Predictive control for an all-air ventilation system in an educational nZEB 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. This is important in rooms with a highly fluctuating occupancy profile, such as classrooms and open offices. However, 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 is lower than predicted. This study focuses on nearly zero energy buildings (nZEB) buildings where the insulation and air tightness of the envelope is high resulting in slower reactions towards disturbances (occupants and solar radiation). Furthermore, internal heat gains have a higher impact on the indoor climate in these type of buildings. A model predictive control (MPC) might be a solution as an MPC takes into account the current situation and the future demand. MPC has already shown savings for hydronic systems in operating buildings as indicated in recent studies which resulted in energy savings of 17-30%.

Previously identified dynamic models for CO_2 and temperature prediction are implemented in a linear MPC framework to evaluate the impact on the indoor environmental quality (IEQ) and energy use. The dynamic models are data-driven (RC and ARX models) and identified using measurement data obtained from an operating building. The building consists of two lecture rooms, each with a capacity of 80 students. Balanced mechanical ventilation is provided with a total supply airflow of 4400 m^3/h. The airflow rate is controlled by VAV boxes based on measurements of CO2-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 are integrated in the supply ducts of each zone so it is regarded as an all air HVAC system.

Different strategies (actual number, lecture schedule, motion) for occupancy prediction are analysed and their effect on the operation of the MPC. The MPC framework is first tested in a simulation environment (Modelica). Results will be presented for the effect of MPC on the operation of the all-air system and the energy use for both the fans and the heating coil. Results of the simulations will be used to improve the current RBC control in a test building. This will result in an optimized energy use while at the same time providing a comfortable indoor climate.

The study showed that with a minimal dataset of the following parameters: indoor, supply and outdoor temperature, solar radiation, airflow rate and occupancy an energy efficient MPC could be developed with respect to thermal comfort. The airflow rate is decreased by 47% compared to the measurements while the heating energy for ventilation (Q_{vent}) is decreased by 56% for the complete period of four weeks during the transition season

KEYWORDS

All-air Ventilation, MPC, Energy saving, predictive control, educational building

1 INTRODUCTION

In school and office buildings, the ventilation system has a large contribution to the total energy use (EnBau, 2010). A control strategy that adjusts the operation to the actual demand can significantly reduce the energy use. This is important in rooms with a highly fluctuating occupancy profile, such as classrooms and landscaped offices. However, a standard rule-based control 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 is lower than predicted. This is especially of concern for all-air ventilation systems where the indoor climate and the air quality are controlled by the ventilation system.

This study focuses on nearly zero energy buildings (nZEB) where slower reactions towards disturbances are expected as a result of a high insulation and high air tightness level of the building envelope. Furthermore, internal heat gains such as occupancy have a higher impact on the thermal comfort in these type of buildings. In addition, there can be a discrepancy between the heating demand and ventilation demand. A model predictive control (MPC) might be a solution to control the thermal comfort while reducing the energy use, as an MPC takes into account the current situation as well as the future demand. Recently, MPC is gaining more interest for implementation in control for HVAC systems. MPC has already shown savings for hydronic systems in operating buildings as indicated in recent studies (De Coninck and Helsen 2016; Prívara et al. 2011; Sourbron, Verhelst and Helsen 2017).

A few studies on MPC for all-air ventilation systems will be highlighted. Huang, Wang, and Xu (2010) created a robust MPC control strategy for a ventilation system with variable airflow volume (VAV). The developed strategy resulted in a more robust control compared to a PI control since less commissioning or user-intervention was needed. Test were performed with a single zone simulation model. The MPC was able to satisfy constraints when used for temperature control. A recent study by Liang et al. (2015) focused on MPC for a HVAC system with VAVs for temperature control. A low order state space model was developed and a Kalman filter was applied for state estimation. Simulations showed savings for MPC of 17,5% on the electrical energy consumption of ventilation. As indicated both studies focussed on temperature control for VAVs while often this is also CO_2 controlled. (Bengea et al., 2014) demonstrated the implementation of MPC with both temperature and CO_2 control in an office building with a rule based HVAC system. Energy savings were 20% during the transition season and 70% during the heating season. CO_2 levels 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.

