Improving Building Energy Efficiency with a Network of Sensing, Learning and Prediction Agents

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ABSTRACT

Nearly 20% of total energy consumption in the United States is accounted for in heating, ventilation, and air conditioning (HVAC) systems. Smart sensing and adaptive energy management agents can greatly decrease the energy usage of HVAC systems in many building applications, for example by enabling the operator to shut off HVAC to unoccupied rooms. We implement a multi-modal sensor agent that is non-intrusive and low-cost, combining information such as motion detection, CO2 reading, sound level, ambient light, and door state sensing. We show that in our live testbed at the USC campus, these sensor agents can be used to accurately estimate the number of occupants in each room using machine learning techniques, and that these techniques can also be applied to predict future occupancy by creating agent models of the occupants. These predictions will be used by control agents to enable the HVAC system increase its efficiency by continuously adapting to occupancy forecasts of each room.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed AI

General Terms

Design

Keywords

Occupancy prediction, Energy efficiency, Environmental sensing, Adaptive-agents

1. INTRODUCTION

Adaptive multi-agent systems are a key component of efforts towards reducing energy consumption, with proposed applications to smart grid and residential HVAC system operation. In this paper, we describe a multi-agent system deployed in a large educational/commercial office building environment that optimizes energy use and occupant comfort. Such a system can significantly reduce energy consumption without decreasing occupant comfort and satisfaction by adding spatiotemporal constraints that limit energy use to zones and intervals where occupants are predicted to be present. These policies are learned by observing patterns of occupant behavior and optimizing HVAC operation in response to the learned occupant models. The techniques described have wide applicability across commercial and residential building environments.

Buildings consume about 40% of all energy used in the United States, divided nearly equally between the residential and commercial sectors, with a significant portion devoted to heating, ventilation, and air conditioning (HVAC) systems [1]. While the HVAC mechanical units themselves have increased in efficiency over the years, there have not been advances in terms of using intelligent agents to improve efficiency. Intelligent agents that robustly learn and adapt to the environments in which they are deployed have the potential to greatly reduce energy consumption by proactively adjusting building HVAC systems to respond to occupant needs along multiple objectives such as minimizing energy while maximizing occupant comfort and satisfaction.

Recently the agents community has begun to develop techniques for energy efficient practices within smart grid and some building domains, primarily residential buildings [9, 10, 12, 7]. Here we focus on HVAC control in commercial buildings, though the techniques should be directly applicable in residential settings as well. The innovative application described is a Building-Level Energy Management Systems (BLEMS) project that is deploying a multi-agent system with 58 multi-modal sensors, multiple learning agents that collaboratively learn and adapt to specific occupant needs, and 74 actuators that correspond to the building's HVAC zones and the two central air handling units (AHUs). The system is shown in Figure 1. Sensor Agents in each room read environmental variables such as temperature, CO2, and sound level every minute, and record these values to a Timeline. Occupancy Estimation Agents (OEAs) use these readings to estimate the number of occupants in each room. The Policy Agent may use these estimates for reactive actions when needed, but primarily these estimates are then used by Occupancy Prediction Agents (OPAs) to predict the number of occupant who *will* be in each room in the next hour. The Policy Agent uses these predictions to adjust the heating or air conditioning actuators so that the respective rooms are warmed or cooled to the desired temperature before the occupants arrive, or to shut down the system when occupants leave. It does this by communicating with the Honey-

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well Enterprise Buildings Integrator (EBI) system used by University to remotely control HVAC operation in many of campus buildings.

The core component of the system is the adaptive Estimation and Prediction agents that observe multiple sensors and learn patterns of occupant behavior. By modeling occupancy patterns, the BLEMS Policy agent can conserve energy by constraining heating and cooling policies to be active only during the hours when occupants are actually in specific rooms and zones of the building. We show that our Estimation Agent can achieve 95% accuracy in the occupancy estimation task, with RMSE of occupant numbers of 0.7. Prediction of the occupancy status of a room is also an important component of the system because the thermal mass of each zone sometimes requires a substantial start-up time to heat or cool the space to a comfortable temperature. We thus need to know whether a room will be in use up to an hour in advance of actual occupancy. This type of information can be inferred or predicted from learned patterns of occupant behavior. We show that we can achieve nearly 90% accuracy in this occupancy prediction task.

2. DEPLOYMENT ENVIRONMENT

The BLEMS system is currently being deployed to a 3-story research and teaching building at the *University (name withheld)*, henceforth referred to as University, as part of a program funded by the U.S. Department of Energy. The building contains lecture halls, classrooms, conference rooms, lounge spaces, and staff and student offices. The wide range of space uses enables us to test the capabilities of the BLEMS agents within different regimes, suggesting applicability to both commercial office buildings and residential spaces, as well as challenging environments such as intermittently used conference rooms. Users of the building include permanent occupants such as professors, administrative staff, and graduate research assistants, as well as temporary occupants including students attending classes and visitors at meetings. The building, along with a floorplan of the first floor showing sensor locations, in shown in Figure 2.

