Development of a Modelica building emulator for model predictive control applications

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Abstract

An accurate emulator model is essential for implementation of model predictive control (MPC), a promising approach applied in building management systems to facilitate energy-efficient operation without sacrificing comfort. In this paper, a simplified one-zone emulator model has been developed to mimic thermal behavior of a Danish university teaching building to be applied in the MPC toolchain BOBTEST (IBPSA project 1, WP1.2 (Blum et al. 2019)). The model has been calibrated and realistic occupancy was introduced based on data measured by various meters installed around the building. Simulation and sensitivity analysis performed on the selected parts of the heating system have helped to improve the emulator implementation and make it BOBTEST-ready. Results indicate that (1) calculations with idealistic controller schedule including the "natural" version of the night setback accepted in office buildings suggests that the model is physically realistic, (2) PID controller setup highly impacts simulation time of the emulator. The emulator is open for any test use in GitHub.

Keywords: Building energy modeling, District heating, Emulator model, model predictive control

1 Introduction

Buildings are responsible for approximately 40% of final energy consumption in EU and US (Cao, Dai, and Liu 2016). Advanced control strategies have been proved to enable significant energy savings for reducing operational costs, greater demand flexibility for providing grid services, and improved occupant comfort. Among them, model predictive control (MPC) has received much popularity over the last decade due to its good performance. However, although there are some case studies of implementation of MPC in real buildings (De Coninck and Helsen 2016; Dong and Lam 2014; Huang, Chen, and Hu 2015; Joe and Karava 2019; Prívara et al. 2011; Prívara, Cigler, Váňa, Oldewurtel, and Žáčeková 2013; Sturzenegger et al. 2016), the majority of studies still investigate MPC on virtual test buildings due to the obstacles of transferring this technology from research to real systems (Cigler et al. n.d.). One of the main challenges is the difficulty to obtain an accurate model for capturing building dynamics.

Building model is a crucial component for MPC implementation (Prívara, Cigler, Váňa, Oldewurtel, Sagerschnig, et al. 2013). Modelling approaches can be categorized as three main types, namely white-, grey- and black-box models. Black-box model can reduce effort to build the model, thus increasing applicability of MPC both in commercial and residential buildings while white-box model may demonstrate higher accuracy in a wider range of parameters. No matter what type of model is adopted, it is widely accepted that model complexity highly impacts performance of predicting thermal behaviors (Bacher and Madsen 2011; Berthou et al. 2014), but finding optimal model complexity for MPC remains a non-trivial and time-consuming task. Moreover, it has been rarely reported in literature how accurate and fast a single-zone model can be to emulate a large teaching building driven by occupancy measurements. Hence, this paper addresses this question in a Danish case study by developing a simplified single-zone emulator and investigating its accuracy and, simultaneously, its computational efficiency.

There are some available commercial tools for building energy simulation, such as EnergyPlus and TRNSYS. However, these tools are not as convenient for developing MPC-oriented models. Modelica stands out as it is a flexible, equation-based and objected-oriented modelling language, which reduces effort for model development and increase scalability for MPC implementation. Recently, some Modelica libraries (Buildings, IDEAS, AixLib) developed for building energy simulation have been validated and demonstrated their abilities.

Factors affecting model accuracy and computational efficiency have been investigated after model development. For instance, parameter setup of local controller, such as proportional-integral-derivative (PID) controller, affects significantly emulator's accuracy and MPC overall performance because MPC (supervisory controller) highly relies on PID (local controller) performance (Wang and Ma 2008). Study shows that calibration of proportional coefficients can reduce the energy consumption of a heating, ventilating, and air conditioning (HVAC) system by up to 29% and can improve meeting temperature setpoints by up to 45% (Wemhoff 2012). In order to obtain a model with high fidelity, some researches implemented self-tuning procedures to adapt the PID controller parameters

(Almabrok, Psarakis, and Dounis 2018; Shao, Xiao, and Han 2009; Visek, Mazzrella, and Motta 2014). Moreover, response speed of system is significantly determined by PID controller’s coefficients (Negash Getu, Khaimah, and Al Khaimah 2016). Apart from PID controller, pressure drop impacts system behavior a lot. Nabil et al. investigated the impact of air filter pressure drop on the performance of typical air-conditioning systems and revealed influence of pressure drop on mass flow rate and energy consumption of the system (Nassif 2012). Jorissen et al. highlighted the influence of pressure drop on simulation time of building energy systems (Jorissen, Wetter, and Helsen 2015). In addition, the use of two-way valve and three-way and associated performance are not often compared in building energy system.
To address the points stated above, this paper (1) developed and calibrated a simplified single-zone emulation model for the entire teaching building using Buildings Modelica library; (2) the model was updated to be suitable for BOPTEST; (3) sensitivity analysis was performed based on three aspects: coefficients of PID controller, pressure drop and valve type. Finally, we summarize model development, performance assessment and model improvement regarding model accuracy and computational efficiency resulting from this study.

