Commissioning and control
Commissioning of HVAC systems in a campus building with regard to the indoor environment and energy performance

Chen Zhang, Adam Stoltenberg Iversen, Anda Senberga, Andras Cedl, Liena Krastina, Vilija Matuleviciute, Evangelia Loukou, Mingzhe Liu, Anna Joanna Marszal
Department of Civil Engineering, Aalborg University, Aalborg 9200, Denmark

Abstract

Today’s HVAC systems in the building sector become more and more complex in order to fulfill the increasing standard of the indoor environment, which typically have many components, sub-systems, and controls. Commissioning is a quality-oriented process to verify and document that the performance of buildings and HVAC systems fulfill the defined objectives and criteria. This study demonstrates the commissioning process in a campus building in Denmark. By analyzing the monitored data from BMS and on-site measurements, some fault operations and controls in the HVAC systems are identified, for example, improper setpoint for heating and ventilation, fault location of temperature and CO2 sensors, too high return temperature for district heating, etc. A building simulation model is developed and validated in order to test the optimization strategies and evaluate the energy conservation potential. An energy saving ranges from 20%-42% is realized after the implementation of the optimization strategies.

Introduction

Nowadays, the HVAC systems in the building sector become more and more complex in order to fulfill the increasing standard of the indoor environment. Among building services, the growth of energy consumption by HVAC systems is especially significant, which accounts up to 48% of total building consumption in EU and more than 57% in the USA (Pérez-Lombard et al. 2008). The performance of the HVAC system may deviate from the design requirements due to improper installation, equipment corrosion, sensor drifts, lack of maintenance, or improper control and regulation systems. The commissioning process is a quality-oriented process to verify and document that the performance of buildings and systems fulfill the defined objectives and criteria (Dorgan et al. 2007). Based on the findings by Annex 40 and Annex 47, most faults identified through commissioning occurred in HVAC systems, for example, air-handling systems, heating and chilled water plants (Friedman et al. 2010; Milesi et al. 2018).

Commissioning could be conducted by tend data analysis and functional test to detect and diagnose the faults in the system and further propose a complete solution and correction action. Monitoring-based commissioning (MBCx) is a highly effective and low cost approach to keep building performance in check (Harmer et al. 2015; Brown et al. 2006). By tracking the energy or indoor environment data from building management system, it allows building owners and operators to ensure that building is running based on design requirements. MBCx is commonly coupled with calibrated building simulation models to extend their diagnostic capabilities through the adoption of dynamic and relevant baselines (Harmer et al. 2015). The goal of commissioning is to reduce the cost of building operation and improve the performance of building systems but does not involve large capital investments on equipment (Wang et al. 2013). Many building owners have realized that commissioning is a useful approach for improving building performance during its life cycle.

This study demonstrates the commissioning process in a campus building in Denmark. The aim of commissioning is to evaluate the building performance in term of indoor environment and energy use, and seek for possible improvements and alternations to the control and operation of the HVAC systems that could benefit the building owners as well as the occupants. The main focus of system analysis is ventilation and heating. The commissioning activities include system observation, monitoring data analysis, and on-site measurements. The collected information and data from the above activities are used to develop a building simulation model and a dynamic simulation software BSim is applied in this study. The validated model can be used as a reference model for on-going commissioning to test the optimization strategies and evaluate the energy conservation potential.

Building and systems description

The building located in Aalborg, Denmark was constructed in 2015 and started to operate in April 2016. The function is office facilities with associated meeting rooms, group rooms, lunchroom and auditorium. The building has two floors and the total floor area is 3198 m². The building is designed so that most of the working rooms, including offices, and meeting rooms, are located towards the external side of the building and the others have windows toward the three centrally located atriums in the building, in order to benefit from the daylight, as it can also be seen in Figure 1. The physic characteristics of building envelopes are listed in Table 1. It is clear to see that the envelopes are designed to fulfill the Danish building regulation BR15 (The Danish Ministry of Economic and Business Affairs 2015).
Table 1: Physical characteristics of building envelop.

<table>
<thead>
<tr>
<th>Building envelop</th>
<th>BR15 U-value [W/m².K]</th>
<th>Case building</th>
</tr>
</thead>
<tbody>
<tr>
<td>Terrain slab</td>
<td>0.15</td>
<td>0.07</td>
</tr>
<tr>
<td>External wall</td>
<td>0.15</td>
<td>0.12</td>
</tr>
<tr>
<td>Roof</td>
<td>0.1</td>
<td>0.08</td>
</tr>
<tr>
<td>Windows</td>
<td>1.4</td>
<td>0.8</td>
</tr>
<tr>
<td>Infiltration @50 Pa [l/s.m²]</td>
<td>1</td>
<td>0.6</td>
</tr>
</tbody>
</table>

A building management system (BMS) is implemented in this building to control and monitors the building HVAC system and lighting, window opening. It manages the data inputs from sensors, performs calculations according to predefined strategies, and practices control over components and parts of the system, e.g., fans, valves, pumps. Figure 1 shows the four different room types regarding control and sensor types. The available information from the BMS is different for these rooms in relation to heating, ventilation, and lighting. The control strategies in different rooms are explained in Table 2.

The building has three ventilation systems installed. VE01 and VE02 are centralized air handling units (AHU) located in the technical room. As shown in Figure 2, the supply section consists of on-off damper, filter, rotary heat exchanger, heating coil and supply air fan, in the end, there is a heating coil, while, the exhaust section consists of: exhaust fan, rotary heat exchanger, filter and on-off damper. VE01 is used to ventilate offices and meeting rooms, while VE02 is only used to ventilate auditorium. VU01-4 includes four exhaust systems, which extract polluted air from toilets. The supply air temperature of AHUs varies based on the outdoor temperature. There is no cooling system in this building, therefore, a night cooling function will be activated if the following conditions are fulfilled: Outdoor temperature is 3 °C lower than room temperature; room temperature is higher than 23 °C; outdoor temperature is higher than 10 °C; less than 5 hours to switch to daytime operation mode. Detail description of ventilation systems refer to Table 3.

The heating system in the building is supplied from the district heating terminal. It is divided into two mixing loops, RA01 for the South/ West facing part of the building, and RA02 for the North/ East orientations, see Figure 3. The supply temperature is controlled by a time schedule that controls the set-points. The time schedule has two modes, day operation and night setback. The day operation is active between 04:00 and 22:00 after which the night setback is active. The day operation starts this soon because the system has to heat the rooms before the occupants show up. The temperature of the return water is controlled and kept below 50 °C, the highest value allowed by the BMS is 60 °C. If those limits are violated the alarm goes off and the pump is shut down.

The heating terminals used in the offices and meeting rooms are radiators. While, the primary heating demand in the auditorium is fulfilled by the ventilation system, supplemented by radiators located at the bottom and top levels of the space. The heating demand (flow rate) of radiators are controlled by thermostatic valves.

Figure 1: Building floor plan, control strategies and measured positions. (a) Ground floor; (b) First floor

Figure 2: BMS interface of VE02 AHU system and the control system.

Figure 3: BMS interface of RA01 heating loop and the control system.
Methodology
Monitor-data from BMS system and energy monitoring are used to conduct trend analysis, which is a critical approach in the process of building commissioning to detect fault operation in the HVAC systems. Beside monitor-data analysis, on-site measurement was performed in a period of one month (2.3.2018-2.4.2018). The purpose of the on-site measurement is to investigate the indoor environment in different types of room and to validate BMS monitored data. Three rooms are selected, one office, one meeting room and the auditorium, and Eltek sensors are placed at different locations to measure CO2, temperature and relative humidity, as shown in Figure 1. At the same time, a blower door test was conducted to exam the infiltration rate and the results are shown in Table 1.

The collected information and data from the above activities are used to develop a building simulation model and a dynamic simulation software BSim is applied in this study. The validated model can be used as a reference model for on-going commissioning to test the optimization strategies and evaluate the energy conservation potential.

Results and Discussion
Ventilation systems
The damper position in relation to the indoor CO2 level and temperature level in three different rooms is analyzed here, as illustrated in Figure 5. It is clear to see that damper only operates in on/off model in the office. The damper is controlled by occupancy monitored by PIR sensors, this is explained why the damper has a short turn off period during the lunch hour. There is no CO2 sensor in the office. Eltek sensors measured the CO2 level at two positions, which indicates a good mixing has been reached in the room. However, it also reveals that the constant flow rate is not able to handle the excess CO2 level, where the CO2 reaches approximately 1400 ppm in 16th March.

The damper in the meeting room can operate in three models: 0%, 40% and 100%. The damper will open to 40% when the PIR sensor detected the occupancy. The damper opening will increase to 100% when the CO2 level exceeds the setpoint of 1000 ppm. However, even the damper operated at 100% opening, the CO2 level still exceeded 1000 ppm in 15th and 16th March. In the weekend, the damper was activated in a short period might due to people enter the meeting room. Large deviation up to 2 °C was found between the temperature monitored by Eltek and monitored by BMS sensor. The reason for the large deviation is because the BMS sensor is located next to a big screen, which releases heat and blocks the sensor.

The ventilation system in the auditorium is a VAV system, where the damper can operate from 0% to 100%. The damper opened 1 hour before the booking time and closed 30 min after the booking time. However, the damper closed 2 hours before the booking time finished in 15th March and didn’t open in 16th March even though the auditorium was booked, which led to the CO2 reached 3800 ppm in 16th March. In addition, the monitored data indicates that damper either be off or operated around 90% opening in the observation period. The high damper opening level might due to the high indoor temperature monitored by BMS sensor. The ceiling height of the auditorium is 7.58 m, and the BMS sensor locates on a cabinet at the lower zone. The cabinet is used to store equipment, which has continue heat loads. Therefore, the indoor temperature monitored by the BMS sensor is above the setpoint all the time, which is generally 2 °C higher than the Eltek sensor located at the same height and 4°C higher than the Eltek sensor located in the middle of the auditorium. Another deviation exists at the CO2 level monitored at the exhaust duct by the BMS sensor and Eltek measured in the lower zone and the middle of the room. The ventilation system in the auditorium is a displacement system, where the exhaust CO2 is expected to be higher than the one in the occupied zone. However, high CO2 level up to 3800 ppm was measured in the occupied zone in 15th and 16th but the exhaust CO2 was below 1000 ppm. This might be caused by the ventilation system didn’t run in 16th March, so the polluted air was not extracted through the exhaust duct.

It is surprised to see that the high CO2 level was observed in all three rooms in 15th and 16th March. It might due to the high outdoor CO2 in these two days. However, due to the lack of monitor data on outdoor CO2 level, we cannot make a solid conclusion.

Figure 4 summarizes the monthly CO2 concentration in the breathing zone in three rooms. The box presents 25%-75% of all measured values during the working hours. The average CO2 level in office and meeting room are 620 ppm and 537 ppm. In the auditorium, the CO2 are measured at three locations: lower zone, a middle zone, and an upper zone, where the CO2 level is 608 ppm, 646 ppm and 700 ppm, respectively. The concentration stratification indicates the displacement effect. It can be noticed that CO2 level exceeds 1000 ppm in all three rooms, although it exists in a very short period, which accounts for 4.1%, 3.6% and 6.3% of the total working hours in the office, meeting room and auditorium, respectively.

![Figure 4: Monthly overview of CO2 level in three rooms in the working hours.](image-url)

Rotary heat exchangers are used in the ventilation systems to recover heat from the exhaust air. Based on the Danish regulation, heat recovery efficiency should not less than 85%. The heat recovery efficiency could be
Table 2: Control strategies for different types of room.

<table>
<thead>
<tr>
<th>Room Type</th>
<th>Activation</th>
<th>Damper Opening</th>
<th>CO2 [ppm]</th>
<th>Setpoint for heating [°C]</th>
<th>Setpoint for cooling (venting) [°C]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Offices</td>
<td>PIR</td>
<td>0% /100%</td>
<td>NA</td>
<td>23</td>
<td>23</td>
</tr>
<tr>
<td>Meeting room</td>
<td>PIR</td>
<td>0%/40%/100%</td>
<td>1000</td>
<td>22.5</td>
<td>23.5</td>
</tr>
<tr>
<td>Auditorium</td>
<td>Booking</td>
<td>0%-100%</td>
<td>900</td>
<td>24</td>
<td>24</td>
</tr>
</tbody>
</table>

Table 3: Description of ventilation systems.

<table>
<thead>
<tr>
<th>Ventilation unit</th>
<th>VE01</th>
<th>VE02</th>
<th>VU01-4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Function</td>
<td>Supply&amp;Exhaust</td>
<td>Supply&amp;Exhaust</td>
<td>Extraction</td>
</tr>
<tr>
<td>Target area</td>
<td>Office, meeting room</td>
<td>Auditorium</td>
<td>Toilet</td>
</tr>
<tr>
<td>Type</td>
<td>Centralized</td>
<td>Centralized</td>
<td>Decentralized</td>
</tr>
<tr>
<td>Control</td>
<td>VAV</td>
<td>VAV</td>
<td>CAV</td>
</tr>
<tr>
<td>Max airflow rate [m³/h]</td>
<td>10800</td>
<td>5700</td>
<td>468</td>
</tr>
<tr>
<td>Heat recovery</td>
<td>Rotary heat exchanger</td>
<td>Rotary heat exchanger</td>
<td>Non</td>
</tr>
<tr>
<td>Distribution principle</td>
<td>Mixing</td>
<td>Displacement</td>
<td>Extraction only</td>
</tr>
</tbody>
</table>

Figure 5: Operation of ventilation system in three rooms (week 11: 12-18 March 2018) and the comparison of measured and monitored indoor environment. (a) Office; (b) Meeting room; (c) Auditorium
calculated based on the monitored temperatures from the BMS system. The average heat recovery efficiency of VE01 and VE02 are 77% and 81%, respectively, which are slightly lower heat recovery efficiency than that required in the BR15.

**Heating system**

The operation of the heating system is analyzed in three rooms, as shown in Figure 6. The valve opening of radiators adjusts according to the temperature sensor connected to the BMS system. If the temperature is lower than set-point (shown in Table 2), the valve will be turned on.

In the office, the valve turns on at 4:00 am to preheat the room before occupants show up. It turns on again in the working hours if the temperature monitored by the BMS sensor is below the setpoint of 23 oC. The temperature in the occupied zone was measured by Eltek sensor at 1.1 m height and compared with the values from the BMS sensor. The deviation is less than 0.5 oC in the weekday but above 3 oC at the weekend. It is surprising to see that the radiator operates in the same way in the weekend, which results the indoor temperature is even higher in the weekend than the weekdays and it wastes of heating energy.

In the meeting room, the valve turns on between 4:00 am to 6:00 am to preheat the room. The valve turns on again in the working hours if the temperature monitored by the BMS sensor is below the setpoint of 22.5 oC. However, the large deviation is observed between the temperature in the occupied zone measured by Eltek with the BMS sensor located on the wall and the temperature difference is above 2 oC. Therefore, the indoor temperature in the occupied zone ranges from 20 oC to 23 oC in the working hours, and from the survey we observe many occupants complained about the low indoor temperature.

In the auditorium, the valve only activates during the booking time and BMS temperature is below the setpoint of 24 oC. However, due to the wrong location of BMS sensor as described in the section above, the actual indoor temperature in the occupied zone is much lower, especially in the first several hours the temperature is even below 21 oC.

The energy efficiency of the heating system is analyzed by observing the supply and return water temperature in the mixing loops. The monitored data from BMS shows the supply temperature between 60-70 oC in RA01 most of the time, accounting to 71% of the measuring period. While, the supply temperature is relatively higher in RA02 loops, 64% of the time between 65-75 oC.

**Figure 6:** Operation of the heating system in three rooms (week 11: 12-18 March 2018) and the comparison of measured and monitored temperature. (a) Office; (b) Meeting room; (c) Auditorium
As stated in the design of the control strategy, the return temperature should be kept below 50 °C. However, RA01 has return temperature above 50 °C 33% of the measured period, while RA02 has 9%. The high return temperature might due to inefficient valve control in the radiator, where the flow rate is too high and the hot water returns back to the loop before releasing sufficient heat. Both of the mixing loops connect to the district heating system and return the water to the grid. In Denmark, the district heating dimensioning temperature is 40 °C for return. The monitored data from BMS shows that studied building had return temperature above 40 °C 77% of the measured period. It is important to control the return temperature in order to use the heat properly before sending it back to the grid as high return temperatures have an economic consequence.

**Energy performance**

Figure 7 shows the building energy consumption from Jan to Nov 2018 in term of electricity and heating. The main consumers of electricity in the building include ventilation systems, lighting, appliances and auxiliary equipment. There is no detail data available on the lighting and applications consumptions, therefore, we divide it into ventilation systems and the others. There is no large variation in electricity consumption during the whole year, where the average monthly consumption is 17 MWh. However, a clear seasonal variation on the electricity consumed by ventilation systems can be seen in Figure 7 (a). It accounts for up to 23% of total electricity consumption during the summer season and reduces to 6% in the winter season. The high electricity usage in summer is because ventilation is used to prevent overheating and the ventilation flow rate is much higher than the one used for maintaining the CO2 level. On the other hand, the lower artificial lighting usage in summer results in no large difference in the overall electricity consumption during the year. The heating consumption is shown in Figure 7 (b), which cover space heating, domestic hot water and heat coil in the ventilation systems. Heating demand has a remarkable seasonal variation, which is about 2.5 MWh in June and 43.8 MWh in February. Due to the lack of data in Dec, the total heating demand in 2018 until Nov is 203.4 MWh and the value for electricity is 203.8 MWh.

**Simulation and Optimization**

A dynamic model is developed in BSim to analyze the building performance in term of indoor environment and energy use, and further use to investigate the impact of several optimization strategies on the overall energy performance. Three rooms (office, meeting room and auditorium) are chosen for the simulation to represent the whole building, as shown in Figure 8. The weather file is developed based on the data logged by the weather station near the case building. Each room is represented by a thermal zone which is able to have individual input on the people and equipment load, time schedule and controls for HAVC system. The input values are defined according to the measured data or the monitored data from BMS in order to represent the building system and operation characteristics to a large extent. However, there several uncertain parameters might lead to the deviation between model and real building performance. For example, the real occupant number and occupied hour might differ from the design values; lack of information on lighting and appliance usage; the model assumes a good mixing in the room lead to a uniform temperature and CO2 level in all positions, etc. To calibrate the model, an iterative process takes place, as explained in Figure 9.

In order to validate the model, the correlation between the on-site measured and simulated temperature and CO2 level are investigated in three rooms. As an example, Figure 10 shows the results in the auditorium in week 10. It is clear to see a good agreement has been reached between the measured and simulated values. The temperature deviation is less than 1 °C in the whole week.
with mean absolute percentage error (MAPE) of 1.12%. The CO2 values correspond well in the weekday, a large deviation of approximately 200 ppm occurs in the weekend, due to the unexpected occupancy. The MAPE of CO2 is 5.87% during the whole validation period. Because the detail energy consumption in the room level is not available, no comparison between the monitored value and simulated value presents here. The accuracy of the model is acceptable and will further use to simulate optimization strategies.

The potential energy saving strategies identified through the commissioning process are summarized below, and their impacts on energy performance are evaluated using the validated model.

1. Adjust heating setpoint: The existing control system indicates that the temperature setpoint for heating and cooling (ventilation) has the same value in office and auditorium, which results in unnecessary energy consumption on heating and ventilation systems to maintain constant indoor temperature. On the other hand, the setpoint temperature for heating is too high and it is suggested to reduce the value to 22 °C in all the rooms.

2. Adjust heating schedule: As shown in Figure 6, the heating system run with the same setpoint in the weekend in the office and meeting room. It suggests lowering the setpoint in the weekend to 20 °C (meeting and office).

3. Adjust ventilation setpoint: The function of the ventilation system is both provide acceptable indoor air quality (controlled by CO2 sensor) and avoid overheating (controlled by a temperature sensor). The setpoint for CO2 is based on EN15251 Category II that less than 500 ppm above outdoor level. However, the comfort temperature in summer season is 23-26 °C. The setpoint temperature for ventilation (cooling) set up as the lowest valve, which leads to unnecessary energy waste. It suggests increasing the setpoint for ventilation to 25 °C in the meeting room and auditorium.

4. Increase heat recovery efficiency: The monitor data shows the heat exchangers do not achieve the optimal efficiency as required in the BR15. It is interesting to find out how much energy could be saved by increasing the heat recovery efficiency to even 85% (class 2020).

Figure 10 summarizes the energy saving potentials by implementing different optimization strategies. It needs to notice only heating demand (space heating and heating coil) and fan power are analyzed here, due to the limitation of the numerical model and lack of detail information on the electricity consumption on other components. As expected, strategy 1 and strategy 2 have a significant impact on the space heating demand in all three rooms, especially in the office the space heating demand decrease from 62 kWh/m².yr to 34 kWh/m².yr, which reduce 45% heating demand. Strategy 3 has a marginal impact on the energy consumption of the fan. It reduces from 19 kWh/m².yr to 14 kWh/m².yr in the meeting room and from 46 kWh/m².yr to 44 kWh/m².yr in the auditorium. The small impact is because no significant overheating exist in both rooms during summer. The last optimization strategy increases the heat recovery efficiency in the ventilation system and effectively reduce the heating need in the heating coil, therefore, the heating demand further decrease in three rooms. By implementing all the optimization strategies,
the energy saving potential in the office, meeting room and auditorium are 44%, 39%, and 20%, respectively. The indoor environment in term of operative temperature and CO2 level are checked in each scenario and it is validated that energy saving strategies do not sacrifice the indoor environment.

**Conclusions**

This paper demonstrates a case study of commissioning in a campus building. The main focus is to investigate the energy performance of ventilation and heating systems and the indoor environment in three representative rooms: office, meeting room and auditorium. A master list of findings is summarized based on the monitoring data analysis and on-site measurements:

- The temperature and CO2 sensor in the auditorium and meeting room cannot represent the real condition in the space and lead to inaccurate operation of ventilation and heating system.
- Heat recovery efficiency of VE01 is 77% and slightly lower than the required value in Building Regulation
- The setpoints temperature for heating and ventilation are the same in the office and auditorium, which result to maintain constant indoor temperature. It is recommended to reduce the setpoint temperature for heating and increase the setpoint temperature for ventilation.
- The return water temperature is too high for the heating systems compared with the value required by the technical document and the recommended value for district heating. It suggests having more precise valve control on the radiator in order to reseal the heat properly before sending it back to the grid as high return temperatures have an economic consequence.

Five optimization strategies have been proposed and their impacts have been evaluated by a validated dynamic model. By implementing all the optimization strategies, the energy saving potential in the office, meeting room and auditorium are 44%, 39% and 20%, respectively.

**Reference**


The Danish Ministry of Economic and Business Affairs. (2015). *Danish Building Regulations 2015 (BR15).*

Abstract

Demand Response is an attractive option to solve the problem of balancing supply and demand while providing flexibility to the grid. Buildings have been identified as highly valuable flexibility resources due to the increase of thermoelectric devices such as heat pumps for space heating and Domestic Hot Water (DHW). However, current methods for estimating the flexibility potential for residential buildings tend to rely on simplified models and often overlook the limitation of on-site control systems, especially for complex thermoelectric devices such as heat pumps. This contribution aims at accounting for this in assessing the flexibility offered by heat pumps for several market-based indicators using a simulation model and Model Predictive Control (MPC). Simulations are carried out to evaluate the proposed formulations and metrics, especially in relation to maximum flexibility potential fluctuations over a day or between seasons. Our results show that flexibility varies throughout the year, with maximum values reached at mid-season. Our results also emphasize the importance of the choice of metrics to assess flexibility.

Introduction

The increase of stochastic and decentralized renewable energy sources (e.g. photovoltaics, wind turbines) makes balancing short/medium-term electric supply and demand difficult. This means that more flexibility will be required from power systems. The traditional approach of power suppliers to tackle this problem is top-down: the power generation is controlled to fulfill the energy demand curves. However, an attractive alternative to adjust demand to the available production is the so-called Demand Response (DR). DR, defined by the Strategic Energy Technologies Information System (SETIS) of the European Commission, is an “intentional modification of normal consumption patterns by end-use customers in response to incentives from grid operators”.

Supply of energy services in urban areas corresponds to more than 60% of global energy consumption, according to Van der Hoeven (2012), and most of this energy is related to buildings. The two main consumption sources are space heating and Domestic Hot Water (DHW) accounting together for around 80% of the total energy consumption of buildings. Shifting the energy consumption for heating and DHW in buildings is thus a lucrative way of applying DR. The capacity of residential buildings to be able to intentionally modify their consumption patterns is often referred as their “flexibility”. This potential is affected by several human, technical and external factors: (1) the inhabitant’s behaviour and their comfort requirements, (2) the building characteristics such as the thermal capacity and the insulation, (3) the heat distribution system including thermoelectric devices, storage tanks and heat exchangers, (4) their control system and the degree of monitoring, and (5) the weather conditions.

An attractive method to perform DR is model predictive control (MPC). It can maximize the flexibility potential while respecting system constraints and user comfort. In this contribution, we evaluate the flexibility offered by heat pumps in residential buildings while using MPC to perform DR. We compare our estimates of flexibility to a more standard method to perform DR actions called Rule Based Control (RBC). Since the other DR solutions available on the market are mostly limited to electricity (PV, electric batteries, electric heaters) we concentrate our efforts to the same.

We characterize flexibility at subhourly time steps for residential buildings with a focus on the effect of two control methods. We investigate the choice of flexibility metrics and discuss the reference used. The potential is assessed with the example of a simulated cluster of buildings, which is supplied by water-to-water heat pumps, during typical days.

After a review of related work in flexibility characterization and similarity measures for time series, the second section introduces the framework used to investigate the flexibility potential of a residential neighbourhood. Several flexibility indicators and the methods to compute them are presented along with the evaluated control algorithms. The use of typical days...
is elaborated on. Results and a discussion of the indicators, the methods and the control algorithms presented is found in the third section.

Related work

Flexibility definition

The term “Energy Flexibility” is used in many different domains related to electric power systems but is understood differently by physicists, thermodynamicists or control engineers, which leads to almost as many definitions as papers published. It still lacks a universally accepted definition. For this reason, Reynders et al. (2018) review and evaluate existing definitions and quantification methodologies applied to flexible energy in buildings. They found that for systems with multiple time constants, such as buildings, it is more appropriate to quantify flexibility by analyzing flexibility events at specific time points rather than relying on cumulative energy profiles. They identified several focus points but they did not provide an overall definition for flexibility.

Flexibility potential estimation

There are even more indicators and quantification methodologies than there are definitions for energy flexibility. Indeed, it can hardly be described by a single indicator (Stinner et al., 2016). In this paper, the authors develop a method that integrates the particular aspects of both the electrical grid and the building energy system. However, their work relies on a simplified model that does not account for the control aspects nor variation in efficiency, which is especially important when analyzing complex thermoelectric devices such as heat pumps.

The literature presents several recurrent concepts that are derived to compute the different indicators. The metrics often include the concept of time, power, energy and cost which can be connected to create more specific indicators. Zhang et al. (2019) present different DR applications with a focus on defining many indicators specific to each actor of the energy sector. They rely on a detailed structure of a residential energy system and two algorithms enabling to test “partial” and “full” DR call. Compared to most studies, they also consider DHW and account for rebound effect. However their flexibility estimation is based on simulated scenarios rather than using optimization control algorithms.

Junker et al. (2018) propose to define a “flexibility function”, which enables the description of energy flexible transients without relying on a baseload estimation. The system is, however, assumed time invariant and linear. They further make the assumption that the system providing flexibility is smart and able to respond to an external penalty signal, which is not true yet in most buildings.

Most of the flexibility potential estimations for residential buildings tend to rely on simplified models. Only a few papers, describe results obtained from pilot, such as the one presented by Dhulst et al. (2015). Experiments show that the flexibility potential throughout the day is “highly asymmetric”.

In order to cover the gaps in literature mentioned above, we developed a simulation and optimization framework accounting for the effect of local control constraints. We account for the fact that the system can fail to comply with external penalty signals. Our framework allows us to test several DR configurations, especially in relation to maximum flexibility potential fluctuations over a day or between seasons. In this paper, we define flexibility as “any feasible change in power (increase or decrease) for a particular system, over a period of time, based on signals from the market/grid”. Here, power refers only to electricity and not thermal power.

Methods

In this section, the flexibility metrics used in this case are introduced. Two control algorithms to provide flexibility are presented: RBC and MPC. They are used to dynamically change systems set-points to react to Demand Response calls. Then, we discuss a clustering method to reduce simulation time while ensuring a good assessment of flexibility potential over a year. Finally, the general framework is presented with focus on the parameters used to evaluate the flexibility potential of buildings. Note that the framework presented here is specific for residential buildings heated by Water-to-Water Heat Pumps (WWHP), but can be generalized for other systems and technologies.

Indicators and metrics

As a reminder, we define flexibility as any feasible change in power (increase or decrease) for a particular system, over a period of time, based on signals from the market/grid. Here, power refers only to electricity and not thermal power. We also consider only the controllable loads of buildings, such as heat pumps and electrical heaters.

The first indicator accounts for the maximum power deviation of a cluster. Given the index of the heat pump $n$ with $1 \leq n \leq N$, the Flexhour index $t_0 \leq t_0 \leq 23$, corresponding to the hour of the call, the call duration $(d_{DR})$ and the time index $t$ with $t_0 \leq t \leq (t_0 + d_{DR})$, the amount of aggregated power consumption load $P$ that can be increased $(UP)$ to a maximum or reduced $(DN)$ to a minimum operation level is computed with the following two approaches. The first one computes the maximum power difference relative to the current power level at $t_0$ as in equations (1) and (2), while the second, equation (3), is based on the difference with the baseload power $P_{BL}$. The terms $UP$ and $DN$ have to be differentiated from the existing upward and downward reserve services provided by conventional generators.
In this work, “Upward” (UP) refers to an increase in power consumption, which, looking at the market side, is “equivalent” to a decrease in power production (downward reserve).

\[
F_{1_{UP}} = \sum_{n=1}^{N} \frac{\max(P_{n,t} - P_{n,t_0})}{P_{n,55^\circ C}}
\]

(1)

\[
F_{1_{DN}} = \sum_{n=1}^{N} \frac{\max(P_{n,t_0} - P_{n,t})}{P_{n,55^\circ C}}
\]

(2)

with \(P_{n,t_0}\) the current power level and \(P_{n,55^\circ C}\) the power level of the heat pump when operating at a departure temperature of the condenser at 55°C.

\[
F_{2_{UP}} = \sum_{n=1}^{N} \frac{\max(P_{n,t} - P_{n,BL})}{P_{n,55^\circ C}}
\]

(3)

Both maximum deviation indicators \(F\) are normalized by the power consumed in DHW mode with an operating temperature of 55°C.

The second indicator describes the energy deviation in kWh (FlexEnergy) for a cluster of buildings for a specific duration call \(d_{DR}\). Similar to the first set of indicators, these indicators are computed with two methods. The first one, equation (4), assumes that the current energy consumption at \(t_0\) is maintained over the entire call duration. The second, equation (5), is based on the difference with the baseline energy consumption. Here, \(P\) values are discrete with a sampling time \(ts\) in seconds.

\[
E_{1_{UP}} = \frac{ts}{3.6e^6} \sum_{n=1}^{N} \sum_{t=t_0}^{t_0+d_{DR}} (P_{n,t} - P_{n,t_0})
\]

(4)

\[
E_{2_{UP}} = \frac{ts}{3.6e^6} \sum_{n=1}^{N} \sum_{t=t_0}^{t_0+d_{DR}} (P_{n,t} - P_{n,BL})
\]

(5)

The third indicator tries to assess the rebound effect. It is computed as the energy deviation after the end of a DR call with the baseload as reference. For computational reasons, the rebound is computed for a period \(d_{rebound}\) of four hours following the DR call.

\[
R_{t_0} = \frac{ts}{3.6e^6} \sum_{n=1}^{N} \sum_{t=t+0+d_{DR}}^{t+0+d_{rebound}} (P_{n,t} - P_{n,BL})
\]

(6)

The time taken to satisfy and maintain the change in power is an important metric of the quality of the flexibility supplied by the system. The changes in consumption patterns also have to respect the technical constraints of the systems and not compromise the comfort of users. This implies the need for a control methodology that can predict power curves and adapt over time, and makes MPC a good candidate for this work.

**Control**

Many studies discard the control aspect based on the assumption that “the system providing the flexibility is smart in a manner that it is able to respond to an external penalty signal” (Junker et al., 2018). On the contrary, we consider the local control aspect, as most systems cannot be forced but need to be encouraged to react to penalty signals. We assume that the heat pump is modulated only by the different operation temperatures and between two states (on/off), as most of installed devices do. Three main manipulated variables are identified and used to control the heat pumps.

1. The indoor temperature set-point \(T_{in}\) used to compute the supply temperature \(T_{sup}\), via the equation of the heat curve.
2. The DHW temperature set-point \(T_{DHW}\), at which the HP will start heating the DHW storage tank.
3. The state of the HP \(S_{HP}\) is either off, the HP is shut down, or on the HP can be, but is not necessarily, switched on.

The default control for each building is simulated by a heat curve, equation (7), and several dead-band controllers for the storage tank, with specific cut-in and cut-out temperature.

\[
T_{sup} = \text{slope}(T_{in} - T_{ext}) + T_{in} + \text{Level}
\]

(7)

where \(T_{ext}\) is the average external temperature over a period of time. At each specific DR time call, flexibility is evaluated for two different control approaches: RBC and MPC. In the case of RBC, the default control is run until a DR call to provide upward or downward flexibility is received. From this point onward and for the whole duration of the call \(d_{DR}\), set-point values are put to their maximum/minimum values respectively. After the call, the set-points are set back to default values.

The MPC maximizes flexibility potential while respecting system constraints and user comfort. The MPC implementation is deterministic in nature and uses weather data collected from Meteonorm (Remund and Kunz, 1995). The time horizon of the optimization \(h_p\) is equal to 24 hours, with a timestep \(\Delta t\) of 15 minutes. The MPC cost function in equation (8), is a representation of the operational costs including the electricity price, the discomfort and the penalties for changing the behaviour from the base load. The optimization problem can be formulated as:

\[
\min \sum_{n=1}^{N} \left[ \sum_{t=t_0}^{t_0+d_{DR}} 
\left( c^{act} P_{n,t} + c^{Tc} \Delta T_{n,t} + c^{cut} \Delta u_{n,t} \right) 
\right]
\]

(8)
where \( S_{sh} \), \( S_{dhw} \) and \( S_{HP} \) are binary variables and \( w_{1,n,t} \), \( w_{2,n,t} \) and \( w_{3,n,t} \) are weights [0, 1].

\[
\forall n, t : q_{n,t}^{hp} = Q_{35} w_{1,n,t} + Q_{45} w_{2,n,t} + Q_{60} w_{3,n,t} 
\]

\[
\forall n, t : p_{n,t} = P_{35} w_{1,n,t} + P_{45} w_{2,n,t} + P_{60} w_{3,n,t} 
\]

\[
\forall n, t : S_{sh} + S_{dhw} \leq 1 \quad \text{(9a)}
\]

\[
\forall n, t : S_{HP} \geq S_{sh} \quad \text{(9b)}
\]

\[
\forall n, t : S_{sh} + S_{dhw} = w_{1,n,t} + w_{2,n,t} + w_{3,n,t} \quad \text{(9c)}
\]

\[
\forall n, t : \text{SOS2}(w_{1,n,t}, w_{2,n,t}, w_{3,n,t}) \quad \text{(9d)}
\]
Simulation framework

Dynamic simulations of the cluster of buildings are carried out with MATLAB® SIMULINK® using a modified version of the Carnot toolbox (Wemhöner et al., 2000). In order to limit simulation time, buildings are reduced to a one zone model with four nodes: the external mass \( T_{\text{ext}} \), the internal mass \( T_{\text{int}} \), the floor \( T_f \) (for floor heating) and the air inside the buildings \( T_{\text{air}} \). Heat is delivered to the building by radiators or floor heating. The heat distribution consists of three loops, which link the building with the buffer tank, the buffer tank with the heat pump and the heat pump with a heat source as displayed in Figure 1. This is a typical design for buildings supplied by heat pumps. The storage tank for Domestic Hot Water is linked to the heat pump through an external heat exchanger. The storage tanks are both modelled to account for thermal stratification. The dynamic behaviour of the heat pump is computed using piece-wise linearization of the source and sink thermal power and electrical power given by manufacturer data. The outlet temperatures of the condenser and the evaporator are calculated by two differential equations.

The MPC algorithm is implemented in python using the gurobipy library (Gurobi Optimization, 2018) to generate and solve the optimisation problem. Simulation values, DR parameters and control set-points are exchanged between SIMULINK® and python every 15 minutes in simulation time. The optimisation problem is updated at every call. Since the problem is formulated as a MILP, the optimisation is stopped when a solutions falls below 5% of the MIPgap or after 40 seconds in order to limit the computational time. If the problem is infeasible, the default control set-points are sent to the simulation controller to avoid failure of the run.

Each combination of typical day (Extreme winter, Winter, Mid-season, Summer) and DHW profiles (there are four) are simulated with one minute time steps. There are 24 runs for each combination, corresponding to each hour of a day. The flexibility is evaluated at different hours of the day (Flexhour) and for different durations \( d_{\text{DR}} \) (15, 30, 60 minutes). Each run has an initialization period of a day, and stops four hours after receiving a flexibility call at the beginning of the corresponding Flexhour.

