Co-simulation approach to evaluate MPC strategies for all-air systems: case study

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Abstract
To use energy in buildings more efficiently, control of the heating, ventilation and air-conditioning (HVAC) system is a key parameter. Recently, model predictive control (MPC) is gaining more attention. To evaluate the potential of a MPC strategy, the control is first tested in a simulation environment. This requires a co-simulation approach to couple the MPC framework with the emulator model. In this paper a co-simulation framework is developed and results are verified with measurements. The co-simulation approach was then used to simulate two MPC strategies and compare them directly to a rule based control (RBC). Results indicate that comfort could be guaranteed using the predictive control while reducing the energy use for the fans and heating coil.

Key Innovations
- Occupancy based predictive control
- Co-simulation approach
- MPC for all-air systems

Practical Implications
Always do include both forecasts and measured data when performing co-simulations to evaluate the energy saving potential and performance of model predictive control strategies.

Introduction
Worldwide buildings are reported to use approximately 36% of the total energy use, and account for 39% of the total worldwide CO₂ emission (IEA (2019)). Heating, ventilation and air conditioning (HVAC) is reported to use 50% of the energy use in buildings (Pérez-Lombard et al. (2008)). To reduce this high energy use in buildings the control of the HVAC is a key parameter. However, HVAC systems are challenging to control due to time varying dynamics, and varying internal and external disturbances (Afram and Janabi-Sharifi (2014); Killian and Kozek (2016)). Currently, in buildings relative simple schedule based systems remain the most common control strategies in non-residential buildings (Young et al. (2019)). The study of Naylor et al. (2018) suggests that high energy savings can be achieved by a combination of real-time reactive and future predictive control to optimize the conditioning of a space. A model predictive control (MPC) could be a solution to control an HVAC system more energy efficiently since it takes into account the current measurements and the future demand. In buildings with hydronic systems the reported energy reductions after implementation of a predictive control are significant (De Coninck and Helsen (2016); Sturzenegger et al. (2016)). However, less is known about the energy saving potential of MPC for all-air systems. Since, the time dynamics of the system are faster compared to hydronic systems the saving potential might be smaller. In literature, a few examples can be found of real implementation of a MPC for an all-air ventilation system. Bengea et al. (2014) showed that by controlling both the room temperature and CO₂ concentration in an office building energy savings can be obtained up to 20% for the HVAC system, while guaranteeing the comfort. West et al. (2014) implemented an optimized supervisory grey-box MPC for the HVAC system in two commercial buildings. The developed MPC framework controlled either the zone temperature set-point, or the supply air temperature to guarantee the thermal comfort while reducing the energy use. Energy savings achieved for the HVAC system were in the range of 19% up to 32%.

The focus in this study is on large spaces, such as open plan offices and lecture rooms, served by an all-air ventilation system. In these spaces there can be a contradiction between the fresh air demand and the heating demand, due to oscillations of CO₂ affecting the temperature control Schibuola et al. (2018). Using a model predictive control (MPC) this dual optimization problem could be solved by minimizing the energy use, while at the same time guaranteeing the indoor environmental quality (IEQ). Typically, in rooms the occupancy schedule is varying over time. This could be a beneficial condition to implement a predictive control that is based on occupancy since the contentiously changing heating...
and fresh air demand. For example, occupancy based control already showed significant energy reductions for both fans and heating in real application (Goyal et al. (2015)).

To predict the performances of a newly developed predictive control strategy it needs to be tested in a co-simulation framework, including both the building model and the predictive control framework. Wang et al. (2019) indicated the potential of data-driven building climate control by use of co-simulations. However, the study did not verify the building model with real data and the forecasts were considered as perfect predictions. In real application of MPC, there is uncertainty in the forecasts since unexpected changes may occur. To overcome this problem uncertainty has to be introduced in the co-simulations by using a combination of forecasts and real measurement data. This is already indicated for weather forecasts (Oldewurtel et al. (2012); Petersen and Wieck (2014)).