2 Methodology

2.1 OU44 model

Complying with Danish 2020 standard, OU44 building is a highly energy efficient teaching building at the University of Southern Denmark in Odense(Jradi et al. 2017). The building has a surface area of 8500 m^2 and can accommodate maximum 1350 people. There are 3 above-ground floors containing classrooms (40% of floor area), study zones (25%), offices (15%) and common spaces (20%). There is also a basement level containing main HVAC facilities and the main heat exchanger connected to district heating. The building system consists of mainly two parts:

1. a hydronic heating loop supplying heat to the building. It has two branches: one goes to indoor radiator, the other proceeds to air handling unit preheating supply air to specific temperature set point. A district heating system is providing heat to ensure supply the hydronic heating circuit.
2. a CO_2-driven ventilation system that controls indoor CO_2 concentration to specified level. Mass flow rate of supply air is controlled ensuring that indoor CO_2 concentration does not exceed specific level.

Schematic of the building heating system is illustrated in **Figure 1.** The building is modelled as a single zone using Buildings library in Dymola (**Figure 2**.). Domestic hot water is supplied by separate system which is not included in the model. The model has been calibrated based on measured data which is collected by numerous sensors. The layout of the district heating pipes is not known and therefore some of the parameters were estimated from building energy consumption for this part.

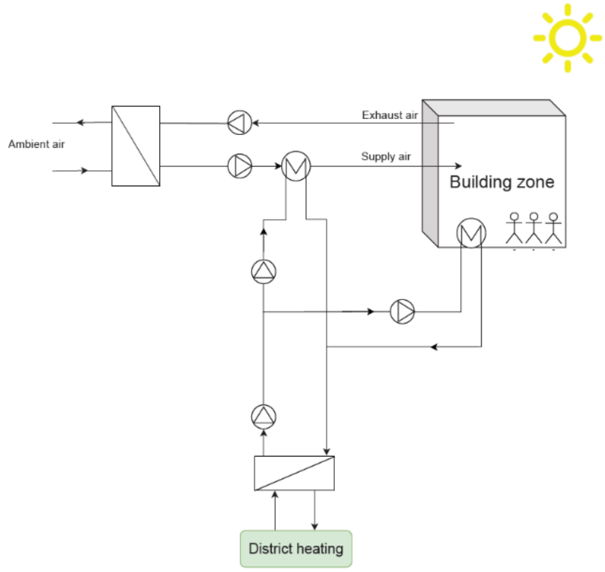

Figure 1. Schematics of OU44 building heating system.

2.1.1 Building envelope

The building thermal envelope is comprised of three different opaque constructions: ground floor, external wall and roof. The interior walls are modeled by a single-layer generic construction representing medium-weight partitions. All the opaque construction layers and thermal characteristics are described on **Table 1**. All windows are modeled using the same construction type, based on a triple-glass window model from Buildings library with the following layers: triple pane, clear glass 3mm, air 12.7mm, clear glass 3mm, air 12.7mm, clear glass 3mm.

2.1.2 HVAC system design

The actual building is equipped with 4 balanced Air Handling Units (AHU) with heat recovery wheels and pre-heating coils (**Figure 3.**) and each room is equipped with radiator heating. A district heating grid is providing heat to meet building energy demand (**Figure 4**.). Two pumps are configured in district heating system. However, only the pump supplying heat water to buildings can be controlled since the other pump in district heating loop is operated by district supplier directly. As the emulator is a single-zone, four AHUs are presented by a single AHU oversized by a factor of 4 and all radiators are lumped with a single radiator. The following description covers the HVAC design as implemented in the model, and not the HVAC system in the actual building. The AHU contains two identical fans, one for supply air and one for extract air. The nominal air volume flow rate capacity is 140000 m^3/h.

Both the radiator and the pre-heating coil in the AHU are connected to the main heat exchanger connected to the district heating grid. The water flow to the radiator and AHU's pre-heating coil is controlled with two 3-way valves. In real building, supply air of ventilation is controlled via adjusting damper position. Additionally, temperature of supply air from ventilation has been controlled to be 21°C. Constant efficiency of heat exchanger in air handling unit and district heating is assumed.

Occupancy: the building is equipped with camera-based sensors that estimate real-time occupant number. Occupancy data is extracted from our internal database and stored in "occ.txt" file in the model. The internal gain per person is 120W and it is evenly distributed over the floor area (i.e. 120 W / 8500 m^2). Occupant interacts with zone climate via generating heat and CO_2, the heat generated per occupant is divided as 40% radiant, 40% convective and 20% latent heat. Since the whole building is modelled as a single zone, a scaling factor for occupant CO_2 generation is introduced to match the energy consumption of fans in AHU, the scaling factor will be estimated and validation in next section of this paper.

