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Implementation of a Predictive Control for an All-air Ventilation System in an Educational Building

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ABSTRACT

In school and office buildings, the ventilation system has a large contribution to the total energy use. A control strategy that adjusts the operation to the actual demand can significantly reduce the energy use while guaranteeing a good indoor environmental quality (IEQ). This is important in rooms with a highly fluctuating occupancy profile, such as classrooms and open offices. A standard rule-based control (RBC) strategy is reactive, making the installation 'lag behind' in relation to the demand. As a result a good indoor climate is not always guaranteed and the actual energy saving potential can be lower than predicted. In addition, with all-air systems conflicts can occur between the fresh air demand and the heating demand. A predictive controller can be a solution as the controller takes into account the current situation and the future demand. To study the potential of predictive control for all-air ventilation systems the control is implemented in a case study building with two lecture rooms in Belgium. The model predictive control (MPC) framework is based on an auto regressive with exogeneous input (ARX) model to control the room temperature and CO_2 concentration. Through the BACnet interface of the AHU the optimized control outputs for variable air volume (VAV) damper position and supply air temperature are written to the ventilation system set points. This paper evaluates first measurement results, during spring 2020, of the IEQ in a lecture room after implementing a predictive controller for the all-air ventilation system in an educational building. The data driven ARX model is a simple regression model but the results indicate that the model is able to predict the future room conditions accurately. The measured thermal discomfort is minimal and CO2 concentrations in the room could be maintained below the setpoint. The VAVs react well to the heating and ventilation demand in order to control the IEQ. Using a simplification the optimization problem can be solved using a linear approach reducing the computation time.

INTRODUCTION

Facing the climate change, the building sector has to significantly reduce the total energy use. Buildings in Europe and worldwide are reported to use approximately 36% of the total energy use and are responsible for 39% of the carbon dioxide emission (IEA, 2019). One of the aims of the EU is to achieve a highly energy efficient and decarbonised building stock by 2050 (EPBD, 2018). Heating, ventilation and air-conditioning (HVAC) systems are reported to use 50 % of the energy use in buildings (Pérez-Lombard, Ortiz, & Pout, 2008). In order to have a more efficient energy use in buildings the control of the HVAC system could be optimized. HVAC systems are challenging to control, for example due to time varying dynamics and varying internal/external disturbances (Afram & Janabi-shari, 2014; Killian & Kozek, 2016). A smart ventilation system that adjusts the operation to the actual demand can significantly reduce the energy use (Ahmed, Kurnitski, & Sormunen, 2015; Merema, Delwati, Sourbron, & Breesch, 2018; Wachenfeldt, Mysen, & Schild, 2007). This is important in rooms with a highly fluctuating occupancy profile, such as classrooms and landscaped

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offices. Most used control inside an HVAC system is an on/off or a PI(D) control because of their simplicity however, this may result in inconsistent performance (Afram & Janabi-shari, 2014). This is of concern for all-air ventilation systems where the indoor climate and the air quality are controlled by the ventilation system. This can result in a contradiction between fresh air demand and heating demand since the system uses a feedback controller. For example, during the start of the day at 07:30h the system first is in heating mode to meet the heating temperature setpoint. Afterwards at 08:15h the first class starts with 50 students resulting in a fresh air demand, since the CO_2 setpoint is exceeded. At the same time the heating demand decreases and sometimes due to the high occupancy even results in a free cooling demand. Furthermore, the occupancy pattern is varying in time resulting in changing disturbances and dynamics inside the room. To optimize the control of the all-air system a predictive control could be used to solve the dual optimization problem of both the fresh air demand and the heating demand. A predictive control could be used to control an HVAC system more energy efficiently since it takes into account the current measurements and the future demand. Already in buildings with hydronic systems the reported energy reductions after implementation of a model predictive control (MPC) are significant (De Coninck & Helsen, 2016; Sturzenegger, Gyalistras, Morari, & Smith, 2016).

