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Impact of Occupancy Modeling and Horizon Length on HVAC Controller Efficiency

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***Abstract*— Controlling heating, ventilation, and air conditioning (HVAC) to improve its energy efficiency or implement ancillary services (e.g., demand response or frequency regulation) requires compensating for occupants and the computers/equipment they use, which significantly impact the thermal dynamics of buildings. Several studies have explored the use of either binary models or online learning for occupancy within model predictive control (MPC) frameworks, but the use of more fine-grained predictive models for occupancy has been less well-studied. This paper uses real data from an HVAC testbed to develop predictive models of occupancy and heating load, evaluate the predictive accuracy of the occupancy model, and then quantify its efficacy in achieving energy reductions in conjunction with a learning-based MPC (LBMPC) controller. We conclude by conducting a simulation study to determine the optimal horizon for an LBMPC controller. In particular, we find there is a trade-off with increasing the horizon length between decreasing prediction accuracy of occupancy heating load and the ability of the MPC to better anticipate thermal dynamics due to occupancy and weather.**

I. INTRODUCTION

Though occupancy within a room or building is an important factor in the design of heating, ventilation, and air-conditioning (HVAC) systems, it has been traditional to configure and operate HVAC based on the maximum number of occupants that are anticipated in the room or building [1]. However, occupancy is dynamic, and better consideration of its variation when controlling HVAC can lead to substantial energy savings [2]–[4]. Despite such successes, the interplay between occupancy prediction and the design of energy-efficient HVAC control is still not fully-understood.

One unresolved question is the impact on energy-efficiency of model predictive control (MPC) horizon length and prediction accuracy of occupancy models: Because the accuracy of occupancy models decreases the further in the future they are used to make predictions, there will be a trade-off between MPC horizon length and energy-efficiency of the closed-loop system. Our goal in this paper is to construct models of occupancy and then quantify the trade-off between horizon length and energy-efficiency, using real data from a physical testbed in the Philippines. We will specifically focus on the setting of a single room, because most air-conditioning systems currently found in tropical environments, like in the Philippines, is for a single-room.

A. Predicting Occupancy

Autoregressive-moving-average (ARMA) models, artificial neural networks (ANN), logistic regression, and Markov chain models have been used to make binary (i.e., predict 1 if the room will be occupied, and predict 0 if the room will be empty) occupancy predictions [5], [6]. However, the amount of heat generated by occupants and the equipment they use, such as computers increases in proportion to the *number* of occupants in the room. Hence, binary predictions of occupancy are not detailed enough for use in MPC where continuous model predictions can be easily incorporated [7], [8]. More sophisticated models attempt to predict the number of occupants in a room. Agent-based models and graphical models [9], [10], Markov chain models [11], and machine learning [12] have been used to predict occupant count in a room by using sensor data. In this work, we make use of occupancy data to predict future room occupancy count with continuous update for every of data from the testbed. Formulation of occupancy count prediction model is made to be scalable for varying prediction horizon length.

B. Control with Occupancy Information

Several papers have used occupancy prediction for energy-efficient HVAC control. Binary occupancy predictions [5], [6], [13]–[15] are used to impose strict constraints on room temperature when there are occupants and relax constraints when there are no occupants. Occupant count predictions have also been used: One approach is to determine average or worst-case occupancy counts and then adjust HVAC configuration to ensure comfort and efficiency at that occupancy level [16], while [17], [18] adjust airflow based on occupancy counts to ensure indoor air quality (IAQ) is maintained within acceptable levels. Predictive control has also been used in conjunction with day-ahead prediction [19], continuous occupancy predictions [20] or with short-term estimates of heat due to occupants [2]–[4].Together with occupancy count prediction, this project makes use of LBMPC with occupancy prediction as a parameter of the temperature model with varying prediction horizon.