To test the BLEMS system prior to full deployment at University, we deployed two identical BLEMS agents within two different lab spaces at the University, which we'll refer to as Lab1 and Lab2. The labs are located in two different buildings, and are used by 4-10 students on an intermittent basis. The spaces were chosen because they represent the most challenging environment for the BLEMS agents, where multiple students share the space and have individually variable schedules. Sometimes Lab1 is completely empty for the entire day, whereas other days there are as many as 10 people in the space. Figure 7 shows probability of atleast one occupant on a typical Business day in Lab1. The BLEMS Occupancy Estimation Agent and Occupancy Prediction Agent learn the behavior patterns of these users over the course of a month of observation, and use this learned behavior to adjust heating and air conditioning policies based on the OEA and OPA estimates and predictions.

3. RELATED WORK

There is an expanding literature on agent-based HVAC control and occupant behavior modeling techniques for reducing energy consumption in residential and commercial building settings. Most of the agent literature on efficient HVAC control centers on residential settings where occupancy is considerably easier to model, and where HVAC systems are also much simpler, or on smart grid related technology [9, 10, 12, 7]. In the commercial office settings described in this paper, occupant schedules are much more variable, with professors often traveling, teaching, or attending meetings elsewhere, and where large inflows and outflows of students into classroom spaces occurs regularly. Furthermore, the HVAC system has many more interlinked controls, including central air handling units that deliver cooled air throughout the building ductwork, and individual airflow control and heating units in each zone/room. This makes the BLEMS Policy Agent's task more complex.

Occupant behavior models have also been explored by many researchers in civil and industrial engineering. The closest in spirit to the current work is a model developed by Page et al. [6], which models occupancy using a Markov chain. They develop a time series model of an occupant in particular zones of the building. This model was shown to simulate occupant behavior well in the aggregate, for example producing PDFs of arrival times that matches the actual distribution relatively well. However, the model does not attempt to predict actual occupancy on any given day and time, rather it only produces a probability density for occupancy at that day and time. Furthermore, it does not attempt to estimate the number of occupants in zones where more than one person may be present, e.g., labs or conference rooms.

In general, other work on occupancy models suffer from the same drawback. The outputs of these models tend to be probability densities, rather than specific predictions. As we will show in this paper, in many cases we can achieve higher accuracy by using other input features to a machine learning-based predictor, instead of simply counting and using the historical probabilities, or using survey data. The reason much of this work differs in spirit from our current paper is a difference in goals: for the related work, the occupancy models were used to create simulations of overall building occupancy, from which engineers could calculate a building's thermal loads and thus correctly size and provision an HVAC system. Use of these simulations in the operation of the HVAC system would typically be relegated to computing a reasonable start and end time for the HVAC system to be turned on. In marked contrast, our goal is to dynamically operate the HVAC system on a zone by zone basis, with potentially different behavior for each zone and each day and time. We actively use the occupancy models we develop to operate the HVAC system. Thus, our models cannot simply produce an aggregate probability density; instead we need accurate estimates of occupancy for every day, time, and zone.

For completeness, we survey some of this related work: [5, 11] attempted to create statistical occupancy time-series model based on occupancy survey of the people on a regular day. Richardson et al. [5] generated realistic occupancy using this model.The generated occupancy is binary information on a 10-minute resolution, which is similar to our study of prediction accuracy analysis where we have surveyed occupants of a building and generated data using probabilistic selection of occupant's typical schedules. Liao et al. [8] developed an agent-based model to simulate the occupant behavior and developed a graphical model on the probabilistic factors that effect agent behavior. Their experiment was