A related study by Walker et al. (2017) developed a distributed MPC approach for temperature and CO_2 concentration control in a natural ventilated building and compared it to a centralized MPC. For a 3 zone model it was shown that the distributed MPC achieved performances close to a centralized MPC. The dynamic model used was a grey box model which was linearized in order to utilize it as a linear time invariant (LTI) dynamic model inside the MPC framework. An important parameter that is needed for MPC is the occupancy information for both temperature and CO_2 control. Occupancy can be a high internal heat load in nZEB buildings. (Oldewurtel, Sturzenegger, & Morari, 2013) showed that incorporating occupancy information into an MPC resulted in a significant energy saving potential for offices. Both perfect predication and occupancy schedules were used in the MPC. Energy savings found for the HVAC system when comparing to a RBC was 34-50%. More sophisticated occupancy prediction methods did not result in significant energy savings compared to instantaneous occupancy information.

The aim of this study is to show a method on how to implement a simple identified model in a linear MPC framework. The objective of the MPC is to maintain the comfort in the room with respect to indoor temperature and CO_2 concentration while minimizing the heating energy use and fan energy use. The outline of the paper is as follows: section 2 demonstrates the method used for the MPC framework and highlights the case study building. Next section will present the results for the room temperature and CO_2 concentration of the MPC ventilation system Finally, a conclusion and discussion is given for the used approach and the future application in the MPC.

2 METHOD

Previously identified dynamic models for CO_2 and temperature prediction using of an educational building (Merema, Breesch, Saelens, 2019) are implemented in a linear MPC framework. The dynamic models are data-driven (ARX models) and identified using measurement data obtained from an operating educational building described in section 2.1. In the optimal control problem soft constraints are implemented for the indoor environmental quality (IEQ) to optimize the energy use whit respect to the IEQ. Afterwards a method is shown to solve the problem using a linear optimization. This framework is discussed in section 2.3.

2.1 Description of the case study building (Merema, Delwati, Sourbron, & Breesch, 2018)

An education building located in Ghent (Belgium) is used for the case study. The building consists of two lecture rooms, each with a capacity of 80 students. 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. The control for the ventilation system is a rule-based control (RBC) strategy. 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. The U-values for the envelope are given in Table 1.

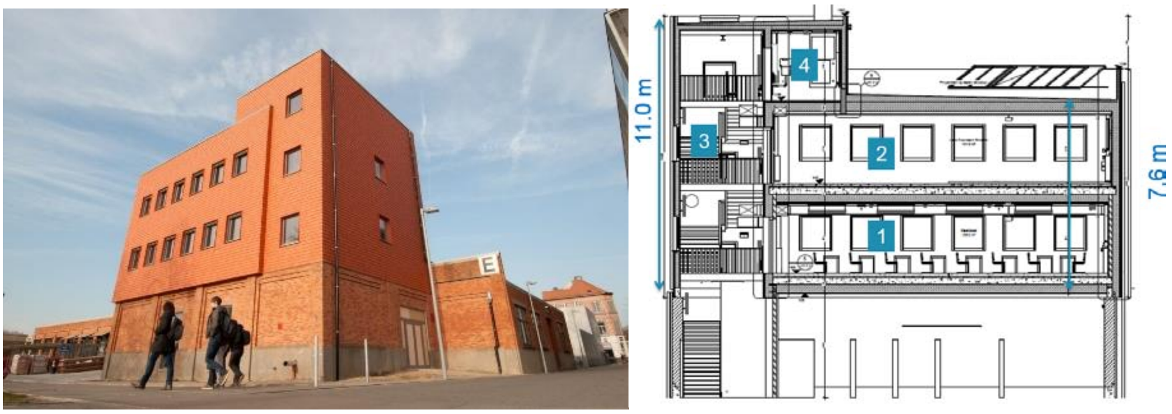

Figure 1; (left) Impression of the case study building, (right) cross-section of the case study building with 1: lecture room, 2: lecture room, 3: staircase, 4: technical room

Table 1: U values for the construction elements

Construction part	U-Value (W/m²K)
Wall	0,15
Roof	0,14
Floor	0,15
Glazing (glazing)	0,60
Glazing (frame)	0,90

2.2 Measurement data

A set of sensors has been installed to monitor indoor and outdoor conditions and are listed in Table 2. The building includes a weather station monitoring the main outdoor parameters:

global horizontal solar radiation, outdoor temperature, relative humidity and wind speed and direction. For the indoor conditions, the indoor temperature, the CO_2 concentration and the indoor humidity are continuously monitored. The occupancy of the lecture room is measured by counting cameras installed near the entrance of the room. Measurement data is collected during four weeks on a 1 minute time-interval. The following parameters were used to identify the ARX models (Merema, Breesch, Saelens, 2019) implemented in the MPC framework: outdoor- , indoor- and supply air temperature, solar radiation(global horizontal and on façade), air flow rate, room CO_2 concentration and occupancy.