For the sake of simplicity, we consider only one flexibility call per run, and only the maximum and minimum upward/downward flexibility is requested per call. The time of a flexibility request is assumed to be previously unknown to the system.

Results

Characterizing the flexibility of buildings over a year at high resolution (one minute time step) is not only computationally challenging but also difficult to summarise visually. Demand Response calls usually last for rather short periods of time, which motivates looking at hourly/daily timespans. Therefore, simulating typical days is a good way to analyse the flexibility of building clusters as they are shorter to simulate but still represent a pertinent summary of a year. In this section, we present results for two control strategies to provide flexibility. The flexibility is characterized by three different indicators and two different methods to compute the indicators are compared.

Figure 2 displays a DR call for providing upward flexibility for a typical mid-seasonal day sent to a small cluster of buildings. The DR call starts at midnight and lasts for 30 minutes (period between the two dashed vertical lines). The baseload and the power deviation of the two evaluated control strategies (RBC and MPC) are compared not only during the call but also during the following four hours. It can be seen in those subplots that the cluster with an MPC controller for cost minimization presents a baseload that is clearly lower than the one with a RBC, which makes it difficult to compare the flexibility they offer. In this example, the total variations...
of energy between the flex loads and the baseloads are similar in both cases, but, the respective patterns are different. In one case, the deviation is large but lasts for a short period of time. In the other case, it is smaller but persists for the call duration. The so-called rebound effect after the DR event is not always easily observable, in particular for such a small cluster of buildings. However, in the top subplot of Figure 2, the load resulting from the flex call at midnight seems to return to the baseload after less than four hours. In the case of DHW, we would need to look at longer periods, as charging/discharging cycles usually last longer than four hours.

Figure 3 displays the same upward flexibility call as presented in Figure 2, zoomed in to the building level. It illustrates two different cases of successful activation. In the top subplot, the heat pump is already activated and providing space heating when the DR call starts. After an initial decrease during the first six minutes, the power consumption increases by 10% compared to the value at the beginning of the call. This behaviour corresponds to a switch from the heat mode to the DHW mode of the heat pump. When the call is received, the bottom temperature of the storage tank is lower than the current heat pump operation temperature, which explains the decrease in electrical power. One can observe that the DHW cycle was started one hour earlier. Computing flexibility with reference to the initial power (method 1) results in only a small energy increase. Looking at the baseload, the heat pump would have normally stopped during this period but was kept on by changing its set-points. Therefore, computing flexibility with reference to the baseload (method 2) gives a much bigger energy increase. The bottom subplot with MPC illustrates the opposite behaviour. At the start of the call the heat pump is off, but it switches on after 2 minutes. However, looking at the baseload, one can observe that the heat pump would have started on its own anyway. In this case, computing the flexible energy with method 2 results in half the amount obtained with method 1.

In Figure 4, results are grouped by the control options MPC (left) and RBC (right) and by the flex methods used to compute the flexibility. The blue half corresponds to the difference relative to the current power level and the orange half to the difference relative to the baseload. When the flexible energy is aggregated and observed over all typical days, there are no major differences between the two ways of computing this indicator. However, the difference is slightly bigger when looking at the maximum power deviation. The violin plots have two peaks: one occurring around zero and the other at a higher value. This shape can be explained by the fact that the heat pumps considered have fixed speed compressors. They can be either on or off. The only power variation results from the increase in operating temperatures, which in the case of space heating, happens over several hours (longer that the call duration). A heat pump turning on, as a consequence of a DR call would therefore create a significant energy increase. This effect would probably vanish for bigger cluster sizes.

As one could expect, the MPC controller provides a bit more upward flexibility than the RBC controller for mainly two reasons: First, the system is operated at lower temperatures, which means the heat pumps have a higher chance to be turned off when a DR call is received. Second, the MPC controller finds the best choice of set-points to maximize the power deviation by predicting it over a longer horizon. However, it can also decide not to provide flexibility if it would mean violating comfort constraints. Negative values of upward FlexEnergy results from the heat pumps stopping during the DR call due to a cycle duration limit or too high operating temperatures.

Figure 5 shows, for each hour of each typical day, the
maximum power deviation with the base load as reference ($F_{2UP}$). This indicator is normalized by the power consumed in DHW mode with an operating temperature of 55°C which explains why its values can exceed one. Each violin plot is split to show the MPC (left, blue) and RBC (right, orange) distributions. The two top subplots correspond to extreme winter and winter days. One can observe that upward flexibility is almost zero throughout the hours of the day. This increases for the mid-season day, with around half the values closer to one than to zero. In summer, heat pumps only operate to provide DHW. The fact that they are turned off most of the time and that their operating temperatures are high, can explain why the highest power deviations are found in summer.

Hourly patterns can also be identified, especially during the mid-season day. Between 8 AM and 6 PM, power deviations are closer to their maximum values. The external temperature increases during the day, decreasing the departure temperature set-point of the heating system, which results in more “off” time of the heat pump. In reality, the building’s heat distribution system can be operated with night setbacks. A night setback will lower the set-point temperature at night. The distribution of FlexPower would therefore be flipped, compared to the one in Figure 5. Night time would have the highest maximum deviation potential. One can observe the effect of the peaks of consumption in the morning, 7 to 8 AM, and in the early evening, around 6 PM, when DHW storage tanks become empty.

Figure 6 displays the aggregated flexible electrical energy in kWh of the five residential buildings considered for each FlexHour. The duration of the call considered here is $d_{DR} = 30$ min. For this duration, the theoretical maximum flexible energy of the system considered is less than 20 kWh, assuming that all heat pumps turn on at the beginning of the call to provide DHW throughout the entire duration. As previously discussed in 5, the FlexEnergy is low for winter days but the deviations are wider. The bands represent the results obtained for different DHW profiles. In winter, DHW cycles have a significant impact on the overall system as they often interrupt heating cycles. In summer, upward flexibility results only from an increase of the DHW temperature set-point $T_{DHW,\text{set}}$. The thermal energy that can be stored in a DHW storage tank is an order of magnitude lower than the one that can be stored in the building mass. Once the storage tank is full, the heat pump cannot provide any flexibility for several hours. DHW charging cycles typically range from 15 minutes to maximum one hour if the storage is empty. This is why the value of the FlexEnergy would not increase much even for a longer duration $d_{DR}$. The same remark can be made for winter periods, where off times are usually very short. Depending on the method used to compute the flexibility, results could be very different. For mid-season days, however, increasing $d_{DR}$ up to one hour per day would result in higher FlexEnergy upward potential because heat pumps are more often turned off during those days and more thermal energy can be stored in the mass of the building.

Table 1 shows the means and the extrema of the results presented in Figure 6. It shows that on average MPC provided at least 25% more FlexEnergy than RBC. For mid-season, this increase goes up to more than 50%.

**Conclusion**

This paper proposes a framework to assess the maximum energy flexibility potential for a cluster of buildings with a focus on complex thermoelectric devices such as water-to-water heat pumps. A key contri-
Table 1: Mean, minimum and maximum of the FlexEnergy potential in kWh. This potential was computed with MPC and method 2 for $d_{PR} = 30$ min, over four typical days. The percentages in brackets correspond to the increase of flexibility compared to the one obtained with RBC.

<table>
<thead>
<tr>
<th>Typical day</th>
<th>FlexEnergy [kWh]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
</tr>
<tr>
<td>Ext. winter</td>
<td>1.2</td>
</tr>
<tr>
<td>Winter</td>
<td>1.9</td>
</tr>
<tr>
<td>Mid-season</td>
<td>5.8</td>
</tr>
<tr>
<td>Summer</td>
<td>8.8</td>
</tr>
</tbody>
</table>

Distribution is the incorporation of the two control methods RBC and MPC in the characterization process of a small residential cluster. This addition is made computationally feasible by the use of typical days to simulate the year. Two different methods to compute the flexibility indicators, related to the reference chosen to account for deviation, are discussed. Simulations are carried out to demonstrate the value of the proposed formulations and metrics, especially in relation to maximum flexibility potential fluctuations over a day or between seasons. Our results show a high seasonal and lower hourly variation of flexibility with a maximum potential reach for Mid-season days. We also find that the flexibility offered by heat pumps could benefit from a control method such as MPC capable of predicting and optimizing the set-point values. However, the robustness and scalability of the method for larger cluster sizes will have to be investigated alongside the evaluation of the MPC objective function.

Acknowledgment

This project has received funding from the European Union’s Horizon 2020 research innovation programme under grant agreement No. 695965. The authors would also like to thank the partners of the Sim4Blocks project for their invaluable support and help without which this paper would not have been possible.

References


Dynamic Energy Model-Based Automatic Building Performance Testing for Continuous Commissioning

Muhyiddine Jradi, Na Liu, Aslak Johansen, Krzysztof Arendt, Claudio Giovanni Mattera, Mikkel Baun Kjærgaard, Christian Veje, Bo Nørregaard Jørgensen
Center for Energy Informatics, University of Southern Denmark, Odense, Denmark

Abstract
Relying on the fact that a building has met its energy targets at the design stage doesn’t guarantee that it is going to perform properly in the operational phase. Generally, there is a clear mismatch between the actual energy usage and the expected levels, referred to as the ‘building performance gap’. This paper presents an innovative framework for building energy performance monitoring and evaluation using a set of performance tests targeting various building energy subsystems. The framework employs a calibrated whole-building energy model to provide a dynamic baseline for assessment. The presented framework serves as a backbone for an automatic and continuous building commissioning process, supporting systematic building fault detection and diagnostics. The framework implementation in a highly energy efficient case study building is presented and discussed. A specific case of a malfunctioning ventilation unit, that was captured and reported by the implemented framework, is presented. This highlights the technical and economic added value of the framework in reducing the building performance gap and restoring a proper operation.

Introduction
The building sector has been prioritized by the EU (EU Commission, 2010), with a clear statement that improving the newly built and existing buildings energy performance is a major step towards achieving future energy and environmental goals. However, relying on the fact that a building has met the energy requirements and specifications at the design stage doesn’t guarantee that it is going to perform as expected in the operational phase (De Wilde, 2014). In the majority of cases, there is an obvious mismatch between the actual energy usage and the predicted levels, defined as ‘building performance gap’(Frei, 2017). Dealing with the building performance gap and considering the causes at the different building phases, a number of studies has developed methodologies and frameworks aiming to better characterize this gap and improve the building performance monitoring and evaluation. In a recent study, Van Dronkelaar et al. (2016) have investigated 62 buildings and compared the measured energy use with the numbers reported at the design stage. The results reported a 34% deviation in average between the actual and expected numbers. One of the major factors leading to buildings performance gaps is the lack of continuous building commissioning and the absence of any feedback to designers, engineers and owners after both building construction and handover and during the operational phase. IEA Annex 40 (Visier and Buswell, 2010) has defined building commissioning being a “quality-oriented process for achieving, verifying and documenting whether the performance of a building’s systems and assemblies meet defined objectives and criteria”. Building commissioning process at the end of the construction stage was found to provide substantial benefits in terms of having a smoother building start-up and enhanced occupants comfort. Nevertheless, continuous commissioning beyond this stage into the building operation phase helps ensuring a long-term energy efficient performance of the building. This will provide high capabilities to implement feasible control and management strategies to improve the energy supply systems operation and thus raises the flexibility quotient of the building (Markoska et al., 2016).

Considering this added value of continuous building commissioning, there is an urgent need for a set of tools to improve and facilitate the initial building commissioning process at the design and construction stages, in addition to implementing an automated continuous commissioning process that runs throughout the building operational phase. Such tools could aid in verifying if the energy performance indicators are met and could help in developing and implementing operational strategies to optimize the performance of different systems in the building and enhance the flexibility quotient. In addition, continuous building commissioning and energy performance monitoring is an indispensable requirement for a systematic and effective fault detection and diagnostics process for energy conversion and supply systems operation. In general, this will lead to both technical and economic benefits in terms of avoiding excess energy use and increased operational costs due to malfunctioning of components. A recent study by the National Renewable Energy Laboratory (Kim et al., 2018) has indicated that there are significant energy and economic savings potential in the small commercial building sector through energy performance monitoring and implementing automated fault detection and diagnosis processes. However, these opportunities are not fully exploited due to the limited availability of automatic and continuous cost-effective building commissioning and monitoring tools. In addition, the report highlights the importance and the added-value of dynamic energy model-based continuous building commissioning and
fault detection and diagnosis tools in improving the holistic energy performance of buildings. In 2017, the 20 top-priority faults in the US small-commercial buildings have resulted in around 52750 GWh energy losses in addition to substantial $7 billion in operational cost (Kim et al., 2018). Moreover, based on data collected from 26 non-residential building sites, it was reported that implementing a proper building continuous commissioning process has the potential to save up to 35% on the building energy consumption, with a payback period of less than 3 years (Bynum et al., 2008). In addition, it was highlighted that the development of a detailed building dynamic energy model has an overall payback period of around 1-2 months, considering the potential of using such models to aid decision-making in terms of design, operation, control and commissioning (HOK, 2016).

In the recent years, multiple tools have been developed and implemented for automated and non-automated building continuous commissioning (Building Advisor, 2018; HVAC-Cx, 2017; CommONEnergy, 2013). However, these tools rely in the continuous commissioning process on static thresholds and baselines as well as historic data and trends. The current study presents an innovative framework for automatic and continuous building energy performance monitoring and evaluation using a set of performance tests targeting various building energy subsystems and employing a calibrated whole-building energy model to provide a dynamic baseline for assessment. Such approach has not been reported in the literature and implemented in a real case building before. The major contribution of the study is using holistic dynamic energy performance models as a basis for continuous commissioning and fault detection and diagnostics in buildings. This will lead to reducing energy performance gaps in the operational phase and ensuring a proper operation of different building subsystems. The presented framework has two pillars: simulations from whole-building dynamic energy performance model and actual data collected onsite from various meters. The framework development and implementation in a highly energy efficient case study building is presented and discussed in this paper, along with building energy performance analysis and evaluation. The paper will present first the case study building considered for the analysis. Then, an overview of the energy performance monitoring and evaluation framework design and implementation is provided, including the full-scale dynamic building model development, model calibration, implementation of the developed framework in a case study university building in Denmark and the establishment of an online dashboard platform for performance visualization. Finally, a specific case of a malfunctioning unit that was captured and reported by the implemented framework is presented.

**Framework for Continuous Building Commissioning**

To serve as a basis for building automated continuous commissioning, a model-based framework for building energy performance monitoring and evaluation is designed and developed in this study. Figure 1 provides an overview of the developed framework, which has a list of performance tests targeting whole-building performance and energy sub-systems operation. In overall, the performance tests have two major inputs:

- performance simulations provided by the developed calibrated dynamic building energy model
- electricity and heating consumption data provided by the metering infrastructure implemented in the building

The developed building energy performance monitoring and evaluation framework comprises the following steps:

- A dynamic full-scale energy performance model is developed considering different building specifications and characteristics in terms of physical envelope and energy supply systems.
- Data collected from various energy meters in the building, recorded weather data, occupancy counts, and energy systems operational parameters are used to calibrate the dynamic building model.
- Continuously, the calibrated dynamic energy model is used to predict the energy performance of the building.
- Performance tests are executed for the different energy systems in the building, comparing both simulations from the building model and actual data from the corresponding meters.
- Performance gaps are automatically and continuously calculated and reported.

![Figure 1: Continuous building commissioning framework overview.](image)

Gaps identified based on the performance testing serve as a basis for the building fault detection and diagnostics. In case if no faults are identified, a re-calibration of the building energy performance model is then performed. In overall, the presented framework aims to establish an automated continuous commissioning process to ensure a proper operation of the different energy systems in the building, and as a result an energy efficient holistic building performance. The calibrated dynamic energy model is set to simulate the building performance on a daily basis, considering weather data, occupancy counts and operational parameters and setpoints implemented for...
Within the international research project COORDICY (2015), the OU44 building has been established as an energy living lab to carry out different research activities and projects. Such activities include investigating overall continuous building commissioning, energy supply systems and components, occupancy behaviour and patterns, data collection and validation, model-predictive control strategies, and demand-response events implementation. To aid this, the building has been equipped with a large number of energy meters and sensors on various levels, providing significant potential for detailed performance monitoring and effective operation control and management.

The metering infrastructure provides data on the overall electricity and heating consumption of the building, in addition to the energy usage of the 4 ventilation units, lighting consumption by zones and plug loads. In particular, 4 fully equipped test rooms have independent heating, electricity, lighting and equipment energy meters. The ventilation and heating systems in the building are equipped with multiple temperature and pressure sensors in addition to flow meters. Each room in the building has a set of sensors including CO₂, temperature, humidity, illuminance and PIR motion sensors. On the energy systems components level, all the rooms in the building are equipped with radiator valve position sensors, ventilation damper opening sensors and blinds position sensors. Considering that occupants behaviour and occupancy patterns have a significant impact on the energy use in buildings, 17 3D stereo-vision cameras were installed at different building entrances, corridors and in specific test rooms, to provide an estimate of the occupancy counts. The building has also an onsite weather station on the roof allowing instant recording of ambient temperature, wind speed and solar irradiation. The metering and sensor infrastructure is interfaced through the Simple Measurement and Actuation Profile (sMAP) protocol (Dawson-Haggerty et al., 2010) exposed through a central platform. sMAP facilitates data collection, labelling and pre-processing. In addition, it simplifies the post-processing and utilization of data for different applications including data validation, model calibration and occupancy prediction. The building chosen as a case study is a living lab empowered by a large number of meters and sensors, however this is not necessarily the case of any other building. In this regard, it should be noted that the required metering infrastructure for the energy model development and calibration along with the continuous building commissioning framework implementation constitute of the overall electricity, total heating, ventilation electricity and lighting meters and sub-meters. Saying that, additional indoor comfort sensors and floor and room level meters along with occupancy cameras would provide additional potential for detailed building performance monitoring and evaluation.

Performance Testing Dashboard Platform

A dashboard platform is developed to better report and visualize the performance tests results. The developed Dashboard is a Python application, built using 'Dash', a

![Figure 2: OU44 university building.](image)
Python framework for building web application (Dash, 2018). It monitors and evaluates building energy performance by reporting the performance tests results and comparing actual building performance with simulated building performance. The dashboard platform developed is specific to the building case study considered. Moreover, the current dashboard version monitors thermal comfort and indoor air quality and visualizes the average hourly temperature and CO$_2$ levels of the 27 large teaching rooms and study zones in the building. Figure 3 illustrates the data interactions within the dashboard application.

There are two types of data in connection with the application - actual data and simulated data. Actual data is generated by physical meters and sensors which are equipped inside the building. The generated meter data is then read and transmitted to the data repository smoothly through an EnergyKey driver and the generated sensor data is read and pushed to the data repository through KNX drivers. The simulated data is provided by the performance simulator, which uses weather data and occupancy counts from the cameras as inputs to simulate the building energy performance. The simulator is scheduled and configured automatically through an automation service in Java. Currently the simulator is scheduled to be executed on a daily basis, simulating the energy performance of the building for the last 2 weeks. The dashboard application deals with data streams from the centralized data repository. It first queries the data repository using an SQL-like syntax. Based on the resulting data it then calculates the energy performance and indoor comfort results. The calculated results are displayed on the user interface (UI), which is composed of gauge charts generated by dash_core_components library and updated through dash functions. The gauge charts for building energy performance are updated on a daily basis and the gauge charts for thermal comfort and indoor air quality are updated every 30 minutes.

**Building Energy Model Development and Calibration**

**Building Energy Modelling**

A full-scale detailed dynamic building energy performance model was developed for the OU44 building case study, considering different building design specifications and characteristics including physical envelope properties, internal loads and schedules and technical energy systems. The holistic whole-building energy modelling and performance simulation developed by Jradi et al. (2018) was implemented in this case, employing a package of tools, SketchUp Pro, OpenStudio and EnergyPlus. An overall architectural 3D model of the building was developed first in Sketchup Pro providing an accurate representation for the different rooms and zones orientation and geometry within the building. The detailed 3D model was imported into OpenStudio where all the building envelope characteristics, energy supply systems properties, loads, schedules, weather conditions and occupancy patterns are defined and characterized. Openstudio allows linking the 3D model development details in SketchUp with the Energyplus tool, providing a user-friendly and flexible interface for the development of the holistic building energy model. The energy model developed in OpenStudio is later exported to an IDF file and introduced in EnergyPlus for additional features definition including setpoints, operational parameters and CO$_2$ sensors allocation. EnergyPlus was chosen for energy simulation as it is a free, validated, robust and well-documented energy modelling and simulation software. Figure 4 depicts a SketchUp Pro 3D model of the OU44 building. The resulting building model comprises 190 thermal zones over 3 floors and a basement with detailed representation of the building constructions and materials along with different energy conversion and supply systems including heating, ventilation, lighting, equipment and PV sub-systems.

**Figure 4: OU44 building 3D architectural model.**

**Energy Model Calibration**

The whole OU44 building dynamic energy performance model presented in the previous section has been calibrated using actual collected data from the different energy meters and submeters in the building. This will ensure that the dynamic energy model can predict and simulate the energy performance of the building with a sufficient detail and acceptable accuracy. In addition, a calibrated dynamic energy performance model is a key factor in achieving effective building performance monitoring and evaluation process and establishing a systematic continuous commissioning process (Van Dronkelaar et al., 2016). The dynamic energy model is calibrated considering a period of 3 months from February to April 2018. This period was chosen as it has the full set of meter data required for calibration with no missing or corrupt data. In the calibration process, collected weather data from the weather station, occupancy counts from the 3D stereovision cameras and energy systems operational setpoints and parameters, including ventilation and heating units, are used as input along with the reported actual energy use. The occupancy...
profile generated based on the camera counts for the considered calibrated period is shown in Figure 5, with a reported maximum occupancy of around 930 people.

![Occupancy Counts](image)

**Figure 5:** OU44 building overall occupancy counts from Feb to Apr 2018.

Using actual weather conditions, occupancy counts and systems operational parameters, the OU44 model was calibrated using Hale et al. (2014) suggested dynamic energy performance modelling calibration process. However, calibration using overall building energy usage for heating and electricity suggested was substituted by a more detailed calibration on the level of the individual energy supply systems, including ventilation units, lighting per floors, solar PV system and heating system. The main parameters selected for the dynamic model calibration include the space infiltration rates, pressure rise across ventilation units, fans, pump and equipment efficiencies in addition to loads and operation schedules. In terms of heating consumption, infiltration rates were found to be the parameters with the highest impact. Considering that the building complies with the Danish building regulation 2015 at the design stage, parameters set by the Danish BR15 were introduced in the calibration process with a set range of variation. Considering the different calibration parameters, a large number of simulations were considered and the scenario with the lowest deviation in terms of the individual energy systems consumption on a daily basis was chosen to be used as a basis for the continuous building commissioning and performance testing.

Figure 6 (a to d) shows the calibration process results comparing the actual and simulated energy use for (a) heating, (b) lighting and two selected ventilation units (c-d). In overall, the calibrated dynamic energy performance model was found to predict the actual building energy performance with an acceptable accuracy. The reported maximum deviation based on a daily level is -7.48% for the PV electricity supply, 5.94% for the ventilation units’ electricity consumption, 1.38% for lighting electricity consumption per floor and -4.67% for the heating consumption. It shall be mentioned that a negative deviation characterizes a lower predicted energy use compared to actual numbers.

**Automatic Building Performance Testing Implementation**

The building automated continuous commissioning framework described earlier is implemented in the considered OU44 building case study aiming for building energy performance monitoring and evaluation. The calibrated building energy model is employed as a basis for the continuous building performance testing process, serving as an expected reference to compare and evaluate the actual performance on the level of the whole-building as well as the operation of the individual energy supply systems. Results from the dynamic energy performance model simulations are continuously and automatically used by the multiple performance tests as a baseline for comparison with actual data collected for the same period.

**Figure 6:** Actual vs Simulated energy use for monthly (a) heating, (b) lighting, (c) Southeast ventilation unit and (d) Southwest ventilation unit.
Based on the performance tests, a performance gap between the actual and the expected performance is reported in a continuous manner as well. The current implemented performance tests include:

1. Overall building heating consumption
2. Overall building electricity consumption
3. PV solar system electricity production
4. Electricity consumption for each ventilation unit
5. Lighting consumption in each floor

Monitoring the performance of the individual ventilation units and the lighting floor levels in addition to the overall heating and electricity consumption provides a more detailed view in terms of evaluation and analysis and allows for better and more accurate performance monitoring. The dynamic energy performance model uses collected weather conditions data, occupancy counts and systems operational setpoints to continuously and automatically simulate and predict the building energy performance on a daily basis. Regarding weather conditions, the weather station at the top of the building provides instant recordings for ambient temperature, wind speed and solar irradiation levels which are stored in the centralized data platform to be used in simulations. While the simulations are carried out every day, the dashboard platform developed shows the cumulative performance gap between the expected model simulations and actual building operation for the last 2 weeks, aiming to better characterise and evaluate the performance.

![Building Energy Performance](image)

**Figure 7:** OU44 building overall energy performance in the first two weeks of May.

![Ventilation System Electricity Performance](image)

**Figure 8:** OU44 building ventilation units performance in the first two weeks of May.

Figures 7 and 8 show the performance testing results reported by the dashboard platform on May 14, covering the period from 1 to 14 May. Within this period, an acceptable performance of the building was reported as shown in Figure 7. The cumulative performance gap reported for the overall building electricity and heating consumption is -8% and -25% respectively. In addition, the performance testing of the solar photovoltaic system electricity production reports a cumulative performance gap of -9% for the considered 2 weeks. Regarding lighting electricity consumption, the dashboard platform shows the performance results of the lighting energy usage per floor, with a respective cumulative gap of -9%, 31% and 9% for the ‘Parterre’, ‘Ground’ and ‘First’ floors. In the current dashboard performance testing version, a performance gap exceeding -20% to the left was considered to highlight a ‘worse’ condition. In addition, Figure 8 gives a more detailed insight on the performance of the individual ventilation units in the 4 building quadrants within the same period. The figure shows that there are some differences in the performance gap reported for the 4 ventilation units with a cumulative performance gap of 21%, -2%, 7% and -7% for the Southeast, Southwest, Northeast and Northwest ventilation units’ operation respectively.

While Figures 7 and 8 report the cumulative energy performance gap as a result of the OU44 building energy performance testing in the first two weeks of May 2018, a more detailed performance evaluation on a daily basis is carried out. Figures 9, 10 and 11 show the results of the building energy performance testing of the heating system, Southeast ventilation unit, and Southwest ventilation unit on a daily basis for the first two weeks of May. As depicted in the three performance monitoring figures, the heating system and the two ventilation units exhibit an acceptable performance compared to the expected simulation results reference.

![Heating System Performance](image)

**Figure 9:** Heating system performance (Actual vs Simulated).

![Southeast Ventilation Unit Performance](image)

**Figure 10:** Southeast ventilation unit performance (Actual vs Simulated).
Considering the results provided for the first two weeks of May, the following daily evaluation and observations could be highlighted regarding the performance of the heating system and the two ventilation units:
1. High heating consumption during May 2-5.
2. Relatively low electricity consumption of the Southeast ventilation unit through the whole period.
3. Relatively high electricity consumption of the Southwest ventilation unit on May 1, 6, 12 and 14.

**Reported Malfunctioning Ventilation Unit**

The continuous building commissioning and performance testing framework developed is currently implemented and has been running in the OU44 building to automatically monitor and evaluate the overall building energy performance. As highlighted earlier, continuous building commissioning and performance testing is a major requirement for a systematic and effective fault detection and diagnostics process considering different energy conversion and supply systems operation. In this context, a specific case is reported in this study to highlight the added-value of implementing such approach in buildings, concerning a malfunctioning ventilation unit. Figure 12 shows the evolution of the cumulative performance gap reported regarding the operation of the Southeast ventilation unit in November 2018. As shown in the figure, the cumulative performance gap reported has drastically increased from -5% on Nov. 21 to -120% on Nov. 29. The negative sign characterises an actual energy use higher than the expected consumption. The spikes on 24 and 25 Nov. are due to being a weekend period with much lower expected consumption, and thus corresponding to larger performance gap as highlighted.

Considering these results, a more detailed investigation was carried out concentrating on the rooms supplied by the Southeast ventilation unit. It was found that one of the air diffusers in a large teaching room (U181) on the first floor, has a reported damper position of 100% (totally open), for most of the period from 21 to 29 November. As the air supply diffuser opening is driven by the CO₂ level in each room and a 100% opening corresponds to CO₂ level higher than 900 ppm, the CO₂ level in the U181 room was checked and a normal behaviour was observed with limited periods where CO₂ level exceeds 900 ppm.

**Conclusion**

In this study, a framework for automatic and continuous building energy performance monitoring and evaluation is presented, composed of a set of performance tests targeting different building energy subsystems. The core of the presented framework is a whole-building calibrated dynamic energy performance model providing a baseline for assessment. The automated performance tests serve as a basis for the continuous building commissioning aiming to better monitor, characterize and evaluate the performance on different levels. A case study of an energy efficient university building in Denmark is considered. A full-scale building energy performance model was developed in EnergyPlus and calibrated using actual weather data, occupancy counts from 3D stereovision cameras and operational setpoints. Employing the
calibrated model, the automated continuous commissioning process was tested considering a period of 2 weeks in May, where performance testing results were visualized using a developed online dashboard platform. Finally, as part of the building fault detection and diagnostics, a specific case of a malfunctioning ventilation unit reported by the continuous commissioning process is presented. Based on the investigation, a fully-open VAV damper was noticed in one of the large teaching rooms for an extended period in November. This has led to around 84% increase in the electricity consumption of the ventilation unit in the malfunctioning two-weeks period. The problem was related to the logic of the corresponding VAV diffuser controller. After resolving the problem, a proper operation of the ventilation unit is reported with a cumulative performance gap of -10.2% a week later. The average monthly avoidable costs due to eliminating the problem was calculated to be around 2664 DKK. Although the framework presented in this study is implemented in a specific case study building, the framework is generic in principle and scalable to be applied in a wide range of buildings, with slight modifications regarding the performance tests considered to characterise the specific building energy systems. In addition, the manual work associated with the detailed model development will be reduced drastically with the evolution in the field of Building Information Model to Building Energy Model (BIM to BEM). Thus, a large amount of the information needed to be defined and characterized in the energy model development will be read and transferred from the available BIM, saving time and resources.

References


State estimators applied to a linear white-box geothermal borefield controller model

Iago Cupeiro Figueroa1,2, Ján Drgoňa1, Lieve Helsen1,2
1KU Leuven, Celestijnenlaan 300 - box 2421, 3001 Leuven
2EnergyVille, Thor Park 8310, 3600 Genk, Belgium

Abstract

Modelling of geothermal borefields for building energy simulations (BES) has always been a complicated task due to the challenge of implementing both their short-term and long-term responses. Besides, in model-based optimal control of geothermal systems, a simplified version of a borefield control-oriented model is desired. Typical prediction horizons used in optimal control of buildings range from hours to a few days, inviting to reduce the complexity of the controller model down to the short-term range. However, the long-term thermal behaviour of the ground is crucial with respect to the heat pump COP and availability of direct cooling. In a white-box controller model, the states keep their physical meaning. Thus, the long-term dynamics can be captured from the model used for dynamic simulation, i.e. the emulator, and updated to the controller model at each optimisation time-step. Nevertheless, since in a real implementation the availability of data is much more limited a state estimator is necessary. In this paper, three state estimators (Stationary Kalman Filter, Time-Varying Kalman Filter and Moving Horizon Estimator) for a linear borehole model are compared using real data from a building combining a geothermal heat pump and a thermally activated building system (hybrid-GEO&TABS). In general, all investigated linear estimators are capable of accurately estimating the ground states.

Introduction

The worldwide building sector consumes over 36% of global final energy use and is responsible for 39% of energy-related carbon dioxide ($CO_2$) emissions when upstream power generation is included (Dean et al. (2016)). One building concept that could help to improve energy efficiency in the building sector is the MPC hybrid GEO&TABS concept (Himpe et al. (2018)). It combines GEOthermal heat pump and Thermally Activated Building Systems (TABs) to achieve superior heat pump performance. To tackle the challenges that TABS high inertia presents, a hybrid system is installed to face the sudden changes in heat load and model predictive control (MPC) is implemented to anticipate future predictions.

In order to obtain reliable predictions, it is crucial to have an accurate controller model. When coming to the prediction of the heat pump’s coefficient of performance (COP), the supply temperature into the heat pump’s evaporator, i.e. the return temperature of the geothermal borefield, significantly influences this efficiency. Besides, it is important that the MPC guarantees long-term sustainable operation of the borefield. Hence, a reliable borefield model for MPC is of vital importance.

In the literature, we can find different approaches to model the borefield component (Atam and Helsen (2016)) for MPC. Verhelst and Helsen (2011) applied model order reduction (MOR) to a 1D ground heat diffusion model. De Ridder et al. (2011) trained a first order model to describe the dynamics of the underground storage by using the average temperature of the borefield, with sampling periods of one week. Atam et al. (2018) identified nonlinear Hammerstein-Wiener models for different configurations. All these approaches are however limited to identifying the model based on the available operational data. Physics-based, i.e white-box, models would keep the physical meaning of the different states, allowing the controller to have a better idea of the behaviour of the underground. Moreover, they would not require any sort of historical data since they are based on equations that describe the heat transfer physics. To the best of the authors’ knowledge, there exist two works based on physical models suitable for MPC. Witte et al. (2018) developed a physics-based model, however axial heat transfer due to advection was not modeled and the fluid temperature is lumped by using the borehole thermal resistance $R_b$. Laferrière and Cimmino (2018) used a model that requires a discretised thermal response factor as input to compute the ground thermal response.

Since the MPC prediction horizon is in the order of several days for building control, we propose to model only the short-term dynamics of the borefield including advection to accurately predict the fluid temperature, and approximating the ground temperature response with a resistance-capacitance (RC) network. In a dynamic simulation environment, since the states of a white-box model have a physical meaning, perfect state update at each control time-step could be applied by evaluating the model used for simulation. The long-term behaviour would be implicitly inherited from the state update without having to use the thermal response factor that augment the complexity of the MPC formulation due to the application of temporal superposition. However, when coming to a real implementation this information is not available since temperatures...
inside the borefield are usually not measured (e.g., borehole wall and ground temperatures at different depths), but only the inlet/outlet fluid temperatures of the borefield and the associated mass flow rates are available. Hence, a state estimator is needed.

Typical state estimators used in buildings belong to the family of Bayesian Estimators, namely Stationary Kalman Filter (SKF), Time-Varying Kalman Filter (TVKF) and Moving Horizon Estimator (MHE). To evaluate the prediction accuracy of these state estimators, we extend the methodology used by Cupeiro Figueroa et al. (2018) by validating the emulator with historical data and including a comparison between the non-measured states of the controller model and its physical representation in the emulator. Therefore, the main contribution of this paper is the application of state estimation techniques to a borefield model and the evaluation of its performance based on the state estimation error.

Methodology

Modelling and State Estimation

Figure 1 shows the methodology applied in this paper. A physics-based emulator of a borefield is calibrated using the technical sheets of a real building. The model is subsequently validated by historical data from the Building Management System (BMS): the output error $y_e^{emu}$ between the measured return temperature $T_{Ret}$ and the emulator return temperature $T_{Ret}^{emu}$ is assessed to evaluate the validity of the non-measured states $x^{emu}$, which represent fluid, grout and surrounding ground temperatures at different points. A non-linear (NL) controller model is developed approximating the dynamics outside the borehole with a discretised RC network and assuming a fixed temperature $T_p$ placed at the diffusivity length as described by Fick Bird et al. (1960). The model can subsequently be linearised around the hydraulic pump operating working conditions by considering a constant mass flow. The states error $x_e$ and output error $y_e$ of both non-linear (subscript NL) and linear (subscript lin) models against the emulator are checked. For the linear controller model, three linear state estimators $L$, more specifically Stationary Kalman Filter (SKF), Time-varying Kalman Filter (TVKF) and Moving Horizon Estimation (MHE) are applied and assessed by re-evaluating the output error $y_e^{lin}$ and estimated state error $x_e^{lin}$ of the linear model.

Building and measurement data

In order to check the validity of the emulator and later assess the state estimators performance, we use real data from a 10 year old cooling-dominated medium-sized office building located in Dilbeek, Brussels. The building uses a hybrid GEOTABS system whose borefield is composed of 37 boreholes of 94 m deep, piped with double-U tubes in parallel configuration and a relative distance between them of 6 m. An hydraulic pump can circulate a maximum 38 m$^3$/h 30% glycol-water mixture flow through the borefield.

The measurement data for this experiment are extracted from the Building Management System (BMS) of the office building for the period 22-02-2018 to 11-09-2018, where measured data is stored each 8 minutes. The measured data includes: the mass flow rate through the borefield $\dot{m}$ measured by the calorimeter and the supply $T_{Sup}$ and return $T_{Ret}$ borefield temperatures measured by two temperature sensors located in the building cellar.

Borefield modelling

To build up the emulator we use the model integrated into the open-source IBPSA Modelica library (Laferriere et al. (2019)). The short-term radial heat transfer within the borehole is modeled using the RC networks developed by Bauer et al. (2011), whose parameters are calculated based on the physical properties of the fluid, piping and grout. The model is discretised vertically and coupled with advection heat transfer equations in the axial direction. The long-term behaviour outside the borehole is given by the $g$-function calculated following the methodology of Cimmino and Bernier (2014) using the finite line source solution. The model has been adapted to compute the ground temperatures at selected distances.