C. Outline

Though MPC can use occupancy prediction for designing energy-efficient HVAC controllers, the tradeoff between

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TABLE I
CATEGORIZATION OF ROOM OCCUPANTS

	Grad Student	Undergraduate	Staff	Total
GSL	14	0	0	14
CNL	2	12	5	19
PSSL	0	23	1	24

MPC horizon length and energy-efficiency has not been well studied. In this paper, we more closely explore the relationship between occupancy models, room thermal dynamics, and energy-efficiency of the resulting HVAC controller. Sect. II describes an HVAC testbed we have constructed in a tropical environment. Next, Sect. III describes three rooms we collected occupancy data from for the purpose of constructing and comapring several predictive models of occupancy counts. Sect. IV builds a model of the thermal dynamics of the testbed. Finally, Sect. V explores the tradeoff between MPC horizon length and HVAC energy-efficiency.

II. UP-BRITE TESTBED

The UP-BRITE testbed is located in one of the buildings at the University of the Philippines, Diliman. The room is occupied by graduate students who do research, teaching, and coursework. The number of occupants varies throughout the day as the students do not follow a strict schedule, with peak occupancy of 14 people. The room has a volume of 288 cubic meters, which is conditioned by the two VRF air conditioning units. These two air conditioning units are controlled by a Raspberry Pi which sends control commands simultaneously to both units. Off-the-shelf temperature sensors were used to log the room temperature, and weather data is pulled from a weather station database. This testbed is similar to the BRITE testbeds [2]–[4] previously located in UC Berkeley. The control algorithm used was LBMPC which utilizes two models, a static and a learning model for indoor room temperature to determine the length of time the air conditioning units are turned on for every fifteen minute interval. In this paper, we add an additional parameter of occupancy count to model the indoor temperature of the room testbed. The prediction horizon was also varied in order to determine how it affects the performance of the system.

III. ROOM OCCUPANCY COUNTS

Four weeks of weekday occupancy data was collected from three rooms: the Graduate Student Laboratory (GSL), Computer Networks Laboratory (CNL), and the Power Systems and Simulations Laboratory (PSSL). Note that the GSL is the room in the UP-BRITE testbed. Occupancy data was gathered using an Android app in which occupants log each entry and exit to the room. The app obtains the total number of occupants in the room every minute, and the average number of occupants is calculated every 15 minutes. Occupancy data was gathered using an Android app in which occupants log each entry and exit to the room. We acknowledge that this may lead to some inaccuracies, which we plan to address in future work.

A. Categorizing the Room Occupants

The occupants of PSSL, CNL, and GSL are summarized in Table I. PSSL has the highest number of occupancy (24), while CNL (19) and GSL (14) have a similar number of occupants. In the data, we observed that the peaks of occupancy differ between days as well as between weeks. Moreover, the maximum occupancy in these rooms often was smaller than the total number of occupants. The number of occupants generally increased towards midday and decreased during the night. We also noticed that the arrival and departure times of the occupants varied substantially. All of the occupants in GSL are graduate students; their schedules are highly variable, and they have no restrictions on times-of-day they are allowed in the building. On the other hand, the majority of the occupants in CNL are undergraduate students working on capstone projects and other course requirements. However, undergraduate students can stay in the building only up to 9:00pm. CNL has the most staff personnel, who have a regular 8:00AM-5:00PM daily schedule corresponding to the office hours in the Philippines.

B. Occupant Count Prediction Models

Our model for the prediction at time n of the number of occupants k time-steps into the future is given by

$$o[n+k] = \Big[\tfrac{1}{m}\textstyle\sum_{i=1}^{m} o_i[n] + \tfrac{1}{w[k]}\textstyle\sum_{j=1}^{w[k]} \epsilon[n-j]\Big] \cdot s[n+k] \quad (1)$$

where:
m : number of training weeks
k : prediction horizon
n : current time step with 15-minute increment
i : weekly index of occupant count training data
$o[n+k]$: predicted number of occupants
$o_i[n]$: number of occupants at time n of i-th week
$\epsilon_i[n-j]$: error term from past predictions
$w[k]$: number of past error terms
$s[n+k]$: predicted binary occupancy state at time $n+k$

