The Impact of Occupancy Prediction Accuracy on the Performance of Model Predictive Control (MPC) in Buildings

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Abstract
Model Predictive Control (MPC) is a promising approach for mitigating energy consumption and for enabling efficient building climate regulation without sacrificing occupants’ comfort. At the same time, occupancy is one of the leading factors influencing the performance of MPC. In this paper, we investigate the impact of occupancy prediction accuracy on the performance of building MPC in terms of energy consumption and thermal discomfort. The obtained results indicate that MPC consumes more energy than conventional rule-based controllers. Occupancy predictions with low accuracy (prediction error) can lead to lower energy consumption at the expense of comfort violations. However, the result also indicates that the negative influence of prediction error can be partially mitigated by adopting longer optimization horizons.

Key Innovations
This paper incorporates a prediction model for occupant counts in MPC optimization procedure. It contributes to understanding the building MPC performance gap between ideal simulation studies and implementation with the prediction of occupancy.

Practical Implications
The paper analyses the practical implication of occupancy data availability and quality for practitioners of MPC algorithms. Results hint to a potential solution for low prediction accuracy data to be handled by adjusting the optimization horizon.

Introduction
Globally, buildings are still responsible for nearly 40% of total energy consumption among other sectors (Cao et al., 2016). From this quota, the consumption from the Heating, Ventilation, and Air Conditioning (HVAC) accounts for nearly 50% of the total energy consumption in both residential and commercial buildings (Pérez-Lombard et al., 2008). In an effort to optimize building energy consumption and to achieve a comfortable indoor environmental condition for its occupants, various strategies such as the concept of Model Predictive Control (MPC) for systematic building management have been proposed. These strategies are estimated to facilitate up to 5% to 30% building energy savings (Costa et al., 2013).

Recently, the concept of MPC, in contrast to the conventional rule-based controls (RBC), has received considerable popularity over the past 10 years. This is because of its reliability and superior performance (Afram and Janabi-Sharifi, 2014). For instance, unlike RBC for building controls, MPC requires an accurate model of a building to forecast its expected future states for a set of input parameters such as outdoor temperature, solar radiation, and the occupant behaviors in the building. Given these parameters and a number of conflicting objectives (such as increased thermal comfort and reduced energy consumption), an MPC framework engages an optimization process that is continuously calibrated at each time step to produce a considerable overall performance (Mirakhorli and Dong, 2016).

While there exists a wide range of parameters for MPC-based building controls, the accurate estimation of occupancy in buildings constitutes a major factor for achieving considerable ambient comfort and energy saving within buildings (Goyal et al., 2012). This is because, the mere presence of occupants within buildings largely influences the indoor climate and more so, occupant’s interactions with various building systems such as adjusting temperature setpoints, and door and window opening contribute immensely to the energy profile of a building. For instance, the empirical study conducted by Lutzenhiser et al. (1987) indicates that identical residential units with different occupant behavior may have energy usage profiles that vary by as much as 200-300%.

In this work, we investigate the impact of occupancy prediction accuracy on the performance of MPC-based building controls via comparing MPC using ideal occupancy information and MPC using predicted occupancy information (prediction error). As a simulation setup, we have developed and calibrated a grey box model representing the HVAC system in a case study building, which serves as a virtual testbed to test different MPC controllers. Subsequently, we have deployed a number of 3D stereo-vision cameras to obtain accurate occupancy counts in this building. Based on the obtained historical occupancy counts, we have developed a data-driven occupancy prediction model that enables predicting upcoming occupant counts starting at certain time point. In our evaluation, we compare two MPC-based building controllers, based on multiple-shooting optimization (Arendt and Veje, 2019) using the occupancy counts from both the deployed cameras and the data-driven prediction.
model. These two MPC-based building controllers are further compared with a conventional RBC controller in terms of energy consumption and indoor thermal discomfort.