The aim of this study is to develop and verify a co-simulation framework where predictive control strategies can be evaluated. In the MPC framework we include real forecasts and measured results to include the uncertainty that is present in a real environment. For this purpose, an educational building is used as a case study building. In this building a predictive control is implemented to control the all-air system. A previously verified Modelica model of the case study building is used as a simulation model (Merema et al. (2021)). For co-simulation this simulation model is coupled with the developed MPC framework. The simulated performance of the MPC is verified with measured results of the implemented MPC to make a fair comparison with a baseline rule based control (RBC). The structure of this paper is as follows: first a description of the case study building is given. Afterwards the developed MPC framework is explained and presented. The next section presents the co-simulation approach that is used. Finally, the results for three scenarios are shown, and the simulated MPC is compared with the implemented MPC to analyze the performance of the co-simulation approach.

Case study building: Test Lecture Rooms, Ghent

The case study building is an educational building, built according to the Passive House standard, shown in Figure 1 and located in Ghent, Belgium. The building is built on top of an existing university building and contains four zones: two large lecture rooms, a staircase and a technical room. The floor area of the lecture rooms is 140 m² with a volume 380 m³ and a maximum capacity of 80 students each. The building is in use while at the same time it is a test facility for research on building energy-efficiency strategies in a “real use” environment. Therefore, the lecture rooms are thermally insulated from the outside, to the adjacent zones and each other.

![Outside view of the test lecture rooms in Ghent (Belgium)](https://example.com/image)

**Building envelope**

The U-value of the construction parts are listed in Table 1. The solar heat gain coefficient for the glazing is 0.52. The window to wall ratio is 26% for the north-east and 27% for south-west façade. Air tightness at 50 Pa (n50) of the lecture rooms is 0.29 1/h for the first floor and 0.47 1/h for the second floor. Movable external blinds are applied on the windows on the south-west side. Blinds are closed when the incident solar radiation exceeds 250 W/m² with a dead band of 50 W/m², this reduces the g-value to 0.08.

<table>
<thead>
<tr>
<th>Construction element</th>
<th>U-value (W/m²K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wall</td>
<td>0.15</td>
</tr>
<tr>
<td>Roof</td>
<td>0.14</td>
</tr>
<tr>
<td>Floor</td>
<td>0.14</td>
</tr>
<tr>
<td>Glazing</td>
<td>0.60</td>
</tr>
<tr>
<td>Frame</td>
<td>0.90</td>
</tr>
</tbody>
</table>

**HVAC system**

The HVAC system consists of a demand controlled ventilation (DCV) system with an air-to-air heat exchanger (with an efficiency according to the manufacturer data of 78%). A scheme of the AHU and the ventilation system is shown in Figure 2. The Variable Air Volume (VAV) boxes are located in the supply and extract of each room. The VAV damper controls the air flow rate based on measurements of CO₂ concentration and operative temperature in the lecture rooms. The maximum air flow rate per room is set at 2200 m³/h and the minimum at 400 m³/h. The fan speed is variable and based on a constant pressure control inside the ducts of 200 Pa. Two heating coils of 8 kW are integrated in the supply ducts to control the supply air temperature. The heating production system consists of a condensing wood pellet boiler with an internal storage of 600
1. The maximum heating power is 8 kW with a maximum efficiency of 80%. The supply and extract fan have a maximum power of respectively 1.57 kW and 1.33 kW with an efficiency of 71%. The efficiency of the fan motors is 85%. Indirect evaporative cooling (IEC) is provided with a maximum capacity of 13.1 kW. In addition, window opening is controlled to allow night-time ventilation, which is extensively described in Breesch et al. (2018).