Calibration and validation of the emulator

The simulation borefield model has been calibrated with parameters from the technical sheets. Since no thermal response test (TRT) was performed, the SmartGeotherm (2017) tool is used to determine the ground properties. The deeper layers of the ground are mainly composed of clay sand.

A validation test is set-up by imposing the supply borefield temperature and the mass flow rate measured by the temperature sensor and the calorimeter, respectively. The simulated return temperature of the borefield is compared to the measured one. Results are shown in Figure 2.

We observe that the error increases when no mass flow was introduced into the borefield. A deeper analysis shows that this fact was caused by natural convection.
Figure 2: Validation of the emulator. Top: Measured mass flow rate ($\dot{m}$), supply ($T_{Sup}$) and return ($T_{Ret}$) temperatures and simulated outlet ($T_{emu}^{emu}$) temperature of the borefield. Bottom: Output emulator error $y_{emu}^e$. 

around the sensor located in the cellar, which the model does not take into account. For a better understanding and fair comparison, these values with zero mass flow rate have been filtered. The main unknown of the validation is the history of the borefield: the system has been operative for 10 years while the data available only accounts for the last 7 months. A considerable relative mismatch can be appreciated at the start due to the initial guess of the borefield far ground temperature, which did not take into account the effects of the previous years.

Although the undisturbed ground temperatures in Belgium are about 11 °C, a far ground temperature of 13.3 °C and a geothermal gradient of 0.01 K/m show a good fit due to the unbalance that the cooling-dominated building generates. However, since the measurements started by end-February (end of the heating season) the ground temperatures in the neighbourhood of the boreholes are lower. The error decreases as the effect of the inaccurate ground temperatures at the initialization fades over time, resulting in an error oscillating between +0.2 and -0.5 °C. For the considered period, the mean absolute error is 0.15 °C, therefore temperatures are well validated. However, these small errors can have a large effect on the computation of the borefield heat exchange, since a small increase in temperature difference can be translated into a large difference in the heat exchanged.

Nonlinear controller model

The short-term controller model within the borehole, i.e. the fluid, piping and filling RC network is identical to the one of the emulator. Each vertical discretisation $n_v$ introduces two fluid states and two grout states in the case of single-U pipes and four fluid states and four grout states in the case of double-U pipes. These states represent the fluid and grout dynamics, i.e. their temperatures. The developed model can be reduced in complexity either by reducing the number of vertical discretisations or by eliminating the dynamics in the fluid/grout by considering steady-state conditions. The advection heat transfer component is kept which introduces a non-linearity into the model.

To model the long-term behaviour outside the borehole, we use a radial 1D RC network that discretises the ground into a mesh of rings for each vertical discretisation, as shown in Figure 3. The mesh introduces an additional number of states $n_v, n_h$, with $n_h$ the number of radial discretisations. These states represent the surrounding ground temperatures at a given distance. A summary of the states of the model can be found in Table 1. The RC parameters are calculated from the physical properties of the ground. The mesh is discretised from $r_b$ to a boundary radius calculated using the diffusion length $r_B = 2\sqrt{\alpha_g \tau}$ and provides a measure of how far the temperature has propagated by diffusion in time $\tau$ (Bird et al. (1960)), with $\alpha_g$ the ground diffusivity and $\tau$ the time constant, by default 1 week to fully cover the affected range in a typical MPC prediction horizon timeframe. The cell size $\Delta r$ is calculated using Eskilson (1987) guidelines, with a resolution time $\Delta t$ of 60 seconds.

$$\Delta r = [\Delta r_{min}, \Delta r_{min}, \Delta r_{min}, ..., \beta^n \Delta r_{min}, ..., r_B]$$ (1a)

$$\Delta r_{min} = \text{min}(\sqrt{\alpha_g \Delta t}, h_b/5)$$ (1b)

Linearisation of the controller model

The described model is non-linear due to (i) the advection heat transfer component associated to the movement of the heat carrier fluid and (ii) the convective heat transfer coefficient which depends on the Nusselt number. For a constant mass flow rate, we linearised the model and obtained the state space model (SSM) in the following form:

$$x_{k+1} = Ax_k + Bu_k + w_k, \quad (2a)$$

$$y_k = Cx_k + Du_k + \nu_k, \quad (2b)$$
Figure 3: Discretisation of the ground layer (Picard and Helsen (2014)).

Vectors $u$, $y$ and $x$ represent supply, return and internal borehole temperatures, respectively. In reality the model is subject to uncertainties, where model uncertainty is represented by the process noise variable $w_k$ and measurement uncertainty is defined by the measurement noise $v_k$.

**Validation of the controller models**

The two controller models are validated against the emulator using the same procedure as for the validation of the emulator. Both models have 10 vertical discretisations $n_v$ and 10 radial discretisations $n_h$, including fluid and grout dynamics, which makes a total of 190 states for the double-U configuration. The same data are imposed to the models as for the validation of the emulator, but for the sake of clarification of results, only 30 days of operation are shown in Figure 4. The results show the return fluid temperature, the ground temperatures at the eighth radial discretisation length $r_8 = 0.36m$ and at the boundary diffusion length $r_B = 1.54m$ for the mid-vertical discretisation $n_v = 5$. The non-linear controller model shows good agreement with the emulator for the first weeks of operation, but its accuracy decays over time since the temperature at the boundary radial layer remains constant. The effects on the ground temperature at the boundary diffusion length start to be visible at the 5th day of operation. In the long-term operation, the model needs state updates to be able to incorporate the long-term heat transfer effects such as the interaction between boreholes.

The model was linearised around the average working point of 4.98 kg/s. The higher the deviation of the mass flow rate from the selected linearisation point, the higher the output error of the linear model. Still, the error is in general low since the influence of the convective thermal resistance around the working point is small. Concerning the ground temperatures, these additional linearisation errors fade more the further the states are from the borehole since the boundary temperature remains constant. The linear model output can be corrected by means of state estimation.

**State estimation**

The objective of the estimator is to minimize the estimation error defined as the difference between real and estimated states $\hat{x}_{k+1} - x_k$. Because the real state measurements are not available from the borefield considered we use the states from the validated high-fidelity emulator to evaluate the state estimator performance. Because the controller model $2$ is linear, we restrict our choice to the following linear estimators: stationary Kalman Filter (SKF), time-varying Kalman Filter (TVKF), and Moving Horizon Estimation (MHE).

**Stationary Kalman Filter**

In the case of stationary Kalman Filters (SKF), the estimator gain $L$ is computed by the off-line solution of the discrete Riccati equation given by eq. (3).

$$L = \frac{APC^T + Q}{CPCT^T + R + Q}$$

Where $P$ represents estimation error covariance $E((y_k, \nu_k)^T)$, $Q$ stands for process noise covariance $E(w_k w_k^T)$, and $R$ for measurement noise covariance $E(v_k v_k^T)$. In this paper MATLAB’s dlqfe function is used to compute $L$ for SKF. In general a Kalman Filter consists of two stages, an update and a prediction phase. In the prediction phase (eq. (4b)) predicts the state at the current time step $k + 1$ based on the previous state and the model (2). In the update phase (eq. (4a)) the measurement is used to refine the predicted state estimate from the previous time step by introducing feedback into the system.

$$\hat{x}_{k+1|k} = \hat{x}_{k|k-1} + L_k(y_k - C\hat{x}_{k|k-1} - Du_k) \quad (4a)$$

$$\hat{x}_{k+1|k} = A\hat{x}_{k|k} + Bu_k + Ed_k \quad (4b)$$

**Time-varying Kalman Filter**

In the case of time-varying Kalman Filters (TVKF) the off-line construction of the estimator gain $L$ is replaced by a recursive on-line computation, defined by the update phase eq. (5) and prediction phase eq. (6).

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + L_k(y_k - C\hat{x}_{k|k-1} - Du_k) \quad (5a)$$

$$L_k = \frac{P_{k|k-1}CT}{R_k + CTP_{k|k-1}CT} \quad (5b)$$

$$P_{k|k} = (I - L_kC)P_{k|k-1} \quad (5c)$$

The only difference with SKF eq. (4) is the addition of the recursive updates for the error covariance matrix $P$ via eq. (5c) and eq. (6b) and for the estimator gain $L$ by eq. (5b).

$$\hat{x}_{k+1|k} = A\hat{x}_{k|k} + Bu_k + Ed_k \quad (6a)$$

$$P_{k+1|k} = AP_{k|k}A^T + Q_k$$

**Table 1: Summary of the states $x$ of the controller models.**

<table>
<thead>
<tr>
<th>State meaning</th>
<th>Quantity</th>
<th>Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fluid temp.</td>
<td>$2n_v$ (U-tube)</td>
<td>$T_{f,i,n_v}$</td>
</tr>
<tr>
<td></td>
<td>$4n_v$ (2xU-tube)</td>
<td>$0$ (steady-state)</td>
</tr>
<tr>
<td>Grout temp.</td>
<td>$2n_v$ (U-tube)</td>
<td>$T_{g,i,n_v}$</td>
</tr>
<tr>
<td></td>
<td>$4n_v$ (2xU-tube)</td>
<td>$0$ (steady-state)</td>
</tr>
<tr>
<td>Ground temp.</td>
<td>$n_hn_v$</td>
<td>$T_{g,i,n_h,n_v}$</td>
</tr>
<tr>
<td>Boundary temp.</td>
<td>$n_v$</td>
<td>$T_{B,n_v}$</td>
</tr>
</tbody>
</table>
The moving horizon estimation (MHE) is described by the following optimisation problem:

$$\min_{x_{k-N+1} \in X, u_i \in U} \sum_{i=k-N+1}^{k-1} \left| \|w_i\|_Q^2 + \sum_{i=k-N+1}^k \|v_i\|_R^2 \right|$$

subject to:

$$x_{k+1} = Ax_k + Bu_i + Ed_k + w_i, \ i \in \mathbb{N}_{k-N+1} \tag{7c}$$

$$y_i = Cx_i + Du_i + v_i, \ i \in \mathbb{N}_{k-N+1} \tag{7d}$$

$$x_1 \in \mathcal{X}, \ u_i \in \mathcal{U}, v_i \in \mathcal{V}, \ i \in \mathbb{N}_{k-N+1} \tag{7e}$$

where $x_k$, $u_k$, $d_k$, $w_k$ and $v_k$ represent the values of states, inputs, disturbances, process and measurement noise respectively, predicted at the $k$-th step of the estimation horizon $N$. The predictions are obtained from the controller model given by Eqs. (7c) and (7d). Limits on state and noise are defined by eq. (7e). The term $\|a\|_Q^2$ in the objective function represents the weighted squared 2-norm, i.e., $a^TQa$, with the weighting matrices $Q$, $R$, and $P$ given as positive definite diagonal matrices. The first term of the objective function stands for the so-called arrival cost, which represents the summarized effect of data from previous timesteps outside the estimation window $N$. In this case we define the arrival cost explicitly based on previous state estimates at the $(N+1)$-th step.

In general the optimisation variables include: the estimated state over the horizon, the estimated state update error ($W$) and the estimated measurement error ($V$). The first element of the optimised estimated state over the horizon ($\hat{x}_{k-N+1}$) is selected and the current estimated state $\hat{x}_k$ is calculated by integration using $W$ via the so-called state condensing method. This technique can efficiently reduces the number of optimisation variables and as such speed up the solver time.

**Case Study with Real Measurements**

**Simulation Setup**

The state estimators are constructed and results are evaluated using the BuiSim MATLAB toolbox (Droga and Helsen, 2019), which is built upon the modelling and optimisation toolbox YALMIP (Löfberg, 2004). In case of MHE, the objective function (Eq. (7b)) is quadratic and all constraints are linear, therefore problem (7) can be solved as a strictly convex quadratic programme (QP). For solving problem (7) the state of the art optimisation solver GUROBI (Gurobi Optimization, 2012) is used.

The estimator performances are evaluated using four key performance indicators (KPIs): average absolute error (AAE) per state per sample defined by Eq. (8) and where $N_{sim}$ stands for the number of simulation steps, maximal state estimation error $\max(\hat{x}_{sim})$, mean of estimation error $\text{mean}(\hat{x}_{sim})$, and overall simulation time.

$$\text{AAE} = \frac{1}{N_{sim}} \sum_{k=1}^{N_{sim}} \left| \hat{x}_{sim,k} - x_{k} \right|$$

In accordance with the frequency of the measurement data, the sampling period was chosen equal to $T_s = 480$ s. Based on available measurement data from the borefield installed in the real office building, the overall simulation period is chosen to be 200 days. All three state estima-
tors are tuned by engineering insights and corrected by trial-and-error such that they provide accurate output estimations by lowering the output error. The tuning factors are the process noise covariance $Q$ and the measurement noise covariance $R$ matrices, which are designed as diagonal positive definite matrices, with their values summarized in Table 2.

**Results**

The performance of the estimators is demonstrated on estimated states $\hat{x}_{\text{lin}}$ and emulator states trajectories $\hat{x}_{\text{emu}}$. For capturing the dynamics of the states and for intuitive understanding of the differences between the results of the individual estimators, the subsequent plots show trajectories of a single week. Simulated state trajectories of the emulator model and estimation profiles of TVKF are given in Fig. 5. For the sake of keeping the paper length, SKF and MHE profiles are not shown, but their trajectories are similar. Bottom plots represent the state trajectories as classical time-series plots. For a more intuitive understanding of the dataset the upper plots show the 3D ribbon plot of the same profiles. Here, the individual state trajectories are plotted in parallel next to each other in a 3rd dimension. The states are sorted in different sets from top to bottom, and from nearest to farthest from the borehole in the case of the surrounding ground temperatures. The first 40 states correspond to the fluid temperatures. The following 40 states correspond to the grout temperatures. The next 100 states correspond to the surrounding ground temperatures. The last 10 states show the boundary temperatures. This setup allows us to examine the trajectories of a higher dimensional dataset visually, and by a proper ordering of the variables also capture the physical dependencies between states. The visual comparison of estimated trajectories $\hat{x}_{\text{lin}}$ reveals a relatively good fit with the emulator states $\hat{x}_{\text{emu}}$ for the problem considered. Despite estimating 190 states with one single output, all estimators are able to capture the dynamic patterns of the states with small deviations from the emulated states. Such visual inspection tells us a priori that TVKF shows the best match when estimating the internal states.

Fig. 6 compares box plots of the estimation errors for different estimators for the full dataset of 200 days. Both SKF and TVKF have very similar performance when estimating the fast-dynamics of fluid and grout temperatures. In contrast, SKF has a higher number of outliers when estimating the slow-dynamics of the surrounding ground and boundary temperatures than TVKF, the further we move from the borehole wall. This points its difficulty to estimate the ground temperatures. Surprisingly, the MHE performance is the lowest among the three estimators. This is probably caused by a large number of optimised variables w.r.t. the number of available parameters which results in an optimisation problem with a large number of degrees of freedom. While SKF and TVKF tend to underestimate the states, MHE tends to overestimate them.

These statements are confirmed by the numerics presenting the overall performance comparison based on selected KPIs. The evaluation on a full dataset of 200 days is given in Table 2. SKF and TVKF provide similar performance when estimating the fast-dynamics within the fluid and the grout. However, TVKF seems to provide more accurate estimates of the slow-reacting ground temperatures, especially at the boundary. Our hypothesis is that its ability to recompute the Kalman Gain at each time-step is able to cope better with the slowly changing dynamics of the ground.

As already observed in the previous figures, the performance of the MHE is the lowest among the investigated estimators. Moreover, from a computational point of view, MHE is significantly more demanding when compared to SKF and TVKF. Nevertheless, considering that the number of seconds per time-step for the computation is lower than 1, MHE is still feasible for real implementation purposes, where the time-steps typically vary from 15 minutes to 1 hour.

**Conclusion**

Three state estimation methods have been compared to demonstrate the possibility of estimating the states of a borefield solely based on its linearised mathematical model and measurements of the supply and return temperature. In particular, stationary Kalman filter (SKF), time-varying Kalman filter (TVKF) and moving horizon estimation (MHE) were investigated in the context of MPC of
hybridGEOTABS buildings, where both short- and long-term are important for sustainable operation.

The borehole can be well described by the linear model presented in the short-term. The state estimation techniques aim to re-initialize the states of the borefield to capture the long-term dynamics from the measurements. The simulation experiments with real measurement data were conducted for a period of 200 days. In general, all the three investigated estimators are able to provide decent accuracy. SKF and TVKF performed better with average absolute errors below $0.5^\circ C$ compared to the case of MHE, with average absolute errors up to $1.5^\circ C$. The estimation of the ground temperatures seemed more challenging for the SKF rather than for TVKF. The tuning of the MHE, with a high number of optimization variables, is the main challenge towards improving its accuracy. Note that we are estimating 190 unknown states solely based on one available measured output.

The question remains whether adding the non-linearities into the controller model would lead to significant improvement in the estimation accuracy. Besides, the influence of the level of complexity of the model determined by the number of states needs to be evaluated. Eventually, the variable of interest in MPC is the prediction of the return temperature from the borefield. A good re-initialization of the states is needed. The ground temperatures may be also useful for estimating the saturation level of the borefield and formulate its long-term balance. How-

---

Figure 5: Left: Simulated states trajectories of the emulator model. Right: TVKF trajectories of estimated states. Top figures: 3D profiles, where trajectories represent the fluid temperatures, grout temperatures, surrounding ground temperatures and boundary temperatures, from blue to yellow. Bottom figures: 2D profiles.

Figure 6: Box plots of the estimated state errors of the 190 states for each estimator.
ever, a firm conclusion about these statements needs to be supported by direct comparison of the linear and non-linear estimators for different levels of complexity on the same dataset and setup. Future work will thus verify or falsify this hypothesis by comparison of linear and non-linear estimators for the borefield state estimation problem. The difference in accuracy and dynamic behaviour (short- vs long-term) between the different sets of states encourage us to decompose the problem and apply different estimation techniques to each set in the future. Also, the effect of variations in states complexity, initialization and tuning of estimators will be rigorously evaluated.

Acknowledgments

Both authors Iago Cupeiro Figueroa and Ján Drgoňa contributed equally to this paper. The authors acknowledge the financial support by the European Union through the EU-H2020-GEOT6CH project Geothermal Technology for Economic Cooling and Heating and within the H2020-EE-2016-RIA-1A programme for the project Model Predictive Control and Innovative System Integration of GEOTABS;-) in Hybrid Low Grade Thermal Energy Systems - Hybrid MPC GEOTABS (grant number 723649 - MPC;-); GT).

References


On Formulation and Training of Grey-box Thermal Model for Low-rise Residential Buildings

Zixiao Shi\textsuperscript{1}, Guy Newsham\textsuperscript{1}, Ajit Pardasani\textsuperscript{1}, H. Burak Gunay\textsuperscript{2}
\textsuperscript{1}National Research Council Canada, Ottawa, Ontario, Canada
\textsuperscript{2}Carleton University, Ottawa, Ontario, Canada

Abstract
This paper details the methodologies for creating and training grey-box thermal models for low-rise residential buildings. This paper covers different aspects of model development such as model vectorization, cost function definition and parameter estimation. Different computing strategies such as GPU accelerated calculation are also explored. This paper also briefly demonstrates the possibility of rearranging the model equation for predictive control purposes. The performance of an example grey-box model is tested against common data-driven machine learning models using a dataset of over 500 dwellings. Overall the grey-box model achieved good temperature prediction accuracy at a 4-hour forecast horizon and produced meaningful insights from the estimated parameters. The possibilities of using grey-box models for more advanced applications, such as model predictive control and remote auditing are also discussed.

Introduction
Recent advancement in smart home and smart grid infrastructure has led to a significant growth in the data collection capabilities in low-rise residential buildings. This leads to the possibility of training tailored thermal models using data driven methods for each individual household. These models can be used in a wide variety of applications, such as model predictive controls for heating/cooling, fault detection, and dwelling characteristics extraction.

Three categories of models can be adopted to quantify building thermal processes: first-principle models, grey-box models and black-box models. First principle models are derived from fundamental physical phenomena and are usually used for detailed forward simulation with predefined model parameters. While some authors have tried using first principle building simulation engines such as EnergyPlus and esp-r to automatically generate models of existing buildings (Eisenhower, O’Neill, Narayanan, Fonoberov, & Mezić, 2012), this task is still quite challenging due to the high number of parameters that need to be defined/estimated inside the first-principle models.

Grey-box models are simplified models loosely based on first principles. They have a reduced number of parameters and equations, and are flexible to different engineering applications (Déqué, Ollivier, & Poblador, 2000). Grey-box models can be obtained through a model reduction process from first-principle models, or created manually from expert knowledge.

The adoption of quantitative grey-box thermal models for commercial buildings has been widely researched, yet its application on individual residential dwellings is still rare (Déqué et al., 2000; Gianniou, Reinhart, Hsu, Heller, & Rode, 2018). Originally grey-box models were used as surrogate models to detailed building performance simulation (Crawley, Sander, Cornick, & Newsham, 1993). Later researchers found it possible to train grey-box models using data-driven approaches to represent individual buildings. Some of these applications include an R-C model used by Braun and Chaturvedi (2002), and state-space representation using physical parameters (Molina, Lu, Sherman, & Harley, 2013).

A black-box model, as its name suggests, is usually applied without the need to explicitly define its model structure or parameters except for a limit number of hyper parameters. In recent years, many researchers have started to use black-box models derived from statistics and machine learning to predict and monitor building thermal response. Examples of these applications include artificial neural networks (Mustafaraj, Lowry, & Chen, 2011) and support vector machines (Li, Meng, Cai, Yoshino, & Mochida, 2009). While black-box models may provide solutions for complex building thermal processes where grey-box models fail, one major disadvantage is their inability to extrapolate beyond their training target. Further, unlike grey-box models, the parameters derived from trained black-box models retain little physical meaning, and black-box models cannot be rearranged to perform other tasks (Shi & O’Brien, 2019).

Research objective
The goal of this research is to investigate methods to formulate grey-box thermal models for low-rise residential dwellings. Such models can be used for scalable model predictive control, demand response and remote auditing applications. The model template for this research is based on previous grey-box modelling efforts (Braun & Chaturvedi, 2002; Gunay, Bursill, Huchuk, O’Brien, & Beausoleil-Morrison, 2014; Wang & Xu, 2006). The proposed grey-box model is capable of providing reliable short-term (1 to 4 hours) thermal response forecasts as well as estimating reduced thermal parameters. Ways of compiling and computing these models are also explored. Performance of the model is compared against machine learning models using a dataset of over 500 residential dwellings.
Methodology

This section discusses the proposed grey-box modelling scheme. Formulation of the grey-box model and comparison with other modelling alternatives is discussed first, followed by an explanation of the feature selection processes and vectorization to achieve better model quality and training efficiency. Finally, the authors discuss how to customize the cost function and rearrange the model function to expand the model capabilities.

Model formulation

The goal of the grey-box thermal model is to use physics-based parameters $\phi$ inside a model function $f$ to predict the future indoor air temperature vector $\hat{T}$. $\hat{T}$ consists of multiple forecasting horizons $h$ in the future. The model function uses current and historical observations, future weather forecasts and control variables as its inputs. The general form of this model is formulated as below:

$$\hat{T} = \begin{bmatrix} T_1 \\ T_2 \\ \vdots \\ T_h \end{bmatrix} = \begin{bmatrix} f(T_o, X_o, U_o) \\ f(T_1, X_1, U_1) \\ \vdots \\ f(T_{h-1}, X_{h-1}, U_{h-1}) \end{bmatrix}$$ (1)

Where $X, U$ are exogenous state and control vectors that affect the thermal process of a building. The subscript $0$ denotes variables from the current time, and $T_o, T_2, ..., T_h$ denote the forecasted indoor air temperature from the first forecast step to forecast step $h$. In essence this formulation requires one unified model function to iteratively predict future temperature. This approach may cause prediction errors to propagate, making forecasting results less reliable when the forecasting horizon becomes too large. In the scenario where a grey-box model is used, the model function $f$ should be consistent for all time steps since the physical processes being represented by the grey-box model remain unchanged.

As an alternative to mitigate the error propagation issue, some researchers (Srivastava, Pandey, & Singh, 2016) have used dedicated models for each forecast step as below:

$$\begin{bmatrix} T_1 \\ T_2 \\ \vdots \\ T_h \end{bmatrix} = \begin{bmatrix} f_1(T_o, X_o, U_o) \\ f_2(T_o, X_o, X_1, U_o, U_1) \\ \vdots \\ f_h(T_o, X_o, ..., X_{h-1}, U_o, ..., U_{h-1}) \end{bmatrix}$$ (2)

As denoted in the above equation, for each forecast step a dedicated model function is responsible for using all previous inputs to predict the indoor air temperature. While this approach may provide improvements over the iterative process for longer horizon forecasts, it also increases the complexity of the overall forecasting model, making it harder to train. Some other researchers (Srivastava et al., 2016) have used a single black-box model for predicting all forecast steps in a multi-variate vector, and the author argues this approach requires a large covariance matrix instead of several smaller ones as formulated above. In this research the authors will compare the implementation of a grey-box thermal model using equation (1) against dedicated black-box models for different forecast steps based on equation (2).

The general form of the grey-box model function $f$ is:

$$T_i = f(T_{i-1}, T_{oa}, \psi) = T_{i-1} + \Delta t \sum_{n=1}^{delay} \phi_{oa,n}(T_{oa,i-n} - T_{i-n}) + \Delta t \sum_{n=1}^{exo} \sum_{m=1}^{n} \phi_{m,n} \psi_{m,i-n}$$ (3)

Where $T_{oa}$ is the outdoor air temperature, $\psi$ are the $m$ number of exogenous inputs represented in fractions, $\psi \in [0,1]$ such as heating/cooling control and solar radiation. $\Delta t$ is the model time step, $\phi$ represents the reduced parameters for the grey-box model, and $n$ represent the number of trailing (historical) inputs for $T_{oa}$ and $\psi$ to reflect transient effects. The selection of $n$ for each of the inputs are discussed in the following feature selection section.

Feature selection

Similar to the model formulation step, there are multiple approaches to select the best inputs for $f$. This step is called feature selection, part of feature engineering, and is often practiced in machine learning problems. One common approach is to use information criteria, such as the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), to determine relative quality of models constructed from different combinations of inputs (Bozdogan, 1987). This approach is sometimes called a wrapper method since it wraps around all possible subsets of input features. This method is usually very computationally intensive, since it requires all potential models to be trained with all possible subsets of features to evaluate them. The wrapper method is not selected in this research due to its low practicality and scalability.

Instead, the authors decided to use the so-called filter method to use proxy measures to prescreen the best input features and their delays for the thermal model. Since the thermal model itself is analogous to a linear additive model, Spearman correlation coefficients between $\Delta T$ and $T - T_{oa}$, $\psi$ are selected as the proxy. For nonlinear models, nonlinear measures such as mutual information (Frazier & Swinney, 1986) can be used as the proxy instead.

Another approach, regularization, performs feature selection by including additional terms in the cost function to penalize additional features (Friedman, 2004). Still, this approach requires the initial training of the model to include all potential inputs, and is more suitable to black-box models, in which the filter method is less applicable due to model nonlinearity.

Vectorization

The iterative computation scheme used in equation (1) is rather inefficient on a modern computer, i.e. each forecast step needs to be computed iteratively for each prediction. To combat this, the authors propose two methods to improve the computation performance, as shown in equation (4) and (5). The first is to substitute the model function so that the entire $\hat{T}$ can be computed simultaneously. Still, substitution is usually not optimized in numerical computation. The best way to improve computation efficiency is to express everything in matrices. To this end, the model function can be vectorised into matrix form. Vectorization can be achieved by multiplying an augmented vector of $X$ and $U$
with the matrix $A$. $A$ is the Jacobian Matrix of the substituted model function, as in $A = \frac{\partial \hat{T}}{\partial x} = g(\phi)$. To further speed up the computation, the authors also used graphical processing units (GPU) to accelerate the matrix manipulation process.

**substitution:**

$$\hat{T} = \begin{bmatrix} f(T_0, X_0, U_0) \\ f(T_0, X_0, U_0, X_1, U_1) \\ \vdots \\ f(f(T_{h-1}, X_{h-1}, U_{h-1}), X_{h-1}, U_{h-1}) \end{bmatrix}$$

**vectorization:**

$$\hat{T} = xA$$

where $x = \begin{bmatrix} T_0 \\ X_1 \\ U \end{bmatrix}$, $A = \frac{\partial \hat{T}}{\partial x}$

**Model training and cost function**

When training a model the cost function needs to be established to set the target for the model to be optimized on. Since the grey-box model is used to forecast future temperature, the model residuals of all forecast steps may need to be taken into consideration when calculating the cost function. Furthermore, since the model will be trained recursively, observations closer to the training time may be more important due to the underlying seasonal effects. To resolve these two potential requirements, the authors propose two weighting vectors to calculate the model cost $C(f)$:

$$C(f) = [\lambda(T - T')^2] \omega$$

Here a quadratic loss function $(\hat{T} - T)^2$ is used to calculate the residual matrix, $\lambda$ is the horizon weighting vector dictating how important each forecast step is to the total model accuracy, and $\omega$ is the observation weighting vector determining which observations are more dominant to fitting the data. Since quadratic loss is dominant to fitting the data. Since quadratic loss is quadratic, it is usually difficult to program or isolate the effect of a single input term. In some black-box models where the model function is not reversible, separate models that solely predict control inputs have to be trained in order to achieve this task, which further increases the computation requirement.

**Case Study**

The data set used in this study consists of data from 564 dwellings located in Southern Ontario, Canada (Newsham, Pardasani, Grinberg, & Bar, 2016). The dataset contained overall electricity consumption and thermostat data for 527 houses, motion/orient (occupancy) data for 416 houses, and household characteristic data for 254 houses from March 2015 to February 2016. More than 80% of the dwellings are detached houses, the remainder being semi-detached houses or condos. All of the dwellings are primarily heated by natural gas and cooled by electricity through a central forced air system with floating on/off control. Data for each dwelling is collected from a smart (interval) electricity meter, a smart thermostat, multiple infrared occupancy sensors and door contact sensors. Variables recorded in this data set include: indoor air temperature, heating/cooling set point, heating/cooling runtime and system mode (heat/cool/off), electricity consumption, and a total number of occupancy observation weighting is used, where data closer to the time of training is more important. In addition, only the first two forecast steps are used for optimization while the third forecast step is discarded. While only using two forecasting steps may reduce the model accuracy, it could reduce the training time by not calculating the rest of the forecast steps at all during the model training process, in this case theoretically reducing the amount of training calculations by about one-third.

**Model rearrangement**

An additional reason to use a grey-box model is the easiness of rearranging the model function to approximate the required heating/cooling control or any other control term $\psi_c$ over the time step $\Delta t$, if the future indoor air temperature $T_i$ is predetermined:

$$\psi_{c,i-1} = \frac{T_i-f(T_{i-1}a_{db}\psi_{i-1})}{\Delta t_a}, \psi_{c,i-1} \in \psi_k$$

While such functionality is still possible with a nonlinear or a machine learning thermal model through back-propagation, it is usually difficult to program or isolate the effect of a single input term. In some black-box models where the model function is not reversible, separate models that solely predict control inputs have to be trained in order to achieve this task, which further increases the computation requirement.

### Figure 1: Example of empirical risk function for a training size of 10 observations and 3 time step forecast horizon. The left hand side uses linear weighting, and right hand side uses custom weighting.
sensor firings. The temporal resolution of the data set is hourly. Since measurements from the sensors are collected and uploaded through each household’s own wireless network, the temporal continuity is not guaranteed and missing data was not uncommon. On average 27% of the data is missing. The authors interpolated missing data less than 4 hours long, and then discarded the rest. For the weather data, hourly temperature, wind speed and relative humidity data are obtained through Environment Canada services (Environment Canada, n.d.), and hourly solar radiation is calculated using daily solar radiation data from NASA (Rosenzweig et al., 2014). The formulation of the grey-box model for this study is presented as below:

\[ T_i = T_{i-1} + \Delta t \left[ \sum \phi_{\text{occ},n}(T_{\text{occ},i-n} - T_{i-n}) + \sum \phi_{\text{rad},n}(T_{\text{rad},i-n} + \phi_{\text{heat},i-1} + \phi_{\text{cool},i-1}) \right] (8) \]

The delay term \( n \) for each of the exogenous inputs are determined by the spearman correlation with a threshold of 0.3. For this problem \( \Delta t \) is set to 3600 secs to reflect the one-hour data resolution. The model itself is implemented in Python, using scipy, numpy, (Jones, Oliphant, & Peterson) sympy (Meurer et al., 2017) for formulation, and compiled to Tensorflow (Abadi et al., 2015) for GPU acceleration. To avoid local minima, a global optimization algorithm called differential evolution from scipy is used (Storn & Price, 1997).

**Results**

Three major components of the results are presented: first the authors compare the computation efficiency of vectorization with iteration and substitution. Next, different choices of weighting functions \( \lambda \) and \( \omega \) and how they affect the accuracy of the grey-box models are evaluated. Then the authors compare the proposed grey-box model against the other model strategies discussed in the methodology section. Finally, the authors examine the reduced physical parameters and demonstrate how to rearrange the thermal model to predict cooling demand.

**Vectorization**

Table 1 compares the processing time of different computation options. Iteration, substitution and vectorization are performed on an Intel i-5 7600K processor, and GPU acceleration is performed on an Nvidia GeForce RTX 2070. A single computation is the average time needed to predict a two-week temperature change with a four-hour horizon. The model training time is the average time required to recursively train the model with four-week historical data. Since the cost function is convex, gradient-based optimization is used.

As theorized in the methodology section, instead of iteration, adopting substitution to calculate all predictions simultaneously reduced computation time by more than one order of magnitude. Vectorising the model function further decreased the computation time by another order of magnitude. The GPU accelerated vectorization reduced computation time, but only by a smaller margin.

The reduction in computation time for model training is less significant than single computations, but still effective enough to justify the usage of vectorization. The difference between CPU-based vectorization and GPU acceleration is minimal since the size of the matrices are relatively small and GPU tends to scale well with very larger matrices. Yet for a multi-zone grey-box thermal model such as office buildings, GPU acceleration is worth investigating and may scale better.

**Table 1: Computation time comparison**

<table>
<thead>
<tr>
<th>Computation Method</th>
<th>Average Computation Time</th>
<th>Average Model Training Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iteration</td>
<td>1.089ms</td>
<td>Too long</td>
</tr>
<tr>
<td>Substitution</td>
<td>36ms</td>
<td>630ms</td>
</tr>
<tr>
<td>Vectorization (CPU)</td>
<td>1ms</td>
<td>63ms</td>
</tr>
<tr>
<td>Vectorization (GPU)</td>
<td>0.5ms</td>
<td>50ms</td>
</tr>
</tbody>
</table>

**Model comparison**

Table 2 shows the root mean squared error (RMSE) of temperature predictions using different training weights \( \lambda \) for the grey-box thermal model. Using the first two forecast horizons improved the overall forecasting accuracy, while the further inclusion of more forecast steps brings minimal improvements. Still, this indicates the requirement for using multiple forecasting steps, but not all horizons for model training. The following analysis uses the model trained with the first two forecast horizons.

On average, a four-hour horizon has an error of 0.44°C. The mean error is exaggerated by a few dwellings with very high unpredictability in temperature changes, and general uncertainties during the shoulder seasons. When dwellings with high uncertainties are excluded from the analysis, the mean RMSE is further reduced by 40% to 0.26°C. The authors recommend future users of this approach to validate the models recursively before applying them, and to use alternative modelling techniques for dwellings with low grey-box model accuracy.

**Table 2: RMSE of temperature prediction with different training weights**

<table>
<thead>
<tr>
<th>Training weights</th>
<th>1-hr horizon</th>
<th>2-hr horizon</th>
<th>3-hr horizon</th>
<th>4-hr horizon</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1,0,0,0)</td>
<td>0.19</td>
<td>0.31</td>
<td>0.42</td>
<td>0.49</td>
</tr>
<tr>
<td>(1,1,0,0)</td>
<td><strong>0.16</strong></td>
<td><strong>0.28</strong></td>
<td><strong>0.37</strong></td>
<td><strong>0.44</strong></td>
</tr>
<tr>
<td>(1,1,1,0)</td>
<td>0.15</td>
<td>0.28</td>
<td>0.37</td>
<td>0.44</td>
</tr>
<tr>
<td>(1,1,1,1)</td>
<td>0.15</td>
<td>0.28</td>
<td>0.37</td>
<td>0.44</td>
</tr>
</tbody>
</table>

Table 3 compares the accuracy of the proposed grey-box model with its black-box alternatives, specifically support vector regression (SVR). A naïve model, which uses the current observation as the future prediction, served as a
benchmark. Single SVR uses equation (1) to calculate the future temperature iteratively, while dedicated SVR uses equation (2) to compute all forecast horizons simultaneously. All three methods achieved much better accuracy than the naïve model. Encouragingly, the proposed grey-box model achieved a similar level of performance as the dedicated SVR. Interestingly, single SVR based on equation (1) performed much worse than the other two models, which means that careful preparation and formulation are needed even for black-box models.