Related Work

Over time, a number of studies such as highlighted in (Dobbs and Hencen, 2014; Shi et al., 2017) have developed prediction models to forecast building occupancy which are subsequently embedded into the MPC framework for building optimization. Yang et al. (2016) investigated and illustrated the impact of occupancy on the energy efficiency of HVAC systems from three dimensions. These dimensions include occupancy transitions, variations, and heterogeneity. However, building system types and control approaches were not studied in their work. Similarly, Martani et al. (2012) highlighted the dynamic relationship between building occupancy and energy consumption. In order to investigate the potential benefit of employing occupancy information in building climate control, Oldewurtel et al. (2013) compared three different MPC controllers using different occupancy information with a baseline controller. The baseline controller utilizes fixed occupancy schedules while MPC controllers use both occupancy fixed occupancy schedules and ideal occupancy prediction. The result from the study indicates that taking into account occupancy information in building control results in a significant energy-saving potential. These results are consistent with the findings by Goyal et al. (2013). Additionally, Goyal et al further indicates that instantaneous occupancy information already enables a large part of this potential and more complicated occupancy prediction does not add much value on improving energy efficiency. However, both works conducted by Oldewurtel and Goyal used ideal occupancy prediction (i.e. it knows a priori the occupancy information that is realized in the future). In real implementation of building MPC, the ideal occupancy prediction cannot be attained. Instead, an occupancy prediction model will be incorporated into the optimization process. The majority of previous simulation studies on building MPC assume ideal occupancy information available. Studies including the real-time occupancy prediction model into MPC framework can only predict occupancy presence rather than occupant counts (Dobbs and Hencen, 2014; Killian and Kozek, 2019).

MPC controllers may react in different ways to different patterns of inputs such as occupancy profile and seasonal changes. Parisio et al. (2014) compared the results of building MPC controllers with both low and high occupancy. Brooks et al. (2015) recorded an energy savings of 43.4 - 48.2%, 28.3 - 38%, and 23.5 - 26.1% in winter, spring and summer respectively compared to a conventional controller. However, MPC with occupancy information does not always outperform RBC controllers in terms of energy consumption. Garnier et al. (2015) compared an MPC controller with five non-predictive controllers. The result obtained indicates that two of the non-predictive controllers consume less energy than the MPC controller while the others consume more. The MPC controller in this study, however, exhibits the least thermal discomfort among the six controllers.

In this study, we incorporate a prediction model for occupant counts into MPC optimization process and compare its MPC performance with MPC using ideal occupancy information and a rule-based controller. This study contributes to understanding the MPC performance gap between ideal simulation studies and implementation with the prediction of occupancy.

Simulation Setup

In this section, we present our simulation setup composed of the various subsystems used for evaluating the impact of occupancy prediction accuracy on the performance of MPC-based building controls. In Figure 1, we present an overview of the various subsystems. These include an occupancy model for predicting the count of occupants, a control and emulation model in the form of a grey-box model representing the HVAC system in a real case building and lastly, an MPC framework for optimizing and controlling the operations of the HVAC system in the case building.

Occupancy Model

In order to obtain training data for forecasting the count of people in the case study teaching room, we have deployed two units of 3D stereo-vision cameras at the entrances of the case room alongside a cleaning method (Sangoboye and Kjærgaard, 2016). Given the obtained historical occupancy count from the camera sensors, we have developed a single-layer artificial neural engine for forecasting the count of people in multiple temporal resolutions and horizons. Thus, given a prediction time, a pre-processing step is developed to sub-divide the training data into daily profiles and subsequently, the daily profile is divided into input and target feature sets. The input feature set is comprised of all occupancy counts preceding the prediction time from the beginning of a typical day while the target feature set is composed of all occupancy data from the prediction time to a specified temporal horizon. The obtained input and target feature sets are subsequently used to train the neural engine. This neural
engine utilizes a number of rectifier activation functions. The ratio between the input shape and the size of the activation function was cross-validated and regularized using the I2-N to ensure generalization and robustness. Lastly, we have utilized the mean squared error metric as a loss function alongside the Adam stochastic gradient descent optimizer to train the neural engine. Three months of training data were obtained from the deployed camera sensors and used to train the neural engine prior to a specified prediction time. Figure 2 highlights the actual and predicted occupancy counts in the case room with a four-hour prediction horizon for the evaluation days. The neural engine achieved a root mean square error (RMSE) of 5.32 for the three evaluation days.