A few studies about predictive control of all-air ventilation systems are highlighted. Goyal, Barooah, & Middelkoop, (2015) implemented an occupancy based control for a VAV system in a commercial building. In this study a calibrated non-linear RC network model is used to optimize the control of the VAV. The results indicate that the thermal comfort and IAQ of the zone is maintained in the acceptable range that was defined. At the same time the airflow rate was minimized and the supply air temperature optimized with the aim to minimize the heating use. In a study by Liang et al. (2015) the focus is on MPC for a HVAC system with VAVs for temperature control in a multizone building. A low order state space model was developed and a Kalman filter was applied for state estimation. Simulations showed that the multizone VAV control was able to operate the building as good as the original control while using less energy. Bengea et al., (2014) demonstrated the real implementation of MPC with both temperature and CO_2 control in an office building with a rule based HVAC system. Energy savings for the HVAC system were 20% during the transition season and 70% during the heating season. CO_2 levels and room temperature were maintained below the desired set point. However, the implemented cost function did not include any comfort cost indicating that the main objective of the MPC was to reduce energy use. In literature there are not many examples of real implementation of an MPC for an all-air ventilation system that controls both the room temperature and CO_2 concentration. In addition most studies uses an resistance capacitor (RC) model that requires a lot of effort to estimate the correct parameters for example for the thermal resistance and thermal capacitance (Afram & Janabi-shari, 2014). In this study a simple data-driven ARX model is used inside the predictive controller.

This paper assesses the implementation of a predictive control in a case study building. The operation of an all-air system and IEQ in the building are evaluated. One challenge for real implementation of predictive control in buildings is the uncertainty in the forecasts for both the weather and occupancy, and the robustness of the control since a simple data driven model is used. Another challenge is the use of a predictive controller for both the room temperature and CO_2 concentration, as in most studies the predictive controller only controls the temperature. The paper demonstrates the robustness of the predictive control in an all-air system under uncertainty.

The structure of the paper is as followed. In section 2 a description of the case study building is presented. Section 3 will explain the method used for the predictive control framework implemented in the building. Afterwards results are presented for operation of the all-air system and the IEQ in both lecture rooms. In the conclusion the main results are evaluated and a possible direction for future research is presented.

DESCRIPTION OF THE CASE STUDY BUILDING

An educational building located in Ghent (Belgium) is used as case study (Merema et al., 2018). The building consists of two lecture rooms, each with a capacity of 80 students and a area of approximately 140 m². Balanced mechanical ventilation is provided with a total supply airflow of 4400 m³/h. The airflow rate is controlled by VAV boxes based on measurements of CO_2-concentration and operative temperature in each lecture room. For heating purposes, the air is preheated by an air-to-air heat recovery. Additionally, heating coils (8 kW) are integrated in the supply ducts of each zone so it is regarded as an all-air HVAC system.

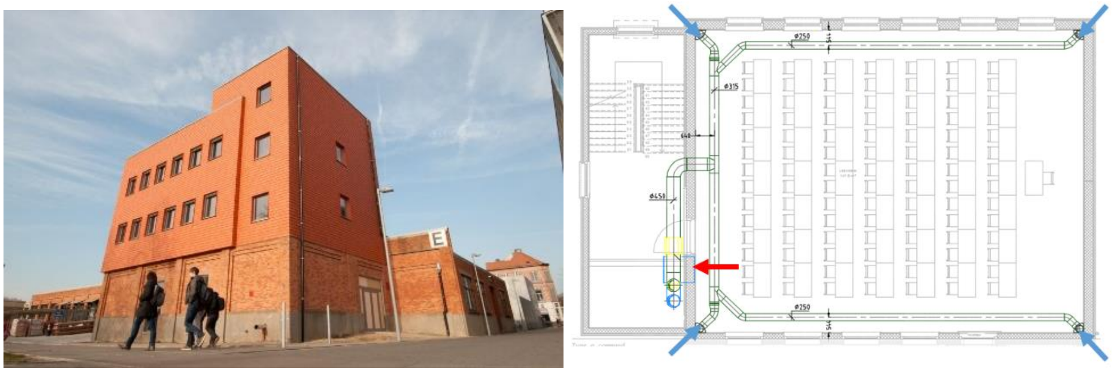

Figure 1 (left) Impression of the case study building, (right) floor plan of the case study building with in red the extract air location and in blue the supply air