The occupant count prediction $o[n+k]$ is determined by averaging the number of occupants at each time point throughout the day using the training data $o_i[n]$, where i is the weekly index of the training data. This is to capture the daily trends in the behavior of people coming to work, taking breaks, and leaving the room. The basis of this model is that the future number of occupants is heavily influenced by the trend based on day of the week and time of day. We add past prediction errors $\epsilon[n-j]$ to account for observable trends like long-term absences during the day of prediction which acts to update the prediction of the model as time progresses throughout the day. The $s[n+k]$ term in the model reflects the binary state of occupancy in the room, with a value of 0 to indicate that the room is not occupied and a value of 1 to indicate the room is occupied (i.e., has at least one occupant). Trailing errors during the night from the occupant count prediction model can be observed. The goal of this parameter is to set when to stop taking in forecasts made by the model by looking at the historical trend of the occupancy state of the

TABLE II

OCCUPANT COUNT PREDICTION SUMMARY BY MODEL TYPE

		Graduate Student Laboratory					Computer Networks Laboratory					Power Systems Simulation Laboratory				
	Model Type	Prediction Horizon														
		15 min.	1 hrs.	2 hrs.	3 hrs.	4 hrs.	15 min.	1 hrs.	2 hrs.	3 hrs.	4 hrs.	15 min.	1 hrs.	2 hrs.	3 hrs.	4 hrs.
MAE	Unrestricted	0.4013	0.7969	0.8378	0.8279	0.8072	0.5691	1.4972	1.5362	1.5051	1.5469	0.8231	2.4322	2.8577	2.8848	2.8960
	Rule-based	0.4051	0.7844	0.8072	0.7930	0.7758	0.6192	1.4063	1.3623	1.2791	1.2582	0.8155	2.1387	2.3818	2.3514	2.3067
	Decision Tree-based	0.3965	0.7598	0.7866	0.7692	0.7587	0.6613	1.3869	1.3487	1.2729	1.2470	0.9525	2.1436	2.3731	2.3662	2.3318
RMSE	Unrestricted	0.7405	1.3507	1.3714	1.3974	1.3903	1.0238	2.4051	2.4218	2.3849	2.3396	1.5851	3.7531	4.1891	4.2236	4.1788
	Rule-based	0.7462	1.3457	1.3547	1.3770	1.3733	1.1168	2.3683	2.3405	2.2836	2.2025	1.5292	3.5037	3.8856	3.8866	3.8197
	Decision Tree-based	0.7379	1.3310	1.3449	1.3673	1.3695	1.2266	2.3646	2.3557	2.3021	2.2165	1.8812	3.5726	3.9018	3.9181	3.8562

room, thereby reducing trailing errors made by the model particularly during night time.

C. Binary Occupancy Prediction

We have not yet specified the form of the $s[n+k]$ term, which is a binary occupancy prediction, because we will specifically consider three different models for $s[n+k]$.

1) Unrestricted Binary Occupant State: In this approach, the occupancy count predictions are based only on the averaged number of occupants in the training data and past prediction errors. Restated, we set the binary occupant state of the room to $s[n+k] \equiv 1$.

2) Rule-based Binary Occupant State Algorithm: In this approach, the predicted state of occupancy depends on historical occupancy data. The room is marked as occupied if there was at least one occupant in the room at that particular time in the data. This algorithm maximizes the possibility that the room is occupied by considering all occurrences where a past occupancy is observed in the data. More specifically, we use a logical-OR function

$$s[n+k] = \mathrm{OR}(X_1[n+k], X_2[n+k], X_3[n+k]) \qquad (2)$$

where n is the current time index, k is the prediction horizon, and X_i is occupancy state on the i-th week of the data.

3) Decision Tree-based Binary Occupant State Algorithm: A decision tree was developed using the JMP statistical analysis software using 3 weeks of data to determine the state of the room in order to remove trailing errors. The decision tree

$$s[n+k] = f(h[n+k], d[n+k]), \qquad (3)$$

where h is the hour of the day at time $n+k$ and d is the day of the week at time $n+k$, takes into account the time of day and day of the week in determining binary occupancy.

D. Occupancy Count Prediction Results

We used three weeks of data to construct the three occupancy models for each room, and then used the remaining one week of collected data to evaluate the prediction accuracy of each model for each room. Table II shows the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) of the predictions generated by each model for each room.