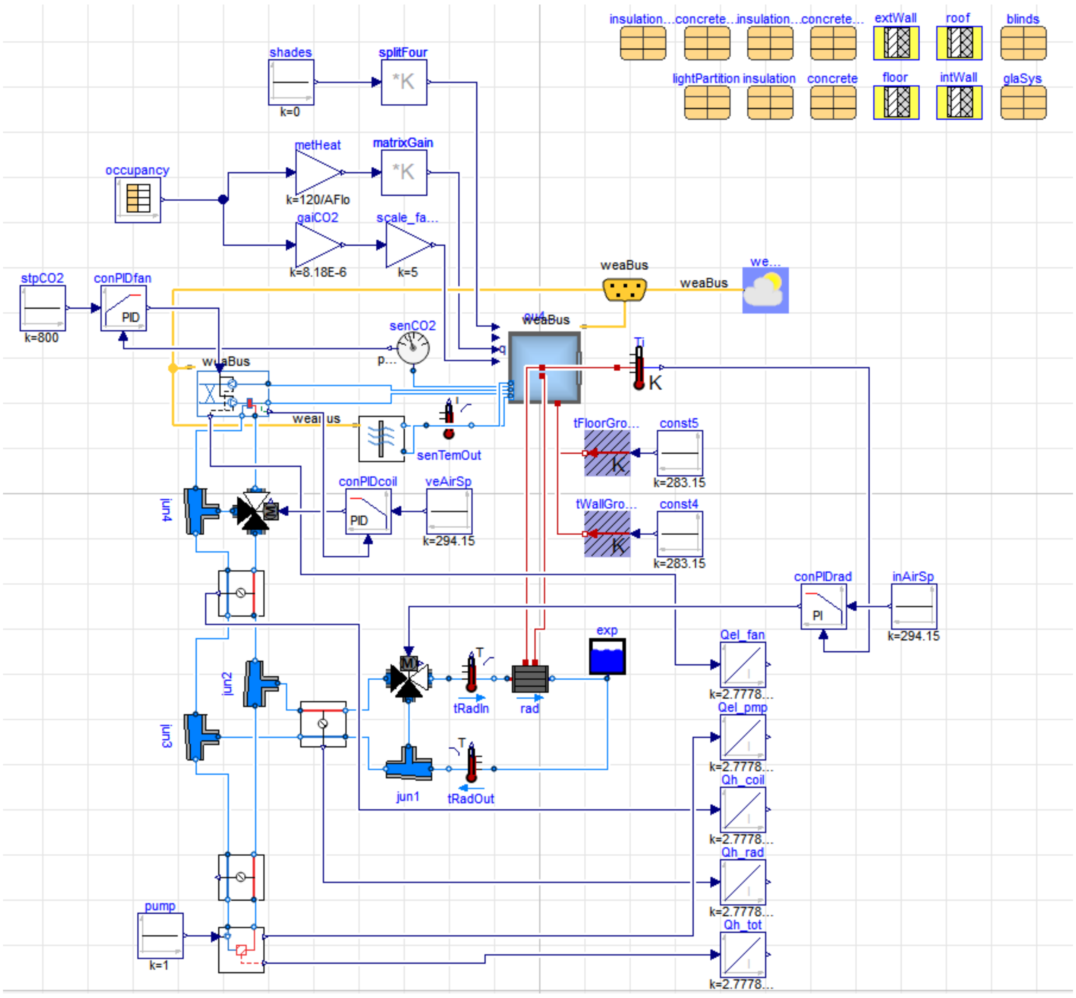

Figure 2. Modelica model of the OU44 teaching building

Table 1. Opaque constructions and their thermal parameters

Construction	Layers	Width [m]	Conductivity [W/(mK)]	Specific heat [J/(kgK)]	Density [g/cm^3]
Floor	Concrete	0.2	1.4	840	2.24
	Insulation	0.15	0.04	1000	0.05
External wall	Concrete	0.2	1.4	840	2.24
	Insulation	0.27	0.04	1000	0.05
Roof	Concrete	0.27	1.4	840	2.24
	Insulation	0.52	0.04	1000	0.05
Interior wall	Generic material	0.15	0.5	1000	0.25

Weather profile: the weather data is based on Copenhagen Typical Meteorological Year.
Ground boundary temperature: constant ground temperature of 10°C is adopted.
Infiltration model: infiltration is assumed to have constant ACH (air changes per hour) of 0.2.
Shading and lighting: shading of windows and lighting are not considered in the zone model.

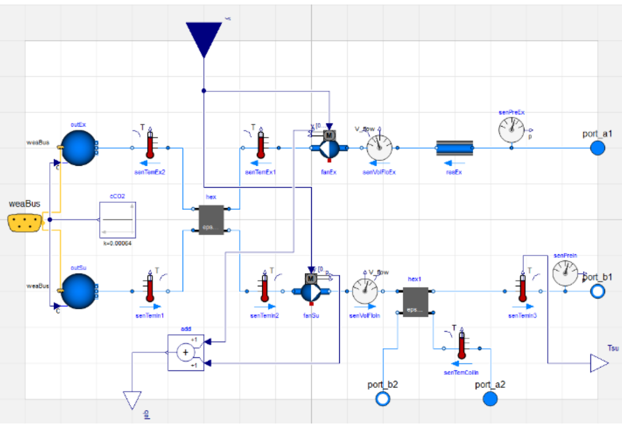

Figure 3. Air handling unit in Dymola.