ARX PREDICTIVE CONTROL FRAMEWORK

To understand the process for the implemented control, Figure 2 illustrates the complete predictive control framework. In the first step the forecasts of internal and external disturbances are collected using the DarkSky weather API (DarkSky, 2020), for the outdoor temperature and global horizontal irradiation, and weekly lecture schedules made available by the administration service of the university. The weekly schedules indicate the start and end time and the expected occupancy for the lecture. In addition, measurement values for room temperature, CO_2 concentration and Q_{vent} are read for both rooms through the Building automation and control network (BACnet) (ANSI/ASHRAE Standard 135, 2004) interface of the AHU. All these aforementioned parameters are needed inside the predictive controller to predict the room temperature and CO_2 for the prediction and control horizon. Based on the forecast of occupancy, comfort criteria are defined and correspond to the time and occupancy status of the room. The following three conditions are defined for the comfort criteria of the predictive control:

1. 18:00 – 07:30h 16˚C
2. 07:30 – 18:00h unoccupied 20˚C
3. 07:30 – 18:00h occupied 22˚C

In step 2 all the forecasts and measurements from step 1 are forwarded to the predictive controller that is based on previously identified ARX models (Merema, Breesch, & Saelens, 2019). In the predictive controller the control output for the supply air temperature and the air mass flow rate for both rooms are optimized. The optimization process is written in Python using the CVXPY (Diamond & Boyd, 2016) package allowing to solve convex optimization problems. The selected solver is OSQP (Stellato, Banjac, Goulart, Bemporad, & Boyd, 2020), i.e. the default solver used in CVXPY to solve quadratic optimization problems. The optimization problem is split up in two separate parts (1:CO_2 2: Temperature) to solve the problem as a linear-problem, as illustrated in Figure 3. To avoid using a non-linear approach first the CO_2-MPC calculates the minimal required airflow to control the indoor CO_2 concentration based on the following inputs: CO_2 concentration room (previous time step), occupancy forecast and outdoor CO_2. Maintaining the CO_2 concentration below the desired set point of 1000 ppm has the highest priority in the CO_2 MPC. Since the CO_2 ARX model is linear the minimal required airflow for CO_2 control can be calculated and optimized by the CO_2-MPC. In the second step the optimized CO_2 airflow from the CO_2 MPC is used as an input constraint in the Temperature MPC. In the Temperature MPC, Q_{vent} is optimized using the predictions from the temperature ARX model for the room temperature. Post-processing the results from the linear MPC is required to obtain the actual set points for the supply air temperature and the air mass flow rate that is needed to determine the required VAV damper position.

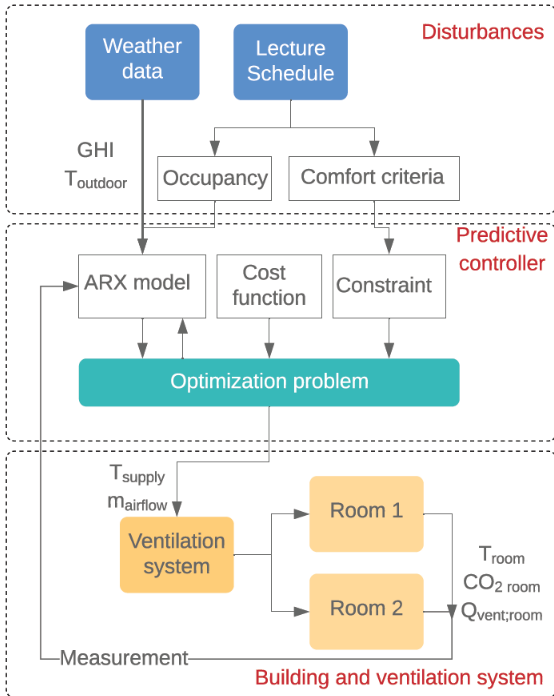

Figure 2 Linear MPC framework for all-air ventilation system

The optimized variable Q_{vent} obtained from the linear T-MPC containts the required optimized variables T_{supply} and $m_{airflow}$. First the mass flow rate that is obtained from the CO_2 MPC is fixed in equation 1. From here T_{supply} can be calculated using the following strategy and equation 1. If T_{supply} > 40°C, T_{supply} is set to 40°C and the mass flow is increased using equation 1. Using this simplified approach the optimized variables T_{supply} and $m_{airflow}$ can be obtained.