Table 2. Properties of the installed sensors used for the MPC framework (Merema, Breesch, Saelens, 2018)

Parameter	**Type sensor**	**Accuracy**
CO_2-concentration	VAISALA GMW83	±30 ppm + 3% of reading
Room temperature	SE CSTHR PT1000	± 0.1 °C
Supply temperature	SE CSTHK HX	± 0.4 °C
Occupancy	Acurity Crosscan Camera	± 5%
Outdoor temperature	Vaisala HMS82	± 0.3 °C at 20°C
Solar radiation	SP Lite2 Silicon Pyranometer	4.5% of reading

In Figure 2, measurement data for outdoor temperature, solar radiation and occupancy is illustrated. The data is used in the MPC framework as forecasts to optimize the airflow rate and the supply air temperature. For the outdoor CO_2 concentration a constant of 420 ppm is used as forecast for the CO_2 MPC since this parameter is not measured in the current situation.

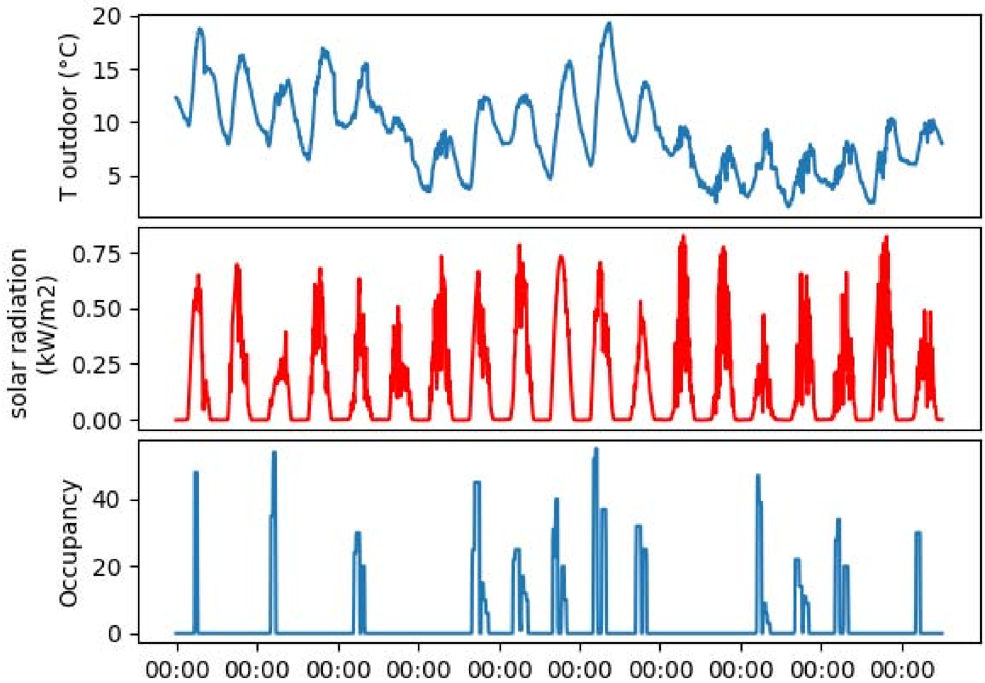

Figure 2; Parameters ($T_{outdoor}$, solar radiation and occupancy) measured used as forecast input for the MPC

2.3 MPC framework

This MPC framework is written in Python using the CVXPY (Diamond and Boyd, 2016) package allowing to solve convex optimization problems. The selected solver is QSOP, i.e. the default solver used in CVXPY to solve quadratic problems.

The ventilation MPC is split up in two separate MPCs (1:CO_2 2: Temperature) to solve the problem as a linear-MPC, as demonstrated 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, outdoor CO_2. Maintaining the CO_2 concentration below the desired set point has the highest priority in this VAV control. Since the ARX model is linear the minimal required airflow for CO_2 control can be calculated and optimized by the CO_2-MPC. Future predictions for room CO2 concentration are performed by the underlying ARX model afterwards the control output is optimized in the MPC. The control output is feedback to the ARX model to calculate the measurement output by including some random white noise on the feedback signal.

