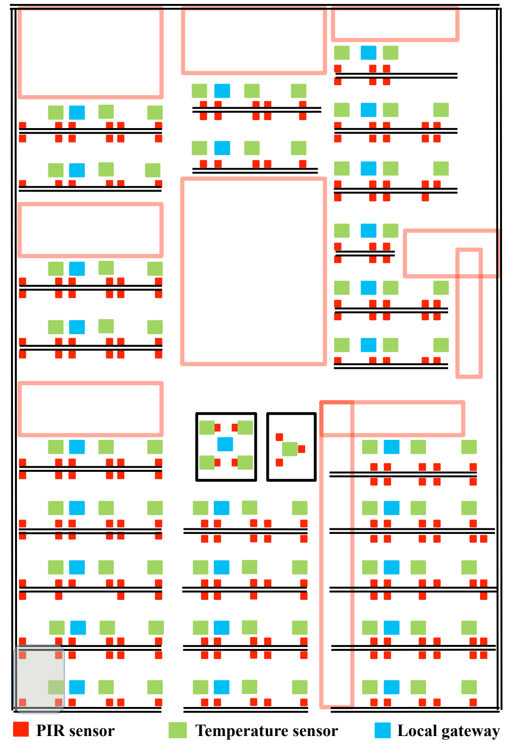

Figure 3: Layout of the office floor where pilot was conducted. It depicts the locations of various sensors and gateways. The red regions represent areas outside coverage and squares in the middle are meeting rooms. The shaded region at the bottom-left exemplifies a single zone consisting at least 4 seats, an HVAC vent and a temperature sensor.

4.2 Derived Data Computation

The temperature data was obtained directly from the sensors. On the other hand, occupancy and power consumption data were computed as described below.

4.2.1 *Computing Occupancy Information*

To decrease false negatives in motion detection, a window size of 10 minutes was considered to determine occupancy status of a zone, i.e. a zone will be considered occupied at time t if and only if there is any motion detected between the time range $(t-10, t)$. False positives were reduced by orient-

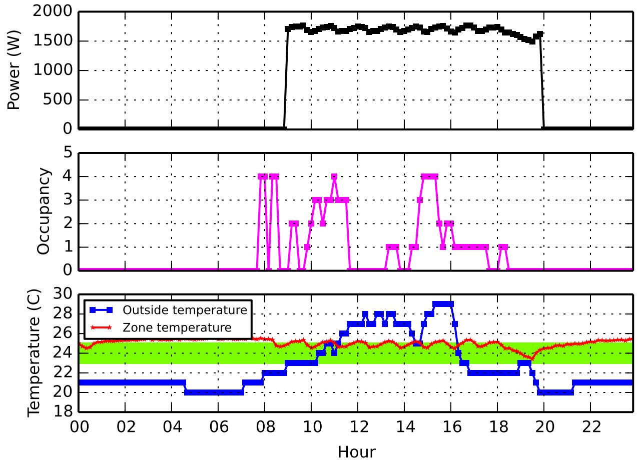

Figure 4: Illustrative power, occupancy, zone temperature and outside weather values for a zone at the pilot location. (Cooling operational hours (08:30AM - 08:00PM) was provided by the building management team.)

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ing the fresnel lens of PIR sensors away from the adjacent pathways.

4.2.2 *Computing Energy Consumption*

Since the floor was not instrumented with separate energy monitors to measure energy consumed by each zone, we computed $W^{HVAC}(t)$, the energy consumed for cooling a zone at a time instant t, using the following formula:

$$W^{HVAC}(t) = \text{COP} c_p \dot{m}_a(t) \left(T_z(t) - T_{supp}\right). \tag{10}$$

The above equation is based on the first law of thermodynamics applied to the supply stream of conditioned air, which is supplied at a mass flow rate of $\dot{m}_a(t)$ and a temperature of T_{supp}. Here, we assume uniform mixing, that is the return air from the zone has attained the zone temperature $T_z(t)$. The zone level mass flow rate, $\dot{m}_a(t)$, was estimated based on the assumption that the mass flow rate provided by the air handling unit (AHU), which is a known quantity, is divided equally among all the zones, since all terminal vents are equally sized. T_{supp} was set to 12.8^0 C based on available measurements. The parameters c_p and COP represent specific heat capacity of air and the coefficient of performance of the chiller, and are set to 1.005 kJ/kg-K and 3.0 respectively. From (10), it can be observed that a high value of $T_z(t)$ indicates high air-conditioning power consumption. This is reflective of the fact that a high $T_z(t)$ indicates a higher return air temperature, and hence higher thermal load in the zone.