**Current control HVAC system**

The lecture rooms are used during the academic year, which counts 124 days with courses and 53 days with exams (in January, June and August-September). Holiday periods are in April (2 weeks), July and the first half of August (6 weeks) and December-January (2 weeks). The lecture rooms are in use from Monday to Friday between 8:15 h and 17:30 h. The air handling unit (AHU) is operating from 07:30-18:00 h during weekdays, these setting were chosen by the facility manager. The CO\(_2\) set point for the DCV system in use is set at 1000 ppm, which corresponds to IDA class 3 with an airflow of 28 m\(^3\)/h.pers (EN 16798-3 (2017)) or 16 m\(^3\)/h.m\(^2\). The set point for the heating system is set at 22 °C with a dead band of 0.5 °C. Standby temperature during non-operating hours is set at 15 °C. The airflow rate and/or supply temperature is increased when one of the aforementioned set-points are not met. The heat exchanger is bypassed when the outdoor temperature is above 16 °C or when the room temperature in one of the lecture rooms exceeds 24 °C.

**Model predictive control framework**

An MPC framework is developed including three steps needed to optimize the desired control outputs. The aim of this all-air predictive control is to minimize the energy use while guaranteeing the indoor air quality (IAQ) and thermal comfort. For this purpose the room CO\(_2\) concentration and room air temperature are controlled by the predictive controller. To understand the process for the developed MPC framework, Figure 3 illustrates the complete predictive control framework. The predictive controller actuates the VAV damper position and the supply air temperature set point for each room.

The first step includes the collection of the data of the disturbances. The forecasts are collected for global horizontal irradiation, outdoor temperature and occupancy for the complete prediction horizon. The weather forecasts are collected using the DarkSky weather forecast API (DarkSky (2020)), which allows to collect hourly weather forecasts. For occupancy, the number of persons are obtained from the weekly lecture schedules made available by the university administration. The comfort criteria include the heating set point and minimum airflow rate set point. During operating hours the heating set point of the rooms is a function of the occupancy status of the room and thus an occupancy based control. The following three conditions are defined for the thermal comfort criteria of the predictive control:

- 18:00 – 07:30h standby 16°C
- 07:30 – 18:00h unoccupied 20°C
- 07:30 – 18:00h occupied 22°C

Based on these conditions, the room temperature heating set point constraint is set accordingly. All the collected information is then forwarded to the predictive controller.
The second step in the MPC framework is the predictive controller. Based on historical data, suitable models were identified to capture the heating dynamics of the building and system (Merema et al. (2019a)). In addition, a model was identified to capture the CO₂ generation rate by humans to enable CO₂ predictions for future time steps. The identified models can predict the room CO₂ concentration and the room temperature for the complete prediction horizon of 2 hours (time-step of 15 minutes). The predictive controller used in this study includes either a resistor capacitor (RC) model, or an auto-regressive with exogenous terms (ARX) model, depending on the scenario tested. The RC model is formulated using stochastic differential equations where the unknown physical parameters are estimated using the maximum likelihood estimation. ARX models are a type of dynamic linear regression models and describe the input effects u(t) on the output y(t). Time lags are used to describe the effect of inputs to the output value.

A quadratic cost function, given in equation 1, is defined for the predictive controller. The aim of this cost function is to minimize the energy use for both the fans and heating coils with respect to the (thermal) comfort. This cost function includes terms for room CO₂ (zCO₂) and room temperature (zT) violations as well as the electric energy use for the fans (Q\textsubscript{elec}) and thermal energy used to heat the air (Q\textsubscript{vent}). The cost function is active for all steps (k) in the prediction horizon (Hp). The slack variables $z_{CO_2}$ and $z_T$ are used for the comfort constraints to penalize set point violations and to avoid using hard constraints. For the room operative temperature a lower, and upper bound were defined, where for CO₂ concentration the set point was set at 1000 ppm. For each cost function parameter a weight factor is used. These weight factors have been determined using a Pareto front to obtain the Pareto optimal solution for this cost function.