<table>
<thead>
<tr>
<th>Forecast RMSE (°C)</th>
<th>1-hr horizon</th>
<th>2-hr horizon</th>
<th>3-hr horizon</th>
<th>4-hr horizon</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naïve model</td>
<td>0.43</td>
<td>/</td>
<td>/</td>
<td>1.02</td>
</tr>
<tr>
<td>Proposed grey-box</td>
<td>0.16</td>
<td>0.28</td>
<td>0.37</td>
<td>0.44</td>
</tr>
<tr>
<td>Single SVR</td>
<td>0.18</td>
<td>0.47</td>
<td>0.57</td>
<td>0.66</td>
</tr>
<tr>
<td>Dedicated SVR</td>
<td>0.18</td>
<td>0.28</td>
<td>0.36</td>
<td>0.42</td>
</tr>
</tbody>
</table>

**Parameter estimates**

As covered earlier, one advantage of the grey-box model is the easiness to convert its model parameters into meaningful physical insights about the houses. Figure 2 provides an example of such an application. Maximum heat gain rate (HG Max) and maximum heat loss rate (HL Max) are estimated by applying the model parameters to the 5% weather condition from the TMY2 file, while cooling capacity (CC) and heating capacity (HC) are parameters directly inside the reduced thermal model.

Upon examining the figures the author discovered a trend of undersized cooling capacity and over-sized heating capacity. This means that to combat a lack of cooling capacity, households either have to use larger sized AC units or use longer duty cycles through the cooling season, which is consistent with the predictions from the local jurisdiction (Ontario Energy Board, 2016). Furthermore, some dwellings are observed to have high heat loss potential but smaller heating capacity, which may lead to thermal comfort issues.

The grey-box model presents many other opportunities for parameter estimation and housing stock analysis, such as estimating a dwelling’s orientation, occupant schedule, solar gains, its window-to-wall ratio, and other characteristics. However, this analysis requires a more complete dataset with ground-truth surveys to validate its effectiveness.

**Cooling load estimation**

The authors also tried to rearrange the model function to predict the cooling/heating needed to maintain the indoor air temperature. Figure 3 provides an example of such application for one dwelling during the summer. Overall the predicted and the actual cooling load agrees reasonably well, with an error of 0.21. The authors are currently working on expanding this functionality with electricity models to perform automated load shifting for the residential dwellings. Future work is needed to further validate this application.
Discussion and Future Work

Overall the accuracy of the indoor air temperature forecast from the grey-box model performs at a similar level as the dedicated black-box model while being more interpretable. The proposed model also achieved more than 50% improvement over the naïve model. Results from cost function selection suggests that including two forecast steps in the training function provides a noticeable improvement over model accuracy, while including further forecast steps increases model training complexity and brings only diminishing returns. As a result, on average, the proposed grey-box model could forecast indoor air temperature with a 4-hour horizon with a $0.44^\circ$C uncertainty for the 500 dwellings included in the case study. A better $0.26^\circ$C uncertainty can be achieved by discarding dwellings with poor model fit. The authors have also tried to use future known set point as a predictor for indoor air temperature, but the prediction accuracy was poor. This further suggests that predicting the thermal response of a house given the vast contributors to uncertainty is a challenging task.

On implementing the grey-box model itself, the authors also demonstrated the importance of adopting vectorization when computing and optimizing the reduced thermal model. However, as the model computation time becomes faster, the time needed to preprocess the dataset starts to bottleneck the entire workflow.

The parameter estimation results suggest some inconsistencies with respect to equipment sizing and the actual cooling/heating demand. Based on this particular dataset in southern Ontario, Canada, under-sizing is generally observed for cooling equipment and over-sizing is more likely for heating equipment. This may provide some guidance in terms of future policies, such as to provide incentives to avoid equipment over-sizing, and to estimate the increase in future electricity demand due to households increasing cooling capacities to deal with the climate change patterns.

The issue of under-sizing and over-sizing also identified a potential application for model predictive control in this location. Model predictive control could mitigate the effect of under-sized cooling by pre-cooling the building to reduce the risk of uncomfortable indoor conditions, thus reducing the requirement for larger air conditioning units. On the other hand, it could also put a capacity usage threshold on over-sized equipment to reduce frequent on/off cycling and reduce peak demand, which is critical to practical applications. Some inherent limitations to thermal model observability still exist, such as uncertain heat transfer from occupant’s actions and appliance cycling.

Conclusion

This paper demonstrated various techniques for formulating and constructing a grey-box thermal model for residential buildings. The selection of the cost function heavily affects the accuracy of the thermal model, especially for longer prediction horizons. A properly constructed grey-box thermal model could perform as well as a black-box model for indoor temperature forecasting, with the added benefit of providing meaningful parameter estimates and control estimation. The authors also discussed the importance of vectorization to significantly improve model efficiency and reduce computation time, which is critical to practical applications. Some inherent limitations to thermal model observability still exist, such as uncertain heat transfer from occupant’s actions and appliance cycling.

Acknowledgement

The authors would like to acknowledge High Performance Building Program at National Research Council for supporting this research. The authors would also like to thank Dr. Araz Ashouri, Dr. Adam Wills and Dr. Trevor Nightingale for providing feedback to this work. Finally, the lead author would like to thank his new born son Joey for giving him sleepless nights to think creatively.

References


Jones, E., Oliphant, T., & Peterson, P. (n.d.). {SciPy}: Open source scientific tools for {Python}.


Development and Analysis of Simplified Control-oriented Models for a Group of Institutional Offices

Jayson Bursill¹, William O’Brien¹, Ian Beausoleil-Morrison¹
¹Carleton University, Ottawa, Canada

Abstract

Most zone or room level control-oriented models are developed with opaque and varying workflows. The workflows vary depending on whether the models are white or black box. In this paper the focus is applied to inverse modelling. The contribution of this paper is the application of a simple prescribed workflow for generating inverse models of a group of offices that can be applied by those less experienced with inverse modelling. The goal of the models is to predict indoor air temperature at the next time step for each room with reasonable accuracy. Measurements were taken in 27 offices for a period of one month. These data were used to fit and validate office level control-oriented inverse models using the MATLAB System Identification Toolbox. The maximum mean absolute error (MAE) for any office over the two-week validation period was 0.31°C and the average MAE for all 27 offices was 0.15°C.

Introduction

Model-based predictive control (MPC) has demonstrated the potential to save up to 50% of heating and cooling energy in commercial buildings (Dong, O'Neill, & Li, 2014). The quality and suitability of the underlying modelling is essential to achieve this potential. A balance between model accuracy and computational efficiency for scalability is necessary.

Control-oriented modelling is a critical component of zone-level MPC (B. Gunay, O’Brien, & Beausoleil-Morrison, 2016; H. Burak Gunay, Bursill, Huchuk, O’Brien, & Beausoleil-Morrison, 2014). Modelling for zone-level MPC can vary in detail from white box software-based modelling (e.g., EnergyPlus (Zhao, Lam, Ydstie, & Karaguzel, 2015)) to black box function-based modelling (e.g., state-space models (B. Gunay et al., 2016)). At the zone level in commercial buildings, black (or grey) box models have been found to provide a compromise between model accuracy and development time (H. Burak Gunay et al., 2014). Data storage limitations are no longer a major challenge for control-oriented modelling due to the increase in building automation system (BAS) data storage seen in the mid-2000s (Salsbury, 2005).

Several studies have investigated control-oriented inverse modelling using measured data. Gunay et al. (2016) applied a recursive approach (including an extended Kalman filter) to 16 offices in an institutional building to obtain control-oriented state-space models. Other studies have provided a workflow for MPC, but remain focused on the implementation of the algorithm itself (Froisy, 2006; Joe & Karava, 2016). Despite the efforts of recent studies, the details of the workflow have remained complicated and difficult to implement for non-expert inverse modellers or unsuitable for state-space temperature modelling by focusing on extensive and often physical properties that are difficult to estimate.

The contribution of this paper is the application of a clear data-driven inverse modelling workflow to simplified models that is accessible to less experienced inverse modellers. In this study the workflow is applied to a group of actively utilized offices with a large suite of integrated sensors while describing the details of the data acquisition and cleaning process, something often overlooked. Previous studies have utilized detailed simulation as the source for inverse modelling data, where real disturbances cannot be measured (Candanedo & Athienitis, 2011; H. Burak Gunay et al., 2014). Model form and node quantity is another important consideration (Kim & Braun, 2014), where multi-node models were selected as a compromise between simplicity and accuracy.

This paper describes a standard workflow to generate control-oriented state-space models from the BAS data of an institutional building office block. This process is then applied to the 27 rooms introduced in this study, and the resulting model parameters and characteristics are discussed. Background and application (in the context of this study) are described in separate sub-sections of the modelling workflow methodology section. The resulting models can be used within zone level detailed MPC algorithms in office buildings with modern building automation systems and office-level sensing to reduce computation time while maintaining accuracy (when compared to detailed models).

Modelling workflow methodology

While it is acknowledged that many unique workflows are viable (and potentially easily implemented), the proposed workflow utilized in this study offers a transparent approach for a zone level control-oriented modelling case. The target audience is users less familiar with deriving inverse models. The limitations and assumptions of each step in the workflow will be elaborated following the list in Figure 1.

The following sections outline the requirements of each step and demonstrate the application of the workflow in an institutional building in Ottawa, Canada during the cooling season. The workflow and its iterative paths is provided in Figure 1.
Data was acquired from 27 newly-constructed occupied offices. The offices serve as a living laboratory, in that the researchers designed the instrumentation, but do not control occupants’ use of the space.

**Data acquisition - methodology**

Sensor data storage from the BAS that controls and monitors the studied offices was essential to developing control-oriented models. Without long-term data storage (sensor logs with more than one day of data) inverse modelling, operational analytics, and troubleshooting become difficult and qualitative. The volume of available data renders the selection of appropriate sensors for modelling a non-trivial task. This section is largely application based to provide context to the example and supplement the literature for data acquisition and collection. The following application focuses on describing the building studied and collecting bulk data that can be pared down after the model selection process is complete.

**Data acquisition - application**

In this study data was logged in an industrial computer for long term storage. The desired points from the BAS upload data to the industrial computer every four hours (with short term logs at the controller level that typically log for much longer than four hours but overwrite when full). Data can be stored for years on the industrial computer, and even longer in an adjacent cloud storage service. Sensor data were collected from 27 rooms in the institutional building studied (façade shown in Figure 2). The initial data was eventually processed and reduced to only the required inputs for the proposed model (as determined by model selection). The building automation system was completed in the summer of 2018, therefore only roughly six months of data is available at the time of this study (three of which are from the cooling season). Models in this study were trained with two weeks of data, validated with the following two weeks, and the models were utilized in an MPC algorithm for the remaining weeks of the cooling season.

The external wall glazing ratio was calculated to be 0.3 for rooms with one of four walls being external and 0.8 for corner rooms.

The zone level cooling system consists of a variable air volume (VAV) terminal unit to regulate airflow that serves between one and four rooms. Airflow was driven by a fan at the air handling unit where air was initially cooled to a temperature that meets the highest zone demand for the floor. The airflow to each office was assumed to be an equal division of the zone airflow measured at the VAV box. The mechanical drawings show that each office is the same size, shape, and has the same diffuser location and orientation. Ducts from the VAV boxes to the diffusers would vary in geometry according to the number of rooms in the zone (e.g., one to four branches). When cooling is required, airflow is modulated via the VAV zone level air flow damper to allow the space to achieve a setpoint as defined by the occupant. The setpoint could be adjusted by the occupants of each room via the thermostat and could vary from 20°C to 25°C. Most rooms maintained a setpoint between 21.5°C and 23.0°C. The VAV box also provides the outdoor air supply requirement and is active on a schedule from 7:30AM to 7:00PM supplying an average of 1,700 l/s to the entire office group when active (and no airflow when inactive). The floor level air handling unit operates 24 hours per day every day of the week because it supplied lab spaces as well and had an average supply air temperature of 14.1°C. Due to the large amount of exhaust air from the lab spaces the outdoor air fraction was greater than 0.9 for most of the data acquisition period to maintain building pressurization.

Data was sampled at 5-minute intervals for analog inputs (e.g., temperature) and upon state change for binary inputs (e.g., window opening). Binary values from passive infrared occupancy sensors were utilized to infer thermal loads from occupants and equipment (e.g., lighting and plug in equipment) as suggested in the literature (B. Gunay et al., 2016). This was found to be acceptable when the model accuracy was assessed. Analog BAS readings were verified within ±10% via independent spot measurements. All offices are oriented with the primary façade facing 30 degrees North of East and are equipped with motorized blinds with solar and visible transmittances of 3% and 4% respectively. Motorized blinds were automatically closed after 5:00PM and reopened at 7:30AM on weekdays and could be manually overridden by the occupant. A diagram of a typical office and the adjacent portion of the cooling system is provided in Figure 3, with a mapping of the sensor schedule in Table 1. The thermistors and resistance temperature detectors had bias errors of 0.2°C, while the illuminance sensors and pressure transducers had errors of 2% and 1% full scale respectively (equating to 20 lux and 5 pascals).

**Data processing - methodology**

Data processing has a high degree of difficulty largely due to data tagging issues within most building automation systems. Consistency in naming of points (e.g., “VAV_FLOW…” means VAV flow) is uncommon and

![Figure 1: Modelling workflow flowchart](image)
nomenclature can even vary within buildings and floors if multi-stage fit-ups and retrofits/renovations occur. Data tagging difficulties are a known issue and efforts are being made within ASHRAE and other international organizations to create standards for naming (Charpenay, Käbisch, Anicic, & Kosch, 2015; Dibowski, Vass, Holub, & Rojiček, 2016). Single fit-ups with a consistent control programming team are ideal cases for control point naming consistency and rapid data processing. Another important consideration when processing measured data for inverse modelling is the alignment of sampled data. Analog inputs measuring different quantities (e.g., airflow, temperature) are frequently logged at different rates to save space within room/zone level controllers. This necessitates either the discarding a large portion of the data or interpolation. The method that is more suitable is dependent on the rate of change of the input with a lower sample rate. These issues are compounded when aligning the time stamps of event-base data, which will likely occur outside of regular sample intervals. Resultantly, even the simple task of obtaining a complete data set with both continuous and event-based data can be a difficult task in some buildings. Event-based data can be attributed to the nearest continuous sample to the event (e.g., a state-change at 12:02AM can be mapped to a 12:00AM continuous sample). Attributing the event-based data to continuous samples can lead to errors of event-based input run time of up to one whole sample interval (half of an interval on each side) and can propagate significantly if frequent cycling occurs. The conclusion of the data processing step is often indeterminate, and further lends to the cyclical nature of the proposed workflow.

Data processing - application

In the studied building, a consistent naming convention was utilized, and no renovations occurred prior to the study period because it was recently constructed (substantially completed in summer 2018). Event based data is the occupant state, inferred by the passive infrared sensor binary feedback. No sensors utilized in the applied modelling workflow were found to be faulty, and data processing was without complication (which is often not the case). Complications in data processing are common but can be mitigated with a consistent BAS programming and tagging approach during construction or retrofits as described in the data processing - background section.

Model selection - methodology

Model selection as presented in this paper refers to selecting the appropriate inputs for single node linear time-invariant (LTI) state-space models. While there are virtually limitless potential model types, single node LTI state-space models were selected in this paper because they were found to be appropriate for MPC applications and both robust and simple (Bursill, O’Brien, & Beausoleil-Morrison, 2018). The scope of model selection can become very large when many different types of models are evaluated and compared.

This paper will focus on applying the workflow to a state-space model that is an analogue of a typical thermal resistance and capacitance model (Gouda, Danaher, & Underwood, 2002). In practice this workflow could be applied for different model types, but it is assumed a general model type is pre-selected. The model selection process is a topic of many publication in the literature, where the following are merely a starting point: (Athienitis, 1994; Bacher & Madsen, 2011; Gouda et al., 2002; H. Burak Gunay et al., 2014; Joe & Karava, 2016). Figure 4 shows a typical first-order grey box model of room indoor air temperature that includes aggregate thermal resistance R, aggregate thermal capacitance C, outdoor air temperature T_o, and total heat input Q_{in}. The model in Figure 4 is a good starting point for the proposed state-space models. Total heat input can be replaced by
individual energy flows and inferred as a proxy of their respective input values in the state-space model form (e.g., \( u_4 \) to \( u_5 \) in Table 1). Cases where a simplified state-space model are not applicable may exist where extremely non-linear conditions occur. It is assumed that the same procedure can be implemented with modifications to the model form and volume of required data.

Several approaches for inverse model input selection exist, including (but not limited to): forward selection (Bacher & Madsen, 2011), back propagation, and principle component analysis (Yang, Rivard, & Zmeureanu, 2005). The three approaches presented are described in detail in the referenced literature and provide approaches for simple models with a small number of inputs, complicated black box models, and models with many inputs respectively. Forward selection (the simplest approach presented) relies on comparing the error of model forms with different numbers of inputs to determine the best trade-off between complexity and accuracy. Back propagation is mostly applied to artificial neural network models to quickly pare down many hidden layers simultaneously. Principle component analysis utilizes clustering and linear correlations to determine the usefulness of model inputs.

![Diagram of typical RC grey box model](image)

**Figure 4: Diagram of typical RC grey box model**

### Model selection - application

For the state-space IAT models in this study, higher order models add complexity and increase the programming requirements within MPC algorithms and BAS databases. Time-variant modelling (where parameters update over time to improve prediction accuracy) also adds complexity and the requirement of determining an appropriate retraining rate or the addition of a recursive approach.

Identifying and stating assumptions of the proposed model is central to the model selection process. Many are described in the Data acquisition section, but further assumptions regarding the model itself are provided here. Perhaps the most important assumption is that inputs can be linearized within the range of conditions observed in this study for the linear models. It is also assumed that the lux sensor can be used as a proxy for solar radiation. This was confirmed in the literature (Bursill et al., 2018; B. Gunay et al., 2016).

Assumed room properties included negligible air side thermal short-circuiting and steady-state cooling between sample periods. Heat transfer to adjacent conditioned spaces is minimal. All thermal storage was attributed to the single node room air temperature model. Perfectly mixed air is assumed in this model.

Indoor air temperature (IAT) was selected as the predicted state of the state-space model because it can be directly compared to the desired setpoint for each space to estimate if heating or cooling is required (and is a requirement of many MPC algorithms). In this study a combination of forward selection and principle component analysis was utilized to retain simplicity and handle the large number of inputs. Linear correlations between the predicted value (IAT at the next time step) and inputs at the current time step were evaluated to determine appropriate model inputs. Only physically sensible inputs with a linear correlation coefficient of greater than 0.2 were selected. The threshold of 0.2 was chosen because a gap of 0.08 was present between this threshold and the next tier of inputs, which was significantly larger than other gaps between correlation coefficients in the data used in this study. Additionally, inputs that were strongly linearly related to inputs already selected were removed to promote orthogonality (i.e., the absence of correlation between inputs). Pure forward selection was not utilized because there were between 80 and 115 inputs for each room in this study. A limitation of this approach is that poor linear correlations could indicate that an input is a poor indicator of IAT change or that the linear model is inappropriate. The latter case is mitigated through cross-validation of the proposed model in the following section.

Linear correlation analysis of all sensors and variables within the BAS controller databases using the previously mentioned criteria yielded the selected model form to predict IAT. The correlation analysis was limited to the linear correlation of individual inputs with IAT prediction for one time step and did not look at the effects of combining multiple inputs simultaneously or compounded predictions over multiple time steps. Equation 1 presents the general form of the proposed state-space model where \( T \) is the indoor air temperature, \( t \) is the time index, and \( A \) and \( B \) are matrices of constants generated from fitting the model to the data. Equation 2 utilizes air flow rate \( (\dot{V}_f) \), IAT \( (T) \), and VAV box outlet temperature \( (T_o) \) to estimate a cooling energy proxy \( u_z(t) \) assuming constant air properties and neglecting latent cooling. The previously listed inputs were selected as a result of the linear correlation study. Sensible cooling loads were found to be dominant, where sensible heat fractions of 0.6 to 0.9 were observed at the coil of the air handling unit over the cooling season for the zones served. Latent cooling, though not unsubstantial, was not considered in this study due to the high observed inaccuracy and bias error of the installed relative humidity sensors and could be the focus of future work in the presence of improved humidity sensing. Equation 3 presents the form where each element of the matrix \( B \) is mapped to inputs from Table 1 and Equation 2 for the single node case. Only the first four inputs were used in the cooling season model. The ellipse in Equation 3

---

**References**

- Bacher & Madsen, 2011
- Yang, Rivard, & Zmeureanu, 2005
- Bursill et al., 2018
- B. Gunay et al., 2016
represents the location to add sensors for different model forms or to include heating terminal units in the heating season. Equation 3 can be used to describe the model in Figure 5, a state-space adaptation of the model in Figure 4.

\[
T(t + 1) = AT(t) + Bu(t) \quad (1)
\]

\[
u_2(t) = V_r(T(t) - T_p(t)) \quad (2)
\]

\[
T(t + 1) = AT(t) + B_1u_1(t) + B_2u_2(t) + B_3u_3(t) + B_4u_4(t) + \cdots \quad (3)
\]

![Figure 5: Diagram of selected state-space model](image)

**Model training and validation - methodology**

The selected model form will have a large impact on which software and techniques are utilized for training. MATLAB offers a large array of training and analysis functions for different model forms, but large functional libraries for inverse modelling are also present in Python and other languages (Ljung, 1995). For this study MATLAB was selected for its training functions due to ease of implementation.

Model cross-validation is one of the simpler tasks within the proposed workflow, where the proposed model is applied to a portion of the collected data. In this case half of the data is used for validation, but different distributions of training and validation data may be used depending on the application (Shahin, Maier, & Jaksa, 2004). A model is considered valid if the error metric, mean absolute error in this case (MAE), is below the bias error of the sensor obtaining the measurement.

**Model training and validation - application**

Sample intervals and time steps of 30 minutes were selected because most continuous BAS data is monitored at this frequency or higher (or only needs to be interpolated once from hourly data). The building studied had a sample interval of five minutes, but this is acknowledged to be uncommon in most existing commercial buildings. To adjust from five to 30 minute sample intervals only every sixth sample from the initial data was used. In previous analysis it was verified that model stability was retained at five minute time steps and accuracy was increased. The shorter time step also increases the computational requirements for MPC exponentially due to square matrix operation requirements (Wang, 2009). Thus, a time step of 30 minutes is a compromise of accuracy and efficiency in the room and zone level control-oriented modelling case for a three hour prediction horizon.

One month of sample data was divided equally into training and validation sets. The MATLAB System Identification Toolbox ssest function was used to obtain the matrices \( A \) and \( B \) of Equation 1 for each office from the sample data using the subspace method (Zhou, Pierre, & Hauer, 2006). Training was executed with two weeks of measured data from IAT and the inputs \( u_1, u_2, u_3, \) and \( u_4 \) from Table 1 and Equation 2.

A static value of bias error was chosen from the highest observed flow rate and temperature differential to encompass a conservative estimation of uncertainty. Input bias errors were obtained from catalogue information, where the bias error of the air temperatures was 0.2 °C. The precision error was found to be half of the bias error for the temperature sensors (0.1°C).

One month of data split into two equal two week portions for training and validation was found to be suitable for model preparation, and the literature suggests that a week for each is suitable (B. Gunay et al., 2016).

**Model application**

Once an appropriate model has been selected, trained, and validated, it must be utilized in the algorithm it was designed for. This is the most open-ended portion of the proposed workflow and is on the edge of the scope of this paper. Some notable applications of the resulting indoor air temperature inverse model (or similar models) are:

- Embedded MPC feedback (e.g., predicting the future time step energy balance for the room).
- Predictive information for occupant engagement (e.g., visible feedback of future office thermal conditions to the occupant).
- Fault detection of anomalies such as incorrect terminal unit operation or envelope degradation (e.g., sensor feedback suggests the IAT should increase but it does not).

**Results and Discussion**

The resulting models from the workflow for the cooling season and their characteristics are presented in this section. A description of the parameters is provided in Table 2. Parameter values and the MAE are reported. Average, mean, maximum, minimum, and the coefficient of variation (CV) as defined in Equation 4 are reported in Table 3 for the model form shown in Equation 3 and Figure 5.

Coefficient of variation is a useful metric to determine the consistency of estimated values when a typical value is not present in the literature for comparison (as is often the case with unique inverse model forms). While the distribution of the model parameters may not necessarily be Gaussian, the CV provides insight into which values obtained from inverse modelling are more consistent within the sample rooms. The input parameters that varied the most were related to cooling energy and outdoor air temperature. The high variation of the cooling energy proxy parameter (B2) and outdoor air parameter (B4) suggests that the rooms modelled react diversely to
cooling and outdoor air conditions. Diversity of B2 could be attributed to differences in zoning (zones varied from one to four rooms per VAV unit), while B4 variation could be attributed to window usage (as confirmed by window data). The airflow was assumed to be divided equally between the rooms in each zone in the model, which could also be a source of error in both the proxy and the parameters. However, the inferences of these parameter variations are anecdotal, and the linear model parameters are not an absolute reference of relative room properties.

\[
CV = \frac{\text{Standard Deviation}}{\text{Average}}
\]  

(4)

It is notable that the rooms with the highest MAE had significantly higher glazing ratios than the majority of the rooms (0.8 and 0.3 respectively). The high MAE of these rooms suggests that spaces with high glazing ratios are less suitable for linear parameter state-space modelling due to the impact of solar radiation on the indoor air temperature. In these models, solar radiation is inferred using illuminance sensors as a proxy, and solar radiation has a non-linear relationship with IAT. The effect of the two previously mentioned sources of error becomes significant when the glazing ratio is high and solar radiation becomes a dominant source of heat transfer for the room. Error could be mitigated in this case with more model nodes and potentially adding a non-linear relationship with the solar inputs. Both suggested solutions require a significant increase in model complexity and computational time.

The use of a unified model form for a subset of controlled rooms is a boon to scalability. Model and algorithm scalability are often cited as limitations of state-of-the-art MPC implementations. A singular model form (albeit with differing parameter values) reduces scaling complications related to commercial adoption. While the corner rooms had different glazing ratios, additional exterior walls, and higher model MAE, the resulting error was still comparable to the rooms more suited to the selected model form. In future work the model selection step in the workflow could include dividing the set of modelled rooms by envelope and orientation characteristics into different model categories. Such classification has been previously examined in the literature and found to be appropriate for commercial buildings (Shi & O’Brien, 2018).

**Table 2: Parameter descriptions**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Relation to IAT of previous time step</td>
</tr>
<tr>
<td>B1</td>
<td>Relation to illuminance (as a solar proxy)</td>
</tr>
<tr>
<td>B2</td>
<td>Relation to VAV cooling</td>
</tr>
<tr>
<td>B3</td>
<td>Relation to outdoor ait temperature</td>
</tr>
<tr>
<td>B4</td>
<td>Relation to occupancy</td>
</tr>
</tbody>
</table>

**Table 3: Model parameter values for the cooling season.**

<table>
<thead>
<tr>
<th>Room</th>
<th>IAT MAE (°C)</th>
<th>A (no unit)</th>
<th>B1 (°C/hux)</th>
<th>B2 (s/L)</th>
<th>B3 (°C)</th>
<th>B4 (no unit)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1*</td>
<td>0.247</td>
<td>0.999</td>
<td>3.2E-4</td>
<td>2.4E-4</td>
<td>1.3E-2</td>
<td>-0.063</td>
</tr>
<tr>
<td>2*</td>
<td>0.273</td>
<td>1.003</td>
<td>7.1E-4</td>
<td>6.6E-4</td>
<td>4.1E-3</td>
<td>-0.094</td>
</tr>
<tr>
<td>3</td>
<td>0.154</td>
<td>0.994</td>
<td>7.5E-4</td>
<td>2.3E-4</td>
<td>6.6E-3</td>
<td>-0.197</td>
</tr>
<tr>
<td>4</td>
<td>0.072</td>
<td>0.996</td>
<td>5.9E-4</td>
<td>1.7E-4</td>
<td>3.9E-3</td>
<td>-0.046</td>
</tr>
<tr>
<td>5</td>
<td>0.134</td>
<td>0.993</td>
<td>6.4E-4</td>
<td>2.6E-4</td>
<td>6.3E-3</td>
<td>0.000</td>
</tr>
<tr>
<td>6</td>
<td>0.165</td>
<td>0.991</td>
<td>3.0E-4</td>
<td>1.9E-4</td>
<td>9.4E-3</td>
<td>-0.104</td>
</tr>
<tr>
<td>7</td>
<td>0.163</td>
<td>0.993</td>
<td>5.5E-4</td>
<td>1.9E-4</td>
<td>7.7E-3</td>
<td>-0.324</td>
</tr>
<tr>
<td>8</td>
<td>0.147</td>
<td>0.990</td>
<td>6.2E-4</td>
<td>2.1E-4</td>
<td>1.1E-2</td>
<td>0.305</td>
</tr>
<tr>
<td>9</td>
<td>0.084</td>
<td>0.996</td>
<td>1.1E-3</td>
<td>1.9E-4</td>
<td>3.4E-3</td>
<td>0.035</td>
</tr>
<tr>
<td>10</td>
<td>0.128</td>
<td>0.998</td>
<td>6.3E-4</td>
<td>2.6E-4</td>
<td>2.2E-3</td>
<td>0.144</td>
</tr>
<tr>
<td>11</td>
<td>0.130</td>
<td>0.997</td>
<td>5.2E-4</td>
<td>2.0E-4</td>
<td>2.6E-3</td>
<td>-0.499</td>
</tr>
<tr>
<td>12</td>
<td>0.125</td>
<td>0.997</td>
<td>5.2E-4</td>
<td>1.7E-4</td>
<td>2.0E-3</td>
<td>-0.055</td>
</tr>
<tr>
<td>13*</td>
<td>0.170</td>
<td>0.992</td>
<td>3.0E-4</td>
<td>1.6E-4</td>
<td>8.4E-3</td>
<td>0.034</td>
</tr>
<tr>
<td>14*</td>
<td>0.203</td>
<td>0.989</td>
<td>5.6E-4</td>
<td>2.1E-4</td>
<td>9.4E-3</td>
<td>-0.017</td>
</tr>
<tr>
<td>15*</td>
<td>0.258</td>
<td>1.001</td>
<td>3.2E-4</td>
<td>1.5E-4</td>
<td>5.8E-3</td>
<td>0.211</td>
</tr>
<tr>
<td>16</td>
<td>0.127</td>
<td>0.995</td>
<td>6.3E-4</td>
<td>4.5E-4</td>
<td>3.5E-3</td>
<td>-0.092</td>
</tr>
<tr>
<td>17</td>
<td>0.147</td>
<td>0.994</td>
<td>4.7E-4</td>
<td>4.3E-4</td>
<td>6.2E-3</td>
<td>-0.007</td>
</tr>
<tr>
<td>18</td>
<td>0.077</td>
<td>0.998</td>
<td>4.3E-4</td>
<td>1.1E-4</td>
<td>1.5E-3</td>
<td>0.000</td>
</tr>
<tr>
<td>19</td>
<td>0.132</td>
<td>0.989</td>
<td>5.0E-4</td>
<td>2.1E-4</td>
<td>1.0E-2</td>
<td>0.178</td>
</tr>
<tr>
<td>20</td>
<td>0.096</td>
<td>0.997</td>
<td>4.3E-4</td>
<td>9.4E-5</td>
<td>2.6E-3</td>
<td>0.060</td>
</tr>
<tr>
<td>21</td>
<td>0.147</td>
<td>0.995</td>
<td>4.0E-4</td>
<td>1.3E-4</td>
<td>5.2E-3</td>
<td>-0.244</td>
</tr>
<tr>
<td>22</td>
<td>0.224</td>
<td>0.992</td>
<td>6.5E-4</td>
<td>1.8E-4</td>
<td>6.3E-3</td>
<td>-0.030</td>
</tr>
<tr>
<td>23</td>
<td>0.125</td>
<td>0.997</td>
<td>4.5E-4</td>
<td>1.2E-4</td>
<td>2.7E-3</td>
<td>-0.199</td>
</tr>
<tr>
<td>24</td>
<td>0.095</td>
<td>0.995</td>
<td>4.2E-4</td>
<td>1.9E-4</td>
<td>3.9E-3</td>
<td>-0.140</td>
</tr>
<tr>
<td>25</td>
<td>0.117</td>
<td>0.995</td>
<td>3.4E-4</td>
<td>1.8E-3</td>
<td>3.7E-3</td>
<td>-0.111</td>
</tr>
<tr>
<td>26</td>
<td>0.103</td>
<td>0.998</td>
<td>3.1E-4</td>
<td>1.2E-3</td>
<td>1.4E-3</td>
<td>0.030</td>
</tr>
<tr>
<td>27*</td>
<td>0.308</td>
<td>1.010</td>
<td>3.5E-4</td>
<td>1.9E-4</td>
<td>1.8E-2</td>
<td>0.060</td>
</tr>
<tr>
<td>Max</td>
<td>0.308</td>
<td>1.010</td>
<td>1.1E-3</td>
<td>6.5E-4</td>
<td>1.3E-2</td>
<td>0.305</td>
</tr>
<tr>
<td>Min</td>
<td>0.073</td>
<td>0.989</td>
<td>3.0E-4</td>
<td>1.8E-3</td>
<td>1.8E-2</td>
<td>-0.499</td>
</tr>
<tr>
<td>Range</td>
<td>0.234</td>
<td>0.022</td>
<td>7.6E-4</td>
<td>2.4E-3</td>
<td>3.1E-2</td>
<td>0.804</td>
</tr>
<tr>
<td>Average</td>
<td>0.154</td>
<td>0.995</td>
<td>5.1E-4</td>
<td>8.2E-5</td>
<td>3.9E-3</td>
<td>-0.048</td>
</tr>
<tr>
<td>CV</td>
<td>39.9%</td>
<td>0.5%</td>
<td>33.3%</td>
<td>579.5%</td>
<td>153.3%</td>
<td>-344.7%</td>
</tr>
</tbody>
</table>

Model cross validation yielded maximum and average MAE for the single node temperature models of 0.31 °C and 0.15 °C, respectively. The values compare to a thermistor uncertainty of 0.2°C. Some offices experienced illuminance values beyond the maximum value for the illuminance sensors (the offices with the higher MAE), increasing model error. Offices where the illuminance readings remained within the sensor range did not exceed a MAE of 0.22°C. Without data from the high illuminance cases it is difficult to determine if the model error can be attributed to model for or sensor limitations. The effect of input ranges for individual offices can be observed by the relative value of the corresponding linear parameters, where outliers can be anecdotally linked to physical characteristics of the respective office. Improper sensor calibration is a current limitation within in-situ buildings research and is a source of error for any data-driven studies.

**Demonstrated application of IAT model**

Usage of the inverse models developed in this study is demonstrated in Figure 6, where two days of IAT prediction are shown for a typical office on unoccupied
(July 29th) and occupied (July 30th) days. Predictions are compounded over one, three, and six time steps using weather and occupant prediction data from CanMETEO and simple logistic models to predict inputs. The use of input predictions and modelling was similar to the approaches described in the literature for MPC (Bursill et al., 2018; H Burak Gunay, O'Brien, Beausoleil-Morrison, & Bursill, 2016). The maximum IAT error for individual one (30 minute), three (1.5 hour), and six (3 hour) time step predictions for the sample room are 0.2°C, 0.5°C, and 0.7°C respectively. Throughout the two-day period reasonable conformity of the model to the real IAT is observed. Further error at extended prediction periods (i.e., greater than 30 min) can be attributed to inaccuracy of input predictions and is difficult to quantify within the scope of this study. For MPC applications a thorough analysis of appropriate prediction and control horizons should be executed.

The model form presented in this paper was found suitable for the offices within the building studied. Similar inputs were found suitable in other buildings and are common in new construction. Model form may vary depending on location, season, thermal mass, façade orientation, space type, and many other factors. Differential pressure (as a proxy for air flow rate) was the limiting sensor with respect to propagated error, having a bias error of 1% of full scale (correlating to 2.5 Pa). The 2.5 Pa of differential pressure bias error typically converts to 30-100 L/s of VAV airflow error depending on the conversion factor of the space. Airflow measurement bias error is frequently an order of magnitude higher than the other bias errors from most room level sensors (e.g., temperature, illuminance). If the bias error of the pressure transducer was halved a similar effect would be found with the propagated bias error for cooling energy (the typical measured quantity for comparing MPC algorithms in the cooling season), improving the value of energy-centric studies.

Inverse modelling, as presented in this paper, has limitations relative to detailed modelling approaches. Linearization and the range of data in the training period are the most prominent. Nonlinearity can be encompassed in detailed modelling using software that has nonlinear (or pseudo-nonlinear) approaches to longwave and shortwave radiation calculations (Crawley et al., 2001). Further, cases where inputs are often beyond typical values in the training phase can yield less accurate results. In the case presented in this paper (and the proposed inverse modelling workflow) the benefits of simplicity, calculation speed, and intrinsic calibration are assumed to overcome these limitations.

Sensor logging sample resolution of 30 minutes was found to be appropriate in this study at the room level, but this will vary depending on the complexity of the system and the thermal mass present. Rooms and zones are typically thermally slow to respond (compared to plant level equipment such as boilers, chillers and air handlers) and can have a longer logging interval. Shorter sample intervals have the benefit of easing fault detection, troubleshooting, and providing additional time step selection options. An argument could be made for both longer and shorter sample intervals depending on the building characteristics and control-oriented model application. A procedure for determining the critical time step for reduced order thermal model stability is provided in the literature (Athienitis, 1994). Larger and faster systems may merit the additional accuracy achieved by increasing sampling rate by default.

![Figure 6: Two typical days from a sample room with one, three, and six time step IAT predictions.](image)

**Figure 6:** Two typical days from a sample room with one, three, and six time step IAT predictions.

### Conclusion

This paper proposed a workflow for developing control-oriented inverse models and presented the results of a case study utilizing the approach. Data acquisition, data processing, model selection, model training and validation, and model application are defined as the minimally necessary steps for inverse modelling. The proposed workflow follows a generic outline with recommendations for newer data-driven modellers on the execution of each step.