$$Airflow = \rho * c * Q_{vent}/(T_{supply} - T_{zone}) \tag{1}$$

Subject to:

- $T_{supply} \geq 16^{\circ}C$
- $T_{supply} \leq 40^{\circ}C$
- Airflow ≥ 0 m^3/h (07:30 -18:00h Airflow ≥ 400 m^3/h)
- Airflow ≤ 2200 m^3/h

To solve the optimization problem the following two normalized quadratic cost functions are defined to minimize the energy use with respect to the indoor CO_2 concentration (2) and room temperature (3). Slack variables (zCO_2 and zT) are used for the comfort constraints to penalize exceeding the set point and to avoid using hard constraints. In this way the hard constraints are transformed into soft constraints enabling violating the setpoints without terminating the optimization process.

$$CO2\ control: Min\ \sum_{k=0}^{Hp}(zCO2)^2 + (Airflow)^2 \tag{2}$$

Subject to the following constraints:

- CO_2 room ≤ 1000ppm + zCO_2
- Airflow CO_2 ≥ 0 m^3/h (07:30 -18:00h Airflow CO_2 ≥ 400 m^3/h)
- Airflow CO_2 ≤ 2200 m^3/h
- $zCO_2 \geq 0$

$$Temperature\ control: Min\ \sum_{k=0}^{Hp}(zT)^2 + (Q_{vent})^2 \qquad (3)$$

Subject to the following constraints:

- $T_{room} \geq 22^{\circ}C - zT$ (with occupancy)
- $T_{room} \geq 20^{\circ}C - zT$ (no occupancy and time = 07:30 -18:00h)
- $T_{room} \geq 16^{\circ}C - zT$ (18:00 – 07:30h)
- $T_{room} \leq 26^{\circ}C + zT$
- $Q_{vent} = 0.34 * m_{air}(Ts_{supply} - T_{room})$
- $-6\ kW \geq Q_{vent} \leq 12\ kW$
- $zT \geq 0$

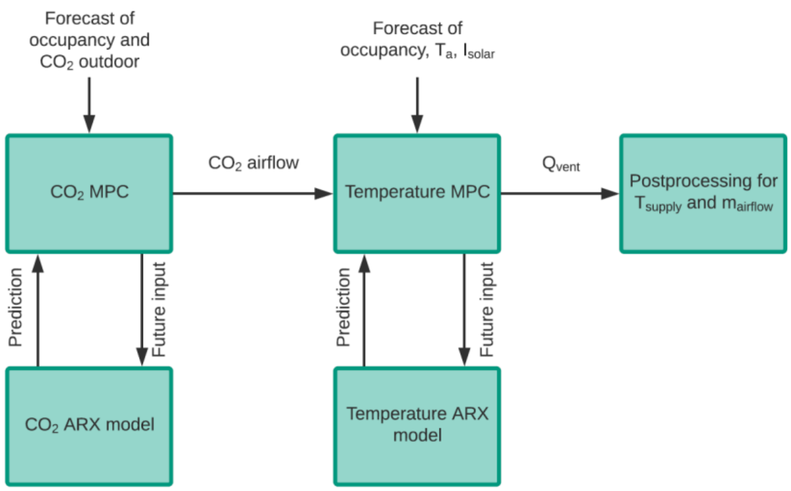

Figure 3 Method for implementation of the linear ARX predictive controller

For the optimized control the comfort cost function is only active during operating hours of the AHU. During non-operating hours of the AHU the weight factors for comfort are set to 0. In addition, the airflow is set to a minimum airflow rate during operating hours when comfort constraints are not exceeded. Operating hours of the AHU are defined as follows: active 07:30-18:00h and not active 18:00-07:30h, in the weekends the AHU is not operating. In the last step the optimized supply air temperature and airflow rate, that is translated to the requested VAV damper position, are sent to the ventilation system. Through the BACnet interface of the AHU the optimized values are written on the corresponding BACnet objects for the VAV request position and the supply air temperature.