We first discuss accuracy for GSL: The decision tree-based occupancy state model performs the best in term of both MAE and RMSE. This is mainly from the way the rule-based and decision tree-based models limit trailing errors in the occupancy count model using the forecasted state of the room. MAE and RMSE of the three models for each prediction horizon differ by a factor in the hundredths as shown in Table II. This can be explained by the occupant profile of the room where the arrival and departure times of the occupants are generally inconsistent, which is why the rule-based and decision tree-based algorithm for occupancy state do not have a significant difference in terms of RMSE.

For CNL, the rule-based and decision tree-based models are a significant improvement over the unrestricted model. For longer prediction horizons, the MAE of the decision tree-based model is consistently lower than that of the rule-based model. The RMSE of decision tree-based model's is generally higher than in the rule-based model, except for the one-hour prediction RMSE where it is lower. It is only for the 15 minute ahead prediction that the unrestricted model performs better than the two other models.

Next, we discuss accuracy for PSSL: The decision tree-based model incurs more errors in most of the prediction horizons since it tends to be more restrictive of the allowable predictions made by the model. In this room, the rule-based model generally performs best across the range of prediction horizons. It can also be observed that for longer prediction horizons, both the rule-based and decision tree-based models significantly lower the MAE and RMSE of the occupancy count predictions as compared to the unrestricted algorithm. Even for the short term prediction horizon of 15 minutes, the rule-based model has the best performance among the three when both MAE and RMSE is taken into account.

E. Comparison of Occupancy Prediction Models

We can draw some general conclusions about the accuracy of these models. In terms of MAE, the decision tree-based model performs well on GSL and PSSL. However, the rule-based model performs better than the decision tree-based model for CNL. In terms of RMSE for the four hours ahead prediction, the rule-based model performs better than the decision tree-based model for both GSL and PSSL. Only for GSL is the RMSE of the decision tree-based model marginally better than the rule-based model. Generally, for short-term predictions, it is best to use the unrestricted occupancy state since it can correct itself in the next prediction using the prediction error of the previous forecast. For longer prediction horizons of 1 to 4 hours, it may be better to use the rule-based model to retain the scalability of the room occupant count prediction model. The computational and

TABLE III
OCCUPANCY PREDICTION COMPARISON AMONG ROOMS

	Room	Prediction Horizon				
		15 mins.	1 hrs.	2 hrs.	3 hrs.	4 hrs.
MAE	GSL	0.0502	0.0996	0.1047	0.1035	0.1009
	CNL	0.0300	0.0788	0.0809	0.0792	0.0814
	PSSL	0.0349	0.1025	0.1202	0.1214	0.1219
RMSE	GSL	0.0926	0.1688	0.1714	0.1747	0.1738
	CNL	0.05388	0.1266	0.1275	0.1255	0.1231
	PSSL	0.0661	0.1582	0.1761	0.1774	0.1755

TABLE IV
TEMPERATURE PREDICTION ACCURACY

	Model Type	Prediction Horizon				
		15 min.	1 hrs.	2 hrs.	3 hrs.	4 hrs.
MAE	with occupancy prediction	0.0811	0.2133	0.4264	0.6336	0.7728
	with lumped heating load	0.0905	0.2295	0.4576	0.6775	0.8166
RMSE	with occupancy prediction	0.1085	0.2681	0.5195	0.7869	0.9591
	with lumped heating load	0.1259	0.2874	0.5549	0.8359	1.0361

modeling time for the decision tree-based model may not be worth the effort in further decreasing the MAE and RMSE of the predictions and in some cases may cause overfitting to the data. **For the rest of this paper, we use the occupancy prediction model with the rule-based algorithm for the occupancy state prediction.**

It is also interesting to compare prediction accuracy between rooms. We do this by normalizing the prediction error metrics by dividing the respective MAE and RMSE of the three rooms with the range of actual average occupant count seen within the one week of data used for validation. Table III summarizes the normalized results, and this shows that the occupancy count prediction is more accurate for CNL than for GSL and PSSL. This behavior can be attributed to the nature of the occupants in CNL, where a significant number of the occupants are staff who have fixed schedules of arrival and departure. The habitual nature of staff personnel makes the occupancy profile of CNL easier to predict as they constitute 26% of the total occupants in the room.