Based on the modelling results of the case study, the single node linear time-invariant state-space indoor air temperature models were determined to be suitable to predict room air temperature at the next time step for control applications. The models also proved to be effective at predicting IAT several time steps ahead with appropriate input predictions from CanMETEO weather files and occupant prediction models. In the case presented in this paper a maximum single time step MAE of 0.31°C was observed, with an average MAE of 0.15°C. The simplified models were less accurate for the highly glazed rooms in this study and similar rooms may require more detailed modelling for certain applications in future work. Higher errors in highly glazed rooms is likely a result of coupling the surface temperature and air temperature into one node. The models presented are suitable for control-oriented applications due to their computational speed and relative accuracy.

Future work should include utilizing the same approach for the heating season and additional offices to determine...
if acceptable model accuracy is achieved. Additionally, the extension of these models from standalone temperature prediction to MPC calculations would further validate the approach.

Acknowledgement

This research was supported by Natural Sciences and Engineering Research Council (NSERC) of Canada, Delta Controls Inc. and Carleton University Facilities Management and Planning which are gratefully acknowledged.

References


Model-based Fault Detection and Diagnosis for HVAC Systems
Using Convolutional Neural Network

Shohei Miyata¹, Yasunori Akashi¹, Jongyeon Lim¹, Yasuhiro Kuwahara², Katsuhiko Tanaka³
¹The University of Tokyo, Tokyo, Japan
²MTD CO. Ltd., Tokyo, Japan
³Tokyo Electric Power Company Holdings, Inc., Tokyo, Japan

Abstract
In building heating, ventilation, and air conditioning (HVAC) systems, fault detection and diagnosis (FDD) is crucial for achieving high energy efficiency. In this study, a novel method for FDD is proposed, which includes fault database generation by detailed simulation, convolutional neural network (CNN) training using a database, and FDD of real data using the trained CNN. The CNN is a classifier with sufficiently high accuracy for diagnosing the subtle fault features emerging in the fault behavior data of HVAC systems. It was confirmed that FDD of real data was possible by the trained CNN, in addition to learning the generated database with high accuracy. Thus, this methodology can assist in analyzing real data because it is possible to locate the fault and assume its relative severity approximately.

Introduction
Faults that occur in heating, ventilation, and air conditioning (HVAC) systems degrade the energy efficiency and indoor environment. Some faults, such as equipment malfunction, affect the system supplying the heat load, whereas other faults deteriorate the system performance, although the indoor environment is properly regulated. These are the target faults that are detected and diagnosed in this study. Faults generally cause 5–30% degradation in commercial buildings (Katipamula and Brambley, 2005; Roth et al., 2005; Fernandez et al., 2017). Therefore, it is crucial to detect, diagnose, and eliminate them. Fault detection and diagnosis (FDD) is defined as the detection of the presence of faults and their location (Hyvärinen et al., 1996).

An optimally controlled system does not have faults such as inappropriate controls. Thus, the control optimization is included in the concept of FDD and fault elimination. However, to avoid complicated discussions, we define it as the standard condition calculated by the simulation, with reference to the design specifications.

The ideal FDD scheme is depicted in Figure 1. The existence of faults is first detected, followed by the diagnosis of the type of fault and location, after which the severities of the diagnosed faults are determined. The severity of the fault determines the fault that is to be eliminated first; hence, identification is included in this scheme. As we had previously addressed fault detection (Miyata et al., 2016), the objective of this study is diagnosis.

FDD methods are mainly classified into three classes: anomaly detection, rule-based method, and model-based method. For anomaly detection, Yoshida and Kumar (1999) proposed methods to determine abrupt faults using an autoregressive exogenous model and extended Kalman filter. However, anomaly detection cannot detect faults other than the abrupt ones. For the rule-based method, Schein and Bushby (2006) presented a flow chart of the hierarchical FDD algorithm and Veronica (2013) computerized an expert system logic for detecting control faults. However, the constructed rules cannot be applied to all systems, and rule-construction for a target system is expensive. For the model-based method, Wang et al. (2009) proposed a method for detecting sensor faults using a regression model and principal component analysis. Frank et al. (2016) modelled a VAV system and classified the fault data obtained by simulation, using a machine learning method such as the support vector machine. However, its accuracy was insufficient, and it was not applied to real data. The model-based method has difficulty in generating data with sufficient quality and quantity, and in processing the data appropriately. Based on the development of machine learning and system simulation, we decided to adopt the model-based method. We considered the FDD as a classification problem in the machine learning field and diagnosed the fault features emerging in the system behavioral data using a convolutional neural network (CNN). The CNN requires training data, which includes the fault behavior with the fault label. Real data cannot be used as training data because the training data should be labelled appropriately. Hence, to generate training data for the CNN, we performed dynamic simulation for generating complicated system behaviors with faults. In addition, we analyzed the influence of the fault severity on the diagnosis results.

![Figure 1: FDD scheme](https://doi.org/10.26868/25222708.2019.210311)
Methods

Target system
We targeted a real system in an office building whose area is approximately 160,000 m² in Tokyo, Japan. The target system was water-side of the HVAC system, i.e., a heat-source system (Figure 2) comprising four chillers and thermal water storage tanks. The system utilizes sewage from a treatment plant adjacent to the building, instead of cooling towers, and charges heat from 22:00 to 08:00 and discharges from 8:00 to 22:00.

Heat source system simulation
To generate the training data for the CNN, we constructed a dynamic model of the system (Figure 3) following the first principles model for generating complicated system behaviors with faults (Bourdouxhe et al., 1998). The input values included the heat load, sewage temperature, and a few set values. The pumps and valves were controlled every minute, based on the input and control logic, and system behaviors, such as the water flow and temperature, were also calculated every minute.

In addition, control logic, including the heat charge and discharge, and proportional-integral (PI) controls were incorporated in the simulation. The pumps and valves were regulated by PI controls, according to set values. The threshold and waiting time for the controllers to change the number of operating pumps were also incorporated.

The flow rate was calculated considering the pressure and flow balance in the pipe network. The calculation is based on Kirchhoff’s laws: one is that the sum of the water quantity flowing toward any node and away from it is zero, while the other is that the sum of the pressure in any loop is zero.

Figure 2: Target system.

Figure 3: Flow of the system simulation.
The total pump head and flow rate were determined from the specification curve, which was reshaped based on the inverter frequency (Figure 4). The pressure loss in the pipes was calculated using the Darcy–Weisbach equation (1), while that at the valves was calculated with the degree of opening and flow rate in an equal proportion.

\[ \Delta P = \frac{1}{2} \frac{\rho}{D^2} v^2 \]  

where \( \Delta P \) is the pressure loss [Pa], \( \lambda \) is the flow coefficient [-], \( l \) is the pipe length [m], \( D \) is the hydraulic diameter [m], \( \rho \) is the density of the fluid [kg/m\(^3\)], and \( v \) is the flow velocity [m/s].

The temperature in the tanks and heat exchanger were calculated theoretically and the outlet temperature of the heat exchanger was calculated using equations (2)–(4), as follows:

\[ \dot{Q} = KA(\text{LMTD}) \]  

\[ \dot{Q} = G_c c(T_{h,in} - T_{h,out}) \]  

\[ \dot{Q} = G_c c(T_{c,out} - T_{c,in}) \]

where \( \dot{Q} \) is the exchanged heat [W], \( K \) is the heat transfer coefficient, \( A \) is the heat exchange area [m\(^2\)], \( \text{LMTD} \) is the logarithmic mean temperature difference [°C], \( G \) is the flow [kg/s], and \( c \) is the specific heat of the fluid at constant pressure. Subscripts \( h \) and \( c \) refer to the hotter and the colder side, respectively, and \( \text{in} \) and \( \text{out} \) refer to the inlet and outlet, respectively.

The performances of the chillers were calculated using the specification curve (Figure 5) that expresses the relationship among the partial load, condenser-water-outlet temperature, and coefficient of performance (COP) (generated heat/power consumption); however, the outlet temperature was calculated using the COP and the inlet temperature. Therefore, the curve for the chillers requires convergence calculation.

Finally, 120 items, including the flow rate, temperature, and power, were output every minute.

The monitored data and simulation results of the chilled water temperature and flow rate in a representative week were compared (Figure 6). It was confirmed that the behaviors were similar, and that the simulation results exhibited the same phenomenon as in the real system. Because both data corresponded to 1-min intervals, their values oscillated sharply, when the operation number of pumps was controlled.

**Table 1: Faults generated by the system simulation**

<table>
<thead>
<tr>
<th>Label</th>
<th>Fault type</th>
<th>Fault detail and severity</th>
</tr>
</thead>
<tbody>
<tr>
<td>F0</td>
<td>No faults</td>
<td>First principles model without faults</td>
</tr>
<tr>
<td>F1</td>
<td>Performance of chillers</td>
<td>Due to condenser fouling, the pressure loss of condenser increases by 50% and efficiency deteriorates by 10%</td>
</tr>
<tr>
<td>F2</td>
<td>Sewage pump set value</td>
<td>The approach temperature is set to 1.0 °C from 2.0 °C</td>
</tr>
<tr>
<td>F3</td>
<td>Heat exchanger efficiency (CHEX)</td>
<td>Heat exchange area becomes half</td>
</tr>
<tr>
<td>F4</td>
<td>Temperature sensor (outlet of CHEX)</td>
<td>The sensor measures the value lower than the true value by 1.0 °C</td>
</tr>
</tbody>
</table>
Faulty behaviors for 1,952 days were generated. The input data of the simulation was assembled from the real data for the corresponding period. The fault database was utilized to train the CNN such that the CNN can diagnose real data from July to September in 2015, which is a year after the learning-data period.

For analyzing the impact of the faults on energy efficiency, system coefficient of performance (COPsys) (supplied heat/power consumption) was calculated. F1, F2, and F3 decreased the COPsys by 9.18%, 3.22%, and 2.88%, respectively (Table 2), whereas F4 improved it by 2.48%. The supplied heat was almost the same from F0–F4, each fault was under the control of supplying heat load.

With respect to the system behavior, the power consumed by chiller, TR2, the sewage pumps (SPs), and chilled water pump, CHP5, increased because of F1, F2, and F3, respectively (Figure 7). The SPs are controlled as per the outlet condenser water temperature of the heat exchanger (SHEX); therefore, its set value affects the pump power and condenser water temperature, which is a chiller performance parameter. The chilled water supply pump, SHP5, is controlled as per the outlet chilled water temperature of the heat exchanger (CHEX); therefore, the reduction in the heat exchange efficiency of the CHEX resulted in greater flow and power at CHP5. F4 can be regarded as a fault because the chilled-water-supply-temperature increased, even though the COPsys improved.

Fault detection and diagnosis by CNN

To utilize the generated fault database as the learning data for the CNN, it is necessary to preprocess the database appropriately. In this study, we converted 24-h data into an image because a day is the minimum cycle for the HVAC system behavior, and decision making for fixing the fault would be implemented in a period longer than a day. Real data was collected for 15 min, and the database was converted from 1-min data to 15-min data by averaging the values.

Each value was then standardized from 0 to 1 and converted into images (Figure 8). As the column-direction represents the time axis and the 15-min data for a day is the data for the image, the number of values in column-direction was 96. The number of rows was set to 120, which is the number of items output by the simulation. In this study, by applying imaged data to the CNN, it was possible to learn the fault features in the column direction for the time series feature, and in the row direction for the relationship between items. Because all the images appear similar, it was assumed that it would be difficult for a conventional neural network or other machine learning methods to extract the features. Therefore, a CNN, which recognizes images using a network modelled with reference to the visual cortex of the brain (Fukushima, 1982), was adopted in this study.

The CNN was structured with reference to Simonyan (2014) (Figure 9). It has six layers including two convolution layers, two max pooling layers and two full connection layers. The number of filters was set to 36. The parameters for convolution, max pooling and number of filters were decided based on try and error.

![Figure 7: System behavior with faults.](image)

![Table 2: Impact of faults on energy performance.](table)

<table>
<thead>
<tr>
<th>Fault</th>
<th>Supplied heat [GJ]</th>
<th>Power consumption [MWh]</th>
<th>COPsys</th>
<th>COPsys ratio [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>F0</td>
<td>24338</td>
<td>1394</td>
<td>4.85</td>
<td>-</td>
</tr>
<tr>
<td>F1</td>
<td>24338</td>
<td>1535</td>
<td>4.40</td>
<td>-9.18</td>
</tr>
<tr>
<td>F2</td>
<td>24338</td>
<td>1441</td>
<td>4.69</td>
<td>-3.22</td>
</tr>
<tr>
<td>F3</td>
<td>24338</td>
<td>1436</td>
<td>4.71</td>
<td>-2.88</td>
</tr>
<tr>
<td>F4</td>
<td>24338</td>
<td>1360</td>
<td>4.97</td>
<td>2.48</td>
</tr>
</tbody>
</table>

The CNN that diagnose real data outputs the probability of each label and it expresses which types of fault behavior the real data is close to. The meaning of the value of the probability is discussed later.
We divided the database into training and validation data. Each fault included 122 data, among which 20 were assigned randomly as validation data and the remaining as training data. To moderate the bias of this data assignment, the assignment was implemented 30 times and 30 CNNs were trained. In the test phase, the trained 30 CNNs diagnosed the real data from 2015, during the period corresponding to the learning data. The program was coded using TensorFlow (Abadi et al., 2016).

**Results**

**Training accuracy of CNN**

The average validation accuracy of 30 CNNs was 98.4% (Figure 10). Hence, it can be regarded that the CNN learnt the fault features sufficiently.

**Diagnosis characteristics of the trained CNN**

When the trained CNN diagnoses real data, it outputs certain probability values. Considering the feature extraction process in the CNN, the probability indicates the degree of the fault pattern recognized in the real data. Hence, the probability was called diagnosis probability and its characteristics were analyzed.
To observe the diagnosis characteristics of the trained CNN, fault behaviors simulated with different severities were generated and diagnosed by the trained CNN. The severity was defined as the amount by which the fault differed from the condition without faults. A severity of 0% indicates no faults and 100% means the same as that described in Table 1. The severity was expressed from 20 to 180% in steps of 20%. For example, 20% severity of F4 is that the sensor measures the value lower than the true value by 0.2 °C. The input values for this simulation were obtained from the real data in 2015.

The impact of faults with different severities on the COPs is nonlinear, although the severities differed linearly (Figure 11). As the HVAC system is highly complicated, the behavior was not linearly affected by the fault severity. This can influence the diagnosis probability, when the fault severity in the real system is different from the assumptions in the simulation for the learning data. System behaviors generated with different severities were then diagnosed by the trained CNN (Figure 12); the displayed diagnosis probability indicates the average diagnosis probability during the target period.

For a single fault, the diagnosis probability decreased as the severity reduced, for severities less than 100% (a-1,2,4). For F3, the diagnosis probability of F1 emerged with the increase in the severity of F3 (a-3) because when F3 is more severe, the performance of the chillers, whose feature is similar to F1, decreases.

To investigate the diagnostic characteristics of multiple faults, F1 and F2 were generated simultaneously, and the severity of F1 was manipulated (b-1). The diagnosis probabilities of F1 and F2 were almost the same at 50%, when the severity of F1 was more than 100% and vice versa (b-2). Similarly, the other combinations were investigated, and the same tendency was observed, except for the combination of F3 and F4.

When F3 and F4 were generated simultaneously and the severity of F3 was manipulated, the more severe F3 was, the lesser was the diagnosis probability of F4 and vice versa (b-3,4). F3 and F4 both occur around the CHEX with opposing influences; therefore, the features of F3 and F4 can cancel out each other.

From the above, the diagnosis probability indicates the existence of the fault feature and the value reflects the severity of the fault. However, if multiple faults occur simultaneously, the values approximately represent the relative severities of the faults. It is difficult to utilize the value of the diagnosis probability directly for the assumption of the fault severity. Therefore, an identification process is required, as described in Figure 1.

**Diagnosis of real data by the trained CNN**

Real data were diagnosed by the trained CNN (Figure 13, Table 3). Figure 13 and Table 3 shows the diagnosis probabilities, where values of multiple faults were proportionally divided. The result indicates that the real system presented F3 primarily. F1 and F4 were diagnosed with lower probabilities throughout the period, and F2 was diagnosed at a specific time.
Analysis of the real data
The diagnosed fault probabilities differed each day. Further, the fault severities of the real data, the assumed fault severities in the simulation (Table 1), and the diagnosis results were compared (Figure 14). For F3, as the real data and the assumed severity were very close, the diagnosis probability was high. For F1, the closer the real data was to the assumed severity, the higher was the diagnosis probability. For F2, when the real data was higher than the no-fault value, the diagnosis probability was almost zero. For F4, the real data was considerably lower than the assumed severity, and the diagnosis probability was also low. The sensor error cannot be observed because its true value never be observed. For F4, a temperature sensor error in the real data was assumed based on the temperature at the outlet of the CHEX and at the chilled water header (see Figure 2).

Discussion
Considering the 98.4% training accuracy, the CNN performed sufficiently in extracting the features of the faulty behaviors of the heat source systems. The results of the real data diagnosis by the CNN corresponded to the real data analysis; therefore, the proposed FDD method is effective for real data. It should be noted that the output of the CNN was called the diagnosis probability, which indicates the existence of a fault feature and the approximate relative severity of the fault. Therefore, to determine the accurate severity of the fault diagnosed by the proposed method, an identification process is required.

In Figure 13, F0, which is the case without faults, was diagnosed second. This may be because of the presence of other faults, which were not available in the fault database. In addition, F3 and F4 can cancel out the fault effects. Therefore, the CNN may have misdiagnosed the status that includes F3 and F4 simultaneously as F0. From the above, expanding the fault types and diagnosing multiple faults considering fault characteristics, such as cancelling out, need to be undertaken in future.

Conclusion
A general FDD methodology for building-heating-source systems had not been established because these systems include various equipment and complex controls, depending on the building. Hence, this study proposed an FDD method involving the generation of a fault database by detailed simulation, CNN training using the generated database, and FDD of the real data by the trained CNN. It was demonstrated that FDD of real data was possible by the trained CNN, in addition to learning the generated database with high accuracy. This methodology can assist in analyzing real data because it indicates the faults emerging in real data with the probability. For example, if the result indicates that the system has a fault in the heat exchanger, the fault can be confirmed by checking the data related to the heat exchanger, instead of checking all the data, based on expert knowledge.

However, as discussed earlier, there is possibility for the CNN to misdiagnose faults and hence, expansion of fault types and diagnosis of multiple faults considering fault characteristics, such as cancelling out, is essential. Considering the cost for generating the fault database and CNN learning, appropriate generation of the database is crucial. It is intended to develop a framework for generating the fault database in future.

Acknowledgements
This work was supported by Grant-in-Aid for JSPS Research Fellow, Grant number JP17J08140 and JSPS KAKENHI, Grant Number JP 18K13879.

References


Study on Efficient Heat Interchange Control in District Heating and Cooling System with Multiple Sub-plants

Hisataka Kitora¹, Yasunori Akashi², Jongyeon Lim²
¹ The KANSAI ELECTRIC POWER CO., INC., Osaka, Japan
² The University of Tokyo, Tokyo, Japan

Abstract
In order to cope with global environmental problems, district heating and cooling which enables energy saving not only for buildings alone but for entire districts, is effective, but it is necessary to analyze even the pressure distribution in the piping, since the transportation power increases. However, the current commercial simulation program does not have the ability so far, we created a simulation having the ability to target the actual plant. By utilizing this, conditions for promoting effective heat interchange between sub-plants in DHC system were investigated. This is beneficial when expanding DHC area.

Introduction
In recent years, it becomes an urgent issue to respond to environmental problems from global to city scale, such as global warming and heat island. In order to solve the problem, it is conceivable to effectively utilize energy not only in one building alone but in the whole area. District heating and cooling (DHC) has been considered as a solution to such problem. DHC plant is expanded with the development of the area, having sub-plants added. When DHC plant has multi sub-plants with performance differences, heat interchange between sub-plants can be one way to increase an energy efficiency of the overall plant. However, when the heat supply is bidirectional, it becomes a complex system and it is difficult to control a whole system. In the case of heat interchange between DHC sub-plants, because the heat conveying distance gets longer, larger conveying power of the secondary pump and the heat interchange pump is needed, and the influence of its behaviour on the system also increases. Therefore, it is indispensable to calculate the power considering the pump head and to grasp the pressure state in the pipe. In order to realize high efficiency operation of a whole plant, it is necessary to analyse the behaviour including control of heat source machines, conveying equipment (e.g., pumps and valves), and pressure distribution in the pipe. However, it is currently the commercial simulation program does not have the ability to do such calculations. Kobayashi (2012) built a simulation model corresponding to the operation optimization of the heat source system that can heat interchange, but when the heat source machine is operating, it is set as a model that requires a certain transportation auxiliary power. Nishiyama (2015) built a simulation model that calculate all the control states at beginning, and based on the resultant valve opening and ON / OFF information of the equipment to calculate the flow rate, but it does not consider pressure distribution in piping. In this study, we have constructed simulation model with high reproducibility that can calculate the behavior of each heat source machine and conveying equipment, and conditions of pressure, flow rate and temperature in each pipe, and temperature condition inside the heat storage tank. We have conducted case studies using the simulation. In this paper, we discuss the effect of thermal load differences on demand sides and performance differences between plants on the effectiveness of the heat interchange.

Target DHC system description
The target system is a renewable energy utilization plant that uses river water as a heat source, and it consists of East Plant which started operation in 2012 and West Plant which started operation in the spring of 2017. Figure 1 is a map of the area. Both plants are adjacent to each other across the road, the building in the East area has a total floor space of approximately 146,000 square meters (application: office, commercial facilities, hall), the building in the West area has a total floor space of about 151,000 m², (use: office, Commercial facilities, museum, hotel). Both plants need to be connected by piping according to the heat supply business law. These pipes allow chilled water and hot water to be exchanged between them. Table 1 lists the equipment specifications and Figure 2 is the system diagram of the chilled water and hot water system. Also, although the performance of the heat source equipment of both plants has a difference of 5 years at the completion time, there is no big difference. The East plant has two types of heat source machines: primary heat source machines (R-01, R-02, R-03, R-04) connected to thermal storage tanks and secondary heat source machines (R-05, R-06) which supply chilled water directly to consumers. The heat

Figure 1. Map of the area
source machines are controlled to supply heat from the thermal storage tanks during the day (07:00–22:00) and store heat in the tanks during the night (22:00–07:00). Calculate the amount of heat storage / release required to complete heat storage / release from a certain time to heat storage / release ending time (Recalculate the required heat every 30 minutes). Add / subtract the amount of heat required for heat storage / release from the heat load of the customer to calculate the amount of heat that the heat source machine shares. From this amount of heat, set the number of operation machine that the heat source machine can operate at the rated point. By these, the partial load is treated with the heat storage / release from the thermal storage tank, so the heat source machine is operated almost at the rated point. In addition, R-03 is a heat recovery-type heat pump that is in use in the winter since there is no heating load in summer. In 2015, the performance of each heat source machines of the East plant was almost operated at a rated point with high efficiency. The coefficient of performance (COP) of the East plant system was 1.45 (primary energy conversion) in 2015, which is the top-level value for DHC plants and exceeds the target design value of 1.3 or more. In this paper, COP of equipment is expressed as secondary.
energy conversion COP, and COP of plant is expressed as COP of primary conversion. The plan for the West plant followed the East plant, because the operating results of the East plant was satisfactory. The West plant has two types of heat source machines: primary heat source machines (R-A02, R-A03, R-A04, R-A05) connected to thermal storage tanks and secondary heat source machines (R-A05) which supply chilled water directly to consumers. Either R-A03 or R-A04 can serve a heat recovery-type heat source. However, in this study, we considered R-A03 and R-A04 as the cooling/heating switching-type and heat recovery-type heat source machine, respectively. These heat source machines have a larger capacity than R-03 in the East plant because the hotel in the West building has a larger heating load compared to the East building. Because R-A03 and R-A04 were adopted as general-purpose heat source machines due to cost considerations, heat source water is heat interchanged using a plate type heat exchanger. Shell and tube type heat exchanger (RHEX-A1) is separately provided because of the risk that pinholes may be produced from using river water in the plate heat exchanger. It is desirable to control both the East and West plants integrally, but it is difficult because it is necessary to perform great repair to control it integrally. At present, the operator inputs the direction and quantity of heat conduction, and it is carried out by heat interchange pump operation or valve opening which connects each plant, the upper limit of the heat amount is 3,887 kW at cooling and 2,791 kW at heating. The heat interchange amount is added/subtracted from the thermal load of the customer of each area to calculate the thermal load that each plant shares, and based on that, the operation control of the heat source machine and the heat storage tank is performed for each plant.

**DHC system simulation model**

**Calculation flow**

Figure 3 is a flow diagram of the simulation model. The simulation model was created using Fortran 90/95. We referred to the characteristic expression of the past literature (Daniel R Clark 1985, Chiba T et al 1998) as a model of pumps, piping and valves. The actual values in 2015 for the thermal load of the East Plant and river water temperature were used as input data. Using the relationship between the design and measured values for the East Plant, the input thermal load of the West Plant was corrected for the thermal load design value of the West Plant, because it was not fully operated. Control of the heat interchange and the number of running equipments, such as heat source machines and heat exchangers, was determined based on the thermal loads of both plants. The characteristics of the heat source machine used the equipment characteristic diagram which made by the manufacturer, we created characteristic formula of load factor of the heat source machine and cooling water temperature were prepared. The opening rate of the valves and frequency inverters for the pumps were regulated through a PI controller based on the system conditions at the previous step. The flow rate at several points in the pipes was calculated by convergence calculation to ensure that the pressure distribution at each point is balanced. The heat interchange amount and direction were used as an input value, and when heat interchange is carried out, energy consumption of each plant was calculated that each plant is responsible for the load that adds or subtracts the heat interchange amount to the load of each area, the conditions of each heat source machine, heat exchanger, and thermal storage tank in each plant were assessed. The calculation interval is 1 min. Since it is expected that the heat loss from the heat interchange pipe will also increase due to heat interchange between the plants, we have constructed a model to calculate the heat loss from the heat interchange pipe during heat interchange. We
calculated the heat loss in a steady state with the temperature and flow rate in the heat interchange pipe being the same as those of the heat interchange pipe inlet, calculated the temperature drop / rise due to heat loss while passing through a length of heat interchange pipe, and calculated the outlet temperature by adding / subtracting the calculated temperature from the inlet temperature. Each physical property value of the circular pipe model of a target system, heat interchange pipe, and a design value are shown in Figure 4.

\[ Q = k' \cdot n \cdot (\theta_{in} - \theta_{out}) \]  \hspace{1cm} (1)

\[ k' = \frac{1}{h_{1} \cdot d_{1} + \frac{1}{2} \ln \frac{d_{1} + d_{2}}{d_{1}} + \frac{1}{2} \ln \frac{d_{2} + d_{3}}{d_{2}}} \]  \hspace{1cm} (2)

\[ Re = \frac{V_{n} \cdot D_{h}}{v} \]  \hspace{1cm} (3)

\[ Nu = 3.66 + \frac{0.065(D/L)R_{e}P_{r}}{1 + 0.04((D/L)R_{e}P_{r})^{2/3}} \]  \hspace{1cm} (Laminar)  \hspace{1cm} (4)

\[ Nu = \frac{f/B(P_{r} - 1000)P_{r}^{2/3}}{1 + 12.7(f/B)^{0.5}(P_{r}^{2/3} - 1)} \]  \hspace{1cm} (Turbulent)  \hspace{1cm} (4)

\[ h_{1} = \frac{Nu \cdot \lambda}{D_{h}} \]  \hspace{1cm} (5)

\[ f = \frac{(0.790 \ln R_{e} - 1.64)^{2}}{3000 < R_{e} < 5 \times 10^{6}} \]

\[ D : \text{Pipe diameter} [\text{m}] \]

\[ L : \text{Pipe length} [\text{m}] \]

\[ P_{r} : \text{Prandtl number} \]

\[ \lambda : \text{Fluid thermal conductivity} [\text{W/(m\text{-}K)}] \]

\[ \theta_{in} : \text{Fluid inlet temperature} [\text{\Celsius}] \]

\[ \theta_{out} : \text{Fluid outlet temperature} [\text{\Celsius}] \]

\[ \lambda_{1} : [\text{W/(m\text{-}K)}] \]

\[ \lambda_{2} : [\text{W/(m\text{-}K)}] \]

\[ h_{2} : [\text{W/(m}^{2}\text{-}K)] \]

\[ \frac{\theta_{in}}{\theta_{out}} = 24 \]  \hspace{1cm} (24 \text{ \Celsius})

\[ Rd \text{: Refrigeration duty} [\text{W}] \]

\[ Q \text{: Heat passing rate} [\text{W}] \]

\[ \\]

The amount of heat loss (the amount of heat passing) Q [W] from the fluid to the outside when the fluid passes through the circular pipe is expressed by the following equations (1) and (2). Since the heat interchange pipe is installed in the underground pit in the same space as the river water pipe, \( \theta_{out} \) was assumed to be the same as the river water temperature. The fluid-side heat transfer coefficient \( h_{1} \) [W / (m\text{-}K)] is considered to change with the flow velocity, and thereby the heat transfer coefficient also changes. Therefore, the fluid-side heat transfer coefficient \( h_{1} \) was calculated by the equations (3) to (5) for each flow velocity with respect to the heat transfer pipe of the target system. If \( Re \) (Reynolds number) <3000, it is discriminated as laminar flow, if \( Re \geq 3000 \), it is discriminated as turbulent flow. Nu (average Nusselt number) is determined from the state of the fluid. We calculated heat transfer rate and temperature change calculated from heat loss amount at \( \theta_{out} = 24 \text{ \Celsius} \) for each flow rate are shown in Figure 5. The heat transfer rate hardly changes with the flow rate when flow rate is around 2 to 5 m\text{}/\text{min}, which can be considered under normal operating conditions. This is the fluid-side heat transfer coefficient \( h_{1} \) is on the order of the cube of 10, so that the term \( \theta_{out} \) can be almost ignored. And temperature change is very small. Since the thermometer installed in the heat transfer tube shows an abnormal value (The magnitude relationship between the inlet and outlet temperature values of heat interchange pipe is reversed), it has not been possible to verify the actual temperature drop / rise.

\[ Q = k' \cdot n \cdot (\theta_{in} - \theta_{out}) \]

\[ k' = \frac{1}{h_{1} \cdot d_{1} + \frac{1}{2} \ln \frac{d_{1} + d_{2}}{d_{1}} + \frac{1}{2} \ln \frac{d_{2} + d_{3}}{d_{2}}} \]

\[ Re = \frac{V_{n} \cdot D_{h}}{v} \]

\[ Nu = 3.66 + \frac{0.065(D/L)R_{e}P_{r}}{1 + 0.04((D/L)R_{e}P_{r})^{2/3}} \]  \hspace{1cm} (Laminar)

\[ Nu = \frac{f/B(P_{r} - 1000)P_{r}^{2/3}}{1 + 12.7(f/B)^{0.5}(P_{r}^{2/3} - 1)} \]  \hspace{1cm} (Turbulent)

\[ h_{1} = \frac{Nu \cdot \lambda}{D_{h}} \]

\[ f = \frac{(0.790 \ln R_{e} - 1.64)^{2}}{3000 < R_{e} < 5 \times 10^{6}} \]

\[ D : \text{Pipe diameter} [\text{m}] \]

\[ L : \text{Pipe length} [\text{m}] \]

\[ P_{r} : \text{Prandtl number} \]

\[ \lambda : \text{Fluid thermal conductivity} [\text{W/(m\text{-}K)}] \]
river water via a separate heat exchanger, and the cooling water temperature became about 3 °C higher than the river water. In the winter, the efficiency of the heat source machine of the West plant was higher and the capacity of a heat source machine to perform efficient heat recovery operations larger in the West plant than in the East plant. As a result, the efficiency of the West plant is higher.

Case study of heat interchange

It is expected that heat interchange is more effective when the performance difference between sub-plants is large. We investigated total 24 cases (see Figure 7) for four patterns of performance degradation for East Plant (100% (actual machine value), 70%, 50%, and 35% (partial load characteristic is similar deformation)) and three patterns of thermal load amount difference in East Plant (100% (actual value), 75%, and 50%) and two pattern of heat interchange (available or not). In addition, to investigate the effect of the difference in use of demand sides on effectiveness of heat interchange, we examined the three types of thermal loads of the West area of the mainly office of the current state, shopping-center, and hospital (see Figure 7). Thermal loads of shopping-center and hospitals is actual load data in the same region was used. Since the cooling peak load is an important factor for selecting the equipment, the similarity conversion was performed so that the peak of the actual load data becomes the same as the peak of the assumed thermal load in the West area. Considering the practicality of operation, we set the frequency of changing heat interchange setting twice a week on weekdays (Monday - Friday) and weekends (Saturday and Sunday). Heat interchange setting consists of three modes, mode 1 in which only independent operation is performed, mode 2 in which only cooperative operation is performed, and mode 3 in which these are combined (Figure 8). The heat interchange direction is 2 patterns of West Plant → East Plant, East Plant → West Plant. Set value of heat

**Table 2. Monthly COP of each heat source machine (Simulation results)**

<table>
<thead>
<tr>
<th>Case</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-A01</td>
<td>5.73</td>
<td>5.73</td>
<td>7.20</td>
<td>-</td>
<td>6.17</td>
<td>6.06</td>
<td>5.89</td>
<td>5.42</td>
<td>5.94</td>
<td>6.24</td>
<td>6.51</td>
<td>5.76</td>
</tr>
<tr>
<td>R-A02</td>
<td>5.64</td>
<td>5.70</td>
<td>5.82</td>
<td>5.81</td>
<td>6.03</td>
<td>5.82</td>
<td>5.72</td>
<td>5.38</td>
<td>5.78</td>
<td>5.93</td>
<td>5.95</td>
<td>5.81</td>
</tr>
<tr>
<td>R-A03</td>
<td>8.32</td>
<td>8.89</td>
<td>8.48</td>
<td>7.89</td>
<td>6.43</td>
<td>6.00</td>
<td>5.57</td>
<td>4.93</td>
<td>5.76</td>
<td>6.50</td>
<td>7.41</td>
<td>8.27</td>
</tr>
<tr>
<td>R-A04</td>
<td>7.90</td>
<td>7.89</td>
<td>7.87</td>
<td>7.82</td>
<td>0.08</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>7.71</td>
<td>7.89</td>
</tr>
<tr>
<td>R-A05</td>
<td>5.59</td>
<td>5.49</td>
<td>5.60</td>
<td>5.70</td>
<td>6.04</td>
<td>5.80</td>
<td>5.60</td>
<td>5.23</td>
<td>5.67</td>
<td>5.99</td>
<td>5.75</td>
<td>5.63</td>
</tr>
<tr>
<td>R-01</td>
<td>5.59</td>
<td>5.60</td>
<td>6.91</td>
<td>6.11</td>
<td>5.97</td>
<td>5.73</td>
<td>5.31</td>
<td>5.03</td>
<td>5.78</td>
<td>6.10</td>
<td>6.42</td>
<td>5.69</td>
</tr>
<tr>
<td>R-02</td>
<td>5.48</td>
<td>5.49</td>
<td>5.60</td>
<td>5.70</td>
<td>6.04</td>
<td>5.80</td>
<td>5.60</td>
<td>5.23</td>
<td>5.67</td>
<td>5.99</td>
<td>5.75</td>
<td>5.63</td>
</tr>
<tr>
<td>R-03</td>
<td>7.81</td>
<td>7.81</td>
<td>7.76</td>
<td>7.74</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>7.77</td>
<td>7.78</td>
</tr>
<tr>
<td>R-04</td>
<td>7.68</td>
<td>8.04</td>
<td>8.07</td>
<td>8.30</td>
<td>7.99</td>
<td>7.45</td>
<td>6.77</td>
<td>5.95</td>
<td>7.12</td>
<td>8.16</td>
<td>8.51</td>
<td>7.91</td>
</tr>
<tr>
<td>R-05</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>6.93</td>
<td>6.79</td>
<td>6.64</td>
<td>6.34</td>
<td>5.97</td>
<td>6.47</td>
<td>7.02</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>R-06</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>6.15</td>
<td>5.77</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

**Figure 7**  Cases for examination  

**Figure 8**  Control image of heat interchange

<table>
<thead>
<tr>
<th>Equipment efficiency</th>
<th>Heat load</th>
<th>Heat interchange</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>100%</td>
<td>Case α 100% Case A Not perform</td>
</tr>
<tr>
<td>Case 2</td>
<td>70%</td>
<td>Case β 75% Case B Perform</td>
</tr>
<tr>
<td>Case 3</td>
<td>50%</td>
<td>Case γ 50%</td>
</tr>
<tr>
<td>Case 4</td>
<td>35%</td>
<td></td>
</tr>
</tbody>
</table>

| 4×3×2=24 cases |

<table>
<thead>
<tr>
<th>Heat load pattern</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Pattern a</td>
<td>Mainly office (Current status)</td>
</tr>
<tr>
<td>Pattern b</td>
<td>Shopping center</td>
</tr>
<tr>
<td>Pattern c</td>
<td>Hospital</td>
</tr>
</tbody>
</table>

---

Proceedings of the 16th IBPSA Conference
Rome, Italy, Sept. 2-4, 2019
interchange amount is eight patterns, 12.5%, 25%, 37.5%, 50%, 62.5%, 75%, 87.5% and 100% (the maximum amount of heat interchange). We selected the most efficient control protocol among 48 patterns for each case. The unit of the day is from 22:00 of the heat storage start time to 22:00 on the next day.