4.3 STEM evaluation

As can be seen from Figure 4, power consumption and occupancy are not well-correlated. As space cooling accounts for a significant share of energy consumption in buildings, we present our analysis to identify energy-inefficient and insufficiently cooled zones.

4.3.1 *Descriptive statistics*

Figure 5 presents STHM values computed (using equation 2) over a day for 57 zones at the pilot site. For this calculation, the reference occupant density value ($\rho^{bc}_{i,j}$ in (1)) was set to 1 occupant per 16 square feet, which is close to occupant density values prescribed by most building codes [9,36] for such office environments. The efficiency of a zone increases as STHM approaches 1, however, values greater than 1 represent overly crowded zones.

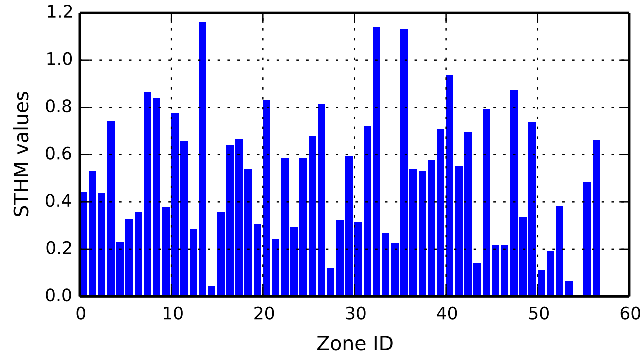


Figure 5: STHM values for a day across different zones at the pilot location. As the value approaches 1, the efficiency of a zone increases, however, values greater than 1 represent zones with comfort issues.