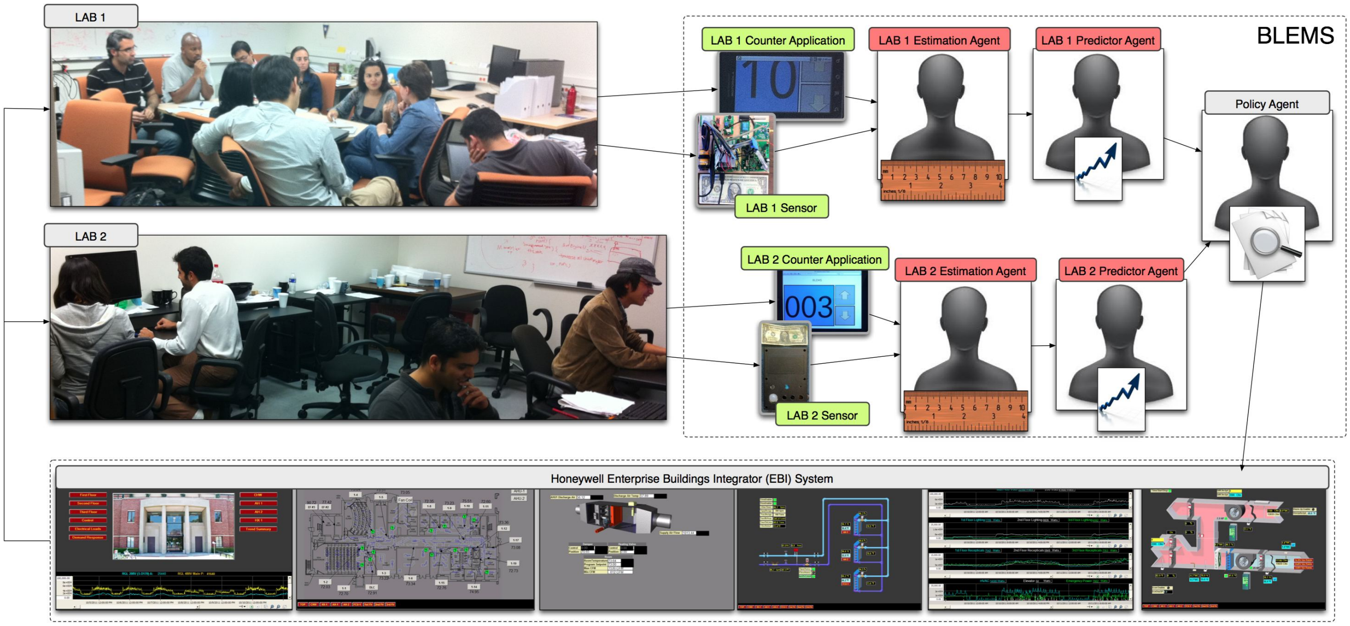


Figure 1: The BLEMS System: Sensor, Estimator, Predictor, and Policy Agents, and the Honeywell EBI.

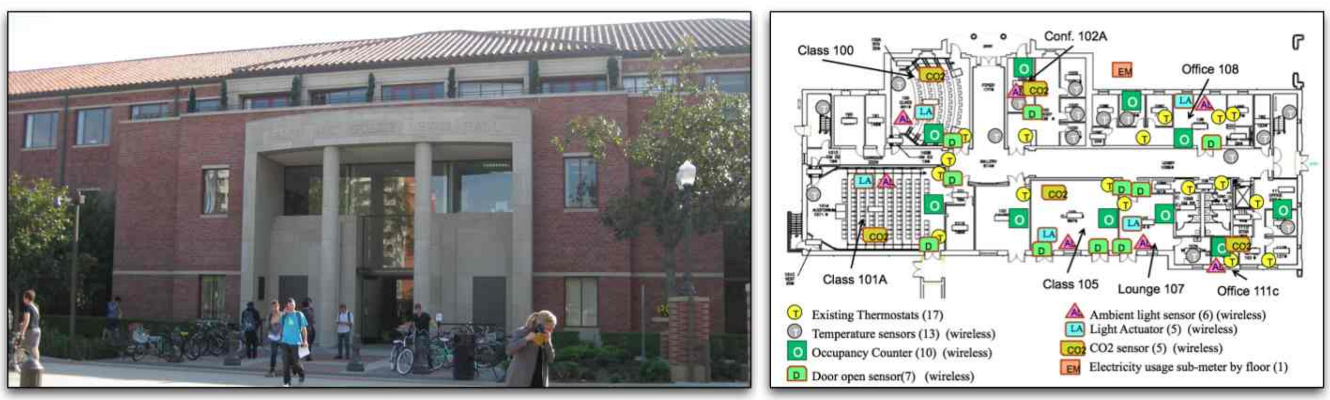


Figure 2: (Left) The BLEMS testbed: University Building. (Right) Floorplan of first floor deployment.

limited to one occupant of a particular room.The probabilistic graphical model alone cannot predict occupancy due to dynamic nature of occupants day-to-day activity. Yu. [14] has applied a rule-based technique on motion sensor data and achieved an accuracy of 83%; they learned the rules with statistical methods in the context of single occupant in a room. In contrast to much of this work, we are building predictive models that can be deployed to a variety of offices, labs, and classrooms throughout campus buildings, and is adaptive enough to quickly learn individual occupant behaviors when deployed in the field.

Lighting is another important, though less significant, component of building energy usage. Controls based on occupancy estimates were shown to result in energy saving of 40% when the control system was able to substitute daylighting in place of artificial lighting [3]. Other types of HVAC systems, such as TABS (Thermally Activated Building System), which uses heated or cooled water circulating through pipes embedded in the floor instead of forced air, have also been investigated [4]. These investigations have used simple probabilistic occupancy models that assume arrival and departure times distributed according to Gaussian or uniform distributions, with a probabilistic rate of temporary absence. Such models are useful for evaluating traditional static policies for building operation. However, as described above, HVAC operations can be significantly optimized by responding to individual occupancy patterns rather than treating the population as homogenous.