$$\text{Min} \sum_{k=0}^{Hp} (z_{CO_2})^2 + (z_T)^2 + (Q_{elec})^2 + (Q_{vent})^2 \quad (1)$$

Subject to:

- $CO_{2\text{room}} \leq 1000 \, \text{ppm} + z_{CO_2}$
- $\text{Airflow} \geq 0 \, \text{m}^3/\text{h} \quad (18:00-7:30 \text{h})$
- $\text{Airflow} \geq 400 \, \text{m}^3/\text{h} \quad (7:30-18:00 \text{h})$
- $\text{Airflow} \leq 2200 \, \text{m}^3/\text{h}$
- $z_{CO_2} \geq 0$
- $T_{room} \geq 16^\circ \text{C} - z_T \quad (18:00-7:30 \text{h})$
- $T_{room} \geq T_{heating-z} \quad (7:30-18:00 \text{h})$
- $T_{room} \leq 26^\circ \text{C} + z_T$
- $z_T \geq 0$
- $-6 \, \text{kW} \leq Q_{vent} \leq 12 \, \text{kW}$
- $T_{supply} \geq 16^\circ \text{C}$
- $T_{supply} \leq 45^\circ \text{C}$

To solve the optimization problem, two approaches were used since the basis of the predictive controller was either an RC or an ARX model. The RC-MPC used the JModelica.org platform (Åkesson et al. (2010)) to solve the non-linear optimization problem. In the RC-MPC the two actuated parameters (i.e. mass flow rate and supply air temperature) were solved directly in the optimization problem. Therefore, a non-linear solver was used, since the optimization includes the product of these two controlled variables. In addition, the RC model includes an unmeasured state, the thermal mass temperature. This unmeasured state was estimated using an Unscented Kalman Filter (UKF). The prediction of this unmeasured state was corrected based on measurements of the room temperature. The ARX-MPC used a linear solver, CVXpy (Diamond and Boyd (2016)). In the ARX predictive controller, the thermal ventilation energy was obtained directly after the optimization, therefore a linear approach could be used. Post-processing was needed to obtain the mass flow rate, and the supply air temperature from the thermal ventilation energy. More detailed information about this used approach for the ARX-MPC can be found in Merema et al. (2019b).

In the last step of the MPC framework, the optimized control output was used to control the ventilation system set points by using the BACnet interface of the Air handling unit (AHU). To control the airflow rate, the VAV damper position was set according to
the optimized signal. For the supply air temperature, the set point was set for each controlled zone. Every 15 minutes, the previously described three steps were repeated. The forecasts of the disturbances and the constraints are updated and passed to the predictive controller to obtain the next control input trajectory.

**Co-simulation approach**

To evaluate different developed control strategies under similar conditions a co-simulation approach is used. The co-simulation couples the emulator model of the building with the MPC framework. Figure 4 illustrates the workflow used for co-simulation that is repeated for each time step in the evaluated period. In Dymola, a functional mock-up unit (FMU) is created of the verified model of the case study building (Merema et al. (2021)). The FMU includes both the building and the HVAC system. The generated FMU is used in a functional mock-up interface (FMI), that is a standardized interface used for model exchange and co-simulation, to couple the MPC framework with the virtual building. To perform co-simulations, the MPC framework, written in Python, and the model of the building, created using the Modelica language and converted to a FMU, can be coupled in a FMI by using PyFMI.

**Design of experiments**

The experiments aim to assess and compare the MPC performance of the two different identified models (RC and ARX) by using the co-simulation environment. In total, four scenarios are evaluated: ARX-MPC measured, ARX-MPC simulated, RC-MPC simulated and RBC simulated. The measured ARX-MPC is used to verify the co-simulation results for the ARX-MPC. The ARX-MPC measured here is the actual measurement result of the real time implementation for the ARX-MPC in the case study building. The time step used in all MPC scenarios for control is 15 minutes with a prediction horizon of 2 hours (i.e. 8 steps of 15 minutes). The evaluated period is 9-13 March 2020. The results of the measured disturbances are shown in Figure 5. In this period, the outdoor temperature varies between 5.8 °C and 14.1 °C. The occupancy counted is at minimum 10 and at maximum 49 persons.