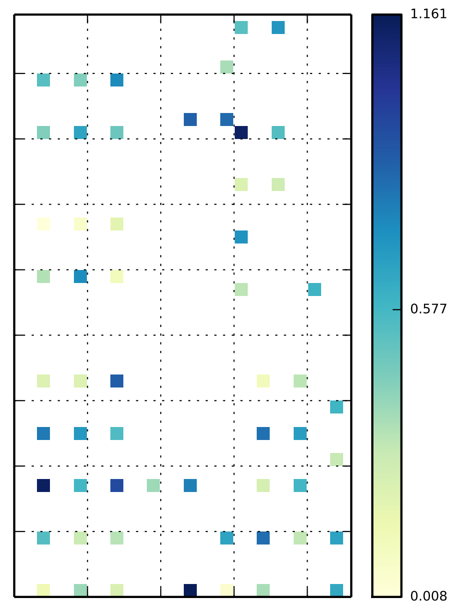
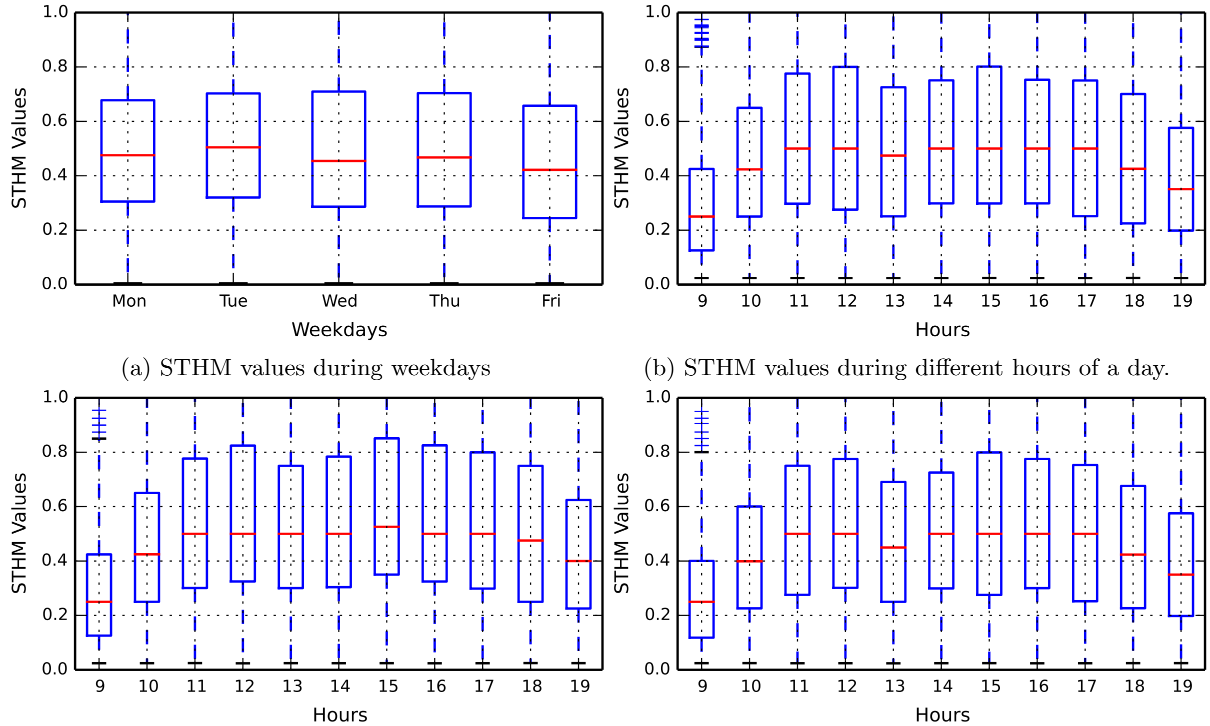


Figure 6: Representing STHM values on a floor map can quickly assist building owners to identify energy inefficient and uncomfortable zones

Figure 6 shows a performance map representing efficiency of each zone on the floor map. Such visualizations could help facility managers to spot problematic zones. Furthermore, these statistics could analyze the performance under various contexts as well. For instance, Figure 7 shows temporal variations in STHM values. The relatively low average values on Wednesdays and Fridays indicate inefficient energy utilization. On further analysis of hourly boxplots for Wednesdays and Fridays in Figures 7c and 7d, the metric reveals that employees are leaving early on Fridays (hours 18 and 19) as compared to Wednesdays, therefore, HVAC could be shut off early on Fridays.



(a) STHM values during weekdays (b) STHM values during different hours of a day.

(c) STHM values during different hours on Wednesdays (d) STHM values during different hours on Fridays

Figure 7: Temporal variations observed in the STHM values for a given context for all the zones

4.3.2 Cluster analysis

As explained above, STEM may not be able distinguish between the two parameters (energy consumption or occupancy) that could affect the metric value. To address this issue, we present clustering approaches for identifying the cause. We explain this approach using two illustrative use cases.

1. Comparing the relative performances of two zones - to identify the relative energy utilization efficiencies of zones, we must identify zones with same occupancy but different energy consumption levels. Similarly, to identify the relative occupant comfort levels of zones, we must identify zones with same energy consumption levels but different occupancy levels.

   Figure 8 plots energy consumption and occupancy-minutes (number of minutes a particular location was occupied) over a day for 57 zones. When the normalized values of these 57 data points were processed using the affinity-propagation clustering algorithm [13], the algorithm generated the four clusters shown in Figure 9. To illustrate the relative performances of the zones in four clusters, figures 10a - 10b plots occupancy and temperature values for a sample zone from two of the four clusters. In Figure 10a, zone temperatures (indicates energy consumption) and occupancy levels are correlated. On the other hand, Fig. 10b depicts an energy-inefficient cluster where the zone temperature is maintained in the range $(25^0\mathrm{C}, 26^0\mathrm{C})$ for ten hours, even though it is occupied for less than an hour during this period.