4. SENSING AGENT

In contrast to other attempts to estimate current room occupancy, we use non-intrusive techniques that do not rely on the video or camera feeds used in prior, related work [2, 13]. Currently the most reliable estimates are based on image recognition techniques. Instead we introduce a multi-modal sensor that is low-cost and non-intrusive. Unlike the ubiquitous motion sensors deployed in "green" buildings today, a multi-modal sensor provides multiple types of readings from which we can more accurately gauge occupancy, including estimating the *number* of occupants in a room. Each modality is incorporated using fairly low-cost, off-the-shelf components. The device has the following raw sensors: sound, wide-field motion detection, narrow-field motion detection, ambient light, temperature, humidity, carbon dioxide, and door state (open/closed).

The Sensing Agent reads the values of these sensors every minute and records a useful transformation of this data onto the BLEMS Timeline. For example, it records onto the Timeline the number of times that motion was detected, rather than the raw value which is a lifetime count of motion activations. For our experiments, the Sensing Agent also retrieves ground truth occupancy counts from a Counter App that is deployed on iPads installed next to the doorways in Lab1 and Lab2. The students in these labs record their arrivals and departures using this app. This enables us to verify the accuracy of our Estimation and Prediction agents. In the future, the Sensing Agent may also receive other inputs, such as feedback from occupants using provided smartphone applications.

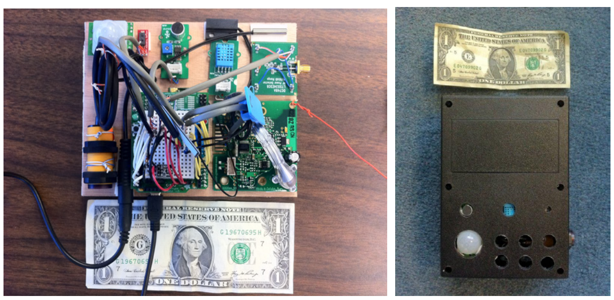


Figure 3: Prototype BLEMS sensor, with and without cover; dollar bill for scale.

5. OCCUPANCY ESTIMATION AGENT

The BLEMS system relies on accurate occupancy estimation (current number of occupants in a room) and occupancy prediction (a prediction of how many occupants will be in the room in the next 15, 30, 45, 60 minutes) in order to adjust the operation of the HVAC system to conserve energy while maintaining occupant comfort. We investigate two estimation problems: 1) estimation of whether or not there are *any* occupants in a room, and 2) estimation of the exact number of occupants in a room. The first problem, binary estimation, is clearly simpler, and we demonstrate high accuracy for that task. Solving this problem allows us to modify HVAC operation so that it is turned off when there are no occupants. The second problem is much harder, given the fairly crude sensors we are given and the goal of estimation an exact number of occupants. However, we also demonstrate surprisingly good accuracy for this task as well. Solving this problem allows us to further tune HVAC operation so that space conditioning energy (flow rate of conditioned air into the zone) is adjusted to match the number of occupants in the space, which increases comfort.

5.1 Baseline: Rule-Based Heuristic

We first implement a simple heuristic that serves as a baseline comparison for the binary occupancy estimation problem. The rule-based estimator takes as input the previous 15-minute interval of sensor data and outputs whether any occupant is present in the room. Presence is output as long as the narrow or wide field motion detector detects motion, or if the sound or CO2 sensor reads higher than the baseline normal.

5.2 Machine Learning Methods

Supervised statistical machine learning techniques use a set of labeled training data to learn the parameters of a prediction model. Here, our training set consists of the feature vectors formed from the sensor readings, where each vector is labeled with the ground truth occupancy. We then use a variety of statistical learning techniques like linear regression, logistic regression, multi-layer perceptron, and support vector machines (SVM) to train prediction models using sensor data labeled with the ground truth data. Given a new feature vector of sensor readings, the trained models can then estimate the occupancy.

It is important to note that the choice of features in the representation of the data often makes a big difference in the accuracy of the trained classifiers, depending on the type of classifier used. As described earlier, the BLEMS Sensor Agent creates a set of features that are based on the original raw sensor readings, but transformed and projected onto useful axes such as the number of times motion was detected in the last minute. The Estimation Agent adds additional knowledge to this feature vector, such as domain knowledge that biases the classification or collaborative knowledge from other agents operating in nearby or similar rooms. This overall set of features includes:

- Time: the time is the minute count from the start of the day,
- Biasing Time: in some experiments we also provide a nonlinear function that encodes the notion that occupants are more likely to be in the room during usual work hours.
- Sound: cumulative sound energy sensed for one minute,
- CO_2 : instantaneous reading of the carbon dioxide sensor,
- Number of times wide-field motion detected in the last minute, where the sensor is mounted to detect motion within the room,
- Number of times narrow-field motion detected in the last minute, where the sensor is mounted to point across the doorway,
- Temperature: Instantaneous temperature of the room recorded by sensor,
- Humidity H: Instantaneous humidity recorded by sensor,
- Motion M : Number of times motion detected by the wide beam motion detector in the last minute,
- Motion N : Number of times motion detected by the narrow beam motion detector in the last minute,
- Motion status M_0: Current wide beam motion sensor status { High=1, Low=0 },
- Motion status N_0: Current narrow beam motion sensor status { High=1, Low=0 },
- $\overline{CO_2(t_1, t_2)}$: Average CO_2 during a window of time from t_1 to t_2 hours in the past,
- $\overline{CO_2(4am, 7am)}$: Average CO_2 during 4am-7am, when occupancy is presumed to be zero,
- $\overline{O(t_1, t_2)}$: Average estimated occupancy count during a window of time from t_1 to t_2 hours in the past,
- $corr(CO_2(t_1, t_2), CO_2(t_3, t_4))$: Correlation of $CO_2(t_1, t_2)$

Figure 4: (Left) iPad mounted beside the lab entrance to gather ground truth occupancy counts. Large touch buttons enable occupants and visitors to easily mark their entrances and exits. (Right) A web application enables quick visualization of the sensor readings and ground truth.

and $CO_2(t_3, t_4)$, where $CO_2(t_i, t_j)$ is the vector of CO_2 per-minute readings during a window of time from t_i to t_j hours in the past,

The classifiers are trained using various subsets of this collection of features. We present results using three different subsets of features:

(i) Time, Sound, CO_2, cumulative motion count difference, cumulative beam count difference, temperature, humidity, and motion sensors,

(ii) All features in Set (i), plus $\overline{CO_2(0,3)}$, $\overline{CO_2(3,6)}$, and $\overline{CO_2(6,9)}$,

(iii) All features in Set (ii), plus $\overline{CO_2(0.5,2.5)} - \overline{CO_2(0,2)}$, $\overline{CO_2(1,3)} - \overline{CO_2(0.5,2.5)}$, $\overline{CO_2(1.5,3.5)} - \overline{CO_2(1,3)}$, $\overline{O(0,2)}$, $\overline{O(0.5,2.5)}$, $\overline{O(1,3)}$, $\overline{O(1.5,3.5)}$, $corr(CO_2(0,2), CO_2(0.5,2.5))$ $corr(CO_2(0.5,2.5), CO_2(1,3))$, and $corr(CO_2(1,3), CO_2(1.5,3.5))$.

Using these features, we estimate the occupancy count $\widehat{O(t)}$ at the current time t. We will omit the notation t when it is clear.

5.3 Experiments and Results

For the results reported in this paper, sensor devices were deployed at Lab 1 and Lab2. Both of these office spaces are shared by multiple graduate students, and the number of occupants ranges from zero to ten, with large variability within and between days. Training data was collected over several weeks. The models were then trained on this dataset. For binary occupancy estimation, we report accuracy of the predictions. For estimation of a numeric occupancy value, we report the Root Mean Square Error (RMSE). We report the average RMSE obtained through 10-fold cross validation, where in each of 10 runs, one-tenth of the training dataset is held out of the training and used as the test set.

To collect the ground truth data (the number of people who are actually in the room at that time), we mounted an iPad with a Counter App next to the doorway of the test lab (see Figure 4). Lab 1 was also outfitted with a camera that snapped an image of the entire lab every minute. Using these images, we verified the accuracy of the data collected by the Counter App, to ensure that students were using the App on a consistent basis. Our results showed that the Counter App data was a reasonable reflection of ground truth.

Rule-based heuristic. Somewhat surprisingly, the rule-based heuristic resulted in very poor results for the simple binary occupancy estimation problem. The heuristic resulted in the wrong answer more often that the correct answer; essentially the opposite of the prediction would have resulted in higher accuracies. This is due to several limitations in the rule-based heuristic. The rules are very sensitive to background fluctuations in average CO2 and sound levels. The rules are also likely to over-estimate occupancy because satisfying any one of the rules will cause the heuristic to predict that there is an occupant in the room.

Learning techniques. The feature sets used to train the occupancy estimators can greatly affect the resulting accuracy. One of the novel aspects of our learning methods is the design of the feature set. To overcome variability in certain environment variables such as CO_2, we constructed features that attempt to measure the change in background CO_2 levels throughout the day. These background changes are often due to the influence of occupants in other rooms of the building, since air is partially recirculated. The correlation features and average CO_2 features enable the classifiers to partially account for these influences. Eventually, as sensors are deployed throughout the University Building, we will be able to use communication between the agents to directly correct for some of these variations.

The core learning algorithms are primarily WEKA (open source machine learning package) implementations of standard machine learning algorithms. We report results using MultiLayer Perceptron, Linear Regression, Gaussian processes, and SVM to estimate the occupants using data from the Sensor Agent. We briefly describe each of these methods here, and provide the parameters used in each case. We did not use cross-validation to optimize the choice of parameters yet; this may be done in future work.