The implemented predictive control is completely written in Python and executed on the industrial PC present in the technical room of the case study building. Communication with the AHU to read measurement values and to write control actions is performed using the Building automation and control network (BACnet) (ANSI/ASHRAE Standard 135, 2004) interface present in the AHU. The MPC is executed every 15 minutes in which the optimal control output is calculated for the VAV damper position and the supply air temperature for both lecture rooms. The prediction and control horizon used in the MPC framework is 8 steps ahead (i.e. 120 minutes).

RESULTS OF THE IMPLEMENTED PREDICTIVE CONTROL FRAMEWORK

To evaluate the predictive control framework the operation of the VAVs is first analyzed. The results of the implemented predictive control is analyzed using the measured values from the building monitoring system. In Figure 4, the optimized values from the predictive control framework of supply temperature and VAV damper position are compared to the actual measurements in both lecture rooms. Overall, it is shown that the optimized values for VAV damper position and supply air temperature are respected by the ventilation system. Only for lecture room 1 on the third day in the morning a high difference between optimized and measured values is noticed. Here it is shown that the VAV damper position remains 0 while the optimized position is approximately 15%. Currently the AHU is activated when in both rooms the optimized damper position is above the mimimum required damper position (VAV >10 %). This will be changed in the future since the heating demand for each room can vary in time resulting in different requests for each room regarding heating, cooling and fresh air. Since the VAV position is remains at 0% also the supply air temperature could not be increased as indicated by the high difference in measured and optimized temperature.