2. Analyzing the temporal variations in a zone - Figure

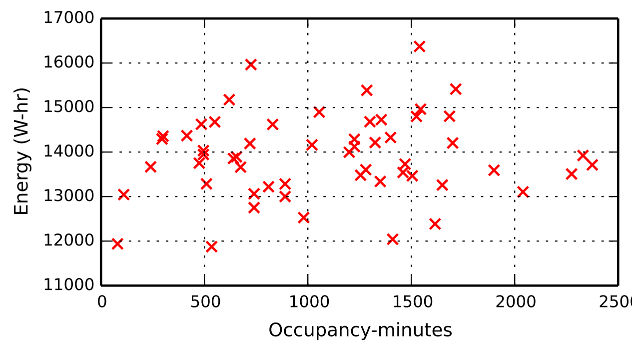


Figure 8: Observed variations of energy usage and occupancy-minutes across different zones for a single day.

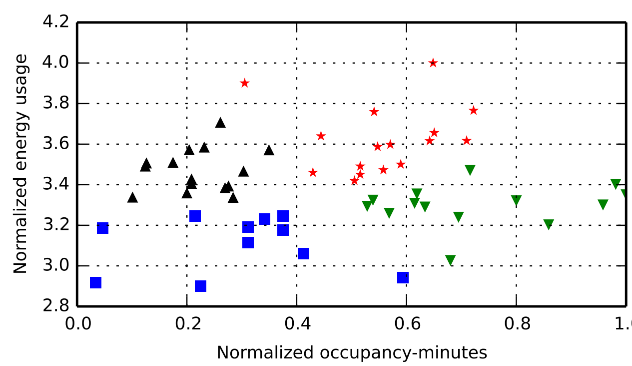
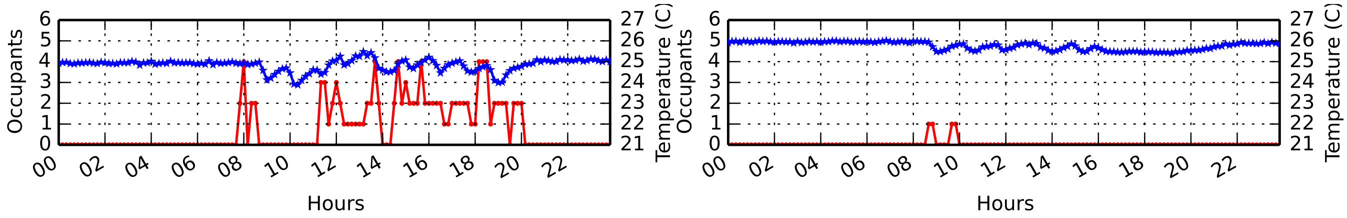


Figure 9: Distributing the zones into four categories for spatial comparison using the affinity-propagation algorithm.



(a) Less energy, low occupancy

(b) More energy, low occupancy

Figure 10: Occupancy (red) and temperature (blue) data for two zones.

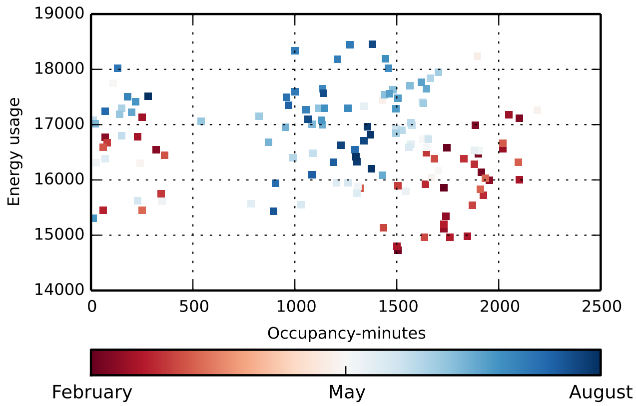


Figure 11: A plot of observed daily energy and occupancy values over the period of 7 months for a particular zone.