MultiLayer Perceptron learning has one linear node in first layer and four nodes with sigmoid activation functions in second layer. The parameters are: Learning rate 0.3, Momentum 0.2, epochs 500, error threshold 20, and one hidden layer with 4 nodes. The model denoted MLP10 is the MultiLayer Perceptron trained on feature set (ii).

Gaussian Processes learning has RBF kernel and noise of 1.0 . It was computationally expensive due the high number of matrix inverse calculations and is very time consuming for training even with a few thousand data points.

Linear Regression uses a ridge regularizer= $1.0e-8$, m5 attribute selection. The trained model estimates the number of occupants based on a linear combination of the input feature values.

SVM Multiclass classifier was also used, and the parameters of ν-SVM are $v = 0.001$, $\epsilon = 0.01$, kernel=radial basis function, cost=1.0. The model denoted SVM15 is this SVM trained on feature set (iii).

Results. Table 1 shows the accuracy and RMSE of the different estimation techniques on cross-validated training data. We show accuracy and RMSE under the two different subsets of features described earlier. For real-valued estimators, an instance is considered to be correctly classified when the estimated value is greater than 0.7 and the ground truth people count is greater than or equal to 1, or if the estimated value is less than or equal to 0.7 and the ground truth is zero.

The average RMSE for estimation with most of these techniques is less than one, which is quite good. The MultiLayer Perceptron achieves an RMSE of 0.82 on the unseen test data from the following week. An RMSE of 0.82 is a good result since the number of occupants varies between zero and ten. It suggests that our occupancy estimate is usually within one of the correct number of occupants. Given that we are using fairly simple and crude sensors, and we have not optimized the learning process extensively, we believe this is an encouraging result.

Moreover, we used an ensemble learning method to combine results across multiple time periods. This method used a voting method to elicit the most popular prediction in the previous fifteen minutes, and used this value as its prediction. In practice, this enabled the occupancy estimator to smooth out occasional irregularities in the data and resulting predictions, leading to considerably better RMSE scores, as shown in Table 1.

Estimation method	RMSE	Accuracy
Rule-based heuristic	–	46%
MultiLayer Perceptron, featureset(i)	0.9	90%
Gaussian Processes, featureset(i)	1.0	91%
Linear Regression, featureset(i)	1.2	86%
ν-SVM-R, featureset(iii)	0.88	92%
MultiLayer Perceptron, featureset(iii)	0.73	95%
Linear Regression, featureset(ii)	1.05	87%
Ensemble Voting, featureset(iii)	0.6	95%

Table 1: Accuracy of different occupancy estimation techniques. The Ensemble Method has the best accuracy and lowest RMSE.

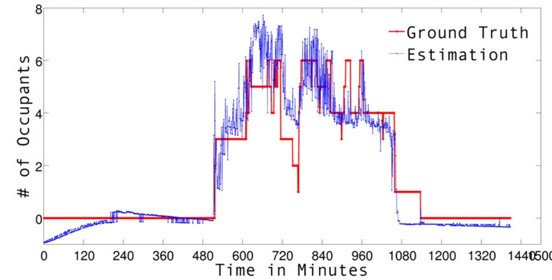
The experiments suggest that CO_2 is highly correlated to the number of occupants. Motion and motion count also correlate to presence of an occupant in room. For example, the Linear Regression learns the following coefficients for estimating the current number of occupants:

$$\begin{aligned}\widehat{O} &= -8.889 + 0.3883 * M - 0.1826 * N \\ &\quad +41.777 * CO_2 + 0.0096 * H + 0.8754 * M_0\end{aligned}$$

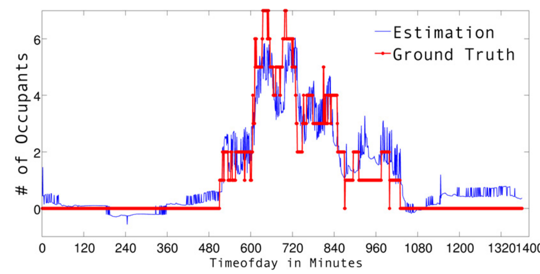
However, it is also clear that this simple classifier, while decent, does not achieve optimal occupancy estimation performance.

To get a better sense of the estimates produced throughout each day, Figure 5 shows plots for the estimated occupancy on a particular day of test data using the different occupancy estimation algorithms. Figure 9 is plot of RMSE of estimation average over a day against different dates. We can see from for Lab1 that SVM15 has low RMSE compared to MLP10. SVM15 includes autocorrelation features, which seems to improve estimation for lab which has CO_2 well correlated to Occupancy.

We also evaluate the performance of cross lab estimation: that is, using a occupancy model trained from one lab's data to estimate occupancy at the other lab. We observed an RMSE of around 2.5-3.5 for estimating Lab 2 occupancy using the Lab1 model, and an RMSE of 1.2-1.6 for estimating Lab1 occupancy using the Lab 2 model. Figure 9 shows occupancy estimation for Lab 2 using a trained model of Lab 1.