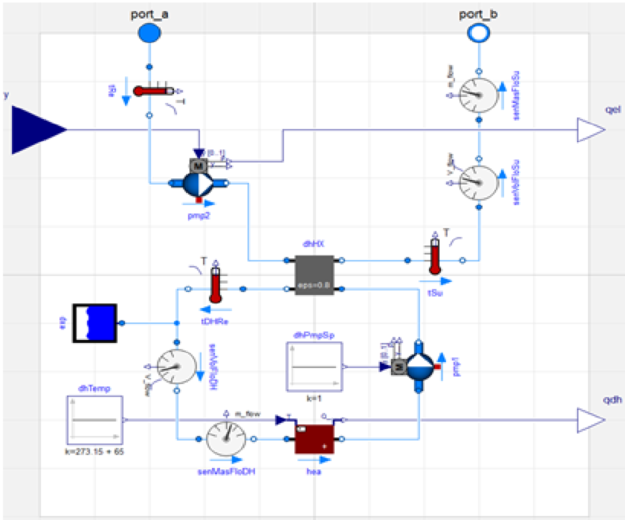

Figure 4. District heating system in Dymola.

2.1.3 Controllers

In order to address the rule-based control logic in the building system, four different low-level controllers are implemented as shown below.
Controller for indoor temperature: a PI controller (K=1, Ti=600) is implemented to control three-way valve in radiation loop based on difference between indoor temperature and the setpoint. The temperature setpoint is 21°C due to that average temperature of the several representative large rooms of the building in January is calculated to be around 21°C, which is shown in **Figure 5.**

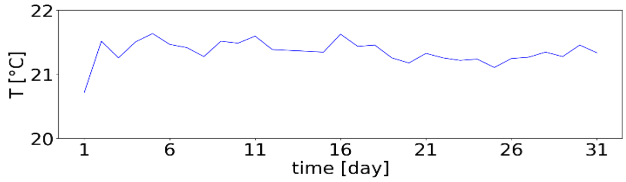

Figure 5. Average indoor temperature of several representative rooms of OU44 in January.

Controller for indoor CO_2 concentration: a PID controller (proportional gain K=0.005, integral time Ti=600, derivative time Td=300) is used to control fan speed in AHU based on indoor CO_2 concentration and CO_2 set point (800 ppm), meaning that fans in AHU will supply fresh air to the zone when indoor CO_2 concentration exceeds 800 ppm.
Controller for ventilation air supply temperature: a PID controller (K=1, Ti=600, Td= 0.1) is applied to ensure constant temperature (21°C) of supply air, three-way valve is controlled based on difference between measured and setpoint of the supply air temperature.
Controller for district heating pump: in the initial model setup, constant control signal of 1 is introduced to district heating pump, indicating that the pump is always running on full power to supply hot water to buildings.

2.1.4 Hydraulic system

There are two pumps in the hydraulic system to support hot water circulation. One is pumping hot water inside district heating loop while the other is moving hot water to building radiator and heating coil. Apart from pumps, two three-way valves are employed to control hot water supply to radiator and heating coil respectively. When temperature is lower than setpoint, the three-way valve will allow hot water flow into coil or radiator, otherwise hot water will proceed to bypass of each valve to avoid overheating. Pressure drops in valves, pumps, junctions, pipes and radiator remains unknown in real building system, the model therefore aggregated all pressure drops in radiator and obtained reasonable lumped pressure drop based on calibration. Pressure drops in other components are ignorable (set to 0 Pa) or empirically assumed.

2.2 Model calibration

Indoor air temperature, CO_2 concentration and energy consumption are the three main metrics adopted in this paper to assess building performance. As a single-zone model emulating the entire teaching building, only one simulated value for temperature and CO_2 is available. However, in practice, temperature is not completely uniformly distributed in the building, besides, not all rooms are equipped with temperature and CO_2 sensors to record measurements. These facts have limited the validation of indoor temperature and CO_2 as compared to measurements. Hence, the objective of model calibration regarding T and CO_2 is to be in reasonable range that can simultaneously reflect thermal dynamic of the building. The calibration methodology of the model only covers matching simulated total energy consumption and electricity consumption of fans in AHU to measurements reference (Jradi et al. 2017). The model is calibrated based on measured data in January. Several factors contribute to the choice of the calibration time period: firstly, the available energy consumption data used for calibration is measured monthly. Secondly, in January, most rooms of the building are heavily occupied due to frequent teaching activities. Besides, the heating demand is higher compared to other months as it is the coldest period of the year. moreover, simulation speed of the model impacts the applicability for MPC in buildings, one-month simulation is therefore conducted to investigate model simulation time needed.

All simulations were performed using Dymola 2019 and Dassl with the default solver tolerance of 1e-4 and a 1.9 GHz i7 processor. One-day simulation test of the model was performed using DASSL integrator to investigate influence of tolerance on simulation time. For tolerance of 1e-2, 1e-4 and 1e-6, simulation time for one-day are 36 s, 76 s and 161s respectively while the total energy consumption under difference tolerance remain unchanged. Therefore, DASSL solver with the default solver tolerance of 1e-4 are applied in all model setup in order to eliminate influence of solver and tolerance on simulation speed.