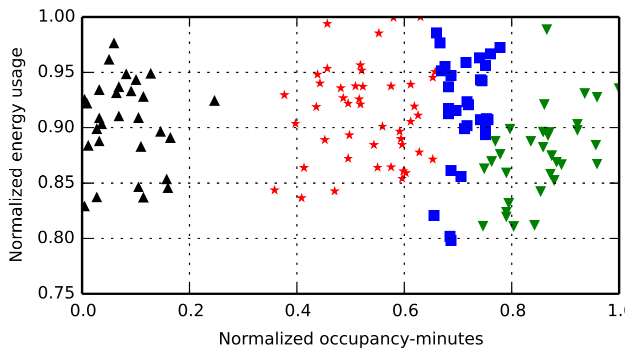


Figure 12: Output of the mean-shift algorithm over temporal energy and occupancy data of a zone

11 depicts the performance of specific zone from February 2013 to August 2013. The zone was energy-efficient (less energy consumption despite high occupancy levels) in February and was energy-inefficient (high energy consumption despite low occupancy) during the months of May and June. It means the energy demand of the zone increased due to factors other than occupancy. Bangalore was hotter during the months of May and June than in February. Hence more energy was needed to cool the zone. Such seasonal performance variations in a zone can be easily identified using density based clustering algorithms. For instance, Figure 12 shows the application of the Mean-Shift [6] algorithm over temporal data points.

4.4 FineTherm

Here, we present proof of concept simulation results to investigate the performance of the occupancy driven thermostat formulation presented in Section 3.2. Comparison with a conventional thermostat control strategy is also presented.

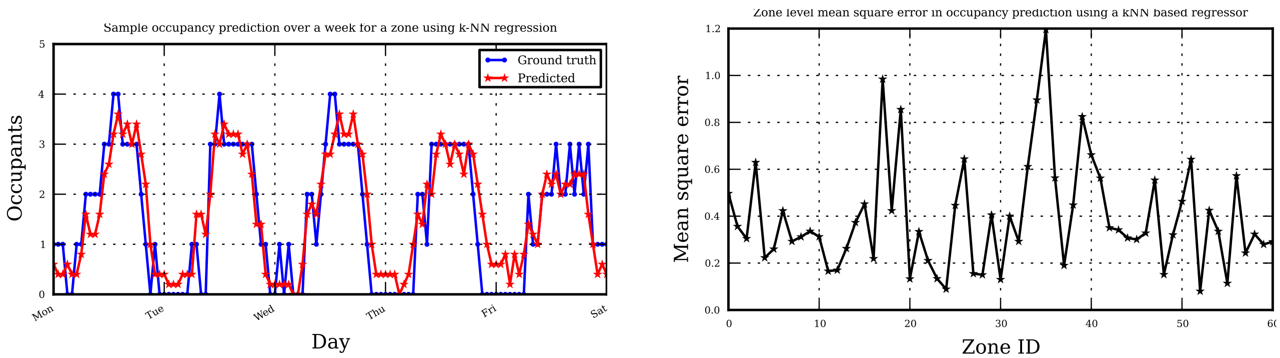
4.4.1 Occupancy prediction

As presented in 3.2.1, regression analysis (KNN) was used to build occupancy models from the data shown in Figure 13a. As shown in Figure 13a, the predicted occupancy was found to match well with ground truth for all days in a week. Also, based on the error analysis shown in Figure13b, we observed that the occupancy prediction errors are consistently small across for all the zones.