(a) MultiLayer Perceptron



(b) SVM with 15 attributes

Figure 5: Occupancy estimation using machine learning techniques.

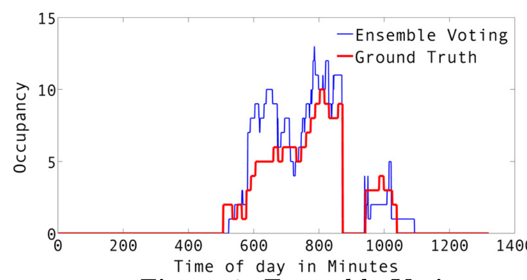


Figure 6: Ensemble Voting .

6. OCCUPANCY PREDICTION AGENT

The previous section shows that we can use BLEMS Sensor Agents to accurately estimate the number of occupants in a shared office space. On its own, this could enable significant gains in energy efficiency by enabling the HVAC system to be quickly adjusted to meet the needs of the current number of occupants. However, if we can predict the future occupancy, efficiency can be increased further. Partly, this is due to the need for unoccupied spaces to be conditioned to within a fairly tight range of temperature, so that a new occupant is not subjected to uncomfortable conditions while the space is brought to an acceptable temperature. Thus, energy is wasted maintaining all spaces within a building to within a few degrees of desired temperature. Accurate prediction of future occupancy would enable the HVAC software to completely turn off heat or air conditioning to un-used spaces. The HVAC can be turned on if occupancy is predicted far enough in advance, so that the system has ample time to prepare the room for occupancy by heating or cooling it as needed. Typically offices and shared lab spaces can be conditioned within one hour, so in this paper, we investigate the use of machine learning techniques to predict the future occupancy of building spaces for up to that interval.

As in the occupancy estimation problem described ear-

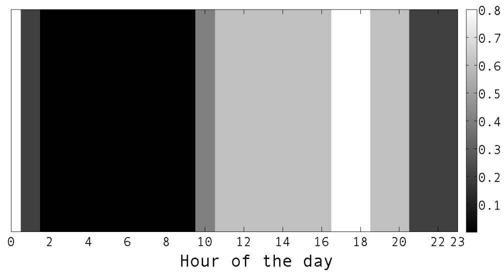


Figure 7: Probability of Occupancy status on a typical Business day over 24hr period. Higher the probability, Lighter is the heatmap.

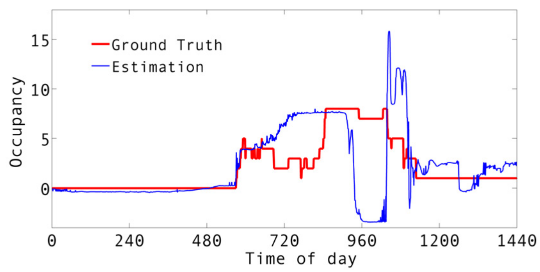


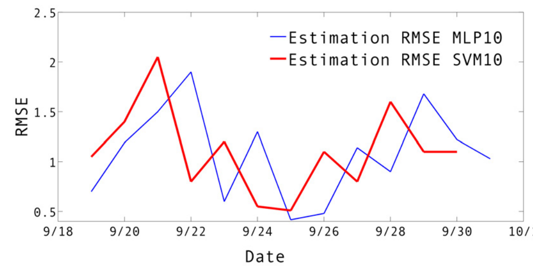
Figure 8: Cross lab testing: Estimating Lab 2 occupancy using model trained on Lab 1 data.

lier, we train the occupancy models using a labeled training dataset. Each day is divided into a feature vector of length 96, where the room's occupancy within each 15-minute interval in the day is represented by one binary feature. We train a separate model to estimate the future occupancy in the room at each 15-minute interval of the day. That is, if it is currently 11:45, to predict the occupancy at twelve noon, we train a model using a training set that has feature vectors describing the occupancy pattern from midnight to 11:45, labeled by the occupancy at noon.

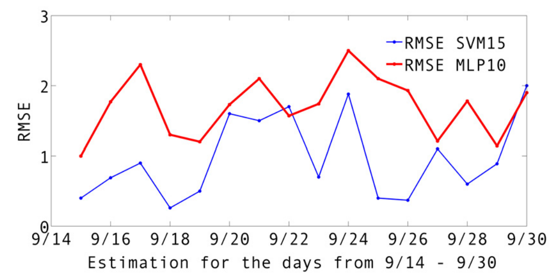
We use two different datasets for this portion of the work. The primary dataset is the same as in the occupancy estimation work, consisting of sensor data and ground truth from the deployed Sensor Agents in the two campus lab spaces described earlier. We predict future occupancy in two different scenarios: (1) assuming we only have access to the estimated occupancy counts outputted by the Occupancy Estimation Agent, and (2) assuming we have access to the ground truth.