**Result and discussion**

**Current heat load pattern: Pattern a**

- Plant characteristics without heat interchange (Case A)
  
The results of Case a are shown in Figure 9. The annual COP of West Plant is 1.586 in any case (Case 1～4), and it is displayed overlapping on the graph. The annual COP of the East Plant is 1.573 for Case 1 and 1.79 for Case 2, 0.924 for Case 3, 0.682 for Case 4, and the total COP for East and West is 1.580 to 0.989. In Case 2, the results of Case α～γ are shown in Figure 10. The annual COP of the West Plant is unchanged from each case, and it is displayed overlapping on the graph. Even if the thermal load in the East area is variable (50% to 100%), the COP of the plant in the East area is not big different from 1.145 to 1.209. It is thought that because the partial load corresponds to the heat storage / heat radiation from the thermal storage tank, the heat source machine is rated operation even if the thermal load is varied.

- Plant characteristics with heat interchange (Case B)

  As an example, the results of comparison of heat interchange perform / not perform in Case 2 β are shown in Figures 11 to 12. In this case, heat interchange is performed from the West Plant which is highly efficient, to the East Plant. The efficiency of the West Plant improved by increasing the load burdened by the West Plant at the time of the cooling-heating switching time when the thermal load becomes the minimum, etc. Although the efficiency of the East Plant declines, since the load shared by the East Plant is small, the monthly COP is improved by 5.6% to 14.2% by heat interchange as a whole of E + W, and total annual COP increase 8.3% from 1.405 to 1.521. The results compared with each heat source machine are shown in Figure 13. Efficiency of each equipment does not change greatly with or without heat interchange. The thermal load share ratio by each heat source machine is increased at the heat source machine in the West Plant. The cooling load in the East Plant became less burden other than R-03 (heat recovery) and R-04 (Inverter turbo) which are high efficiency, and even in heating, heat burden other than R-03 (heat recovery) are reduced. At this case, the power consumption of the heat interchange pump is 0.24% of the whole plant and the heat loss from the heat interchange pipe is 0.22% of the heat transfer amount, which is slight. Table 3 summarizes the efficiency at the time of non-heat interchange and heat interchange in each case and the efficiency improvement rate by heat interchange in each case. In Case 1 where the difference in efficiency between plants is small, even if the load condition is changed, the COP improvement rate of the plant as a whole due to heat interchange is not as large as 2.1% to 2.3%. In each case...
of Case 2 to Case 4, since the efficiency of the East Plant is low, whole efficiency improves by heat interchange from the West Plant to the East Plant, and the difference increases as the efficiency difference increases. As the thermal load on the heat receiving side decreases, the efficiency improvement rate due to heat interchange is decreased. This is because, as shown in Figure 14, as the thermal load on the heat receiving side decreases, the heat interchangeable amount decreases.

Table 4 summarizes the power consumption ratio of the heat interchange pump to the whole plant and the heat loss rate from the heat interchange pipe to the whole heat interchange amount in each case. In each case, power consumption rate of the heat interchange pump is 0.10% to 0.37%, and the heat loss rate from the heat interchange pipe is 0.17% to 0.34%, which is considerably lower than the efficiency improvement rate by heat interchange. In the case of heat interchange with the next block like the target case (piping length is about 100 m), it is considered that the increase of the transportation power and the heat loss from the piping, which due to heat interchange are slight. But if the heat interchange piping gets longer, the transfer power and the heat loss become large and need to be considered.

**Different heat load pattern: Pattern b and c**

Next, assuming the case of heat interchange between buildings of different buildings, we examined by changing the load pattern of the West area. The thermal load pattern used the results of shopping-center and hospitals located in the neighbourhood. Since selection of equipment is often based on peak load, similarity transformation was performed so that the peak value of each data would be the peak value in the west area. Figure 15 shows the monthly thermal load for each building applications.

- **Plant characteristics without heat interchange (Case 1 α A)**
  The examination results are shown in Figure 16. In the summer, there is no big difference in efficiency between each case, but efficiency of the shopping-center in winter is low. This is because the air-conditioning of the shopping-center is exclusively for cooling, operation of the heat recovery machine can not be performed in the winter, and the cooling load is also very small. Also, in the case of the current office load, the efficiency tends to be somewhat lower in the middle term. This is thought to be because the heating load is not so large, and the cooling load is very small. From these trends, it is thought that lengthening the operation time of the heat recovery machine, avoiding operation with a very small load by putting a load on one side by heat interchange will lead to an improvement in the whole efficiency.

- **Improvement due to heat interchange**
  Table 5 summarizes the efficiency at the time of non-heat interchange and heat interchange in each case and the efficiency improvement rate by heat interchange in each case, when the thermal load pattern is changed to the office and the hospital. The plant COP has a higher value in the case either in the case of thermal interchange or not. This is thought to be because the heating load of the hospital has a large and the heating load occurs in the summer, so the heat recovery machine operates effectively. The Plant COP was higher in the case of the
thermal load of the hospital, when perform heat interchange. But the plant COP when not perform heat interchange was also high, so the efficiency improvement rate by heat interchange was low. As an example, the results of comparison of heat interchange perform / not perform in Case 2, when thermal load of the west area is hospital, shows in Figures 17 to 18. Heat interchange is performed from the West Plant, which is highly efficient, to the East Plant, same as pattern a. Although the efficiency of the East Plant declines, since the load burdened by the East Plant is small, the monthly COP is improved by heat interchange as a whole of E + W.

Table 5. Plant COP and improvement rate in each case

<table>
<thead>
<tr>
<th>Efficiency</th>
<th>Host Load</th>
<th>Heat interchange Case A</th>
<th>Heat interchange Case B</th>
<th>Improvement rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>Patern a</td>
<td>1.580 1.586 1.573 1.613 1.612 1.620 2.1%</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Patern b</td>
<td>1.618 1.639 1.643 1.637 1.618 1.757 1.7%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 2</td>
<td>Patern a</td>
<td>1.389 1.586 1.299 1.520 1.612 1.142 9.4%</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Patern b</td>
<td>1.464 1.639 1.299 1.540 1.629 1.154 5.9%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 3</td>
<td>Patern a</td>
<td>1.797 1.639 0.994 1.461 1.608 0.681 22.1%</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Patern b</td>
<td>1.301 1.639 0.994 1.495 1.623 0.681 14.9%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In the future, when the partial load characteristics of the plant is bad, such as when there is no heat storage tank, when the distance of the heat conduit pipe is more longer, when the maximum heat conduction amount is variable, etc. we will consider the conditions under which heat interchange is effective and the control method at that time in various cases. In addition, even when the number of plants increases, using the heat transfer amount and direction as input values, the flow rate at several points in the pipes will be calculated by convergence calculation to ensure that the pressure distribution at each point is balanced, and we will be able to calculate the energy consumption of each plant. Using this simulation, performance verification of the system of the target area will be continued, and furthermore, we plan to investigate efficient system configuration as a whole area when DHC area is expanded or when equipment of plant is updated.

**Conclusion and implications**

Conditions for promoting effective heat interchange between sub-plants in DHC system were investigated using simulation. The targeted system was a best practice, and the efficiency improvement effect by heat interchange was small in the actual plant. However, when there is a difference in efficiency between plants, it has been found that efficiency can be improved by approximately 10 to 40% if heat interchange is performed from higher efficiency plant to lower efficiency plant. In the target plant, the increase of the transport power and the increase of the heat loss are slight because the distance between plants is not so long, so the heat interchange was effective for improving the plant COP. It was also found that by performing the heat interchange, it is possible to increase the operation of the heat recovery machine and to avoid the extremely low load operation, leading to the improvement of whole efficiency. In addition, the tendency is similar for the case where the use of the building is different, it is effective to improve the plant COP by increasing the operation of the heat recovery machine and avoiding the extremely low load operation.

**References**


Advanced Control Strategies For The Modulation of Solar Radiation In Buildings: MPC-enhanced Rule-based Control

Marco Savino Piscitelli¹, Silvio Brandi¹, Giovanni Gennaro¹, Alfonso Capozzoli¹, Fabio Favoino¹, Valentina Serra¹

¹Technology Energy Building Environment research group, Department of Energy, Politecnico di Torino, Italy

Abstract

The present work is aimed at exploring the potentials of extracting control rules of a smart glazing from an optimal control strategy obtained by means of an ideal model predictive controller (MPC). To this sake an ideal deterministic MPC (Model Predictive Control with ideal prediction of disturbances), minimising total energy use, is devised for the control of a smart glazing for a South-oriented enclosed office space in London. Secondly, a data mining-based method is adopted to extract sets of rules from the simulated MPC-controlled data set. Finally, these rules are compared with the ideal MPC performance, and with reference threshold-based control rules.

Introduction

Appropriate integration of smart glazing technologies in building can significantly contribute towards the achievement of decarbonisation targets while maintaining adequate levels of thermal and daylight comfort in the built environment (Aelemei et al. 2019). The control of adaptive façades, including switchable glazing, can be a self-triggered mechanism (passive/smart control) or it can be triggered by an external stimulus (active/intelligent). Active technologies include electrochromic (EC), suspended particle (SPD), and liquid crystal (LCD) devices, in which the modulation of an electrical (for electron injection/removal, or variation of magnetic field) across a transparent conductor induces a variation of the optical properties of the functional layer. During building operations, an adaptive glazing can be controlled to meet multiple (and sometimes conflicting) performance requirements. Therefore, smart glazing performance is highly dependent on the control strategies adopted during building operations (Favoino et al., 2016). For these reasons the design of optimal control strategies for smart glazing technologies is still a significant challenge, strongly influencing their building integration (Lee et al. 2012).

Many researchers investigated the influence of control strategies on the performance of adaptive glazing technologies. Assimakopoulos et al. (2004), Assimakopoulos et al. (2007), Guglielmetti and Bisegna (2003), Jonsson and Ross (2010), Lee and Tavil (2007), show how the switching settings of EC windows can dramatically change indoor comfort levels and energy use of buildings. In general, the tested control strategies are RBC (Rule Based Control), RBC is by far the most adopted control option in the market (Oldewurtel et al. 2012). These are based on simple “if-then” rules adopting single or multiple fixed pre-determined set-points, relative to limited measurements of environmental boundary conditions. The most used parameters in active smart glazing controls are (Favoino et al. 2016): a) solar geometry; b) outdoor horizontal or vertical illuminances; c) outdoor horizontal or vertical solar radiation d) indoor daylight conditions; e) presence of occupants; f) temperature difference between outdoor and indoor; g) presence of heating / cooling loads; h) seasonal building services set-points. Only a small number of cases have explored more advanced controls strategies such as: combination of the above mentioned rules/parameters (Lee et al. 2012); PI and PID controls based on indoor illuminances; fuzzy logic controls based on occupant preferences and environmental conditions (indoor illuminances and temperature, external vertical solar radiation) (Assimakopoulos et al. 2007).

Very few studies compared the performance of rule-based control (RBC) strategies for smart glazings with strategies which are based on an online optimisation of a certain performance indicator (Favoino et al. 2016, Dussault et al. 2012). Moreover, these research studies highlighted the importance of predicting the effect of the entering solar radiation in the optimisation of smart glazing controls. In particular Favoino et al. (2016) showed as a Receding Horizon Control (RHC), including the prediction of the influence of entering solar radiation on the future energy balance of a building, can increase significantly the energy saving achievable by means of a smart glazing, as compared to an optimised rule based control based on current and past conditions. The highest energy savings are realised when the modulation of solar radiation is able to balance the heating or cooling energy use of the building, while in more extreme cooling or heating conditions, the performance of an RHC control is very similar to an RBC.

Nevertheless, real-world implementation of online optimised predictive control strategies (also referred to as Model Predictive Control, MPC) would involve a higher cost compared to RBC ones, as well as a bigger challenge in ensuring the predicted performance. In fact, this would require a calibrated building model, forecasts of weather and endogenous loads, and a larger number of sensors in order to update the model according to the acquired...
The first stage is aimed at simulating an optimal control strategy obtained by means of an ideal model predictive control (MPC) according to Favoino et al. (2016). The simulated predictive controller minimises the total energy use of the room over the prediction horizon (i.e., cooling, heating, lighting), selecting hour by hour the optimal discrete state of the smart glazing.

Given that the simulated MPC leverages on perfect predictions of disturbances, the obtained energy performance can be considered as the best reference solution achievable.

The outcome of the first stage is then a one-year dataset of optimal hourly control signal of the smart glazing together with other influencing variables concerning both indoor and outdoor conditions. By the way, given that the smart glazing modulates the amount of solar radiation entering the indoor environment, the control signals during night hours (i.e., from 09:00 p.m to 06:00 a.m.) were excluded from the training/testing dataset.

The second stage of the analysis is aimed at extracting from the MPC control logic, a set of decision rules capable to: (i) reduce the complexity and the computational cost in implementing the glazing controller, (ii) achieve an energy performance close to the reference optimal solution, (iii) increase the control logic interpretability. To this purpose a decision tree algorithm (i.e., CART) has been employed. In energy and buildings applications classification and regression trees have been used widely for energy fault detection and diagnosis (Yan et al. 2016), estimation of building energy usage (Capozzoli et al. 2015) as well as energy benchmarking (Capozzoli et al. 2016).

In this case study the decision tree is used to predict the hourly optimal discrete state of the smart glazing (during the morning hours) provided by the MPC controller, exploiting few variables related to indoor and outdoor conditions as predictive attributes. In this study, two different trees have been trained and tested assuming different pools of input variables. The first tree is fed only using backward-lagged variables while in the second, also forward-lagged ones are considered (i.e., hourly average outdoor temperature and solar radiation of the next hours).

The optimal size of the classification and regression trees has been assessed through a cost-complexity process, searching for a trade-off between the misclassification error of the predicted discrete states of the glazing and the number of decision rules extracted. In this stage the performance of both decision trees is assessed by an open loop test evaluating their capability in reproducing the MPC control sequence. The third stage of the analysis is aimed at comparing the extracted control logics versus the MPC and other rule-based controllers through a closed loop test embedding them in the building energy model.

This case represents the closest approximation of the controller performance on a real automation system. In fact, the misclassification error made by the controller could cause the occurrence of indoor conditions different from those experienced during the training phase generating a divergence from the optimal solution.
Thanks to this analysis it is possible to assess if the prediction error of the optimal control state of the glazing corresponds to an acceptable reduction of the simulated energy performance. In addition, other post mining analyses were conducted, in order to better describe and characterize the control logic also discussing its limits and strengths in being generalized.

Classification and Regression Tree

Classification and regression trees are machine-learning algorithms aimed at developing descriptive and/or predictive models from a set of records. Each record is a tuple (x, y), where x represents the predictive attribute set while y is the target attribute. Depending on the target attribute it is possible to distinguish classification from regression trees. In particular, tree models designed for a categorical target attribute (e.g., the discrete state of the smart glazing) are called classification trees, otherwise if y is a continuous numerical attribute, they are defined as regression trees (Tan et al. 2005). In this work, the CART algorithm has been employed for addressing a predictive modelling task. CART is a specific machine learning technique that is based on the recursive binary splitting of the records into purer subsets called nodes.

In this way, the decision tree can be represented by means of a hierarchical structure that consists of nodes and directed edges (i.e., branches). The final nodes (i.e., leaves) represent the predicted class labels of the target attribute, and the branches represent the conjunctions of the predictive attributes that lead to those classes.

The development of a classification tree, as in all predictive models, unfolds in two main steps: training and testing of the model. k-fold cross-validation has been used in this paper with k = 10. In k-fold cross-validation, the dataset is divided into k equal sized subsamples. One of the k subsets is then used as the validation set and the other k-1 subsets are put together for the training. This process is then repeated k times, using a subsample at a time for the testing. The error estimation is averaged over all k trials to get total effectiveness of the classification model. In this way, every record is included in a validation set exactly once, and in the training set k-1 times.

For each iteration (the number of iterations is equal to k), all the records are initially grouped in one node (i.e., root node) and the algorithm evaluates the best recursive segmentation of the dataset, using the attribute that minimises the average impurity measure (e.g., GINI index, Entropy) of the child nodes after the splitting. In order to avoid model overfitting, early stopping criteria can be set by the analyst (e.g., minimum number of cases in parent and child nodes, maximum tree depth, minimum reduction in node impurity after splitting).

Even though the early stop criteria have been satisfied, the decision tree may continue to be quite complex. For this reason, the cost-complexity pruning process (i.e., 1-SE rule) was performed. This procedure makes it possible to identify the optimal value of the cost-complexity parameter α in order to prune the original tree obtained by the cross-validation process. The procedure selects the simplest subtree (i.e., with the minimum number of final nodes) that can be considered statistically equivalent to the fully grown one in terms of learning rate (Capozzoli et al. 2018).

Model and case study

The aim of the present study is to compare the performance of controlling a smart glazing by means of an MPC, specifically of an optimised deterministic predictive control (with perfect knowledge of future boundary conditions) and an RBC control, derived from the MPC control by means of datamining techniques (rule extraction).
A simulated case study is adopted to compare the alternative control methodologies and to test the performance of the presented methodology.

The performance related to energy use only is targeted, although it might be possible to include in the present methodological framework multiple constraints related to improvement of comfort conditions. Therefore, the total specific yearly Site Energy (SE) is used as performance indicator, measuring the total specific amount of energy which is delivered to the building, and used for heating, cooling and lighting purposes (1):

\[ SE = E_h + E_c + E_l \]  \[ \text{[kWh/m}^2\text{y]} \]  \[ (1) \]

The data related to the case study, which is briefly presented in this section, are taken from (Favoino et al. 2016).

The virtual test case building is a reference enclosed office room (4 m wide x 8 m deep x 3.5 m high) in a heating dominated climate (i.e. London), with a Window-to-Wall-Ratio of 60% on the South-oriented façade (Figure 2). EnergyPlus version 8.3.3 is adopted for the thermal model and to perform the energy simulations (DOE U.S. 2014). The simulation algorithms in EnergyPlus have been chosen to achieve a balance between accuracy and a reasonable computational time of a single simulation run (solar calculations 15 days, conduction transfer function method with a 10-minute time step, adaptive convection algorithm, initialization period 25 days). The characteristics of the opaque and glazed parts of the façade meet the minimum requirements set in the local national standards and are summarized in Table 1. The opaque portion of the façade is a typical curtain wall construction, while a concrete slab is adopted for the horizontal partitions (Table 1). The transparent portion of the South-oriented wall integrates an active smart glazing with the properties summarised in Table 2.

The test office room is flanked by identical offices on two sides on the same floor and on the floor immediately above and below, while the third side on the same floor is adjacent to a corridor space, with identical characteristics to the office rooms. Indoor comfort is considered as a requirement of the indoor space which is always met by the building services: indoor temperature has fixed set-points for heating and cooling (20 °C and 26 °C respectively) with a nocturnal set-back (12 °C and 40 °C respectively); primary air ventilation rate is set to 1.4 l/sm2 when the office is occupied; threshold of 320 lux is considered for the minimum illumination level, to be maintained by a combination of daylight and dimmable artificial lighting system (at desk level, 0.8 m high, at 1.5, R1, and 3.5 m, R2, far from the façade, cf. Figure 2).

### Table 1: Characteristics of the opaque and glazed parts of the façade.

<table>
<thead>
<tr>
<th>Construction</th>
<th>Unit</th>
<th>Curtain wall</th>
<th>Concrete slab</th>
</tr>
</thead>
<tbody>
<tr>
<td>( U )-value _glass</td>
<td>[W/mK]</td>
<td>2.00</td>
<td>-</td>
</tr>
<tr>
<td>( U )-value _wall</td>
<td>[W/mK]</td>
<td>0.27</td>
<td>-</td>
</tr>
<tr>
<td>Internal thermal capacity</td>
<td>[kJ/mK]</td>
<td>21.7</td>
<td>67.8</td>
</tr>
<tr>
<td>External thermal capacity</td>
<td>[kJ/mK]</td>
<td>23.2</td>
<td>29.3</td>
</tr>
<tr>
<td>Superficial mass</td>
<td>[kg/m²]</td>
<td>54</td>
<td>675</td>
</tr>
<tr>
<td>Time lag</td>
<td>[hrs]</td>
<td>1.63</td>
<td>10.61</td>
</tr>
</tbody>
</table>

### Table 2: Smart glazing properties.

<table>
<thead>
<tr>
<th>State</th>
<th>( \tau_{VIS} )[-]</th>
<th>g-value [-]</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>0.595</td>
<td>0.508</td>
</tr>
<tr>
<td>3</td>
<td>0.446</td>
<td>0.396</td>
</tr>
<tr>
<td>2</td>
<td>0.341</td>
<td>0.325</td>
</tr>
<tr>
<td>1</td>
<td>0.238</td>
<td>0.238</td>
</tr>
</tbody>
</table>

Schedules and peak loads for the building services, lighting, equipment and occupation are defined according to the ASHRAE standard 90.1 (ANSI/ASHRAE/IES, 2013). The lighting power density is set to 12.75 W/m2, the equipment power density is 13.45 W/m2, while the room is occupied by 2 people. A reversible heat pump is considered to provide heating and cooling to the office building, with an average seasonal COP of 3.5 for the winter and Seasonal Energy Efficiency Ratio of 2.5 for the summer. All energy uses are electrical therefore no conversion to primary energy is done. The smart glazing is controlled with three alternative reference controls, the first one is a reference rule-based control, while the last two represent a performance bound to the control devised with the present methodology, that is the maximum performance ideally achievable by controlling a smart glazing with the described properties. The smart glazing is controlled with the three alternative strategies below:

1) **RBC – Passive:** this is based on the amount of incident solar radiation on the façade as follows (Table 3):

### Table 3: RBC reference control.

<table>
<thead>
<tr>
<th>State 4 [W/m²]</th>
<th>State 3 [W/m²]</th>
<th>State 2 [W/m²]</th>
<th>State 1 [W/m²]</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-100</td>
<td>100-250</td>
<td>250-700</td>
<td>&gt; 700</td>
</tr>
</tbody>
</table>

2) **RBC – Opt Hourly:** the smart glazing adopts a state, at 1-hour intervals, which minimizes the total building loads (sum of heating, cooling and lighting loads).
This control option is the best performance achievable by means of an RBC controller aiming at minimizing energy use based on current and past boundary conditions. In order to implement this controller an optimisation problem needs to be solved for each hour of the simulation. The objective function adopted (2) for this optimisation is as follows:

\[
\begin{align*}
\min \left\{ f(X) = Q &= Q_{\text{heat}} + Q_{\text{cool}} + Q_{\text{light}} \left[ \frac{kW}{m^2 \cdot y} \right] \right\} \\
X(t) &= (g - \text{value}(t) [-], \tau_{\text{vis}}(t) [-])
\end{align*}
\]

\( (2) \)

3) MPC: the smart glazing is actively controlled at 1-hour intervals, such that its control sequence minimizes the total site energy use of the building over a certain time horizon. The implementation of this controller relies on the solution of the following optimisation problem (3):

\[
\begin{align*}
\min \left\{ f(X) = SE &= SE_h + SE_c + SE_i \left[ \frac{kWh}{m^2 \cdot y} \right] \right\} \\
X(t) &= (g - \text{value}(t) [-], \tau_{\text{vis}}(t) [-])
\end{align*}
\]

\( (3) \)

In order to optimise the RBC and MPC controls the simulation framework developed by Favoino et al. (2017) is adopted, so called AFast (Adaptive Façade advanced simulation tool). This simulation framework, specifically designed for multi-physical simulation of adaptive building envelope systems, connects multiple building models (i.e. thermal, daylight etc.) by means of a data integration strategy (Trcka et al, 2009), and optimises control strategy of building systems and envelope systems by adopting an optimisation engine. Within this tool the overall simulation, which is constituted by different sub-simulations (relative to different models and consequential days), is managed by means of a MATLAB middle-ware. In particular, for RBC control the planning and cost horizon coincide (i.e. 1 hour), while for the MPC control a planning horizon of 1 day and a cost horizon of 3 days are considered, in order to account for building dynamics (time constant of the building system, weekend occupation and variable set-points), as suggested by Corbin et al. (2013). The length of the pre-conditioning horizon was set to two months in order to minimise the effect of the adaptive façade control on the optimisation results. A hybrid optimisation algorithm (GPSPSOCCHJ) is adopted for the optimisation (Wetter, 2011), as it offers the best trade-off between computational time and optimality of the results when compared with alternative algorithms. For details of the optimisation parameters please refer (Favoino et al. 2016).

### Results

The methodological framework presented in section 2 was applied on the previously mentioned case study. The results of the rule extraction phase (i.e. decision tree 1 and decision tree 2) are presented in this section in order to assess the performance of both decision trees achieved in the open and closed loop test.

In the open loop test the classification accuracy \( A_{\text{th}} \) of the decision trees, has been employed as performance measure suitable for classification and categorical forecasting. The classification accuracy \( A_{\text{th}} \) is calculated as follow (4):

\[
A_{\text{dt}} = \frac{n_{\text{correct}}^t}{n_{\text{tot}}^t}
\]

Where \( n_{\text{correct}}^t \) is the number of hourly discrete states of the smart glazing correctly predicted and \( n_{\text{tot}}^t \) is the number of statistical observations in one year without considering the night hours (i.e., \( 8760 - 3285 = 5475 \)). The two models were developed using different pools of input variables, but for the sake of comparability the same splitting, stopping and pruning criteria have been considered.

In particular, the tree splitting procedure is based on the reduction of the GINI impurity measure (Tan et al. 2005) until the stopping criterion has been satisfied. In this specific case study, the selected stopping criterion was based on the minimum number of observations in the child nodes of the tree (i.e., 10 observations).

#### Table 4: input variables and performances of the two classifiers.

<table>
<thead>
<tr>
<th>D.tree</th>
<th>Variable</th>
<th>Description</th>
<th>Backward lag [hrs]</th>
<th>Forward lag [hrs]</th>
<th>( A_{\text{th}} )</th>
<th>( n_{\text{rules}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( T_{\text{int.h}} )</td>
<td>Hourly Indoor zone temperature ([^\circ C])</td>
<td>-1</td>
<td>-</td>
<td>61%</td>
<td>21</td>
</tr>
<tr>
<td></td>
<td>( T_{\text{ext.h}} )</td>
<td>Hourly outdoor temperature ([^\circ C])</td>
<td>-21, -37, -42</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( S_{\text{R.h}} )</td>
<td>Hourly solar radiation ([W/m^2])</td>
<td>-1, -8, -13, -23, -24, -33, -36, -37, -42</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( T_{\text{ext.day}} )</td>
<td>Daily average outdoor temperature ([^\circ C])</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>hour</td>
<td>Hour of the day</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>( T_{\text{int.h}} )</td>
<td>Hourly Indoor zone temperature ([^\circ C])</td>
<td>-1</td>
<td>-</td>
<td>64%</td>
<td>28</td>
</tr>
<tr>
<td></td>
<td>( T_{\text{ext.h}} )</td>
<td>Hourly outdoor temperature ([^\circ C])</td>
<td>-3, -42</td>
<td>+3</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( S_{\text{R.h}} )</td>
<td>Hourly solar radiation ([W/m^2])</td>
<td>-1, -10, -12, -13, -17, -24, -37, -41</td>
<td>0, +1, +2, +3, +4</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( T_{\text{ext.day}} )</td>
<td>Daily average outdoor temperature ([^\circ C])</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>hour</td>
<td>Hour of the day</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
In addition, the cost-complexity pruning process (i.e., 1-SE rule) was performed for both models (Capozzoli et al. 2018). This procedure makes it possible to identify the optimal value of the tuning parameter \( a \) in order to prune the original tree obtained by a k-fold cross validation as explained in section 3.

Table 4 summarises the input variables considered in the model development, the number of control rules extracted, and the overall performance of the classifiers achieved in the open loop test. Both trees were trained and tested using the same variables but with different lags (automatically selected from the algorithm).

In particular, for the decision tree 1, the algorithm was free to select as predictive attributes, variables with a maximum backward lag of 48 hours (i.e., \( T_{\text{int,b}}, T_{\text{ext,b}}, \text{SR}_b \)).

![Figure 3: Carpet plots of the hourly control signal of the MPC (a) decision tree 1 (b) and decision tree 2 (c)](image)

However, the best performance was achieved by using only few shifted signals. In the same way, the decision tree 2, was developed assuming, for the exogenous variables (i.e., \( T_{\text{int,b}}, \text{SR}_b \)), also a maximum forward lag of 6 hours (compared to the 48th perfect forecast of the MPC). The amplitude of the maximum forward time lag was intentionally limited in order to make its use more reasonable in a real-life implementation. In the open loop test the classifiers perform similarly, with an accuracy of the decision tree 2 slightly higher. This is due to the fact that the forward-lagged tree is capable to better learn the control logic (with a higher number of decision rules) of the MPC that, by its nature, leverages on disturbance prediction for providing the optimal control policy.

Figure 3 shows the carpet plots of the hourly control signal of the MPC, decision tree 1 and decision tree 2. The classifiers are able to reproduce the most significant logics of the MPC controller while simultaneously reducing the number of state changes of the smart glazing during the day. The final stage of the analysis is aimed at comparing the extracted control logics versus the MPC and other rule-based controllers through a closed loop test, by embedding them in the building energy model.

To this sake the extracted rules are implemented in the EnergyPlus model by means of the Energy Management System tool (EMS) (DOE U.S. 2015). Particularly past states were coded as “Trend Variables”, while predictions were interrogated as schedules of boundary conditions with perfect knowledge (no uncertainties in the prediction, as per the simulated MPC benchmark). The implementation of the extracted rules through the EMS represents the closest approximation of the controller performance on a real automation system.

In fact, the misclassification error made by the controller could cause the occurrence of indoor conditions different from those experienced during the training phase generating a divergence from the control sequence reproduced in the open loop test (Figure 3). Thanks to this analysis it is possible to assess the impact of the misclassification error on the global energy performance. The performance benchmark of the rule extracted with the presented methodology is the energy use resulting by operating the smart glazing with i) RBC – passive control; ii) RBC – Opt Hourly control; iii) MPC control; previously introduced in Section Model and Case study.

The results obtained (Table 5) show that the relatively poor learning performances achieved by the two classifiers in the open loop test, correspond to an energy performance (in terms of global primary energy) very close to the one of the MPC controller. In addition, both decision trees perform better than the reference RBC controllers (i.e., passive and H opt), suggesting that the rule extraction process from MPC (even using the only backward-lagged variables – decision tree 1) can successfully lead to an improvement of the standard rule-based control logics for smart glazing technologies. The most promising result is achieved by decision tree 2.

Table 5: Performance comparison between RBCs, MPC and MPC-enhanced RBC controls of smart glazing.

<table>
<thead>
<tr>
<th>Control type</th>
<th>Site Energy Uses [kWh/m²/y]</th>
<th>Performance Reduction vs MPC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SE heat</td>
<td>SE cool</td>
</tr>
<tr>
<td>Passive</td>
<td>20.66</td>
<td>1.47</td>
</tr>
<tr>
<td>H opt</td>
<td>19.17</td>
<td>1.22</td>
</tr>
<tr>
<td>MPC</td>
<td>18.96</td>
<td>1.09</td>
</tr>
<tr>
<td>Decision tree 1</td>
<td>18.16</td>
<td>1.41</td>
</tr>
<tr>
<td>Decision tree 2</td>
<td>18.90</td>
<td>1.19</td>
</tr>
</tbody>
</table>
whose global primary energy demand (expressed in kWh/m²·y) deviates from the MPC one of the -0.95% and from the best RBC reference (i.e., H opt control) of the +11.54%.

Figure 4 shows the daily percentage differences between MPC and decision tree 2, for each energy use during the simulated reference year. The solid lines represent the ratio between the daily and yearly primary energy demand for heating, cooling and lighting achieved of the MPC controller. The dashed lines instead, represent the daily percentage difference between MPC and decision tree 2 for each energy use normalised on the total MPC energy use. It is possible to see that differences occur mainly regarding heating and lighting energy uses, despite some peak differences in cooling. During the middle season the MPC seems to perform better than the decision tree due to MPC is capable to better balance the room energy demand through an effective modulation of the entering solar radiation, minimizing the number of hours during which the HVAC and lighting systems are operated. While, as discussed in Favoino et al. (2016), during more extreme climate conditions, simple rules may be effective as the MPC control.

Discussion and conclusions

This paper has focused on the advanced control of a smart glazing technology. The main objective has been to investigate the effectiveness of a data-driven rule extraction procedure for reproducing the optimal control policy provided by an ideal MPC. To the best of authors knowledge this is the first attempt for the approximation of MPC logics for electrochromic switchable glazing or more in general to modulate free solar gains through building envelope. Differently from similar applications tested for other systems, the approximation of the MPC via decision tree is formulated as a multinomial classification problem since that the considered smart glazing can adopt four discrete states.

In addition, the control logics of the advanced RBC controllers have been extracted from a reference control period of one year. This last assumption increased the complexity of the classification task since the model should extract a set of “if-then” control rules for the glazing, by experiencing indoor and outdoor conditions that could significantly change among the year. On the other hand, through this approach it was possible to develop one yearly model instead of seasonal ones for each characteristic climate condition. In this way there is no uncertainty in selecting the set of control rules to be used during operation.

In order to assess the potentials of the developed RBC controllers, both open and closed loop tests have been performed. The performances achieved in the open loop test are in the range of 60-65% of model accuracy in reproducing the MPC control signal. Comparing the obtained results with the literature the classifiers perform poorly. By the way the performances achieved in the closed loop tests are promising given that the percentage difference between the MPC and decision tree 1 and 2 in terms of global primary energy demand are of -6.51% and -0.95% respectively. There are two main reasons behind this: i) the MPC puts too much effort in switching the glazing even though the impact of the control action is not so relevant, ii) the previous control states of the glazing are not considered as input variables of the classifiers.

Specifically, the selection of the previous control signals as predictive attributes could have improved the performance in the open loop test but at the same time can generate a higher divergence from the optimal solution in the closed loop test. In fact, the misclassification error made by an autoregressive controller could cause the occurrence of indoor conditions different from those learned during the training phase affecting the control action both in the current and future timesteps.

Summarizing, the present study demonstrated that the rule extraction approach can successfully reproduce sophisticated control logics ensuring complexity reduction without losing key information. In this perspective future works will be aimed at simulating the MPC and RBC controllers in a more realistic way (i.e., without perfect prediction of the disturbances) and implementing them on real experimental facilities. In addition, the generalizability (to other case studies) and

Figure 4: Daily percentage differences between MPC and decision tree 2 for each energy use.
scalability (from single window to an entire façade) of advanced RBC controllers will be subjects of further investigations.

References
Use of Multidimensional Scaling for Fault Detection or Monitoring Support in A Continuous Commissioning

Hugo Geoffroy¹, Julien Berger¹, Benoît Colange²-³, Sylvain Lespinats², Denys Dutykh³, Gérard Sauce¹, Catherine Buhe¹

¹ Univ. Grenoble Alpes, Univ. Savoie Mont-Blanc, CNRS, LOCIE, Chambéry, France.
² Univ. Grenoble Alpes, INES, Le Bourget du Lac, France.
³ Univ. Grenoble Alpes, Univ. Savoie Mont Blanc, CNRS, LAMA, Chambéry, France.

Abstract

It is well known that the building energy use represents a significant part of the total energy use, ca. 40% in USA according to the Building Energy Data Book. With the improvement of new construction’s efficiency, the share of equipment’s energy use increases more and more compared to the overall building energy use. This article proposes to study a new approach in building’s systems Fault Detection and Diagnosis (FDD), so as to provide an intuitive FDD tool for every operator of the maintenance staff regardless of their qualifications. This new approach uses a method of multivariate statistics, provides easily understandable outputs allowing a quick comprehension of the equipment fault by building maintenance staff. Thereby the number of unsolved problems can be minimized and the intervention time would be considerably reduced, avoiding unexpected energy use and equipment’s premature obsolescence.

Introduction

Nowadays, thanks to more and more ambitious regulations in terms of energy efficiency for both existing and new construction, it is required to significantly reduce the energy use in the building sector. Nevertheless, the expected energy use of buildings stays under the estimations after comparison with in situ measurements (de Wilde, 2014). One key explanation for this problem is the malfunctioning of systems or their controls (e.g. the improper operation may reach up to 30% of waste of systems energy use for commercial buildings) (Katipamula and Brambley, 2005). The reduction of these unwanted energy use can be reduced by Fault Detection and Diagnosis (FDD) (Li and O’Neill, 2018). It aims at detecting the occurrence of malfunctions during the equipment operation, to inform operation or maintenance staff in the shortest possible time to avoid violating indoors comfort or too high energy use. Since the creation of the “Annex 25” (Hyvarinen et al., 1999) of the International Energy Agency (IEA), the real implementation of this tools in buildings areas remains an open challenge. Furthermore, with the development of smart buildings, a new challenge appears (Lazarova-Molnar et al., 2016). There is a big amount of data to deal with, and old methods are not always able to cope with it. Indeed, even in residential area, it may produce a huge amount of data for regulation of simplest systems, as Air Handling Unit (AHU) with numerous measured data recorded at short time step. This context increase the computing time and makes the FDD complex or too expensive for residential buildings.