For the 15 minute ahead prediction, the normalized MAE of GSL is the highest. According to the gathered occupancy count data of GSL, it can be observed that graduate students generally have a more erratic behavior as they do not have fixed working schedules nor time limits to the room unlike undergraduate students or research staff personnel. This characteristic of graduate students contribute to the reason why the normalized MAE and MRSE of GSL is higher as compared to CNL and comparable to both error metrics of PSSL. When it comes to the medium-term occupancy prediction error metrics, PSSL is comparable to the results of GSL because PSSL has the highest total number of occupants. Having a higher number of occupants result in higher variance as more occupants are being modeled.

IV. THERMAL DYNAMICS OF UP-BRITE

We next describe the relationship of occupancy count and room temperature by incorporating our occupancy count model into a model of the thermal dynamics of UP-BRITE.

A. Collected Data

Room temperature data was gathered from UP-BRITE using a discrete-time sampling period of 15 minutes. Weather information was pulled from an online weather database with hourly weather data. The testbed server generates a random control input $u[n] \in [0, 0.5]$, which indicates the fraction of the sampling period over which the air conditioning units are turned on. A temperature logger was used to measure temperature every minute and sent to the server for storage. Twenty-four hours of data was used for modeling and another set of 24-hour data was used for model validation.

B. Indoor Temperature Prediction Model

We construct models for the thermal dynamics of the UP-BRITE testbed using the methodology described in [2], [3], and we will use the generic model structure

$$T[n+1] = a \cdot T[n] + b \cdot u[n] + c \cdot w[n] + d \cdot o[n] + \hat{q}[n] \quad (4)$$

where $T[n+1]$ is the predicted indoor temperature, $T[n]$ is the current room temperature as measured by the temperature sensor in the room, $u[n]$ is the control input, $w[n]$ is the outside weather temperature pulled from a weather server, and $\hat{q}[n]$ is an unknown function of heating load from external factors. This model is adapted from [2], [3] with the addition of $o[n]$ as the average number of occupants as predicted by our occupancy count prediction model with rule-based occupancy state prediction. With this occupancy count data, we assume a linear relationship between occupancy count and thermal contribution due to occupancy. From this generic model, we consider two different approaches:

The first model includes the occupancy prediction model, and we used semiparametric regression [2], [3] to identify the following model coefficients:

$$\begin{aligned} T[n+1] = 0.9249 \cdot T[n] - 1.2161 \cdot u[n] + \\ 0.0344 \cdot w[n] + 0.0276 \cdot o[n] + \hat{q}[n]. \end{aligned} \quad (5)$$

This integrates the occupant count prediction by substituting the corresponding formula for $o[n]$. Integration of the occupancy prediction into the model enables the consideration of occupancy count in estimating the contributions of the occupants to the thermal dynamics of the system. We identified an average value for the heating load $\hat{q}_i[n]$ of 1.3°C.

The second model does not use the occupancy prediction model. We used semiparametric regression [2], [3] to identify the following model coefficients:

$$\begin{aligned} T[n+1] = 0.9182 \cdot T[n] - 1.1762 \cdot u[n] \\ + 0.0649 \cdot w[n] + \hat{q}[n]. \end{aligned} \quad (6)$$

This model subsumes the thermal impact of occupancy $d \cdot o[n]$ into the heating load term $\hat{q}[n]$. We identified an average value for the heating load $\hat{q}_i[n]$ of 0.733°C.

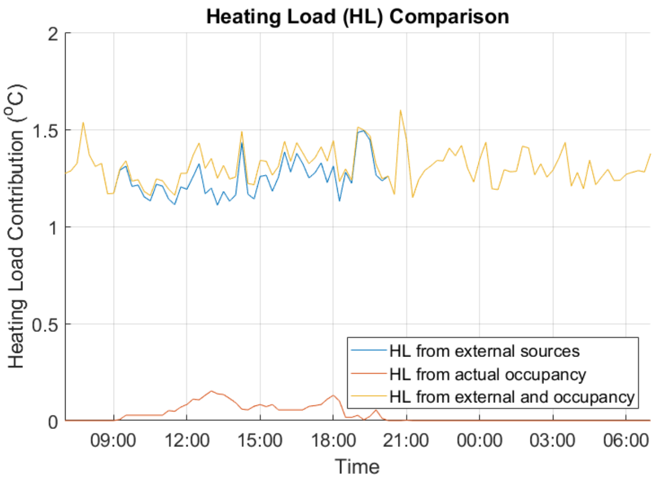

Fig. 1. Heating load comparison of occupancy count and external sources

C. Room Temperature Prediction Model Validation

We used a 24-hour set of data from GSL to evaluate the predictive accuracy of the thermal dynamics models with and without occupancy prediction. The data corresponded to the Wednesday of the fourth week of occupancy data, which was used to validate our models of occupancy count prediction.