![Figure 4: The co-simulation couples the MPC framework and emulator model of the test building through the functional mock-up interface (PyFMI).](image)

![Figure 5: Weather and indoor disturbances: outdoor temperature, global horizontal irradiation and occupancy counting](image)
Evaluation of performance

Performance of MPC is assessed by comfort criteria as well as energy saving potential. Three performance indicators are used to analyze the comfort in the zone; thermal discomfort hours [K*h], CO\textsubscript{2} discomfort hours [ppm*h], and the room temperature cycle [T\textsubscript{cycle}] at each time step, where a change above 1.1 °C is regarded as uncomfortable ASHRAE (2013). To evaluate the energy saving potential, both the electric fan energy use and the thermal heating energy use for the heating coil are analyzed. MPC is compared to RBC, which is defined as an occupancy based control. It is assumed that the occupancy schedule is known for the observed room. Based on the occupancy status of the room, the room temperature heating set point is adjusted, 20 °C for unoccupied and 22 °C for occupied.

Results

Verification

First, the simulated ARX-MPC results are verified with the measurement data to evaluate the performance of the MPC strategy in a co-simulation framework. This involves comparing the simulated ARX-MPC to the implemented control in the real building. The operation of the ventilation system during the observed period is shown on Figure 6. This figure depicts the room temperature, supply air temperature, CO\textsubscript{2} concentration in the room, and the supply airflow rate. For the room temperature, it is observed that both the measured and simulated ARX-MPC show a similar profile with maximum differences up to 1.3 °C. The simulated supply air temperature overestimates the temperature in the morning up to 5 °C compared to the measurements. For the room CO\textsubscript{2} concentration, a high discrepancy between the simulated and measured results is observed on the first day. Here, the difference between simulated and measured result is up to 600 ppm for a short time period of 15 minutes. This might be explained by the higher supply airflow rate in simulations compared to the measurements. In general, it can be concluded that most operational parameters of the ventilation system show a good agreement between the simulated and measured ARX-MPC.

Comparison MPC scenarios

In the second step, the operation of all the simulated scenarios are compared. Figure 7 illustrates the operation of the all-air system during all simulated scenarios for respectively the ARX-MPC, RC-MPC, and RBC scenario. In the top graph, the room temperature is shown for all three scenarios. Here it is noticed that for the MPC scenarios, the room temperature increases earlier compared to the RBC. For example, on the third day in the morning, it is noticed that in the RBC scenario, the room temperature remains around 20 °C, i.e. the heating set point during no occupancy. In contrast, in the MPC scenarios, the room temperature already increases up to approximately 22 °C to meet the set point prior to the start of a lecture. Some differences are also noticed for the room CO\textsubscript{2} concentration between the simulated scenarios during the second day. The RBC scenario maintains the CO\textsubscript{2} levels below the set point of 1000 ppm while for the ARX-MPC controlled scenario the CO\textsubscript{2} levels increases to a maximum of 1500 ppm for a few minutes. From experience, the ARX-MPC is known to have more problems regarding uncertainty in occupancy forecasts and the effect of this uncertainty on the CO\textsubscript{2} predictions. As the ARX model fits coefficients that rely on accurate measurement data and can be easily over fitted, whereas the RC model for CO\textsubscript{2} is the mass balance of CO\textsubscript{2} that includes physical parameters.

To analyze the performance regarding the comfort, table 2 indicates the comfort indicators evaluated for each scenario. In addition, the measured results have been added. It can be concluded that the RBC causes the most thermal discomfort, where the MPC scenarios decreases the thermal discomfort significantly. For CO\textsubscript{2} discomfort it is observed that

![Figure 6: Verification of the simulated compared to the implemented ARX-MPC for the all-air system.](image_url)
Figure 7: Operation of the AHU in case of the predictive control scenarios and the rule based control (RBC).