2.3 Model modification for BOPTEST

The objective of the paper is studying the properties of the numerical model under both “natural” and “artificial” behavior of the building, where the former implies absence of heating and the latter is enforced by the rule-based controlled heating. Building operation under MPC can be thought of as something in between the two behaviors and therefore should benefit from the knowledge of both “natural” and “artificial” properties of the applied system. By this reason, we have chosen the control schedule differently from that in the university teaching building, where the “artificial” daytime heating relies on differently tuned PI/PID controllers, and at night the “off” state is applied similar to night setback (Guo and Nutter 2010; Moon and Han 2011) to give an insight into “natural” dynamics of the building, when it is left with no heating. It is expected that model modification will result in a tailored model setup for BOPTEST.

3 Results and discussion

3.1 Calibration and initial model setup

Since the indoor temperature generally does not fluctuate significantly in practice when considering the size and energy efficiency of the building, the initial model setup is comparatively similar to building realistic operation mode with constant indoor

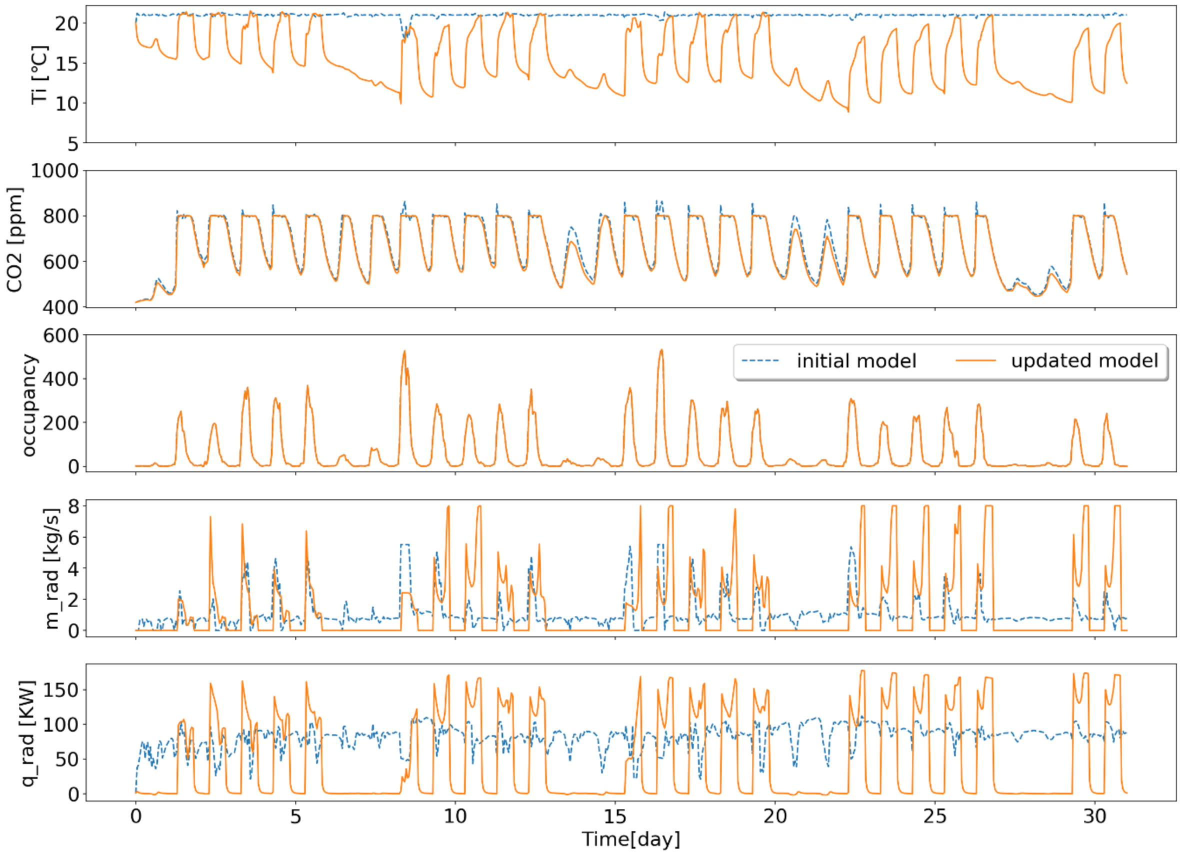

Figure 6. Comparison of simulation results for initial and updated model setup.