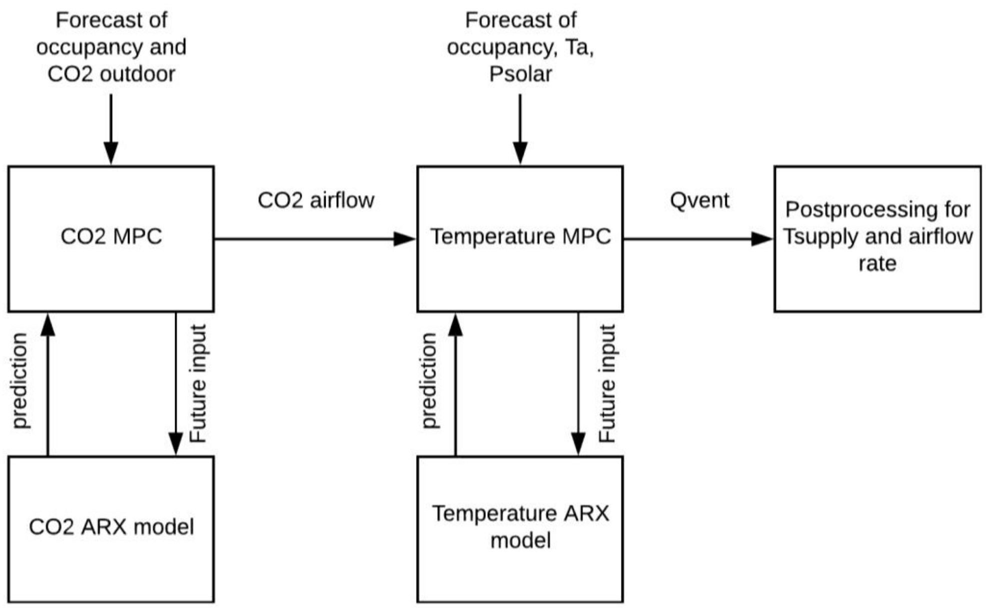

Figure 3; Linear MPC framework for all-air ventilation system

Second, the calculated CO_2 airflow is used as a input constraint in the Temperature MPC. In the T-MPC, Q_{vent} is optimized using the predictions from the temperature ARX model. The optimized control output Q_{vent} is then returned to the ARX model to obtain the measurement output by including random white noise. 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. The optimized variable Q_{vent} obtained from the linear T-MPC is split up in the following manipulated variables T_{supply} and airflow. The mass flow rate is obtained from the CO_2 MPC and is fixed in the equation. From here T_{supply} can be calculated using the following strategy and equation 1. If $T_{supply} > 45°C$, T_{supply} is set to 45°C and the mass flow is increased using equation 1:

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

Subject to:

- $T_{supply} \geq 15\ °C$
- $T_{supply} \leq 45\ °C$
- $Airflow \geq 0\ m3/h\ \ (7{:}30 - 17{:}30h\ Airflow\ \geq 400\ m3/h)$
- $Airflow \leq 2200\ m3/h$

In the ventilation MPC the following non-linear constraint (2) is present. By using a simplification this constraint can be avoided and enabling to solve the problem using a linear MPC framework. The ventilation energy (Q_{vent}) is non-linear as it contains a product of two optimization variables: $m_{airflow}$ and T_{supply}.

$$Q_{vent} = 0.34 * m_{airflow} * (T_{supply} - T_{zone}) \quad (2)$$

The optimal control problem (OCP) is solved every time step (15 minutes) in which the optimal control output is calculated for the complete prediction horizon using forecasts of the disturbances. The prediction and control horizon used in the MPC framework is 10 steps ahead (i.e. 150 minutes). The forecast of solar radiation, outdoor temperature, CO_2 concentration outdoor and occupancy are forwarded to the OCP. For occupancy, the number of persons obtained from the counting camera is used, perfect prediction of occupancy. The optimized control output (supply temperature and air flow) is forwarded to the dynamic model to calculate the future indoor air temperature and CO_2 concentration for the complete prediction horizon. This procedure is repeated every time step. Measurement noise (random white-noise) is added to the measurement results of the dynamic model to include noise between predictions and observed values. At each time step, the future disturbances and constraints are updated and passed to the OCP to obtain the next control input trajectory.