The model without occupancy prediction has a higher MAE and RMSE of up to 0.8166 and 1.0361, respectively, for the 4 hours ahead prediction. Improvements can be observed by taking into account the occupancy count information of the room as seen in Table IV, where the MAE and RMSE of the model with occupancy count prediction are 0.7728 and 0.9591, respectively. The difference in performance between the two models becomes more apparent as the prediction horizon increases. Across all prediction horizons, it can be seen that the temperature prediction model which incorporates occupancy count prediction performs better than the model without occupant count prediction.

The heating load from external sources in the UP-BRITE testbed over a 24-hour horizon is shown in Fig. 1. Also plotted in the figure is the heating load due to occupancy. The heating load from external sources can be seen to vary significantly throughout the day. The figure also shows that the heating load contribution from occupants peaks at around 1:00PM with a value of 0.15°C; this peak was due to a 15 minute averaged occupancy count of 5.53 people, which is substantially lower than the maximum number of 14 occupants in the GSL room. The total heating load from external sources and occupant count is also shown, and we can see in the figure the contribution to heating load from occupants. Starting at around 9:00AM, occupants start to arrive. At 6:00PM, there is an abrupt change in the heating load contribution of occupants when most of the people leave, and by 8:00PM all occupants have left the room.

TABLE V
ENERGY CONSUMPTION OF CONTROL SCHEMES

Energy Consumption					
	LBMPC				Reactive
Horizon	1 hr.	2 hrs.	3 hrs.	4 hrs.	
kWh	68.63	71.47	71.67	71.86	84.55

V. SIMULATING ENERGY CONSUMPTION IN UP-BRITE

We first simulated the temperature, control inputs, and energy consumption of the UP-BRITE testbed under a baseline control algorithm where the HVAC system is set to measure the indoor temperature every fifteen minutes and turn on the air conditioning units for the next 15 minutes if the current room temperature is above 22°C; this baseline control algorithm is often called two-position control, and it used 85.55kWh of energy to maintain indoor air temperature between 21.24-22.65°C. In our simulation, we used a constant heating load from external factors, and the only variation in heating load was due to changes in occupancy. A plot of the room temperature when the air conditioners are operated by this two-position control is shown in Fig. 3.

We compared the above with the simulated energy consumption of a learning-based MPC (LBMPC) [2]–[4], [21] controller in which the horizon was varied between 1 hour to 4 hours, and we specifically use the thermal dynamics model with the occupancy count prediction model in the formulation of LBMPC. The total energy consumption using LBMPC with each horizon ranges from 68.63kWh to 71.86kWh as the prediction horizon increases from 1 hour to 4 hours, as summarized in Table V. A plot of the room temperature when the air conditioners are operated by this LBMPC control with varying horizons is shown in Fig. 3.

It can be observed that the energy consumption increases as the prediction horizon increases, with the most significant change observed between 15 mins and 1 hour with an increase of almost 3kWh. For this particular day of the validation data, the occupant count prediction model tends to overpredict the number of occupants, thus resulting to a slightly higher predicted room temperature as shown in Fig. 2. The number of people inside the room during the time that the validation data was gathered is much lower than the usual occupancy of the room during the training period. This higher predicted room temperature model results in more operation of the air conditioning unit in order to maintain the indoor air temperature at desirable conditions.