Table 2. Influence of PI controllers' parameter on simulation time

	PI fan		PI coil		PI radiator		Simulation time (S)
Parameter	K	Ti	K	Ti	K	Ti	
Base scenario	0.05	600	0.001	600	0.1	600	370
Case 1	0.5						828
Case 2		200					359
Case 3			0.01				362
Case 4				200			962
Case 5					0.01		395
Case 6						200	856

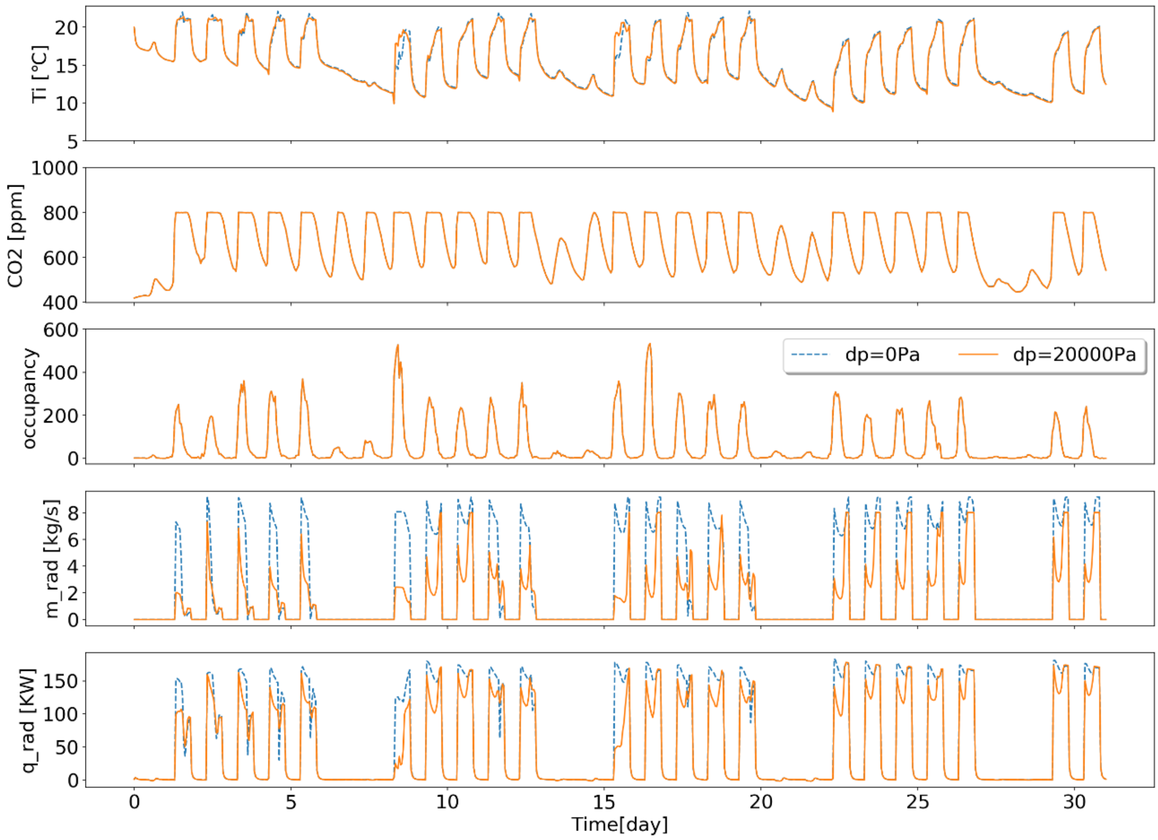

Figure 7. Comparison of simulation results for different radiator pressure drops.

temperature setpoint 21°C. Model is calibrated under the mentioned initial model setup.

Most pressure drops in the model were not known for the building and were initially either ignored or set empirically. Consequently, the radiator pressure drop is calibrated to the value of 20000Pa by matching simulated total heating consumption (69MWh) to measured data (70MWh). Moreover, the scaling factor for occupant CO_2 generation is calibrated via fitting simulated fans' electricity consumption (1.3MWh) to measured data (2MWh), obtaining a scaling factor of 4. The simulation takes around 17 minutes and simulation results are shown in **Figure 6 (blue curve*)***. The subplots from top to bottom refer to indoor temperature, CO_2 concentration, occupant number, mass flow rate of radiator and heating supplied by radiator. Some peaks of CO_2 concentration exceed 800ppm even under PID controller due to that the parameter in fan's PID controller is not set efficiently. In particular, the proportional coefficient (K) is too small. The indoor temperature can be almost maintained at 21°C, which is consistent with realistic indoor temperature, indicating the good ability of PI controller to regulate indoor temperature. However, the constant indoor temperature setpoint is achieved by continuous heat supply as shown in subplots of radiator mass flow rate and heating power. The big drop of temperature at some points is due to that high occupancy leads to more ventilation supply air and the supply air may be lower than 21°C.

3.2 Tailored model setup for BOPTEST

The initial model setup complies with the realistic operation scheme of the building and controllers can maintain indoor temperature to be 21°C and CO_2 concentration to be lower than 800 ppm.