4.4.2 Parameters for occupancy driven thermostat simulation

To keep the anaylsis simple, we simulate a single-zone commercial building where the assumed occupancy variation on a given day is shown in Figure 14. The time instant $t = 1$ is assumed to represent 8 am, and lunch hours correspond to the time window noon - 2 PM. The values chosen for the parameters appearing in the formulation (section 3.2) are shown in Table 1. We assume that the ambient temperature varies as shown in Figure 15 and that the internal heat generation in the zone due to sources other than occupants is given by $\hat{Q}_{int}(t) = 0.04\hat{n}_o(t) + 0.025$ KW. Here, we have assumed that each occupant uses a laptop computer which on average releases 40 W of heat to its surroundings, and other heat sources such as lights contribute 25 W to the thermal load at all instants. Furthermore, we assume that the commercial building is located in India, and there is expectation of a power outage between 1-2 PM, when diesel generator based backup sources are employed. The price of electricity is assumed to be INR 5.1/kWh based on [3] during non-outage periods, and INR 18.5/kWh during outage periods based on [2] extrapolated for current diesel prices in India. The upper and lower thermal comfort bounds, $T_{U,1}$ and T_L were determined to be 27.5^{0}C and 23.5^{0}C using ANSI/ASHRAE Standard 55-2010 [30], assuming a clothing insulation parameter $clo = 0.70$ [14]. Since the above bounds prescribe a fairly large range of temperature, we assume that during occupied periods, the building is operated in a narrower temperature range of $[23.5^0C, 25.5^0C]$, that is $T_{U,2} = 25.5^0C$.

To compare the results of the above occupancy driven thermostat with a conventional thermostat, we also simulate an ON-OFF control strategy which is commonly used for thermostat control [28]. This strategy sets the supply air mass flow rate based on the following rule:



(a) Evaluation of predicted occupancy patterns against ground truth for a zone in a candidate office building

(b) Mean square errors in occupancy prediction for various zones in a candidate office building

Figure 13: Occupancy prediction results in commercial offices to enable features like FineTherm

Table 1: Parameters used for implementation of occupancy driven thermostat

Parameter	Value	Units
ΔT	1	Hour
C_z	500	kJ/K
T_{supp}	12.8	^0C
UA	0.0125	kW/K
Q_o	0.1	kW
c_p	1.005	kJ/kg-K
N	3	(dimensionless)
COP	3.0	(dimensionless)
$\dot{m}_{ON-OFF}$	0.035	kg/s
ϵ	0.5	^0C

$$\dot{m}_a(t) = \begin{cases} \dot{m}_{ON-OFF} & T_z(t) > T_{U_2} - \epsilon \\ 0 & \text{otherwise.} \end{cases} \tag{11}$$

Here, $\dot{m}_{ON-OFF}$ and ϵ represent the mass flow rate delivered when the air-conditioning is turned ON, and a safety threshold, respectively. Their values are also shown in Table 1.

4.4.3 Results

The occupancy driven thermostat described above was simulated for a period of 10 hours, using the 'active-set' algorithm in MATLAB to solve the underlying nonlinear optimization problem (Section 3.2.2). The optimal supply air mass flow rates and resulting zone temperatures are shown in Fig. 16 and 17 respectively. On the other hand, the mass flow rates and zone temperatures corresponding to the ON-OFF thermostat control strategy are shown in Fig. 18 and 19 respectively. Based on these results, the total cooling cost for the building during the time window of simulation was computed to be INR 9.77 for the occupancy driven thermostat. This represents a savings of 32.3% over the conventional thermostat which results in a cost of INR 14.44 for the same time window, and hence demonstrates the benefit of using occupancy in thermal management. These savings can be explained by comparing Figures 16 and 18. It is observed that the occupancy driven thermostat results in lower mass flow rates during periods of high power cost (1 - 2 PM). More detailed evaluation studies are required to establish the true savings potential of occupancy driven thermostats under real world test conditions, and are currently underway.

5. RELATED WORK

Since office buildings are one of the major consumers of energy, there is a significant body of work on building performance analysis and on occupancy based controls.

5.1 Building energy benchmarking and performance analysis

One of the widely used performance indicators for energy-usage assessment in commercial buildings is Energy Use Intensity (EUI) [11], where consumption is normalized with respect to the building area (kWh/ft^2) and the resultant value is used to compare buildings with similar characteristics such as type, location, age, etc. Other advanced approaches are reviewed and classified into several categories [7,39] based on the mathematical approaches used to calculate performance indicators. For instance, Lee has proposed multiple methods - a regression model combined with data envelopment [19], a cooling degree hour based approach [20] and a climate classification based approach [21]. William et al. study [8] a benchmarking technique using a multiple-regression model; however, they accept the complications involved in deploying such models due to the inclusion of multiple factors. Despite being extremely accurate in their representations, these methods have not been widely adopted since they require a large amount of data for the several input parameters used in these models. Moreover, such models are difficult to re across different buildings.