We can see from the LBMPC energy consumption in Table V and temperature prediction MAE and RMSE values in Table IV that both increase as the prediction horizon increases. With one hour ahead prediction horizon, the HVAC system consumes 68.63kWh, which translates to energy savings of about 18.82% as compared to a baseline two-position control algorithm, while ensuring that room temperature is within the acceptable range for indoor temperature. And as shown in Fig. 2 and Fig. 3, there is a trade-off between accurate temperature prediction versus a controller with a longer prediction horizon that allows the MPC to consider more

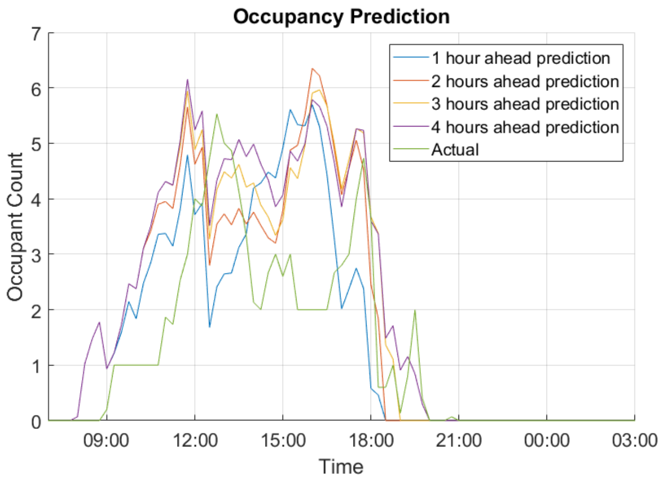

Fig. 2. Comparison of actual average occupancy versus occupancy count predictions over varying prediction horizons.

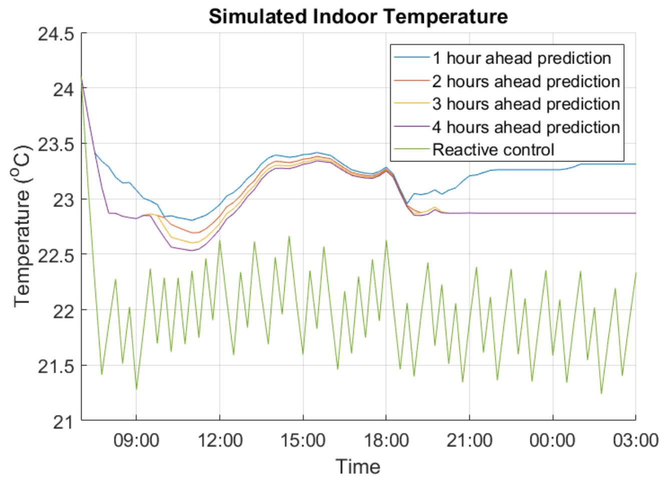

Fig. 3. Simulated indoor room temperature for LBMPC against 2 position reactive control scheme.

information about the future occupancy pattern and weather conditions. However, as prediction horizon increases, there is an increase in the errors produced by the temperature model as shown in Fig. 3, and there is also an increase in energy consumption for the LBMPC controller from 1 hour up to 4 hours ahead prediction horizons as shown in Table V.

VI. Conclusion

In this paper, we explored the relationship between occupancy count prediction, room thermal dynamics, and energy efficiency of an LBMPC controller for HVAC. We developed a model to predict occupancy count, and compared three methods for predicting binary occupancy state. We simulated LBMPC with a room temperature model that integrates a prediction of room occupancy count information. Four weeks of occupancy count data from three rooms was gathered and characterized, as well as 48 hours of temperature data for modeling and validation of indoor air temperature. We also performed a simulation analysis of varying horizon length of an LBMPC controller and characterized the effect of horizon length on the energy usage of the HVAC. Simulations showed LBMPC with occupancy prediction could reduce energy consumption by as much as 18.82% for the UP-BRITE testbed as compared to two-position control.

However, we found a large increase in prediction error and a corresponding increase in overall energy consumption as the prediction horizon of the LBMPC controller increased. Our results suggest that long horizons for MPC control of HVAC may be counter-productive for decreasing energy consumption, and that shorter horizons may be better because they do not lead to overcooling when there is a large overestimation in occupancy or heating load. An important question for future work is to understand how these results change for different environments (this paper uses data from a testbed in a tropical environment) and thermal dynamics (the room in the testbed has a small weather coefficient, which means that incroporating weather forecasts has minimal impact since outside temperature weakly impacts the room temperature).

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