We tested occupancy prediction using ground truth data and sensor occupancy estimation. We have used algorithms as in second dataset (described in following paragraph), except with less training data (15 to 18 days instead of 100+ days) and test data of less than a week. Table 2 shows the accuracy of prediction of estimated occupancy. The accuracy is 0.95 for occupancy prediction using ground truth data and drops to .89 for occupancy prediction using estimated occupancy.

The second dataset is derived from survey data gathered from the University Building occupants. We conducted a survey of the building occupants using a web application that asks for their three most typical schedules during the week. Based on the survey of 30 respondents, we generated simulated data using probabilistic selection of schedules with some noise added. Each of the three schedules is selected with a probability corresponding to the occupant's



(a) Lab 2 Occupancy Estimation RMSE from 9/18-9/30 by MLP10 and SVM10



(b) Lab 1 Occupancy Estimation RMSE from 9/14-9/30 by SVM15 and MLP10

Figure 9: Estimation RMSE for Lab 1 and Lab 2.

	Training Data	Test Data	Accuracy
Lab1 ,Ground Truth	15	5	0.945
Lab2, Ground Truth	18	6	0.93
Lab1, Estimated Data	15	5	0.89
Lab2, Estimated Data	18	6	0.8

Table 2: Occupancy Prediction accuracy (15 min in advance), using real data from live deployment at Lab 1 and Lab 2.

survey response. The occupancy pattern is then perturbed by changing the occupancy bit of each 15-minute interval with 0.2 probability. We use this simulated dataset to investigate the feasibility of predicting occupancy of a room up to 1.5 hours in advance.

The learning methods are trained on different combinations of size of training dataset {100,200} days, and predict the occupancy {15, 30, 60, 90} minutes in advance. The results are shown in Table 3 and Figure 10. We used a multilayer perceptron and logisitic regression classifier. We note that the best possible accuracy is 0.8, since we generated the data with a noise term of 0.2. The table shows that both methods are able to fairly accurately predict occupancy 15 minutes in advance. Prediction of occupancy 30, 60, and 90 minutes in advance is somewhat lower, but is still quite high relative to the absolute maximum of 80% accuracy. With smaller amounts of noise in the generated data, the accuracy is significantly higher, but this shows that the methods will still perform reasonably well with high degrees of noise. On the synthetic survey data, it is interesting to note that the system's performance is actually not as good. Partly we believe this is because occupant schedule are actually not as variable as the data we synthetically generated. We purposefully chose a high noise term of 0.2 in order to produce a challenging dataset. However, our live data shows that

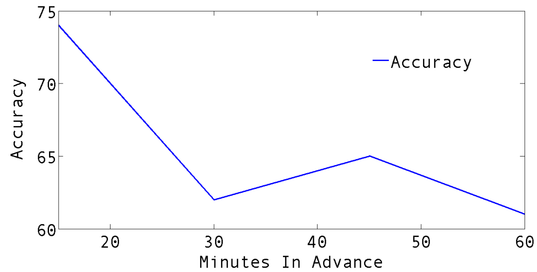


Figure 10: Occupancy Prediction: accuracy vs. time period for advance prediction.

this may have been overly pessimistic. Table 3 shows our accuracy using the survey-based synthetic data, Figure 10 shows how the accuracy degrades as we attempt to predict further into the future (up to an hour in advance).

Prediction method	Training size	Min in advance	Accuracy
Multi-layer Perceptron	100	15	67%
MultiLayer Perceptron	200	15	68%
Logistic Regression	100	15	72%
Logistic Regression	200	15	75%

Table 3: Accuracy of different occupancy prediction techniques for predicting future occupancy 15 minutes in advance, given different amounts of training data(Synthetic data generated from survey of University Building occupants).

7. CONCLUSION

Adaptive multi-agent systems that learn about occupant behaviors and optimize HVAC operation in response to these occupant models promise to greatly reduce energy consumption.We show that machine learning techniques can be used to estimate room occupancy using a set of simple sensors, and that we can use similar techniques to learn agent models that predict occupant behavior. By using these agent models to predict room occupancy up to an hour in advance, the BLEMS system can intelligently control the multi-agent HVAC system to minimize energy usage while maintaining occupant comfort.

We will continue to refine the learning methods. In particular, the current off-the-shelf methods will need to be refined to better handle small training dataset sizes (so that we can predict occupancy without lengthy collection of occupant behavior) and take advantage of additional structure in the data (such as a sequence of beam activation and motion activation indicating occupant arrival). Even with the current methods, it appears that we can handle relatively small dataset sizes of a couple weeks.

The good performance of the system on the live testbed environments enables us to proceed with the project. The BLEMS system is currently being deployed to an entire three-storey office building on the University campus. Experiments in the near future will meter the energy consumption at University Building under control conditions and under the treatment condition with the BLEMS system. We will establish the energy reduction made possible by intelligent sensing, agent modeling, and adaptive control strategies.

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