5.2 Occupancy driven control of VAV boxes in commercial buildings

A body of work exists in the area of occupancy based HVAC control in residential settings. A reactive approach for home heating control called *ThermML* [17] and the commercially available Nest thermostat [27], use GPS data from users' smartphones to turn heating ON or OFF. A proactive control approach, *PreHeat* has also been proposed in [29] which forecasts periods of occupancy using historical data and pre-heats a home in anticipation of an occupied time period. Lu et al [24] present a system referred to as *Smart Thermostat* which uses Hidden Markov Models to estimate occupancy states and uses those predications to takes control actions (turn HVAC ON or OFF). The common theme

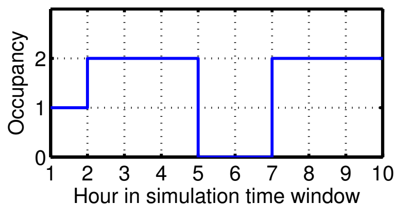


Figure 14: Occupancy profile used to investigate the occupancy driven thermostat

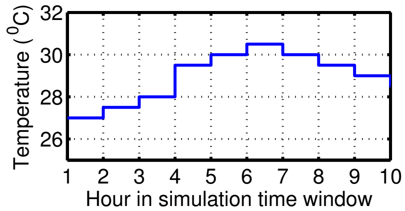


Figure 15: Ambient temperature profile used to investigate the occupancy driven thermostat

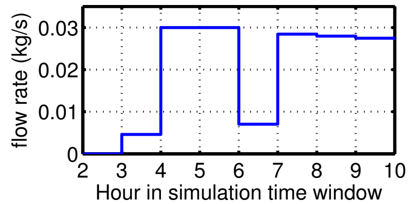


Figure 16: Supply air mass flow rate variation over the simulation time window obtained using occupancy driven thermostat

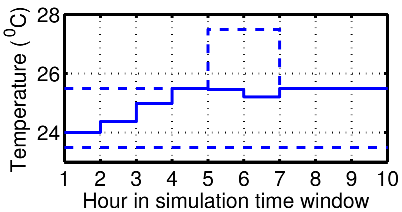


Figure 17: Zone temperature variation (solid line) over the simulation time window obtained using occupancy driven thermostat. Upper and lower comfort limits are shown using dashed lines

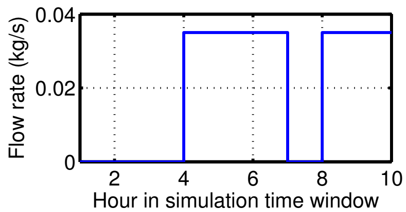


Figure 18: Supply air mass flow rate variation over the simulation time window obtained using conventional thermostat

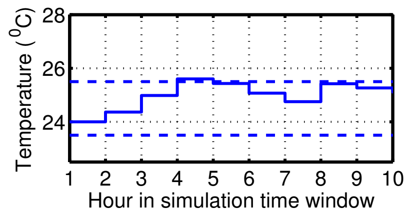


Figure 19: Zone temperature variation (solid line) over the simulation time window obtained using conventional thermostat. Upper and lower comfort limits are shown using dashed lines

in all these aforementioned solutions is to control residential heating and cooling systems using binary control decisions based on detected (reactive) or forecasted (proactive) occupancy levels. In contrast, our work focuses on commercial settings, where VAV systems are commonly employed for thermal management. Moreover, the control actions in our approach are not binary (ON or OFF) decisions, but, involves adjusting the conditioned air mass flow rates in a continuous manner based on forecasted occupancy count.