Figure 2: Occupancy prediction with four hours horizon

Building Control and Emulation Model

Building model is a crucial part in MPC implementation (Privara et al., 2013). The model used in MPC can be classified into three main categories, namely white-, grey- and black-box model (Drgoňa et al., 2020). White-box model is highly detailed and building physics can be well captured, but it requires a large amount of building property data and time for accurate calibration. Black-box model does not consider building physics and is typically generated based on training data. Even though its accuracy is higher than white-box model, black-box model needs massive training data and demonstrates poor generalization capability. Grey-box model, however, provides a compromise solution between white- and black-box model, allowing simplified physical model with some estimated parameters.

A grey-box (R2C2) model of a teaching building has been adopted for this study. Some studies in literature already show that second-order models are sufficiently accurate in capturing single zone thermal dynamics (Bacher and Madsen, 2011; Vogler-Finck et al., 2019; Yu et al., 2019).

Figure 3: Schematic diagram of building energy system

Figure 4: R2C2 model of a thermal zone built in Dymola

This building is equipped with a ventilation system and a hydronic heating loop. This model was developed in Dymola for a 139m² teaching room in the case study building and it is calibrated with measured data from the room. Figure 3 describes the layout of zone model and energy systems, figure 4 illustrates the inputs and the major outputs of the model used for calibration. The input parameters are solar radiation, outdoor temperature, occupancy counts, ventilation damper and radiator valve position while the two major outputs are indoor temperature, CO2 concentration. Given the measured inputs and outputs, the maximum heat supply and ventilation rate of the zone at 2689W and 4800m³ respectively, we have utilized a parameter estimation model – ModestPy (Arendt et al., 2019) to estimate the unknown parameters of the model. ModestPy learns the parameters of the model by fitting the CO2 concentration and indoor temperature to the measured data. Figure 5 compares the obtained results of the estimated parameters with the measured parameters for four days spanning April 9-12, 2018. T_meas and CO2_meas represent the measured indoor temperature and CO2 concentration respectively while T_val and CO2_val are the simulated indoor temperature and CO2 using the calibrated model. The RMSE of indoor temperature and CO2 concentration are 0.98°C and 44.31 ppm respectively, as compared to the measured data. The calibrated model is subsequently adopted by the MPC framework as the building control model. Lastly, a surrogate of the calibrated building control model is used as an emulation model instead of an actual MPC implementation in our case room.

Figure 5: Validation results of the calibrated R2C2 model
MPC Framework

We have adopted MShoot - a python-based software as our MPC framework (Arendt and Veje, 2019). The framework uses the multiple shooting method for dynamic optimization (optimal control problem), in which the prediction horizon is divided into N subintervals with state continuity constraints. Each subinterval is optimized separately using the Sequential Quadratic Programming (SQP) solver. To simplify the control process of the control and emulation models and instead of controlling the damper position and valve position simultaneously, the heating/cooling power [W] will be the only control variable in our setup. In practice, the optimized heating/cooling power can be set as objective and implemented in other low-level controllers (supervisory MPC). These objective function and constraints are formulated as follows:

\[
\begin{align*}
\text{Minimize } & \sum_{i=1}^{N} \left| q_{i} - q_{nom} \right| \\
\text{subject to } & T_{i,\text{min}} \leq T_{i} \leq T_{i,\text{max}}, i = 1, \ldots, N.
\end{align*}
\]

where \( q_{i} \) is the heating/cooling power [W] supplied to the system at each subinterval \( i \) of the optimization, \( q_{nom} \) is the nominal heating/cooling power [W], \( N \) represents the last subinterval of the entire optimization period, \( T_{i} \) is the indoor temperature in Kelvin [K] at the corresponding sub-interval \( i \). \( T_{i,\text{max}} \) and \( T_{i,\text{min}} \) are lower limit and upper limit of indoor temperature constraints, respectively.

Evaluation and Discussion

In this section, we provide details on the evaluation and performance of the MPC-based building controller. We split this section into two subsections. In the first subsection, we describe the evaluation setup consisting of the baseline model and evaluation hypothesis and the evaluation scenarios. In the second subsection, we describe and discuss the obtained evaluation results.