To solve the OCP the following two cost functions are defined to minimize the energy use with respect to the indoor CO_2 concentration and room temperature. Slack variables are used for the comfort constraints to penalize exceeding the set point. In this way the hard constraints are transformed into soft constraints. For temperature a lower and upper bound is defined where for CO_2 concentration the set point is set at 1000 ppm.

$$\text{CO}_2 \text{ control: } Min \sum_{k=O}^{Hp} (zCO2)^2 + (Airflow)^2 \quad (3)$$

Subject to:

- $CO2\, room \leq 1000\, ppm + zCO2$
- $Airflow\ CO2 \geq 0\ m3/h\ \ (7{:}30 - 17{:}30h\ \ Airflow \geq 400\ m3/h)$
- $Airflow\ CO2 \leq 2200\ m3/h$
- $zCO2 \geq 0$

$$\text{Temperature control: } Min \sum_{k=O}^{Hp} (z)^2 + (z1)^2 + (Q_{vent})^2 \quad (4)$$

Subject to:

- $T_{room} \geq 22°C - z\ \ (17{:}30 - 7{:}30\ T_{room} \geq 16°C - z)$
- $T_{room} \leq 26\ °C + z1$
- $Q_{vent} = 0.34 * m_{air}(T_{supply} - T_{room})$
- $-6\ kW \geq Q_{vent} \leq 12\ kW$
- $z \geq 0$
- $z1 \geq 0$

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 07:30-17:30h and not active 17:30-07:30h, in the weekends the AHU is not operating.

3 RESULTS

First results of the CO_2 MPC are shown where the airflow rate is optimized using future predictions of room CO_2 concentration. In 3.2 the final results are depicted for the ventilation MPC. Here, the supply air temperature and airflow rate is optimized using the predictions of the room temperature and results obtained from the CO_2-MPC. To compare the MPC with measurement results, the start- and end time of the AHU is fixed from 07:30 – 17:30h during weekdays. This means that start- and end time of the AHU for both the MPC as the measurements is fixed.

3.1 CO_2 MPC

In order to solve the ventilation MPC first the CO_2-MPC is solved in order to obtain the airflow rate. Figure 4 shows the results for the CO_2-MPC for CO_2 concentration and airflow. It is indicated that the CO_2 concentration is slightly overestimated by the underlying ARX-model. Maximum differences compared to the measurements are up to 200 ppm. The CO_2 MPC exceeds the set point on average by 116 ppm/hour with a total of 18 hours, while the measurements exceed the CO_2 set point by 102 ppm/hour with in total 19 hours exceeding the set point during a 4 week period. Exceeding the set points is attributed to the fact that the system is limited to a maximum air supply rate of 2200 m^3/h. For the airflow results it should be noted that the measurement results for airflow are also influenced by the temperature control. But it can be observed that during use of the classroom on the first day in the afternoon the CO_2-MPC goes to minimal airflow while in reality a maximum airflow rate is used. The CO_2 airflow rate shown in Figure 4 is used as input for the temperature MPC