The FDD techniques in the building sector have been widely described and classified during the last years (Bruton et al., 2014; Kim and Katipamula, 2018). In this study we chose to focus on AHU and their fault detection and diagnosis methods which can be divided in four main branches (Yu et al., 2014) : analytical-based methods, knowledge-based methods, data-driven methods, and a combination of all of those. The analytical-based methods usually compare measured data to modeling data from mathematical model (i.e. first approach) and use the residual to detect fault in systems. The advantage of this method is that, unknown faults may be detected without huge quantity of measured data. However, the models which give the required information can be complex and/or inaccurate. The knowledge-based methods use Artificial Intelligence (AI) along with expert analysis, to extract knowledge from data to detect a fault. These methods do not need model to detect and diagnose a fault, but have to be based on labeled historical data (to apply the AI) and usually did not detect unknown faults. The data-driven methods find relation among data pattern and identified faults. Regarding these methods, the advantage is that it does not require complex model or information to detect fault, even unknown, but the capacity to diagnose can be reduced. Combination of these different methods appeared in recent years to solve the inherent problems of individual techniques. Nevertheless, it is still an open challenge for the real time FDD tools to present the results in a satisfying and intelligible form. It is a major issue to propose a tool understandable to all maintenance operators regardless their qualification to analyze the FDD tools.
outputs.

Aims

The aims of this publication are to explore a new fault detection and diagnosis method for the building area, and to demonstrate the potential of the MDS method as an FDD tool. The proposed FDD tool uses a family of multivariate statistical methods called the MultiDimensional Scaling (MDS) to deal with this huge amount of data such as the early work proposed in (Torgerson, 1952). This method is for example used in the electrochemical energy storage area to detect faults in batteries operation and estimate their lifetimes (Degret et al., 2014). This tool, is part of the data-driven methods, may be used to solve the problem of under-qualified maintenance or operation staff. Indeed, thanks to its ability to reduce high dimension data to two-dimensional representation space whose enhancing all the identified faults, this tool can be easily used and understood by most of the in situ agents. The goal of this new FDD technique is to create a user friendly, autonomous staff oriented tool, which provides real-time results. Furthermore, the possibility of the MDS method to create severity indicators and to represent data according to it may suggest the opportunity of fault prediction.

The present study proposes to apply the developed tool directly on data from a real existing tertiary building system to appreciate its capacity to detect some faults.

Method

The developed FDD method can be divided in two main steps. The first one is a pre-process stage, where the input data are treated to detect faults. The second one is the data treatment stage during which the dimension reduction is performed and the outputs are generated. All these stages, presented and detailed in the following section, are performed in the MATLAB environment.

Pre-process

In the first step of the method the data are treated to create the input data space, which is the evaluation of the chosen logical rules on measured parameters. These input data are usual building energy management system (BEMS) data type, such as temperature, power, or logical values. For the purposes of the numerical analysis of a given practical problem, the data are transformed into dimensionless quantities. Indeed, the floating point arithmetics is built such as the rounding errors are minimal if the computer manipulates the numbers of the same magnitude Kahan and Palmer (1979). In addition, the density of the floating point numbers is the highest in the interval $[0,1]$ and it decreases when we move further from this interval. Thus, it is always better to handle numerically the quantities of the order of $O(1)$ to prevent serious round-off errors. The original data set is defined in the following form:

$$ U = [U_{ni}], $$

where $U_{ni} := U_i(t_n)$ is a measured quantity obtained on a time grid such as the temperature or electrical consumption, $i \in \{1, \ldots, N_m\}$ with $N_m$ the total number of measured quantities and $n \in \{1, \ldots, N_t\}$ with $N_t$ the total number of time acquisitions.

The data are then treated according to the operation rules defined by the user to detect the faults. The operation rules represent some logical statements that must be observed in a regular operation of the building. A rule is defined by:

$$ U_{ni} - U_{nj} = U_{lim}, $$

where $(i,j) \in \{1, \ldots, N_m\}^2$ and $i \neq j$. Here $U_{lim}$ is a chosen limit value so that a fault is detected when the difference $U_i - U_j$ is above this threshold. A total of $N_R$ rules are created and gathered in the following matrix:

$$ \rho = [\rho_{nk}], $$

with $k \in \{1, \ldots, N_R\}$ and $n \in \{1, \ldots, N_t\}$. Each element of the matrix $\rho$ is defined by:

$$ \rho_{nk} := \frac{U_{ni,k} - U_{nj,k}}{\beta_k}, $$

where $(i_k,j_k) \in \{1, \ldots, N_m\}^2$, $i_k \neq j_k$, $k \in \{1, \ldots, N_R\}$ and $n \in \{1, \ldots, N_t\}$. The element $\rho_{nk}$ is a so-called expert rule, where the results of logic rules are treated in a dimensionless form with the factor $\beta$. This factor is used as a gravity indicator to the fault detection process. The result of the expert rules are then processed with an hyperbolic tangent function to create the severity index $SI$ called $\sigma_{nk}$ and computed according to:

$$ \sigma_{nk} := \tanh(\rho_{nk}). $$

Thus, the matrix gathering the severity indexes can be defined:

$$ \sigma = [\sigma_{nk}], $$

where $k \in \{1, \ldots, N_R\}$ and $n \in \{1, \ldots, N_t\}$. It can be remarked that $\sigma \in Mat([1], [N_t, N_R])$ recalling that $N_R$ is the number of rules and $N_t$ is the number of time step measurements. The $SI$ allows to present the results of Eq. (6) in a dimensionless form in $]-1,1[$ regardless of the physical nature of the fault. Figure 1 shows a representation of the $SI$ and how the reading must be interpreted. The factor $\beta$ is another indicator is created to detect the emergence of multiple faults. The total fault severity is denoted by $\lambda$ and defined as follows:

$$ \lambda_n := \sum_{k=1}^{N_R} \sigma_{nk}, $$
where \( n \in \{1, \ldots, N_t\} \) and
\[
\sigma_{nk}^+ \overset{\text{def}}{=} \max (\sigma_{nk}, 0).
\] (8)

Thus, \( \sigma_{nk}^+ \) corresponds to the positive part of the severity, meaning that a fault appeared as illustrated in Figure 1. The last indicator corresponds to the total number of faults appearing simultaneously:
\[
\delta_n \overset{\text{def}}{=} \sum_{k=1}^{N_R} \chi_{[0,1]}(\sigma_{nk}),
\] (9)

where \( \chi_{[0,1]}(\bullet) \) denotes the indicator function of the subset \([0,1]\).

Figure 1: Severity index form.

Data treatment

The data are treated by the MultiDimensional Scaling method to give information on faults occurrences in the system. The MDS methods use the data created in the pre-process phase as input. The usefulness of the multivariate statistic, such as MDS is to represent data of high dimension in view able form, i.e. representation in a two or three space dimensions. In this case, the original dimension is a \([N_t \times N_R]\) matrix, where \(N_t\) is the number of measurements and \(N_R\) the number of rules. For example in our case study, this original space data is scaled by the six rules corrected with the \( \beta \) coefficient \( \rho_k \) for winter operation. Then, the MultiDimensional Scaling (MDS) reduces this high dimensional set of data into a lower dimensional space called a map. This map is the most satisfying representation of the original set of data in the new space. To generate this map within a shortest time, the HASTIE method (Hastie et al., 2009) is used to identify the most \( N_H \) interesting points in the original space. It chooses the point in the original space which minimizes distance to all the other points. Thus, the most representative points of the data set dispersion in the original space are selected. The MDS method (Torgerson, 1952) is then used to generate the map, while preserving the point neighbourhood based on the conservation of the distance among the points. So, the MultiDimensional Scaling method is a mapping
\[
f : \text{Mat} \left( \mathbb{R}, N_H, N_D \right) \longrightarrow \text{Mat} \left( \mathbb{R}, N_H, N_D \right),
\] (10)

which for the matrix \( \sigma \) returns a new matrix \( \tilde{\sigma} \) in a smaller dimension:
\[
f : \sigma \longrightarrow \tilde{\sigma},
\] (11)

where \( N_D \) is the number of dimensions chosen in the reduced space (two or three usually). So, this method allows an easily understandable representation of the initial matrix \( U \) of \([N_t \times N_R]\) size by a matrix of only \([N_H \times N_D]\). The breaking down of the final map regarding the violation to each rule allows the identification of faulty areas and of nominal operation.

Case study

In this paper, the FDD tool is applied to a French existing building, located in the West of the country. For confidentiality issues, this building cannot be identified in details. The construction is a waste treatment center, recently built, which is divided in two parts. The first one is composed of ca. 500 m² of technical premises and will not be studied in this paper. The second, houses the part of the building where the employees with offices, lunch room, cloakroom and sanitary are located on 350 m².

The internal conditions of the office part is maintained thanks to a heating floor, radiators and air treatment, all powered by a geothermal heat pump and solar heating network. In this work, the FDD tool is only tested on the air handling unit (AHU). The justification of this restriction will be detailed more later.

The AHU is a dual flow ventilation composed of a cross flow heat exchanger (to pre-heat the air thanks to exhaust air), two fans, an heating coil (powered by the heat pump), to regulate the air temperature, and several temperature sensors to see the evolution in the system. Figure 2 illustrates the AHU composition and shows the implementation of sensors.

The system data are temperature informations from the different sensors and power information of fans and the heating coil. The equipment power was turned into boolean values to allow their treatment by the MDS method. The temperatures recorded by different sensors will be called as follows in the rest of the paper: \( T_{\text{out}} \), the outside air temperature (read before the heat exchanger) ; \( T_{\text{preh}} \), the pre-heat air (after heat exchanger warming) ; as \( T_{\text{sup}} \), the supply air (reheat by the heating coil) ; \( T_{\text{int}} \), the indoor air (measured in the extraction path) ; and \( T_{\text{exh}} \), the exhaust air (at the end of the ventilation path, after the heat exchanger). As for the temperatures, the energy use of the harvest elements will be renamed : the supply fan energy use as \( P_{\text{fan}} \) and the heating coil...
consumption as $P_{hp}$. In this study case $N_{in} = 7$. The different temperature profiles are presented in Figures 3 to 6.

In this work, since the control sequences of the system are not known, the case study is particularly useful to explore an underrated FDD building area fault: the wrongly configured building system (Lazarova-Molnar et al., 2016). Thus, data values validity regarding several logical control rules will be studied, and the ability of this FDD tool to detect these faults will be used as a benchmark.

As the rules are unknown, some must be chosen to determine the nominal operation of the system. These control rules have been selected, in order to highlight some operation faults judged plausible from the functional analysis of the building system. The rules chosen to study the operation of the system are derived from the AHU performance assessment rules (APAR) (Schein et al., 2006) and summarized in Table 1.

Six rules are for the winter operation ($N_{W} = 6$) and three for the summer ($N_{S} = 3$). Regarding the winter rules, the first rule is composed of two sub-rules,
Proceedings of the 16th IBPSA Conference
Rome, Italy, Sept. 2-4, 2019

**Table 1: Set of rules.**

<table>
<thead>
<tr>
<th>Season</th>
<th>Ident.</th>
<th>Rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winter</td>
<td>1.1</td>
<td>$T_{sup} &lt; T_{exh}$</td>
</tr>
<tr>
<td></td>
<td>1.2</td>
<td>$T_{out} &lt; T_{int}$</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>$T_{int} + 5 , [\degree C] &lt; T_{sup}$</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>$0 &lt; T_{out} - T_{sup}$</td>
</tr>
<tr>
<td></td>
<td>4.1</td>
<td>$T_{int} &lt; 19 , [\degree C]$</td>
</tr>
<tr>
<td></td>
<td>4.2</td>
<td>$T_{prh} = T_{sup}$</td>
</tr>
<tr>
<td></td>
<td>5.1</td>
<td>$21 , [\degree C] &lt; T_{int}$</td>
</tr>
<tr>
<td></td>
<td>5.2</td>
<td>$T_{prh} &lt; T_{sup}$</td>
</tr>
<tr>
<td></td>
<td>6.1</td>
<td>$T_{sup} &lt; T_{int} - 1 , [\degree C]$</td>
</tr>
<tr>
<td></td>
<td>6.2</td>
<td>$P_{hp} = 0$</td>
</tr>
<tr>
<td>Summer</td>
<td>1</td>
<td>$T_{prh} &lt; T_{sup}$</td>
</tr>
<tr>
<td></td>
<td>2.1</td>
<td>$T_{out} &lt; T_{int}$</td>
</tr>
<tr>
<td></td>
<td>2.2</td>
<td>$T_{int} &lt; 22 , [\degree C]$</td>
</tr>
<tr>
<td></td>
<td>2.3</td>
<td>$P_{fan} &lt; 1$</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>$T_{i}(t_{n+1}) - T_{i}(t_n) &lt; 10^{-6} , [\degree C]$</td>
</tr>
</tbody>
</table>

allowing to see if the room is overheating. The second rule shows a control problem with a useless overheating of the air. The third one is used to detect a failure in heating components or bad sensors implantation. The set of rules n°4 is used to know if the coil did not operate when it is needed. The rules 5.1 and 5.2 detect if the coil operates when not necessary. And finally the two rules n°6 show if the heating pump provides energy only when it is needed. Concerning the summer season, only three rules are proposed. The first one checks if the heating pump operates in a bad regime (i.e. heating mode), the second one if the free-cooling is activated, and the third check if the temperature sensors are saturated.

Then the $U_{lim}$ and $\beta$ values must be set regarding the goal, to allow the data treatment. These two coefficients must be selected by the operator for each rule presented above. They are issued from expert knowledge and their determination may be complex. The values of these two coefficients are presented in Tables 2 and 3 for the winter and summer periods, respectively.

**Table 2: $U_{lim}$ and $\beta$ values for winter.**

<table>
<thead>
<tr>
<th>Ident.</th>
<th>1.1</th>
<th>1.2</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$U_{lim}$</td>
<td>0</td>
<td>0</td>
<td>−5</td>
<td>0</td>
</tr>
<tr>
<td>$\beta$</td>
<td>2</td>
<td>5</td>
<td>10</td>
<td>5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Ident.</th>
<th>4.1</th>
<th>4.2</th>
<th>5.1</th>
<th>5.2</th>
<th>6.1</th>
<th>6.2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$U_{lim}$</td>
<td>19</td>
<td>0</td>
<td>−21</td>
<td>0</td>
<td>−1</td>
<td>0</td>
</tr>
<tr>
<td>$\beta$</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

All this information must be detailed for the MDS treatment, since it is the basis for the dimension reduction. After the selection and the code implementation of all these parameters, the dimension reduction with MDS is carried on (Torgerson, 1952).

**Results and Discussion**

In this section we present the results obtained using this method, first the values generated in the pre-process stage and then the map is obtained in the data treatment phase. Regarding the pre-process stage, the input matrix $U$ has a size of $[8512 \times 6]$, the $p$ and $\sigma$ are matrices of size $[4346 \times 6]$ and the $\bar{\sigma}$ matrix has a size of $[1000 \times 2]$. For the results of the data treatment stage, the map generated by the reduction method reflects the behaviour of the system regarding the operational rules described above. The preliminary results are shown in Figure 7 for the winter period. On this representation of the system operation faults, each point represents the state of the system at each time step. On one hand, the color of the marker indicates the total fault intensity. The value shown on the right with the color bar is the results of $\lambda$ i.e. the sum of positive parts of the severity indicators $\lambda_k$ above zero. This value ranges from 0 with a black marker, meaning that the resulting value of the expert rule are under the prescribed limit, up to 2 (white markers) indicating simultaneous faults (two rules severity indicators reach the maximal value of one). A value of the SI of approximately 1 (orange markers) means that there is a complete violation of one of the rules or a partial violation of two rules. On the other hand, the marker shape shows how many faults are potentially appearing simultaneously. A round marker indicates that there is no severity indicator above zero, a square marker means that one SI is above zero, two are represented with a diamond and three with a triangle although this case is extremely rare in the data set. So, on this map it cannot appear a round marker with an other color than black, or a square marker with a lighter color than orange, because the number of potential faults would not match with the $\lambda$ value.

So, the analysis of the projected data shows that the nominal operation of the system is essentially concentrated in the middle of the map. Indeed, all square and blue markers are clustered in the centered area, and, it is obvious that a continuum leads to different faults located on boundary of the map. It can also be noticed that even though square and diamond markers may be close, they are significantly clustered. These fortuitous attributes of the map generated by the MDS method, provide a clear representation and identification of faults. Actually,
since the nominal operation is located in the center of the map, with the identified faults clustering on the boundary, their determination is easy and quick.

The next step is the identification of the different kinds of faults. The expected capacity of the method, is that all the faults are clearly clustered, and avoid a dispersion of the same faults on all borders of the map. An identification of the violated expert rules leads to this new representation of the map of the faults repartition shown in Figure 8. In this map each color as well as the shape of the markers, represents one of the six winter rules. A point is identified as displaying the fault $\rho_i$ if it has the highest severity indicator value $\sigma_i$. So the representation of the point (color or form) indicates the predominant fault. On the Figure 8 is also represented an example of the view showing to an operator on the BEMS. On this map the current operation of the system moves from zone to zone, allowing the operator to know in a second if a fault appears and which kind.

Thanks to the color code, the visualisation of the faults’ location in the reduced space is rapidly understandable. The analysis of this map regarding the faults identification highlights the fact that the method clusters the faults together. This capacity of the dimension reduction method is particularly appreciable for the aims of an Automated Fault Detection and Diagnosis (AFDD) tool. Indeed, the prior data treatment coupled with the MDS reduction method allows the generation of a new reduced space, where all the identified faults are clearly grouped. The analysis of the Figures 7 and 8, shows that the evolution of the operation of the system appears to be continuous. The condition of nominal operation, located in the center of the map drifts to faulty behaviour, which are rather located on the map boundary. The direction of the operation of the system representation indicates which fault type is overriding. Simpler, on the reduced space, the radius length of the localisation can be understood as faults gravity and the angle type of the occurring fault. This representation is user oriented, because it allows a quick and easy identification of the faults.

Thanks to the two different representations of the markers in the above maps, it is straightforward to identify advantages of the this kind of representation for FDD application. Another asset of this FDD tool, is that as the Figure 7 already showed, it allows multiple faulty states detection (markers in diamond or triangle shapes). With the Figure 9 map representation, this multiple fault detection can be more extensively studied. In this new map, as in Figure 8, each different marker shape stands the principal winter fault regarding the severity indicator result. In addition, the marker color indicates the second most significant fault, i.e. the fault with the second most important SI value. The grey points represent the points with at most one fault.

This analysis of the map in Figure 9 reveals that the point of each time step in the new space is also logical regarding the multiple fault occurrences. Indeed, as clearly illustrated in the top right corner area of this map, once again the MDS reduction method allows the creation of a space continuum between the fault evolution, in which the multiple fault appears. In this aforementioned zone, there are two main faults which are the fault number two $\rho_2$, symbolised by the diamond marker, and the fault number five $\rho_5$, represented by the apex down triangle. In Figure 8 we can only see that the boundary of these two faults is located in a common region, with some almost overlying points. However, thanks to Figure 9, these lay-
Figure 9: Combined fault identification for the winter period: second fault appearing after the main one.

Figure 10: Air Handling Unit summer operation map.

Figure 11: Main fault identification for the summer period.

Figure 12: Combined fault identification for the summer period: second fault appearing after the main one.

The operation map for the summer period is shown in Figure 10. As mentioned before, the nominal operation is located in the map center. Figure 11 enables to identify the main fault occurring. On the bottom boundaries, the three main faults occurrences are highlighted. The faults n°1 and 3 are more often with faults n°2. It can be noted that the saturation of the sensor of the outside temperature is well identified using fault n°3. The saturation can also be noticed in Figure 3 during the month of August. When two faults occur simultaneously, they can be distinguished in Figure 12. By comparison between Figures 11 and 12, in the bottom left corner, the main fault corresponds to the rule n°3 and the secondary to rule n°1.

Regarding the Central Processing Unit (CPU) time of this method, it is relatively reasonable comparatively to the engineering time needed to analyse all these data and to extract information. This cost is almost entirely due to the MDS mapping construction. The elaboration of a map of about 1000 points as presented in this study, represent around 20 min, measured on a computer with Intel(R) Core(TM) i7 – 7820HQ and 32, 0 Go RAM and the algorithm complexity is $N_t^2$ with $N_t$ the number of plotted points.
We highlight some further interesting and promising capacities of the developed intuitive FDD tools. A good definition of the severity index seems to be potentially used to make some fault prediction. This flexibility may be contained in the selection of the two crucial values of $U_{lim}$ and $\beta$. These parameters are not trivial to set, and must be chosen carefully by an expert. The fault prediction should be studied more deeply regarding these two parameters.

**Conclusion**

This study shows that the MultiDimensional Scaling provides an interesting and promising methodology for air handling unit fault detection and diagnosis, but more generally for systems. Another interesting area of the research is the possibility to play with the two problems in dimension reduction between tears and false neighbourhoods in the map. Indeed, these two inevitable consequences of dimension reduction methods can be used to increase the efficiency of our FDD approach, and more specifically the tears. This perspective of using this inherent simplification of the reduction method must be an asset for the usage of the multivariate statistics for fault detection and diagnosis.

However the study should be continued further to check the robustness of the tools with, for example, data sets which contain even more than three simultaneous faults. Also, as the tool is tested on real data from an anonymous building, the authors have no feed back on the actual faults, so the tool must be perform on simulated data to estimate the Further investigations should be also made to allow the creation of real automated fault detection tools, as for the identification of the faulty area definition, the faults apparition, etc. And the CPU time should be also reduced even more to have a real-time FDD tool, so more work is needed to reach this aim.

**Acknowledgements**

We thank the CEREMA team for their participation in this study. This project is supported by the Interreg V France-Switzerland European Territorial Cooperation Program and has benefited from a European grant of 607776 € through the European Regional Development Fund (ERDF) as well as federal funds Interreg Switzerland for150001 CHF and 123999 CHF for cantonal and communal aid. The authors acknowledge the Junior Chair Research program “Building performance assessment, evaluation and enhancement” from the University of Savoie Mont Blanc in collaboration with The French Atomic and Alternative Energy Center (CEA) and Scientific and Technical Center for Buildings (CSTB).

**References**


Verification of Control Sequences within OpenBuildingControl

Michael Wetter, Antoine Gautier, Milica Grahovac, Jianjun Hu
Lawrence Berkeley National Laboratory
Berkeley, CA, USA

Abstract
The OpenBuildingControl project develops tools and processes for the performance evaluation, specification and verification of building control sequences. This paper describes the tools developed to verify that building control sequences are implemented as specified in a vendor-neutral, executable specification. The verification is done by testing whether trended time series, compared to the simulated control response, are within user-specified tolerances for time and for the trended variable. Moreover, sequence diagrams are used for inspection of the control response.

The paper gives an overview of the OpenBuildingControl process and describes tools for the control verification. It presents an example in which we successfully verified that an actual implemented control sequence conforms to its vendor-independent specification. It closes with discussion of experiences collected during this verification and with alternate approaches that can improve the operational performance of buildings.

Introduction
A significant fraction of inefficiency in buildings is caused by sub-optimal design, implementation and commissioning of control sequences (Fernandez et al., 2017). Barwig et al. (2002) report that the most frequent control related failures are due to software faults, accounting for 32% of all reported failures. Guerre and Fuller (2017) report that the lack of a non-ambiguous, executable control sequence specification prolongs the commissioning and decreases the quality of the control sequence verification, thereby increasing the fault probability over the lifetime of the system. Moreover, as building control sequences become increasingly complicated, a manual verification as is done today during commissioning becomes difficult due to the various timers, interlocks and mode switches that are present in advanced sequences such as the ones published in ASHRAE Guideline 36 (ASHRAE, 2018).

To contribute to the increased use of advanced control sequences and their error-free implementation, we are executing a project called OpenBuildingControl. The OpenBuildingControl project develops tools and processes for the performance evaluation, specification and verification of building control sequences. It aims to provide methodologies and tools to close the gap between energy modeling tools, controls specification and verification of correct implementation of control sequences. The project specified a workflow, described below, that starts with instantiating and possible adapting a control sequence from a library, optionally test its performance using energy simulation, exporting the sequence in a vendor independent format for cost estimation and subsequent implementation on control product lines by control providers, and formal verification of the correct implementation of the sequence by commissioning providers.

The focus of this paper is to describe the process and software for the verification of this control implementation. Given a set of control input signals, such as measured room and outside air temperatures, the verification tests formally whether measured control outputs, such as setpoints or actuator signals from the building automation system, agree with these signals as computed using the original specification. This process is to be done as part of the building commissioning. Related work from the project can be found as follows: The overall project is documented at https://obc.lbl.gov. Wetter et al. (2018a) describe a vendor-independent language called Control Description Language (CDL), which is a subset of the Modelica language (Mattsson and Elmqvist, 1997) that we use to express control sequences and simulate their behavior. Wetter et al. (2018b) describe the overall workflow and discuss simulation of control sequences with an energy model in the loop. They also show that changing the control sequence for a variable air volume flow system between a sequence published by ASHRAE in 2006 and a sequence published in ASHRAE Guideline 36, annual HVAC site electricity use is reduced by 30%, thereby indicating the importance of control sequences to reduce energy use. Moreover, the large difference of 1/3 of HVAC site electricity use questions the validity of today’s common practice of idealizing control sequences in building energy simulation. To re-
spond to the need for better representing controls and integrate energy modeling with the control delivery process, we are currently redesigning EnergyPlus through a project called Spawn of EnergyPlus (https://www.energy.gov/eere/buildings/downloads/spawn-energyplus-spawn).

This paper is structured as follows: We first give an overview of the control design and deployment process. Next, we present tools developed to conduct verification of the correct implementation of the control sequences. Then, we present an example and we close with discussions and conclusions.

Verification

To put the verification of the control sequence into the context of the overall workflow, we now describe the process that we follow in OpenBuildingControl for selecting, deploying and verifying a control sequence. Given regulations and efficiency targets, labeled as (1) in Figure 1, a design engineer selects, configures, tests and evaluates the performance of a control sequence using building energy simulation (2), starting from a control sequence library that contains ASHRAE Guideline 36 sequences, as well as any user-added sequences (3), linked to a model of the mechanical system and the building (4). If the sequences meet closed-loop performance requirements, the designer exports a control specification, including the sequences and functional verification tests expressed in the Controls Description Language CDL (5). Optionally, for reuse in similar projects, the sequences can be added to a user-library (6). This specification is used by the control vendor to bid on the project (7) and to implement the sequence (8) in product-specific code. Prior to operation, a commissioning provider verifies the correct functionality of these implemented sequences by running functional tests against the electronic, executable specification in a commissioning and functional verification tool (9). If the verification tests fail, the implementation needs to be corrected and the tests repeated until the tests pass.

For closed-loop performance assessment, step (2) in the figure, Modelica models of the HVAC systems and controls (Wetter et al., 2014) can be linked to a Modelica envelope model (Wetter et al., 2011) or to an EnergyPlus envelope model. This can currently be done through the External Interface (http://simulationresearch.lbl.gov/fmu/energyplus/export/index.html). A more direct coupling is in development through the Spawn of EnergyPlus project. Library of control sequences, step (3), have been released with the Modelica Buildings Library 5.0.0 and more sequences are currently added to this library. To export control sequences in a vendor-neutral format, step (5), a translator from CDL to a json intermediate format is being developed at https://github.com/lbl-srg/modelica-json. The json intermediate format is intended to be used as input for cost estimation tools and translators to vendor-specific product lines. This translators also outputs an English language description of the control sequence and its block diagram representation.

Methodology

We will now describe how to verify the correct implementation of control sequences. Note that this step only verifies that the control logic is implemented correctly. Hence, it should be conducted in addition to other functional tests, such as tests that verify that sensor and actuators are connected to the correct inputs and outputs, that sensors are installed properly and that the installed mechanical system meets the specification.

For clarity, we remind that this verification tests whether the implementation of the control sequence conforms with its specification. In contrast, validation would test whether the control sequence, together with the building system, is such that it meets the building owner’s need, which is done in step (2) in Figure 1.

The process is as follows: A commissioning agent exports trended control inputs and outputs and stores them in a CSV file. The commissioning agent then executes the CDL specification for the trended inputs, and compares the following:

1. Whether the trended outputs and the outputs computed by the CDL specification are close to each other.

2. Whether the trended inputs and outputs lead to the expected sequence diagrams, for example, whether an air handler’s economizer outdoor air damper is fully open when the system is in free cooling mode.

Technically, step 2 is not needed if step 1 succeeds. However, feedback from mechanical designers indicate the desire to confirm during commissioning that the sequence diagrams are indeed correct (and hence the original control specification is correct for the given system).

Figure 2 shows the verification flow diagram. Rather than using real-time data through BACnet or other protocols, set points, inputs and outputs of the actual controller are stored in an archive, here a CSV file. This allows to reproduce the verification tests, and it does not require the verification tool to have access to the actual building control system. During the verification, the archived data are read into a Modelica model that conducts the verification. The verification will use three blocks. The block labeled input file reader reads the archived data, which may typically be in CSV format. As this data may be directly written by a building automation system, its units will differ from the units used in CDL. Therefore, the
block called unit conversion converts the data to the units used in the CDL control specification. Next, the block labeled control specification is the control sequence specification in CDL format. This is the specification that was exported during design and sent to the control provider. Given the set points and measurement signals, it outputs the control signals according to the specification. The block labeled time series verification compares this output with trended control signals, and indicates where the signals differ by more than a prescribed tolerance in time and in signal value. The block labeled sequence chart creates x-y or scatter plots. These can be used to verify for example that an economizer outdoor air damper has the expected position as a function of the outside air.
temperature.

Below we further describe the blocks in the box labeled verification.

Modules of the verification test

To conduct the verification, the following models and tools are used.

Input file reader

Input files are read with Modelica.Blocks.Sources.

Unit conversion

Building automation systems store physical quantities in various units. To convert them to the units used by Modelica and hence also by CDL, we developed the Modelica package Buildings.Controls.OBC.

Unit conversion tools are used.

To conduct the verification, the following models and tools are used.

Below we further describe the blocks in the box labeled verification.

Sequence chart

To create sequence charts, we developed the Modelica package Modelica.Utilities.Plotters. This package consists of models that generate time series plots or scatter plots, and save them in one or multiple html files. The plotter allows for example to plot control sequences such as the one shown in Figure 5. The blocks that accumulate the data to be plotted can be activated and deactivated, for example to plot data only when the HVAC system is operating for at least 5 minutes.

Time series verification

We developed a cross-platform, C-based software called funnel (https://github.com/lbl-srg/funnel) to conduct time series comparison. The software reads two CSV files, one containing the reference data set and the other the test data set. Both CSV files contain time series that need to be compared against each other. The comparison is performed by computing a funnel around the reference curve. For this funnel, users can specify the tolerances with respect to time and with respect to the trended quantity. The $L^1$-norm is used to build the tolerance domain. The algorithm then checks whether the time series of the test data set is within this domain. For points outside the domain, it computes the corresponding error.

Examples

We will now present examples for the sequence diagram verification and the time series verification.

Sequence diagram verification

This is an example of the verification that tests whether an implemented control sequence leads to the expected relationship between the values of the control signal and the controlled variable, as visualized in a sequence diagram.

We verified that an implementation of the Guideline 36 supply air temperature heating and cooling setpoint sequence Buildings.Utilities.Plotters.Examples.SingleZoneVAVSupply_u leads to the expected sequence diagram as illustrated in Figure 3. While in this example we used the control output of the CDL implementation, during commissioning one would use the control signal from the building automation system.

Figure 4 shows the verification model that we created using Modelica. On the left are the blocks that generate the control input. In a real verification, these would be replaced with a file reader that reads data that have been archived by the building automation system. In the center is the control sequence implementation. Some of its output is converted to degree Celsius, and then fed to the plotter on the right that generate a scatter plot for the temperatures and a scatter plot for the fan control signal. The block labeled plotConfiguration configures the file name for the plots and the sampling interval.

Simulating the model shown in Figure 4 generates an html file that contains the scatter plots shown in Figure 5. The plots complies with the specification provided in Figure 3.

Sequence output time series verification

The process for the time series verification is as follows: Given a CDL specification of the implemented control sequence, a commissioning agent trends the sequence inputs and the outputs, reads the trended inputs into the CDL specification, executes the CDL specification, and verifies CDL computed outputs against the trended control outputs. This will be done for the top-level sequences as well as for lower level sequences.

In this example we validated a trended output of a control sequence that defines the cooling coil valve position. The cooling coil valve sequence is a part of
the ALC EIKON control logic implemented in building 33 on the main LBNL campus in Berkeley, CA. The subsequence is shown in Figure 6. It consists of a proportional-integral (PI) controller that tracks the supply air temperature, an upstream subsequence that enables the controller and a downstream output limiter that is active in case of low supply air temperatures.

We created a CDL specification of the same cooling coil valve position control sequence, shown in Figure 7, to validate the recorded output. We recorded trend data in 5 second intervals for the supply air temperature, the supply air temperature setpoint, the outdoor air temperature, the VFD fan enable status, and the VFD fan feedback. The output of the subsequence is the cooling coil valve position.

The input and output trends were processed with a script that converts them to the format required by the data readers. The data used in the example begins at midnight on June 7 2018. In addition to the input and output trends, we recorded all parameters, such as the hysteresis offset, shown in Figure 6(a), and the controller gains, shown in Figure 6(b), to use them in the CDL implementation.

We configured the CDL PID controller parameters such that they correspond to the parameters of the ALC PI controller. The ALC PID controller implementation is described in the ALC EIKON software help section, while the CDL PID controller is described in the info section of the model Buildings.Controls.OBC.CDL.Continuous.LimPID. The ALC controller tracks the temperature in degree Fahrenheit, while CDL uses SI units. An additional implementation difference is that for cooling applications, the ALC controller uses direct control action, whereas the CDL controller needs to be configured to use reverse control action, which can be done by setting its parameter reverseAction to true. Furthermore, the ALC controller outputs the control action in percentages, while the CDL controller outputs a signal between 0 and 1. To reconcile the differences, the ALC controller gains were converted for CDL as follows: The CDL PI controller proportional gain, $k_{p,cdl}$, was set to

$$k_{p,cdl} = u k_{p,alc}; \tag{1}$$

where $u = 9/5$ is a ratio of one degree Celsius (or Kelvin) to one degree Fahrenheit of temperature difference, and $k_{p,alc}$ is the proportional gain of the ALC PI controller, as obtained from the settings illustrated at Figure 6(b). The CDL integrator time constant was calculated as

$$T_{i,cdl} = \frac{k_{p,cdl} I_{alc}}{u k_{i,alc}}; \tag{2}$$

where $I_{alc}$ is the ALC controller interval at which the integral error gets updated, and $k_{i,alc}$ is the integral gain of the ALC PI controller, shown in Figure 6(b). Both controllers were enabled throughout the whole validation time. Figure 8 shows the Modelica model that was used to conduct the verification. On the left hand side are the data readers that read the input and output trends from files. Next are unit converters, and a conversion for the fan status between a real value and a boolean value. These data are fed into the instance labeled cooValSta, which contains the control sequence as shown in Figure 7. The plots on the right hand side then compare the simulated cooling coil valve position with the recorded data.

Figure 9, which was produced by the Modelica model using blocks from the Buildings.Utilities.Plotter package, shows the trended input temperatures for the control sequence (top plot), the trended and simulated cooling coil valve control signal for the same time period (middle plot), which are practically on top of each other, and a correlation error between the trended and simulated cooling coil valve control signal (bottom plot).

The small difference we observed between modeled vs. trended results is due to the following factors:
• ALC EIKON uses a discrete time step for the time integration with a user-defined time step length, whereas CDL uses a continuous time integrator that adjusts the time step based on the integration error.

• ALC EIKON uses a proprietary algorithm for the anti-windup, which differs from the one used in the CDL implementation.

Despite these differences, the computed and the simulated control signals show good agreement, which is also demonstrated by verifying the time series with the funnel software, whose output is shown in Figure 10. The exceeding error on the control signal is less than 2% and is located during the startup transient after a long shut off period, representing less than 2% of the simulated time period.

**Discussion**

The example shows successful verification based on a small test case. In this example, we started with an actual implementation and created its CDL equivalent for the verification. In the workflow shown in Figure 1, the sequence in CDL would be a starting point for the implementation of the actual sequence, and therefore this step would not be needed. However, due to differences in the dynamic response of equipment, some control gains may have to be tuned differently in the actual implementation, and some controllers may use autotuning for PI gains. This
may have to be reflected in the CDL implementation used for the verification, unless the differences are within the user-configurable tolerances, which for practical applications can likely be set considerably larger than what we used to generate Figure 10.

While we conducted our verification offline for three days, tools could be extended to conduct continuous verification to ensure that sequences are not getting inadvertently changed or disabled by the operator, such as after a manual override. Such continuous verification could contribute to the sustained high performance operation of buildings.

The difficulties that we have encountered while conducting the verification using trended data were related to the temporal resolution of the trended data and to the lack of information about the proprietary control blocks, such as the PI controller. A small sample time interval is required to capture fast changes in control input and output signals. For large sequences, this may cause problems as today’s building control systems have limited capabilities to trend large data streams at high frequency. More field verification is required to see how big the compounding effect is of model mismatch between CDL and vendor-specific implementations of certain control blocks, such as a PI controller, differences in control parameters that may be tuned in the field, such as PI gains, and communication delays of actual hardware.

We also considered in a development version\(^1\) the use of performance-oriented tests such as “Room air temperature shall be within the setpoint ±0.5 Kelvin for at least 45 min within each 60 minute window and “Damper signal shall not oscillate more than 4 times per hour between a change of ±0.025 (for a 2 minute sample period)”. However, discussions with design engineers and commissioning providers showed that there is currently no accepted threshold that could be used to turn such performance-oriented statements into formal, testable requirements. We believe this is a need that should be addressed, in particular as it can aid commissioning of both, actual implementations as well as simulation models.