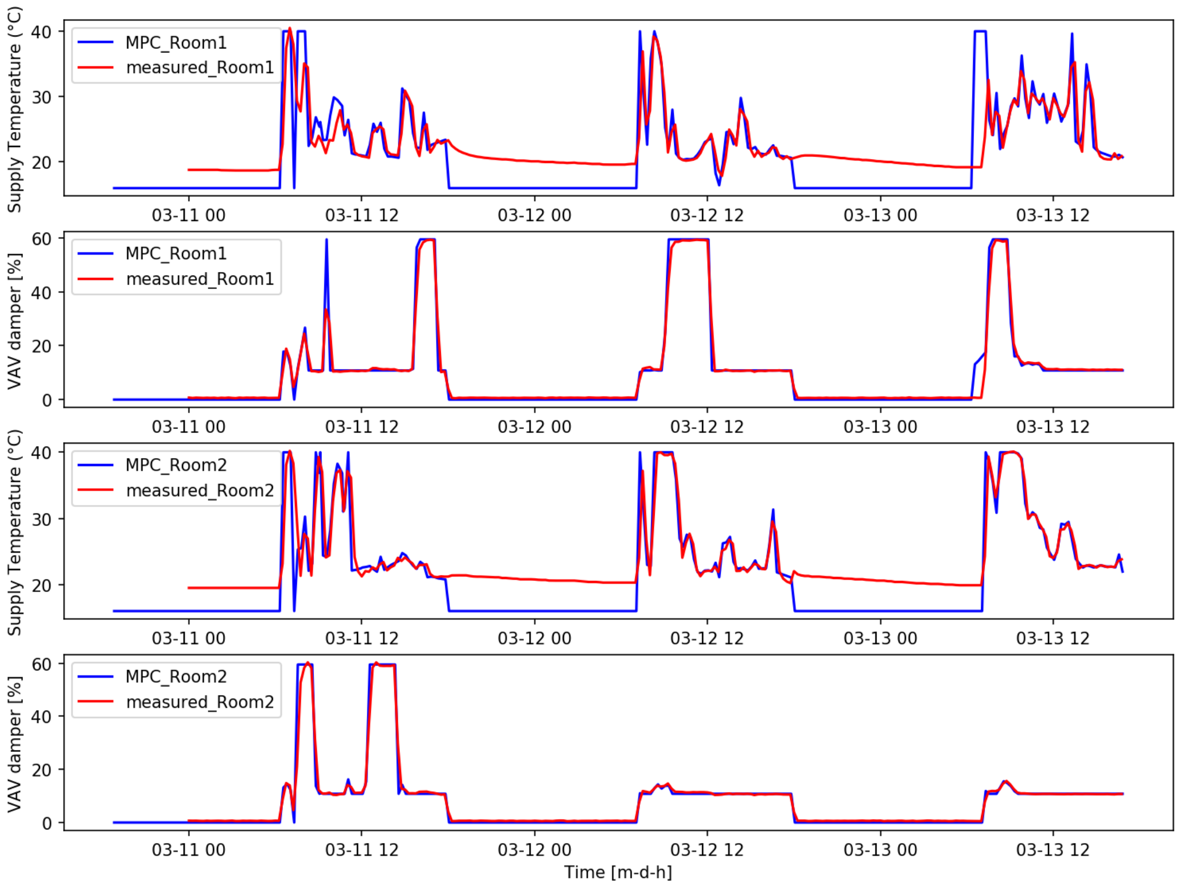

Figure 4 Measured and optimized VAV position and supply air temperature for lecture room 1 and lecture 2

Figure 5 demonstrates the measured data in both lecture rooms with the implemented predictive control. In the first graph of Figure 5 the measured VAV damper position, the occupancy according to the lecture schedule and the CO_2 concentration measured in the room is shown for room 1. The occupancy derived from the weekly lecture schedule indicates, compared to the measured CO_2 concentration, that not all the classes took place, also start and end time can be different compared to the lecture schedule. This indicates that forecasting the occupancy is difficult with the results that in a few occasions the VAV damper position changes since occupancy is expected or the supply air temperature is based on the future expected occupancy. The second plot shows the measured supply air temperature and room temperature for room 1 with in green the indicated heating temperature setpoint according to the lecture schedule. The third and fourth plot in figure 2 is the measured results of the same aforementioned parameters but for lecture room 2.

The reported thermal discomfort of the predictive control is respectively 4.8 Kh for room 1 and 2.25 Kh for room 2. Only for room 1 on the last day it is shown that the heating setpoint is not met during the morning class. The occupancy forecast indicates that 60-80 students are expected for the class during the morning. To avoid a mismatch between measured and forecasted occupancy, currently only the first timestep ahead of occupancy is corrected based on the current measurement of CO_2 and the one step ahead prediction of the CO_2 concentration. For the other remaining steps (2-8 step ahead) in the prediction horizon the occupancy forecasts are based on the lecture schedule. For CO_2 discomfort, violation of the setpoint of 1000 ppm, the reported value is 126 ppmh for lecture room 1 and 221.0 ppmh for room 2. In the figure it is noticed that at the end of classes the VAV damper position already closes to the minimal position. The result is that the CO_2 setpoint is exceeded by up to 200 ppm as indicated on the 12th of March for room 1 after the first lecture. In addition for room 2 on the final day it is shown that the CO_2 setpoint is conitiniously exceeded by approximately 100 ppm. This indicates that the predictive control framework allows small violations of the setpoint in order to minimize the fan energy use.