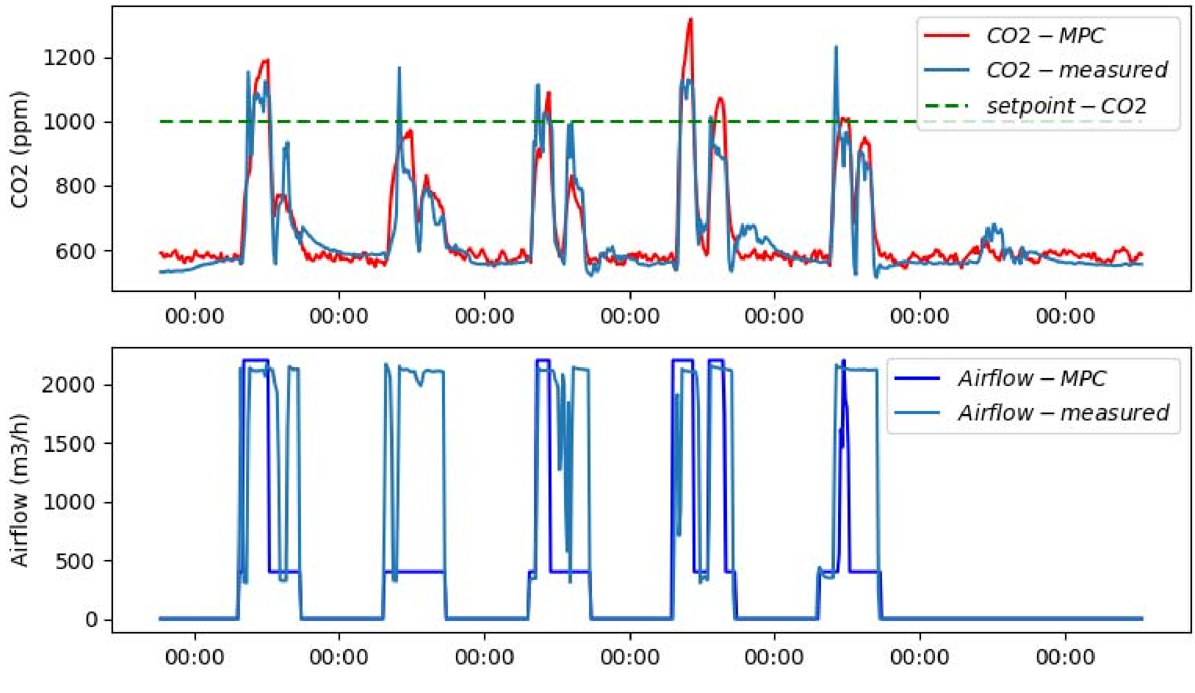

Figure 4; CO_2 concentration (ppm) and airflow rate (m3/h) obtained from the CO_2 MPC and measurements.

3.2 Ventilation MPC

The ventilation MPC results are illustrated in Figure 5 for one week. Results are presented for CO_2 concentration, airflow rate, room- and supply temperature and ventilation energy (Q_{vent}). The airflow and supply temperature presented are the result after post-processing of the results for Q_{vent}.

In order to evaluate the accuracy of the MPC framework the room temperature predictions are compared to the measurements when the AHU is deactivated. In the first weekend of the dataset the temperature decay was 2,0°C for measurements compared to 2.2°C for the MPC. This indicates that the thermal capacity and resistance identified for the predicted model is close to the actual values. The room temperature during measurements is on average 0.22 K/h below the set point while for MPC this is 0.07 K/h. Maximum temperature below the required set point during the day is for measurements 3.2°C and for the MPC 1.6°C. This indicates that the room temperature can be controlled more accurate with MPC compared to the standard RBC in the measurements.