Occupancy based HVAC controls in residential settings using VAVs have also been investigated in [23] and [40]. These papers propose rule based 'reactive' adjustments - such as set-point and/or air mass flow rate adjustments - when occupants are detected. However, our proposed formulation of occupancy driven thermostats represent a 'proactive' approach in which data driven modeling tools are employed to forecast occupancy density and hence their contribution to the thermal loads, and then provides control actions to offset these loads through online optimization. It should also be noted that none of the above literature optimizes thermostat control actions based on cost of energy.

Personalized comfort devices (such as desk level LED lights and air-conditioners) have recently been proposed [14] as an alternative to centralized systems, which can be turned ON/OFF depending on the presence of occupants, thus promoting more efficient use of energy. Although such new paradigms are useful solutions for new and upcoming constructions, their adoption in existing buildings might be limited because of underlying technical and commercial challenges. For example, building operators might be reluctant to change an existing chiller plant due to cost considerations and the inconvenience associated with replacing an established infrastructure. Therefore, we believe that our proposed profiling methodology is useful because it can be applied to existing buildings with minimal capital investments. This is particularly important because it has been predicted that 85% of all buildings that would exist in 2035, exist today [16].

6. CONCLUSIONS AND FUTURE WORK

There has been an increasing interest in energy conservation strategies due to the energy shortage problems and climate change concerns experienced around the world. In this paper, we highlighted the importance of achieving energy efficiency in office buildings and presented two people-centric energy management approaches. First, we presented *STEM*, a convenient metric to assess energy utilization efficiency and comfort levels of occupants. The metric essentially correlates two parameters - energy usage and occupancy levels - and can be used at different spatial and temporal resolutions according to the granularity of available information. We believe both these parameters can be easily gathered in office buildings since they usually have the necessary communication networks. Moreover, energy usage data can be obtained from pre-existing energy meters (usually installed for accounting purposes) and occupancy data can be collected using a few low-cost presence sensors. Even though this metric has several desirable properties, it cannot indicate which of the two parameters led to a particular value. To address this shortcoming, we presented a cluster analysis based approach for identifying the true reason that affected the metric value. We evaluated the performance of metric and cluster analysis using real-world data collected from an office building in Bangalore, India. The results show our approaches can be useful for spotting the areas that are energy-inefficient or uncomfortable. Second, we presented an occupancy-controlled thermostat known as *FineTherm* that can control variable air volume (VAV) systems using projected occupancy and energy prices, in order to perform efficient thermal management of zones in buildings. FineTherm, unlike the other occupancy-based HVAC controls that take binary ON/OFF decisions, adjusts the air mass flow rates in a continuous manner. Using a simulation study, we showed that FineTherm can lead to 32% energy savings when energy prices are differentiated by a factor of 3.6.

We are considering several future extensions to STEM. Firstly, we plan to include existing profiling methods within the ambit of the proposed methodology. Some thoughts were provided in equation (3) but a detailed development and assessment exercise needs to be performed. Secondly, we identify refinements to STEM as an important direction for future work, especially to include the impact of other contributing factors besides occupancy such as temperature, humidity, geographical location, etc in an explicit way. Thirdly, the development of tools for automated detection and diagnosis of performance issues using STEM is planned. This would specifically entail the use of visualization engines and alarms, to facilitate the detection of such issues. Lastly, additional pilot studies involving office buildings of different footprints, topologies, and usage patterns would be performed to gauge the efficacy of the proposed occupancy centric profiling methodology in real world situations.

With regard to FineTherm, we identify three different avenues for future work. Firstly, we plan to explore more accurate models for the zone thermal dynamics. The simulation results in this paper were derived using a physics based model. However, gray box modeling approaches have been reported to be more accurate in literature [4]. Therefore, we plan to integrate such modeling paradigms in FineTherm. Secondly, the formulation presented in this paper involves a decentralized architecture, where a control agent regulates one VAV box. More collaborative control architectures, such as distributed or hierarchical, would be tested in the future to investigate potential improvements in performance. Thirdly, we plan to undertake detailed experimental studies to implement FineTherm in a real world office environment, for a more accurate assessment of the benefits and to identify any practical issues that were not evident from the simulation experiments.

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