Evaluation Setup

In all evaluation cases, we have benchmarked the MPC-based controller with a rule-based controller (RBC). The rule-based controller includes two proportional integral derivative (PID) controllers constructed in Dymola. The first PID controller controls the cooling power supply when the indoor temperature of the case room exceeds a specified \( T_{i,\text{max}} \), while the other PID controller controls the heating power supply when the indoor temperature is lower than \( T_{i,\text{min}} \). In order to solely evaluate the impact of occupancy prediction accuracy on the performance of MPC-based building control, the actual measurements of all other parameters except for the occupancy input parameter are used for calibration.

Furthermore, we propose to evaluate the performance of MPC-based building control using occupancy predictions with multiple temporal horizons. Here, temporal horizon implies the look-ahead period of the prediction method. This is because, generally, obtained occupancy predictions from the neural engine can be slightly inaccurate when compared to the ideal occupancy as shown in the Occupancy Model section. Hence, we hypothesize that an increase in the temporal horizon for obtaining occupancy prediction will reduce the accuracy of the predicted occupancy counts. Given these hypotheses, we propose the following evaluation scenarios:

1. Rule-based controller, no optimization available.
2. MPC controller with ideal occupancy information (hereafter referred to as ideal MPC) that runs at four optimization horizons: h4, h6, h8 and h10 corresponding to four, six, eight and ten hours respectively.
3. MPC controller with predicted occupancy information (hereafter referred to as predicted MPC) that runs at four optimization horizons: h4, h6, h8 and h10.

The prediction horizon for occupancy is consistent with the optimization horizon of the MPC framework in all evaluation scenarios. Four optimization horizons are chosen complying with building system time constant and occupancy prediction ability and following other studies demonstrating good MPC performance (Hilliard et al., 2016).

Lastly, we have evaluated the performance of the MPC-based building controller using obtained datasets spanning three days (5th - 9th of April, 2018) and with two main metrics namely total energy consumption [kWh] and temperature discomfort [K]. As specified in Equation (1), both the total energy consumption [kWh] and the temperature discomfort [K] represent the MPC cost function and optimization constraints respectively. Temperature discomfort is defined as the number of Kelvin-hours [K] when indoor temperature is out of comfort range during occupied time. It is calculated as a sum of each temperature violation multiplied by corresponding duration. All source code and dataset are open sourced at https://github.com/sdu-cfei/occupancy-mpc.

Evaluation Result

The preliminary results in Figures 6a and 6b highlight the indoor temperature for ideal and predicted MPC for the various optimization horizons, whereas Figures 7a and 7b highlight the total energy consumption and temperature discomfort respectively.

As presented in Figure 6a, the zone cools down passively during night. When the zone is occupied during day, internal heat gain increases and additional heating/cooling will be supplied in case indoor temperature is violating temperature set point. Ideal MPC outperforms RBC in terms of indoor temperature regulation for varying optimization horizons. This is due to that MPC is capable of taking into account future disturbance and preheat/precool indoor air to maintain thermal comfort. It can also be intuitively observed that increase in optimization horizon for ideal MPC leads to less temperature violation. However, the upper bound of indoor temperature is violated for all horizons during last
simulation period. It is likely that the limited heating/cooling capacity, relatively high value of ambient temperature and occupant number make it insufficient to keep indoor temperature within constraints even if injecting maximum heating/cooling power. As for case of predicted MPC illustrated in Figure 6b, similar trend of indoor temperature evolution has been found, but the variation in the indoor temperature for different values of the optimization horizon cannot be directly distinguished. We therefore quantitatively analyze simulation results using two MPC performance metrics (total energy consumption [kWh] and temperature discomfort [Kh]).

From Figure 7a and Figure 7b, it can be observed that RBC controller consumes 37.6kWh heating/cooling energy over 3-day simulation, which demonstrates rationality and has been already verified in (Jradi et al., 2017). For 4h horizon, ideal MPC consumes the most energy (53.5kWh) and followed by predicted MPC (44.7kWh), both of which are more energy consuming as compared to RBC (37.6kWh). In contrast, ideal MPC violates indoor temperature the least (7.6Kh), while predicted MPC and RBC has moderate (13.3Kh) and the highest (13.4Kh) temperature discomfort respectively. The same results can be attained and further verified when changing horizon to 6h, 8h and 10h. MPC seeks to find optimal balance between conflicting objectives, namely energy consumption and temperature constraints in our case. Given the soft state constraint setup in the MSshoot optimization package, it is observed in our setup that MPC prioritizes thermal comfort over saving energy, leading to better comfort but higher energy consumption as compared to the rule-based controller. Besides, results also show that errors in occupancy prediction can result in lower energy consumption at the cost of local comfort violation as compared to ideal MPC. It should be mentioned as well that at 4h horizon, predicted MPC exhibits extremely close value of temperature discomfort and higher energy consumption over RBC, we could infer that worse performance of MPC over RBC may happen due to occupancy prediction error.