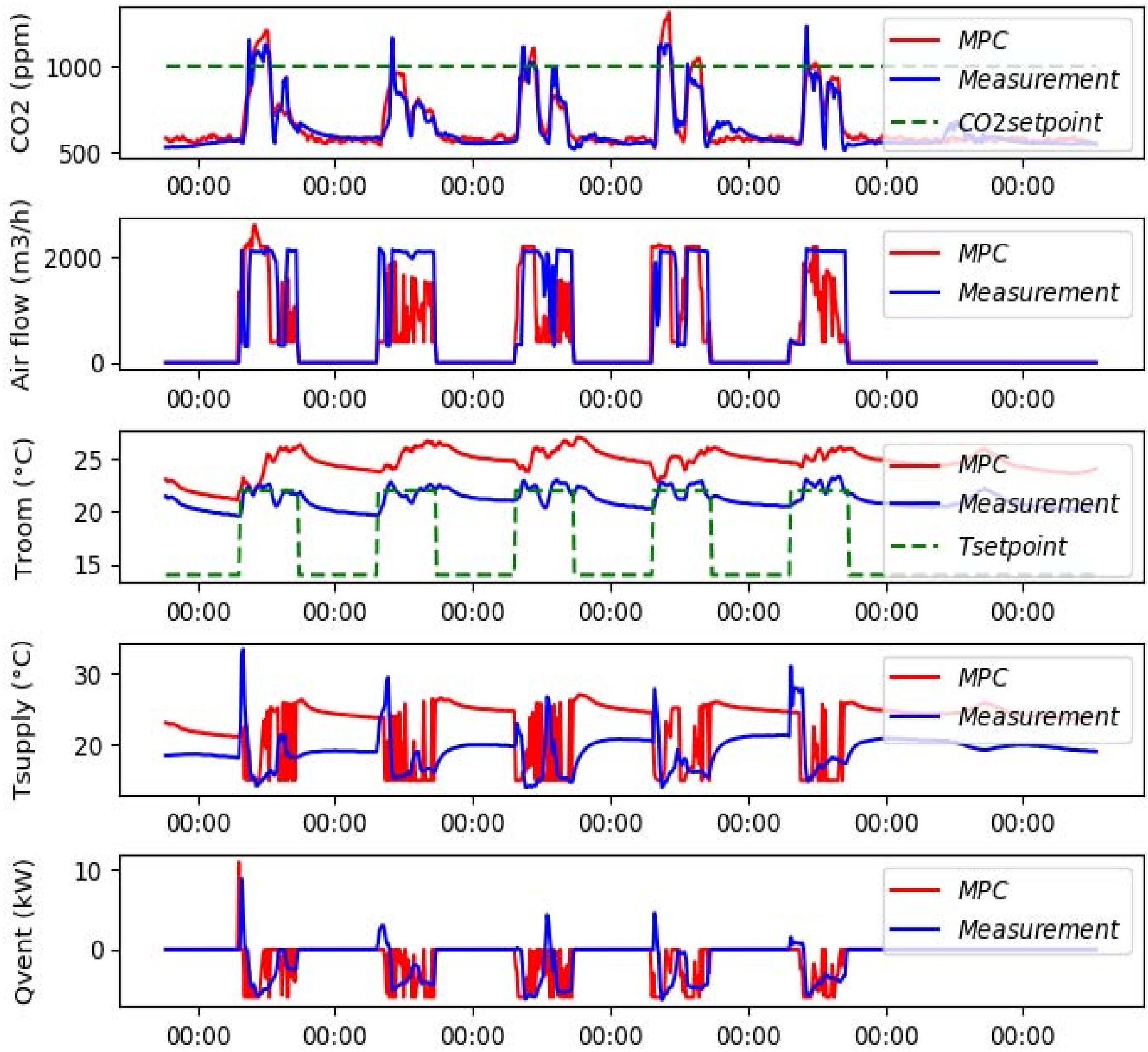

Figure 5; Results for the ventilation MPC compared to the measurements

For the room temperature it is indicated that higher temperature can be expected when the MPC is implemented. In the MPC framework, no penalties are given to the comfort for room temperature within the boundaries of 22-26°C. In practice the adiabatic cooling is activated above a room temperature of 26°C. However, the MPC aims to minimize the future ventilation heating energy. Therefore, difference between MPC and measurements for room temperature can be relatively high, even up to 4°C.

The results for air flow indicate that the MPC ventilation system operates at a lower air flow rate compared to the measurements. This indicates that the airflow is minimized effective by the MPC. The airflow rate is decreased by 47% compared to the measurements. Secondly, the results for Qvent also indicates that the MPC effectively minimizes the energy use. Compared to the measurement results Q_{vent} is decreased by 56% for the complete evaluation period of 4 weeks. These results indicates that the MPC framework enables to reduce the energy use with a better control for the IEQ.

A non-linear MPC might be a better approach to solve the OCP as the constraint for ventilation energy (Q_{vent}) is non-linear, since it contains a product of two optimization variables (supply air temperature and air mass flowrate). In addition, the post processing of the results to obtain the control parameters for supply air temperature and airflow rate might be prone to errors whereas in a non-linear MPC the control parameters can be obtained directly. However, the presented results indicated that the problem can be solved using the presented linear method. This avoids using a non-linear MPC which might be more computational demanding. In addition, a non-linear optimization is sensitive to the initial values.

4 CONCLUSIONS AND FUTURE RESEARCH

This paper discussed the framework of an MPC for an all-air ventilation system. Using a simplification the optimization problem can be solved using a linear approach. In addition, it is shown that an energy efficient MPC could be developed based on a minimal dataset of the following parameters: indoor, supply and outdoor temperature, solar radiation, airflow rate and occupancy. It has to be remarked that occupancy is not measured in most buildings, but in educational building lecture schemes are available for implementation as forecasts in the MPC.

In the future, a non-linear MPC will be tested to compare the results with the linear model, which was discussed in this paper, to evaluate the simplification made to solve the non-linear constraint.

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