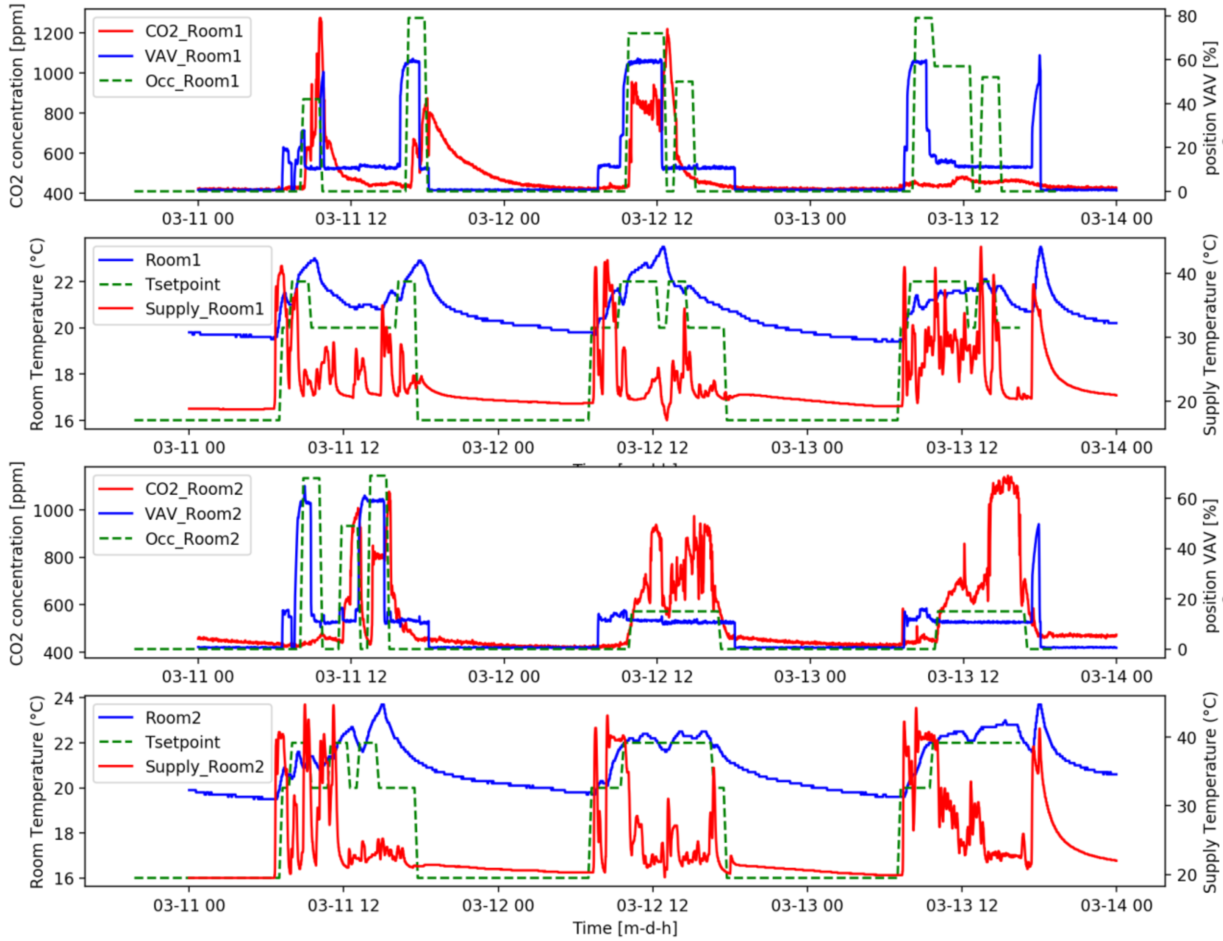

Figure 5 Operation of the all air ventilation system for lecture room 1 and 2

CONCLUSION

This paper presented first measurement results of an implemented ARX based predictive control for an all-air ventilation system in a case study building. The MPC framework controls both the room temperature and CO_2 concentration. Through BACnet the optimized control outputs are written to the ventilation system by controlling the VAV damper position and the supply air temperature. Using a simplification the optimization problem can be solved using a linear approach reducing the computation time. The data driven ARX model is a simple regression model but the results indicate that the model is able to predict the future room conditions. This indicates that data driven control is possible where less effort is needed for model identification. However, still some effort is needed to define the optimization problem and the related cost function. To obtain occupancy forecasts the weekly lecture schedule is used. The results show in general that these forecasts can be used to produce reliable predictions, however, there is some uncertainty in the forecast since classes can be cancelled or end earlier than expected. The measurement results for the operation of the ventilation system indicate that the predictive control framework is able to control both rooms while the measured temperature discomfort is minimal. The current improvement is that the occupancy based heating set-point can be implemented easier using a predictive approach and less conflicts are noticed between fresh air demand and heating demand which reduces energy use. However, some improvements can be made regarding the VAV damper position control, since it was noticed that on one day the VAV damper did not respond to the optimized control action. The VAVs controlled by the MPC react to the heating and ventilation demand in order to control the IEQ. In future research the energy saving potential and comfort performance of the predictivce control framework will be compared to a RBC by a co-simulation approach. Currently, there is not enough data to make a reliable evaluation of the energy saving potential since the implemented control is tested for one week.

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