When varying horizon from 4h to 10h, energy consumption of ideal MPC increases incrementally from 53.5kWh to 75.1kWh while temperature discomfort declines from 7.6Kh to 4.5Kh. Longer horizon enables MPC to consider future disturbance better and control the actuator more intelligently, resulting in more energy consumption and less thermal discomfort. But it has to be noted that increase in horizon might not add much value on reducing temperature discomfort if previous horizon is already sufficient to obtain a considerable performance. As for predicted MPC, slight increase in energy consumption and rough decrease in temperature discomfort have been observed with longer horizon. The results are derived under the impact of both occupancy error and horizon variation, which indicates that the negative influence of prediction error can be partially mitigated by adopting longer optimization horizons. It has to be mentioned that, for MPC with occupancy prediction error, there is only minor improvement of thermal comfort when increasing horizon from 6h to 10h.
Figure 6 implies the temperature violation on the second and the third day may be due to the limited heating/cooling capacity. To investigate this, we therefore conducted an additional simulation with twice the maximum heating/cooling capacity. The corresponding results are shown in Figure 8 and Figure 9.

Figure 8a shows that ideal MPC with all investigated horizons can better regulate indoor temperature within constraints as compared to RBC. On the contrary, for predicted MPC (Figure 8b), the 5 curves are very close to each other and it is hard to tell the difference in performance of each tested case. We calculated the aforementioned MPC performance metrics and visualized the corresponding results in Figure 9.

Figure 9a observed the same results as in Figure 7a: both predicted MPC and ideal MPC consumes more energy than RBC. However, Figure 9b shows that the ideal MPC achieved less thermal discomfort as compared to RBC while predicted MPC obtained higher thermal discomfort as compared to RBC. This result verifies our previous inference that MPC may perform worse than RBC due to occupancy prediction error. In general, the results for the doubled heating/cooling capacity demonstrate similar findings derived from the previous test case.

Our simulation study is carried on a virtual testbed of a university teaching building. In practice, the investigated teaching building is a living lab equipped with an abundance of sensors recording data such as weather profile, occupancy counts, indoor temperature, etc. The installed sensors and engine for data prediction enable deploying MPC and monitoring building performance continuously. The occupancy prediction model applied in this paper can therefore be incorporated into the MPC framework implemented in a real building, however it would require additional instrumentation as compared to a conventionally instrumented building.

**Conclusion and Future Work**

This paper investigated the influence of occupancy prediction accuracy on building MPC performance. MPC controllers using two different occupancy information (ideal occupancy from measurement and forecasted occupancy from occupancy prediction model) were implemented and tested on a virtual teaching room. MPC performance was compared with RBC, based on the study above, the conclusions can be drawn as follows:

- An MPC-based controller in contrast to a rule-based controller demonstrates better indoor thermal comfort and higher energy consumption if there is no occupancy prediction error.
- In our test case, the error in occupancy prediction can result in lower energy consumption when compared to MPC controllers with ideal occupancy, but this can only be obtained at the cost of comfort violation.
MPC with ideal occupancy shows more energy consumption and less temperature discomfort when increasing the optimization horizon. In addition, the negative influence of occupancy prediction error can be partially mitigated by adopting longer optimization horizons. As for future work, it is worth quantitatively analyzing the relationship between occupancy prediction error and MPC performance. Different occupancy prediction error could be introduced in MPC framework. Furthermore, implementing MPC with different occupancy prediction models in real buildings and comparing MPC performance could be further conducted.

Acknowledgment
This work was supported by the Innovation Fund Denmark for the project COORDICY (4106-00003B).

References