The RBC indicates a better performance compared to the two simulated MPC scenarios, although the difference is at maximum 240 ppm*h. This is caused by the high CO$_2$ concentration observed for both MPC scenarios on the 10th of March. Furthermore, it is indicated that in the measured ARX-MPC scenario, the results for CO$_2$ discomfort are 327 ppm*h lower compared to the simulated scenario of ARX-MPC. An explanation could be that in the real building the door is opened in between classes allowing to mix the air with the adjacent staircase.

Table 2: Comparison of achieved comfort between control scenarios simulated (sim) and measured (real)

<table>
<thead>
<tr>
<th></th>
<th>MPC ARX real</th>
<th>RBC sim</th>
<th>MPC RC sim</th>
<th>MPC ARX sim</th>
</tr>
</thead>
<tbody>
<tr>
<td>Too cold [K]</td>
<td>4.0</td>
<td>11.0</td>
<td>3.2</td>
<td>5.8</td>
</tr>
<tr>
<td>CO$_2$ [ppm*h]</td>
<td>1290</td>
<td>1460</td>
<td>1705</td>
<td>1617</td>
</tr>
<tr>
<td>$T_{cycle}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Finally, table 3 summarizes the aggregated energy use for the heating coil and fans during the evaluated period. In general, it is noticed that the differences in energy use between the measured and simulated ARX-MPC are relatively small. For the fans, the simulated energy use is overestimated by 0.6 kWh, while for the heating coil it is underestimated by 0.8 kWh. Furthermore, both the RC-MPC and the ARX-MPC show an energy saving potential when compared to the RBC scenario. Respectively 22% for the thermal energy use for the heating coils and 36% for the electric energy use of the fans.

Table 3: Aggregated energy use for the heating coil and fans.

<table>
<thead>
<tr>
<th>Energy use</th>
<th>ARX-MPC real</th>
<th>RBC sim</th>
<th>RC-MPC sim</th>
<th>ARX-MPC sim</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fans [kWh]</td>
<td>12.6</td>
<td>19.8</td>
<td>12.5</td>
<td>13.1</td>
</tr>
<tr>
<td>Heating [kWh]</td>
<td>65.0</td>
<td>82.3</td>
<td>63.9</td>
<td>64.2</td>
</tr>
</tbody>
</table>

Conclusion

In this study, a co-simulation framework was developed to evaluate the performance of different predictive control strategies under similar conditions. The verification for the ARX-MPC controlled scenario indicated that the co-simulation results are in a good agreement with the results measured for the all-air system in the case study building. Both MPC controlled scenarios indicate an energy saving potential, of respectively 22% for the heating coils and 36% for the fans, while maintaining or even improving the comfort compared to an RBC scenario in this case study.

The difference between the two used identified models, respectively ARX and RC, for the MPC framework is relatively small, indicating that both models are capable to generate accurate predictions for room CO$_2$ concentration and room temperature. However, the ARX model is a much simpler model and required less time to identify. In addition, the ARX model is a purely data-driven model whereas the RC is a combination between a physical model and a data-driven model. Furthermore, the RC model requires more computation time as the ARX model, since the RC-MPC used a nonlinear solver while the ARX-MPC used a linear solver. The complete run time for the MPC framework was 10 seconds for every control time step. Most time is used to request data from the weather forecast API. The optimization process and running the ARX model is executed in a small fraction of time ($\approx$0.05 seconds, 400 iterations). For the RC model more time is lost in compiling, loading and initializing the model (2 seconds), while the optimization time is approximately 0.1 seconds (500 iterations). All these factors combined indicate that for real application the
ARX-MPC is recommended over the RC-MPC.

References