However, the simulation time is around 17 min for one-month simulation, which is quite long and increases

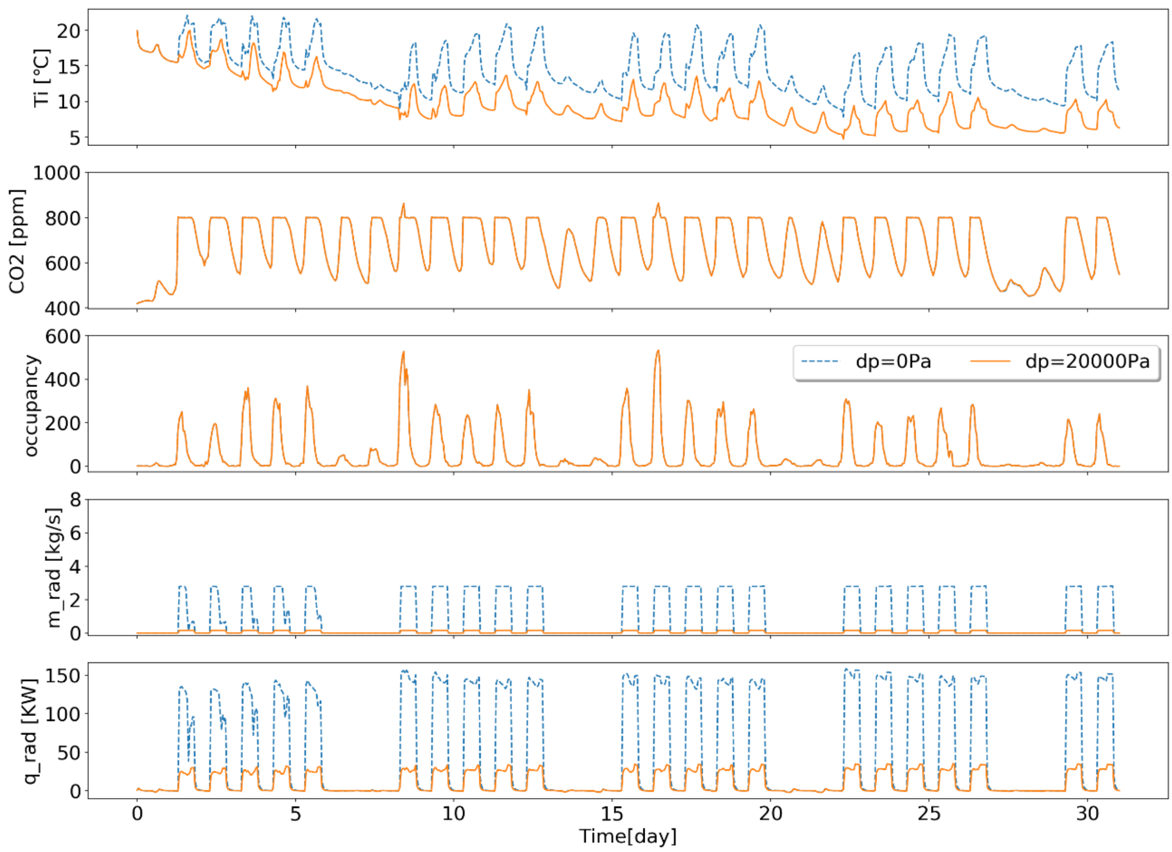

Figure 8. Simulation results for two-way valve in radiator water circuit.

difficulty of implementing model predictive controller. Besides, MPC is exploiting the use of thermal inertia of the building to reduce energy consumption without sacrificing indoor thermal comfort. Stable indoor temperature under initial model setup will question the potential benefits of applying MPC in the building.

In order to check building thermal dynamics as well as specially tailoring the initial model for BOPTEST, updated model setup is done by introducing a varying temperature setpoint to demonstrate building thermal dynamics and thermal inertia, which, as a result, justify the meaning and advantage of using MPC. Additionally, the fact that the district heating pump runs with full power all the time is unrealistic. To address these issues and tailor the model specifically for BOPTEST, the model was updated with a new setup: 1) PI controller for fan (K=0.05, Ti=600), PI controller for coil (K=0.001, Ti=600) and PI controller for radiator (K=0.1, Ti=600); 2) indoor temperature is only regulated to be 21°C from 7am to 19 pm, radiator does not supply heat during night and weekends; 3) the radiator's control signal is used as the control signal for controller on district heating pump.

All these updates result in faster simulation of 6.4 minutes, reducing simulation time by 62%. Based on results **Figure 6 (orange curve)**, we can see indoor temperature are satisfied during occupied period, building will cool down passively during night and weekends, which complies with many studies in literature. Total heating energy consumption is reduced based on this improvement. Also, radiator mass flow rate during night has decreased as compared to results of initial model setup, which again indicates less energy consumption. The updated model is physically realistic, but not entirely representative for OU44.

3.3 Influence of parameters in PI controllers

MPC-based optimal control benefits from faster computational efficiency of the emulator. Therefore, a sensitivity study of the influence of the PI controllers' parameters on simulation time has been investigated. **Table 2.** shows how simulation time differs from base scenario when varying only one specific parameter in each PI controllers. The base scenario is the tailored model setup as described in section 3.2. Simulation results show that case 4 yields longest simulation time (962s) corresponding to the reduced Ti (integral time) value in coil's PI controller. Shortest simulation (359s) time is achieved in case 2 via reducing Ti parameter value in fan's PI controller. It should be noted that increase of K value for fan's PI controller, decrease of Ti value for both coil's and radiator's PI controller results in long simulation time. Conversely, lower Ti value for fan's controller, higher K value for coil's controller and lower K value for radiator's controller lead to fast simulation speed. It can be concluded that setting proper coefficients in PI controllers lead to faster simulation. This can be explained by improving tuning of PI controller reducing the oscillatory behavior of the system. These oscillations may be tracked by a variable time step integrator, resulting in increase of simulation time (Jorissen et al. 2015). The investigation on different scenarios indicate that low-level PID controller's performance directly impact simulation speed of the model. However, tuning of most suitable parameters for local PID controllers remains troublesome, implementing self-tuning procedure is deemed to be one of the potential solutions that facilitate fast and efficient parameter modification.

3.4 Influence of pressure drop in radiator

As stated in section 3.1, pressure drop in radiator is calibrated, it is meaningful to investigate how this value influences the simulation results. In this case, the nominal pressure drop dp_nominal in the radiator has been changed from 20000Pa to 0Pa. Other parameters remained the same. Results in **Figure 7**. shows that dp_nominal have an influence mainly on radiator mass flow rate. When dp_nominal increases, mass flow rate and heating energy consumption decreases accordingly. Pressure drop of radiator has shown almost no influence on indoor temperature and CO_2 concentration. However, changing pressure drop can vary heating energy consumption to match measured data. Therefore, pressure drop can be used as a free parameter to calibrate the model. Moreover, Simulation time in this setup is 6.2 minutes, indicating that change in dp_nominal does not change simulation time considerably as compared to previous simulation time of around 6.4 minutes.

3.5 Influence of valve type in radiator water circuit

Comparison of three-way valve and two-way valve implementation of actuation in radiator water circuit can be important, because it involves active elements, where switching can be a source of events in the simulation and therefore reduce the numerical performance. Results are illustrated in **Figure 8**. If utilizing two-way valve, with high dp_nominal in radiator (20000Pa), the mass flow rate of the radiator will be as low as 0.2kg/s, which is not enough to maintain thermal comfort of the building. Since previous results show that pressure drop has an influence on radiator mass flow rate, the difference of adopting high (20000Pa) and low (0Pa) pressure drop in radiator is subsequently discussed. If dp_nominal is 0Pa, the radiator mass flow can reach around 3kg/s. As a result, indoor temperature is higher and thermal comfort is better during occupied periods as compared to the case of high dp_nominal (20000Pa). However, the performance is still worse than when using three-way-valve in terms of indoor thermal comfort. The indoor temperature difference does not come from varying pressure drop, it owes to the use of two-way valve. Last but not least, two-way valve does not add much value on reducing simulation time as compared to system employing three-way valve.

4 Conclusion

The paper developed a simplified single-zone model to represent a large university teaching building at SDU, Denmark, which ventilation unit is coupled to the local district heating network. Realistic occupancy information and Typical Meteorological Year weather data were provided for simulation. Model was calibrated in January. As the future purpose of the model is an optimized control, sensitivity studies were performed identifying performance bottlenecks and accuracy/performance tradeoffs, when using realistic and imposed conditions to emulate the selected parts of the heating system in the target building. These sensitivity studies include investigating influence of PI controllers' parameter, pressure drop in radiator and valve type in radiator water circuit. Based on obtained results, it can be concluded that:

- A simplified single-zone model is capable of mapping energy consumption of the whole university teaching building and simultaneously demonstrating reasonable indoor temperature and CO_2 concentration.
- Setup of low-level PID controller impacts significantly on performance of model in terms of simulation time.
- Pressure drop of radiator has influence on mass flow rate, subsequently affecting energy consumption of the zone. However, it shows no obvious influence on indoor temperature and CO_2 concentration.
- In our test case, three-way valve outperforms two-way valve for controlling hydronic water circuit and regulating indoor temperature of the zone.

The initial model yields acceptable accuracy as compared to measured data in terms of energy consumption. The tailored model demonstrates building thermal dynamics and achieves relatively short monthly simulation time of 6.4 minutes, making it a suitable emulation model for model predictive control. It is therefore ready for BOPTEST under the scope of IBPSA project 1. The model is open for public use in GitHub(https://github.com/sdu-cfei/ou44-modelica-emulator) and can be served as a case study to compare performance of diverse control strategies in large teaching building, which helps stakeholders for energy-efficient building design, operation and commissioning.

Acknowledgements

This work emerged from the IBPSA Project 1, an international project conducted under the umbrella of the International Building Performance Simulation Association (IBPSA). Project 1 will develop and a BIM/GIS and Modelica Framework for building and community energy system design and operation.

This work is supported by the IBPSA Project 1 CEI - SDU Deltagelse project funded by the Danish Energy Agency under the Energy Technology Development and

Demonstration Program (EUDP Project no. 64018-0518).

The authors thank Valentin Gavan for constructive feedback as IBPSA Project 1 reviewer.

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