Besides these tests, we also considered automatic fault detection and diagnostics methods that were proposed for inclusion in ASHRAE guidelines, and we

\(^1\)Modelica Buildings Library, commit https://github.com/lbl-srg/modelica-buildings/commit/654cc7521c0303d0a3f903acda21322c53fe45f.
Acknowledgments

This research was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy, Office of Building Technologies of the U.S. Department of Energy, under Contract No. DE-AC02-05CH11231, and the California Energy Commissions Electric Program Investment Charge (EPIC) Program.

We thank Chris Weyandt from LBNL for his support with data collection and sequence implementation.

References


A Diagnostic Bayesian Network Method To Diagnose Building Energy Performance

Arie Taal¹, Laure Itard², Wim Zeiler³

¹ The Hague University of Applied Sciences, Delft, The Netherlands
² Delft University of Technology, Delft, The Netherlands
³ Technical University of Eindhoven, Eindhoven, The Netherlands

Abstract

In this paper the implementation of a diagnostic Bayesian network (DBN) method is presented which helps to overcome the problem that automated energy performance diagnosis in building energy management systems (BEMS) are seldom applied in practice despite many proposed methods in studies about this subject. Based on the 4S3F framework, which contains 4 types of symptoms and 3 types of faults, an energy performance diagnosis model can be built in a DBN tool to simulate the probabilities of faults based on the presence and absence symptoms which are related to conservation laws, energy performance and operational state of the heating, ventilation and air conditioning (HVAC) systems. Symptoms of all kinds of detection methods, based on models and rules or data-driven, can also be implemented. The structure of the building energy performance DBN models consists of symptom and fault nodes which are linked to each other by arcs. At diagnosis the probabilities of faults can be estimated by the presence of symptoms. This paper demonstrates how these DBN models can be setup using schematics for HVAC systems.

Introduction

Despite many studies related to energy performance, see for instance Djuric (2009), building energy performance diagnosis is not common use in practice. Recent research (Jing, 2017) demonstrated that energy performance of buildings is still lower than expected which shows the need for energy diagnosis.

We find there are two main reasons why automated energy performance diagnosis is missing in practice. One reason why these systems are not applied in practice is that identification of faults which lead to high energy consumption is often difficult because connecting symptoms and faults to each other is not a straightforward exercise. Detected symptoms can be caused by a variety of faults or a combination of faults. And a specific fault in turn, can lead to a variety of symptoms. In addition to this, errors in diagnosis systems can occur because of uncertainties in the applied methods or in the measured energy data. These can be errors of type I, finding a non-existent fault or type II, missing an existent fault. See for instance Tran (2016) who describes these types of errors in more detail for fault detection in centrifugal chiller systems.

The second reason for which implementation of diagnosis methods is complicated is that most methods are designed for a certain heating, ventilation or air-conditioning (HVAC) system, like specific types of air handling units, chillers and variable air volume systems. This leads to time-consuming implementation in practice because many different methods have to be combined. In addition, it is difficult for HVAC engineers to set up energy performance diagnosis systems.

Zhao (2017) and Verbert (2017) presented recently diagnostic Bayesian networks (DBN) for HVAC diagnosis. In this paper a DBN method is presented which will overcome the problems named here above. The proposed DBN method is an expert system which diagnoses as an HVAC expert does and demands little IT (information technology) knowledge to set up diagnosis models. In addition the DBN models for energy performance fault diagnosis are congruent to HVAC schematics.

First we address the 4S3F framework on which the energy performance diagnosis is based. Then we present the 4 types of symptoms in the 4S3F framework, followed by an explanation of diagnosis by DBNs. Next, we present the structure of the DBN models in the 4S3F framework and we show the application of the method on a thermal energy plant. Finally, we will present conclusions and recommendations for further research.

The 4S3F framework for energy performance diagnosis

In this paper, we focus on the detection and diagnosis of faults in the energy performance of buildings. This section presents the headlines of the 4S3F architecture -- see Taal (2018) in which this architecture is explained in more detail--implemented in this article. Figure 1 presents the detection and diagnosis processes in the 4S3F framework. Measurements from the HVAC system, which can be stored in a database of the building management system (BMS), is used to detect symptoms that a fault can be present.

The presence of faults is determined by analysing 4 different types of symptoms which are shown in Figure 1: Balance symptoms (energy, mass and pressure), energy performance (EP) symptoms, operational state (OS) symptoms and additional symptoms (based on additional information as maintenance information).
The results of the detection phase are entered in a DBN model. In this model symptoms are linked to possible faults. We distinguish 3 types of faults: faults of models used for missing energy data and for balances, component faults and faults of control of components. Figure 2 shows the relationships between the 4 types of symptoms and the 3 types of faults which are implemented in DBN models. For instance, a control fault can lead to EP, OS or Additional symptoms.

**Detection of symptoms**

**Balance symptoms**
Physical balance symptoms can be applied to estimate faults in sensors and models for missing energy states by virtual sensors. The balances are based on conservation laws, like energy and mass balances. They have to be true otherwise a sensor (which is a component) fault could be present.

**EP symptoms**
The energy performance of HVAC (sub)systems can be estimated by energy performance indicators like coefficients of performances (COPs) and efficiencies. This symptoms indicate for instance a control fault.

**OS symptoms**
Next to EP symptoms OS symptoms depict faults. As shown in the project BuildingEQ (2018) OS symptoms can be visualized by energy signatures, like time series plots, scatter plots and carpet plots. Figure 3 presents an example in which the relationship between the supply water temperature of the heat pump and the outdoor temperature is shown in a scatter plot. Green lines depict upper and under control values. Symptom are present when measured values deviates from this bandwidth.

**Additional symptoms**
Additional symptoms could be obtained from maintenance or inspection of the HVAC system to exclude faults. See Zhao (2017) who included this type of symptoms for air handling units (AHU) fault detection and diagnosis (FDD). In addition results from other FDD methods, for instance data-driven methods based on regression formulas, principal component analysis (PCA), support vector machine (SVM), artificial neural networks (ANN) or other pattern recognition methods, can be added. See Kim (2017) who recently presented an overview of FDD methods for HVAC systems. To the authors view component specific FDD methods for HVAC products could be delivered by component suppliers, for instance for heat pumps, boilers and pumps and included in the overall architecture.

**Diagnosis by DBNs**
Almost all FDD methods are specific for one type of component or system. Some methods support a top-down or a bottom-up approach to estimate sequentially faults in aggregated or sub systems. However, not simultaneously. Diagnosis by DBN overcomes this problem because the faults in sub and aggregated systems are estimated simultaneously. Another advantage of the DBN method is that the outcomes are probabilities and not Booleans which is more realistic because of uncertainties by inaccuracies of measurements and assumptions in the detection models and in the parameters of the DBN model. Especially when few detection results and contrary symptoms are present, a probability outcome is more realistic. In addition the DBN works how experts diagnose. Based on experience they estimate the fault probabilities and they first address the faults with the highest probability. In this paper we show that DBN models are congruent to models in HVAC schematics which simplifies the setup of a DBN model, and makes possible to design it at the same time the HVAC schematics is developed.

**DBN method**
In the DBN method Bayesian statistics is applied which is based on relations between state probabilities of events. When the probability that event B is true (P(B)>0), the
The DBN model can be represented in a graphical model in which the relations between variables are displayed. This graphical model consists of nodes, which represents the variables, and arrows, which display the relations between the nodes. Every node contains a probability table in which the state probabilities are represented depending on the connected parent nodes.

**DBN Example**

Figure 4 shows a black box model for the COP of a heat pump. Wcompr is the electricity consumption of the compressor of the heat pump. Qcond is the supplied heat by the condenser of the heat pump and Qevap is the heat at the evaporator of the heat pump during the diagnosis time period.

\[ \text{COP} = \frac{\text{Qcond}}{\text{Wcompr}} \]  

(1)

The COP of a heat pump can be calculated from Eq. (1).

The reliability of the calculated COP depends on the reliabilities of the energy values Qcond and Wcompr. As a simplification we assume in this example that COP is only true (reliable) when Qcond and Wcompr are both true. So we neglect the small possibility that COP can be true while Qcond and Wcompr are false and the faults compensate each other.

In a thought experiment the probability that Qcond (P(Qcond)) is correct, has an arbitrary value of 90% which can be based on historical values of flow rate and temperature sensors from the BMS. The probability P(Wcompr) is set to 95% because Wcompr is directly measured. In this case we can easily calculate the probability that COP is true (P(COP)) because Wcompr and Qcond are statically independent of each other:

\[ P(\text{COP}) = P(\text{Qcond} \land \text{Wcompr}) = P(\text{Qcond}) \cdot P(\text{Wcompr}) = 0.90 \times 0.95 = 0.855 = 85.5\% \]

A graphical representation of the corresponding DBN model is shown in Figure 5.

![Figure 5: DBN model for the COP of a heat pump.](image)

The nodes Qcond and Wcompr have prior probabilities and node COP has conditional probabilities. Table 1 shows the conditional probability table for COP and shows our assumption that COP is true when both Qcond and Wcompr are true. This table is implemented in Genie (2016), a DBN software tool.

<table>
<thead>
<tr>
<th>Wcompr</th>
<th>False (0.05)</th>
<th>True (0.95)</th>
</tr>
</thead>
<tbody>
<tr>
<td>False</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>True</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Conversely, it is also possible to use Table 1 to determine P(B|A) when state A is known, which is wanted for fault diagnosis. When the value of COP is false, so P(COP) = 0 (in reality this would be the result of the detection of a symptom, in this case an incorrect COP), then the probability from the DBN model is 69% that this happens because Qcond is false. The probability that this happens while Wcompr is false is 34.5%. See Taal (2016) where this calculation is explained. In other words, it is more likely that the fault arises because of an incorrect value of Qcond than because of an incorrect value of Wcompr. This is logical because in our example the reliability of Qcond (90%) is lower than that of Wcompr (95%).

**Structure of the DBN models in the 4S3F framework**

In DBNs fault nodes (purple in Figure 2) are linked to symptom nodes (yellow in Figure 2) by arcs. The direction of the arcs is from the fault nodes to the symptom nodes as shown in Figure 2.

Connection nodes can be present between the fault and symptom nodes. See Figure 6 wherein an example of a DBN model for an energy balance for a heat pump is given in which fault and symptom nodes are linked by calculation nodes. Q1 is the condenser heat and Q2 is the evaporator heat which are calculated from temperature and flow rate sensor values. W is the compressor work available for compression of the refrigerant in the heat pump.

![Figure 6: DBN model with calculation nodes.](image)

**Node types**

As can be seen in Figure 6, fault nodes are parent nodes which have prior probabilities which are independent of the state of other nodes. For instance, in the DBN example we see that the prior true probability of Wcompr is 95% while the prior false probability is 5%. Symptom nodes are child nodes with conditional probabilities which means that the state depends on the parent nodes. See Table 1 which shows the probabilities of the true and false COP state depending on the states of Qcond and Wcompr.
In Figure 6 a calculation layer is introduced which increases the readability of DBN models by separating faults in components from faults in models. In addition less arcs to symptom nodes are needed. In the calculation layer enthalpy nodes (H) and heat nodes (Q) are encountered.

We propose to implement the DBN in a graphical oriented software tool like Genie (2016). In Genie the type of the child nodes can be selected. The standard type has the structure as presented in Table 1. Table 1 contains only Boolean probabilities for the symptom node COP. However in reality COP could be true while Qcond or Wcompr is false by faulty measurements. Most of the time it is impossible or time consuming to define the fault probabilities of all combinations. We propose to apply so-called Noisy-Max nodes in which the false parent state indicates the chances of the child states. Table 2 presents this for our DBN example. We see that COP can be 2% true when Qcond or Wcompr is false. LEAK shows here the chance of the COP states when Qcond and Wcompr are both true. Adjustment of the DBN example with the Noisy-Max node presented in Table 2 leads to 1% and 2% false values for Wcompr and Qcond when COP is true, while the false values (34.5 and 69%) remain the same when COP is wrong.

Table 2: Noisy-Max type for node COP in the DBN example.

<table>
<thead>
<tr>
<th>Parent State</th>
<th>Qcond</th>
<th>Wcompr</th>
<th>LEAK</th>
</tr>
</thead>
<tbody>
<tr>
<td>False</td>
<td>0.98</td>
<td>0.98</td>
<td>0.001</td>
</tr>
<tr>
<td>True</td>
<td>0.02</td>
<td>0.02</td>
<td>1</td>
</tr>
</tbody>
</table>

We propose to apply Noisy-Max nodes for all child nodes. The fault nodes have as first state the false state because it is difficult to estimate the probabilities of the child node when one of the parent nodes is true independent of the state of the other parent nodes. In this way the Noisy-Max probabilities can be set up easily because the true state of LEAK can be set to 1.

For the sake of demonstration, only false and true states are proposed for parent and child nodes in this paper. However it can be extended with more states when necessary.

A sensitivity analysis, which is not presented here, showed that relative values are more important than absolute values for the prior and conditional probabilities. We saw that the diagnosis outcomes were relatively the same, meaning isolation of faults remained the same, when prior or conditional fault probabilities were changed with 100-300%, for instance from 2 to 5%. In the DBN example the false probability of Qcond was set higher than Wcompr because one knows that Qcond is more inaccurate by calculation from several sensors. Detailed historical data on probabilities of the states is therefore not necessary, thus no training data, but expertise about the relative frequency of errors occurring which is known by design and maintenance HVAC engineers. Also component knowledge can be taken into account.

HVAC mode nodes

An extensive HVAC installation contains many components. When a component is not active, its false probability should be ignored during the diagnosis time period to avoid it being incorrectly marked as false. Therefore a mode node is present which is a kind of OS node. The mode node is set to true when a subsystem is not active. Table 3 shows an example in which the flow rate FT1 and the temperatures TT1 and TT2 are set to true when the mode node is true.

Table 3: Example noisy-max type for a mode node.

<table>
<thead>
<tr>
<th>Parent State</th>
<th>FT1 True</th>
<th>TT1 True</th>
<th>TT2 True</th>
<th>LEAK</th>
</tr>
</thead>
<tbody>
<tr>
<td>False</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.999</td>
</tr>
<tr>
<td>True</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Subsystems

The proposed 4S3F architecture consists of systems and sub-systems with similar characteristics. Each system contains one or more of the four generic types of symptoms (balance, EP, OS and additional symptoms), as well as one or more of the three types of faults (component, control and model faults).

An example of a possible hierarchical level structure for the systems, is presented in Figure 7 in which HVAC controls are not depicted. At least five levels can be distinguished. For all levels DBN models can be set up based on the three types of faults and the four types of symptoms.

![Figure 7: Example of homologous multi-level systems.](image)

The HVAC system (the first level) can be divided into generation systems, distribution systems and end-user systems (the second level), which contain aggregated sub-systems, for instance heat-pump and boiler systems (the third level) which are part of a heat generation system. These systems contain trade products (e.g. the heat pump), as well as combined systems, including the evaporator and condenser modules (the fourth level). The systems in the fourth level can consist of components including pumps, valves and heat exchangers (the fifth level). All levels can contain control systems, which are not shown here. For example, a heat pump has its own control system (for safety purposes), and it can contain an embedded control for supply temperature, which in turn involves the evaporator and condenser modules. Higher-level controls can also be connected by lower-level sensors and actuators. For example, the heat pump can be...
switched on and off by a time schedule at the level of the HVAC system.

Figure 8: Example of an HVAC DBN model on level 1 and 2.

Genie has the capability to build subsystems from the DBN models. Figure 8 shows a DBN model on level 1 and 2. Three heat balance symptoms on level 1 are present in this model. Furthermore three generation submodels (an aquifer thermal energy storage (ATES) system, a heat pump system and a boiler system) are presented, two hydronic systems (cold and hot water) and three end-user systems (cold water groups, hot water groups and roof collector).

The hydronic systems connect generator and end-user systems together by exchanged energy.

Figure 9: Schematic of heat pump system (from Taal, 2018).

An example of a DBN model on level 3, a heat pump system which schematic is showed in Figure 9, is presented in Figure 10. DBN models on levels 4 (heat pump, condenser and evaporator module) and 5 (pumps, pipes, valves, condenser, evaporator) are not presented.

To the authors view these levels could be implemented by product suppliers who could apply FDD methods to diagnose faults within their products.

Application of the 4S3F method on a thermal energy plant

The 4S3F method was tested on the building of The Hague University of Applied Sciences (THUAS) in Delft. In Figure 11 a simplified block schematic of the generator (heat pump, boiler and ATES), hydronic (hot and cold water) and end-user (hot and cold water) systems in the thermal energy plant is presented. See for instance the P&ID (piping & instrumentation diagram) in Figure 9 how these systems are composed.

Figure 10: Example of a heat pump system DBN model at level 3.

Figure 11: Simplified Block schematic of the thermal energy plant of the THUAS building.

The heat pump system delivers heat when the hot water system in the THUAS building demands heat. The boiler system supplies additional heat when the heat pump has reached its nominal capacity. The heat pump extracts its heat from the warm well of an ATES system by a heat exchanger. Cold is supplied by the cold well of the ATES system. When the ATES system cannot supply enough cold, the heat pump, which functions then as cooling machine, can deliver cold.

Figure 11 shows the calculated annual exchanged energy between main systems in 2013. This annual energy amounts at level 3 are calculated by 16 minutes data which was stored by the BMS in a database.

EP symptoms

For EP symptoms, performance factors are applied which do not taken into account (thermal) energy which is freely available from the environment. As indicators Seasonal Performance Factors (SPFs) are used, like the Seasonal Coefficient Of Performance (SCOP) for heating and the Seasonal Energy Efficiency Ratio (SEER) for cooling for year 2013. Eqs. (2) to (6) show the SPF’s which are analyzed in the case study. See Figure 11 in which the annual exchanged energy amounts are depicted.

\[
SCOP_{th} = \frac{Q_{th}}{W_{th} + W_{pump, heating} + W_{ATES}}
\]

\[
SCOP_{cw} = \frac{Q_{cw}}{W_{cw} + W_{pump, cooling}}
\]
were present. The first one is that the control of the regeneration was faulty with fault probability 100\%, the second one that the control of the ATES system was faulty (98\%).

Based on the schematic of Figure 11 DBN models are built in Genie like in Figure 8. In the generator systems their own SCOP symptoms are present, see Figure 10. The detection results are entered in Genie. Diagnosis showed successfully that two faults with high fault probability were present. The first one is that the control of the regeneration was faulty with fault probability 100\%, the second one that the control of the ATES system was faulty (98\%).

**Conclusions and recommendations**

In this paper the implementation of a diagnostic Bayesian network (DBN) method is presented which helps to overcome the problem that automated energy performance diagnosis in building energy management systems (BEMS) are seldom applied in practice despite many proposed methods in studies about this subject. This method is based on the 4S3F framework, which contains 4 types of symptoms and 3 types of faults. In the proposed DBNs faults are parent nodes and symptoms are child nodes from Noisy-Max type.

The proposed DBN structure contains sub-models on several levels in the same way engineers design HVAC and control systems:

1. HVAC systems
2. Generator, Hydronic and end-user systems
3. Component systems, like a heat pump system
4. Main components, like heat pumps
5. Subcomponents of main components

Models can be set up for HVAC components and systems as designed by HVAC engineers and implemented by control engineers based on HVAC schematics. Caused by this system approach it is possible to set up once a library of DBN models which can be extended with models for new components and systems.

In addition, the DBN can be set up by HVAC experts without IT expertise relating to FDD methods.

A disadvantage of the proposed DBN method could be that the exact error is not estimated, for example a heat exchanger has too low capacity due to a too small heat exchange surface or due to contamination. It is only found that a fault is present in the heat exchanger. However, this concerns faults at level 4 or 5 for which specific FDD methods are available and could be combined in the 4S3F architecture.

In this paper an application on a real HVAC system was presented using historical 16 minutes data all over the year 2013. The same method can be applied on real-time BNS data.

**Recommendations**

DBN applied in the 4S3F framework has as the advantage that detection of symptoms and diagnosis by DBN can be automated. The case study for the thermal energy plant of the THUAS building showed its value. We recommend to

\[
\text{SEER}_{cw} = \frac{Q_{cw}}{W_{hp,cooling + W_{pump,cooling + W_{pump,ATES}}}}
\]

\[
\text{SCOP}_{reg} = \frac{W_{pump,c冷水 + W_{pump,reg + W_{pump,ATES}}}}{Q_{cw}}
\]

\[
\text{SCOP}_{hp} = \frac{Q_{cond,mod}}{W_{hp}}
\]

\[
\text{SEER}_{hp} = \frac{Q_{hp,mod}}{W_{hp}}
\]

Whp is equal to Whp, heating when the heat pump is in heating mode and to Whp, cooling when it is in cooling mode. When the heat pump is simultaneously generating cold and heat for the cold water and the hot water systems A and E (see Figure 11), the electricity is divided proportionally based on the supplied thermal energy to systems A and E. SCOP\(_{reg}\) can be considered as a generic energy performance factor for ATES systems. These measured performance factors are compared with expected ones from guidelines. In this paper, we assume that symptoms are present when the measured SCOP or SEER is 5\% lower than the expected one which is reasonable considering the inaccuracies in calculated energy amount (sensor inaccuracies, ignored transient behaviour, 16 minutes calculation interval, energy model assumptions). In this case study most of the measured performance factors were true. For instance the SCOP\(_{hp}\) of the heat pump was 4.5 compared to 4, the SCOP\(_{hp}\) for heating the hot water system was 3 compared to 3 and the SEER\(_{cw}\) for cooling the cold water system was 60 compared to 40. Also the SCOP\(_{reg}\) of the regeneration of heat for the ATES system 22.3 was higher than the expected value of 20.

In addition to SPF\(_{s}\) also efficiencies are taken into account. An important performance indicator for the ATES system is \(\eta_{reg}\), see Eq. (7), which denotes the thermal energy balance in the ATES system. Dutch regulations demands that thermal equilibrium is present undergrounds which means that the extraction of cold and heat are the same during a year.

\[
\eta_{reg} = 1 - \frac{\text{abs}(\text{heatwell} - \text{coldwell})}{\text{max}(\text{heatwell}, \text{coldwell})}
\]

This heat regeneration efficiency was only 63\% which means that 37\% too less heat was regenerated. Thus a symptom for \(\eta_{reg}\) was found.

**OS symptoms**

In the case study supply and return temperatures to the systems at level 3 were analysed. This led to 3 symptoms: the ingoing and outgoing warm well temperatures were lower than expected and the cold water return temperatures were too high.

All energy amounts and the EP and OS symptoms are estimated in the software tool Matlab, using the BMS data. The actual EP and OS values are compared to reference values based on guidelines and design information. Generally, also results from benchmarks and models (see Verhelst, 2017 for such models) can be used.

**Diagnosis**

Based on the schematic of Figure 11 DBN models are built in Genie like in Figure 8. In the generator systems their own SCOP symptoms are present, see Figure 10. The detection results are entered in Genie. Diagnosis showed successfully that two faults with high fault probability
set up a library of generic DBN (sub)models on levels 1 to 3.

Further research is needed to define the input and output of the DBN models at several levels. For instance, at what level sensor and symptom nodes should be present.

In addition, a software shell is needed which
- process automatically BMS data into symptoms
- implement models from the DBN library in a DBN software tool such as Genie
- has an user-interface for the estimated fault probabilities.

Furthermore, research is needed for diagnosis at several time periods: monthly, daily and hourly scale with real life BMS data instead of historical data with annual diagnosis. And dynamic setpoint values for symptom detection could also be derived from physical (simulation) models instead from guidelines as used in this paper.

Finally, we propose to extend BEMSs with this 4S3F method. The energy data can be derived from BMSs. The BEMS can be setup simultaneously with the implementation of the control of the HVAC in the BMS because HVAC schematics are applied in both cases.

References
BuildingEQ. http://www.buildingeq.eu [accessed 19.03.2018]


Applying Machine Learning to Automate Calibration for Model Predictive Control of Building Energy Systems

Thomas Storek, Asad Esmailzadeh, Philipp Mehrfeld, Markus Schumacher, Marc Baranski, Dirk Müller
RWTH Aachen University, E.ON Energy Research Center, Institute for Energy Efficient Buildings and Indoor Climate, Aachen, Germany

Abstract
About 74% of model calibrations happen manually. This work presents an automated calibration method. A key aspect of calibration is the identification of dominant model parameters, which for energy conversion systems, e.g. heat pumps, strongly depend on the operating state. Starting from energy monitoring data, we analyze the time series and identify characteristic operating periods. The latter can be a start-up phase, continuous operation or a cool down period etc. Training a decision tree classifier with manually assigned data, we process the entire monitoring data automatically and split the data into period specific subsets. Using the Morris-Method for sensitivity analysis enables a ranking of calibration parameters for each subset. Followed by successive calibrations where each only considers the most dominant model parameters, we tune the model. A cross validation finalizes the process.

Introduction
Today, the fraction used for heating, ventilation, air conditioning and refrigeration (HVACR) accounts about two-thirds of the building energy consumption. Hence, there is an urgent need for energy saving strategies, which is also a focus of energy policies in many countries. (Afram and Janabi-Sharifi (2014); Baldi et al. (2015); Killian and Kozek (2018))

Although ”passive” approaches such as retrofitting may reduce the energy consumption for room heating, they are not able to guarantee acceptable comfort levels and tend to be cost intensive. In fact, all the advantages of improved building design may be lost or can become even contra productive, with significant reduction of indoor climate comfort by poor or simplified system control strategies. (Michailidis et al. (2018))

Optimizing the operation of building energy systems shows high potential for energy savings in the building sector (Füttner et al. (2017)). However, due to the integration of renewable energy sources into building energy systems, the system complexity increases significantly. Hence, the reliable implementation of classical control approaches such as On/Off or proportional-integral-derivative (PID) control is cumbersome and can lead to low energy efficiency. Therefore, there is a need for advanced control approaches that are able to handle this complexity. One of the most promising approaches is model predictive control (MPC). In literature, energy savings of around 20% to 35% and reduced operating cost of up to 73% are reported, when compared to classical approaches. Although MPC is a standard technique in plant automation after it was first introduced in the 1970s (Dittmar and Pfeiffer (2006)) and extensive research in the field of building energy management systems (BEMS) has been carried out, the practical application of MPC is quite rare and still objective of ongoing research. (Afram and Janabi-Sharifi (2014); Baldi et al. (2015); Killian and Kozek (2018))

In literature, modelling and calibration are considered as most important and, simultaneously, most time consuming parts. Nevertheless, despite the influence of non-linearities, disturbances, time-varying system dynamics and interdependencies in building energy systems (BES), according to Coakley et al. (2014) about 74% of the calibrations in simulations happen manually using trial and error techniques. Besides the significant amount of time required, manual methods are highly dependent on the engineer’s expertise and experience with the respective simulation model. This indicates the need for a simplified and more effective calibration procedure for dynamic models of energy conversion systems in order to pave the way for commercial MPC implementations.

Due to the high system complexity and the amount of model parameters involved, the calibration of BES-models represents an underdetermined optimization problem, which has a non-unique solutions. Reddy (2006), Coakley et al. (2014) and Fabrizio and Monetti (2015) provide valuable reviews about automating the calibration process for BES. Furthermore, Coakley et al. (2014) define seven issues concerning calibration of BES-models: Standardization, expenses, simplification, low quality of input data, consideration of uncertainty, identification of causes for model discrepancies and lack of automated calibra-
tion methods. The Bayesian calibration, which is gaining attention in the recent years, considers the uncertainty of model input data for calibration. Li et al. (2015) present a generic Bayesian approach for calibrating BES-models including a sensitivity analysis and a meta-model-based optimization of a linear regression model.

Even though the potential is not fully leveraged yet, applying optimization algorithms belongs to the state of the art in calibration technology, where the general idea is the minimization of the deviation between model output and corresponding measurements using gradient based algorithms. In practice these reach their limits for BES-models because the objective function converges either to local minima or does not converge at all. Therefore, we propose a simplification of the optimization problem by reducing the number of parameters that are calibrated simultaneously and split the overall process into multiple successive calibrations. In order to identify the most dominant parameters, we use a sensitivity analysis referring to Eisenhower et al. (2012). Supported by machine learning techniques we automate the process in order to reduce the effort for implementation and maintenance of MPC in BEMS.

**Methodology**

Although automated methods for model calibration bear major advantages compared to manual calibration, one major challenge is yet to be faced. In most cases the simultaneous tuning of multiple parameters in a complex BES-model will not lead to an optimal solution. This is mainly caused by the nature of non-linear optimization problems in energy systems which are often circumvented by using heuristic approaches and specialized solvers in order to provide satisfactory results. However, they are limited in its universal applicability, to the best of our knowledge, none of them can guarantee to find a global minimum for non-linear and non-convex calibration problems. Therefore, we present a new method for automated calibration that devides the calibration process into three sequential parts as illustrated schematically in figure 1. First, a clustering analysis and a classification of time series data is used to separate physical effects based on pre-selected features $X_i$. Second, a sensitivity analysis is performed to identify the most dominant parameters within the characteristic sequences. Finally a mathematical optimization is executed to adjust the parameters for each sequence so that the model discrepancy $\Delta y$ can be minimized.

Figure 2 illustrates a typical supply and return temperature as well as the volume flow as time series data for a heat pump. One can observe that the temperature curves behave in certain patterns (in the following called effects) which occur repetitive. These effects are mainly caused by physical processes in BES. For instance, a valve opens or a pump starts operat-

![Figure 1: Calibration method consisting a classification of physical states, a sensitivity analysis and an optimization (Esmailzadeh (2018)).](image1)

![Figure 2: Typical temperature curves (inlet and outlet) as well as the corresponding volume flow curve for a heat pump.](image2)
require a training phase, in which related patterns between characteristics of the data and the a priori assigned classes are studied by an algorithm. These two types and their applications are often misunderstood in literature. Since both learning categories define fundamentally different procedures, they bear also different advantages and fields of application.

We use unsupervised cluster analysis to gain information about the given data set without involving human experience. The clustered data reveals not necessarily how many, but rather which kind of different physical effects we have to consider for building and calibrating models. The automatically found classes can be passed subsequently to a supervised classification procedure, which then trains an algorithm to identify the classes in a wider range of data. Thus, the unsupervised learning algorithm increases the degree of automation while the supervised learning method adds the ability for up-scaling. (Esmailzadeh (2018))

One of the most used clustering methods is the K-means algorithm, which creates groups of data points based on the euclidean distance between the centroid of the clusters and the considered data point in a multi-dimensional feature space (Béjar (2013)). The predefined features e.g. supply and return temperatures, pressures etc. are evaluated in every time step and the data points are assigned to the clusters accordingly. Since the coordinates of the cluster’s centroid is shifted with each assignment, the assignments are iterated until the coordinates do not change anymore. The number of clusters is set a priori. As an extension of the sequential method we integrate an automated class creation process by using a Mini Batch K-means clustering algorithm. Béjar (2013) gives a detailed comparison between K-means and Mini Batch K-means. The Mini Batch K-means is a more efficient extension of the simple K-means algorithm, which evaluates a randomly selected excerpt of data points in every iteration. This not only reduces the computation time but also the susceptibility to noise effects (Sculley (2010)).

The classification is performed using a decision tree classifier as structurally illustrated in figure 3, a supervised machine learning algorithm that creates rules based on labeled data sets and allocates every data point in the training data set to the corresponding class based on the rules for each node.

Once the training phase with manually assigned data is completed, the created decision tree is applied to a randomly selected and labeled test data set, which accounts for approximately 30% of the total data. Based on the test data set, a cross validation is performed in order to evaluate whether the classes created by the clustering algorithm can be identified by the decision tree. If the cross validation results show that an appropriate identification of the defined classes is possible, the created tree is ready to be used for unlabeled time series data. The validation of the classification algorithm is performed using the precision and recall, two of the most commonly used measures for machine learning methods. Considering both for imbalanced data sets (classes consist of very different amounts of data points) is important in order to evaluate the ability to picture the accuracy of the predictions made by the classifier. For a detailed explanation of the decision tree method and further supervised as well as unsupervised learning algorithms we refer to James et al. (2013). In addition it is worth to note, that there are more advanced extensions of the simple tree classifier e.g. random forest and bagging tree classifiers that usually demonstrate higher prediction accuracy. But as almost always the case in data science, these more advanced classifiers come at a price, which is the loss of interpretability and transparency (Bühlmann (2012)). Therefore, we implement the simple tree method using the Python library Scikit-learn (Buitinck et al. (2013)).

Next, a sensitivity analysis for each individual class is executed to identify the dominant model parameters. Common methods are screening methods, variance based methods and meta-model based methods (Wang and Augenbroe (2017)). According to Menberg et al. (2016) variance based methods provide higher accuracy and hence are suitable for quantitative global sensitivity analysis but also require significantly higher computation time compared to qualitative and local screening methods. As a good compromise between computation time and accuracy we choose the Morris method for analyzing and ranking of model parameters based on the influence they have on the root-mean-squared error (RMSE) between the measured and the simulated output variable. The Morris method is a screening method combined with a factorial sampling design to compensate the disadvantage of derivative-based local methods by scanning the bounded parameter space stepwise (Menberg et al. (2016)). Manually set upper and lower bounds limit the parameter space for each parameter, which is then devided into equidistant parameter variations steps. Each of those describes a point on a trajectory, a vector of parameters which contains the same number of components as the dimension of the parameter space. The number of trajectories as well as the vari-

![Figure 3: Schematic illustration of the decision tree method for classification.](image-url)
ation step size $\Delta$, is defined a priori while the starting point $X^*$ of each trajectory is chosen randomly. Based on these setting parameters, the simulation effort is well known as $t \cdot (p + 1)$ where $t$ is the number of trajectories and $p$ the number of parameters. The appropriate number of trajectories depends on the model complexity. For additional information about sensitivity analysis methods, we suggest the work of Saltelli (2008) and Menberg et al. (2016).

The elementary effects ($EE$) are used to evaluate the dominance of the parameters. This measure describes the influence of a parameter variation $\Delta_i$ on the output $y$ for the $i$-th component of the parameter vector $x$. Equation 1 represents the formula for calculating an $EE$ of the $i$-th parameter. The sensitivity index used to rank the parameters is the absolute arithmetic mean of the $EE$ for every trajectory. Besides the arithmetic mean, a commonly used measure is the standard deviation, which indicates non-linearity and higher order effects. The parameter rankings are forwarded to the optimization stage. The sensitivity analysis is implemented by using the Python library SALib (Herman and Usher (2017)).

$$EE_i = \frac{y(\bar{x} + e_i \cdot \Delta_i) - y(\bar{x})}{\Delta_i}$$

The third step of the sequential calibration method is the optimization in which a cost function is iteratively minimized by varying the parameter values. For this cost function, we apply again the RMSE according to eq. 2). Where $\bar{x}$ represents the parameter vector, $s_i$ the simulation output and $m_i$ the measured output of the $i$-th time step. The advantage taking the RMSE as a cost function is the preservation of the physical unit, which makes it easier to interpret the model discrepancy of the output quantity.

$$RMSE(\bar{x}) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (s_i(\bar{x}) - m_i)^2}$$

The particularity about the optimization here is that it is executed separately for each individual classes with the reduced number of parameters. The most dominant parameters for each class are declared as variables while the less influential ones are held constant. In other words, each parameter is optimized in the respective class, in which it shows the highest sensitivity index. By this means, we ensure that every parameter is only optimized once. Non-influential parameters neglected for the optimization. For fine tuning of parameters that show influence in more than one class, after the class individual optimization we execute a final global optimization for all data points jointly with a significantly reduced step size. The order of classes for the optimization are chosen in a way, such that the one with the most dominant parameters is optimized first. This is important because the subsequent optimization procedures change a subset of parameters, and thus, also the previous results for the already optimized classes. By following this order, we keep the impact of change at a minimum. The interaction between the sensitivity analysis and the optimization is illustrated schematically in figure 4.

The challenge of non-linear and non-convex optimization is widely known in BES modeling since most of the BES-models contain highly non-linear equations and thus are difficult to optimize. The proposed calibration method provides a way to improve the optimization results with commonly available open source optimizers in the programming language Python. However, one required feature of the optimizer is the ability to handle simple boundaries and least squared error problems to realize a RMSE minimization. For this purpose we use the scipy.optimize.minimize function of the Python library Scipy (Jones et al. (2001)). According to the mathematical derivation by Kraft (1988) and Byrd et al. (1995) the selectable Quasi-Newton method SLSQP and L-BFGS-B are well suited for this kind of problems.

**Case Study**

In order to examine the functionality of the presented method we conduct a case study for that we use time series data gained during an independent hardware-in-the-loop (HIL) experiment of a real heat pump (HP). These kinds of tests are dynamic experiments where a building performance simulation is coupled to an energy conversion system on a test bench (Nürenberg et al. (2017)). Figure 5 shows the schematic overview of the experimental setup. The test bench, consisting of a hydraulic part and a climatic chamber, is capable of emulating highly dynamic boundary conditions in terms of heated and cooled water flows (hydraulic part) and thermally
conditioned air in the climatic chamber, e.g. to emulate outdoor air of a winter day.

The used monitoring equipment are sensors for volume flows (water, gas, brine), temperatures and electric power. Their installation positions are displayed in figure 5. With a sample rate of 1 s the data set ensures a dense resolution to perform preprocessing analyses in the context of technical systems that need a sophisticated evaluation from a dynamic point of view. The monitoring equipment positioned around the HP unit itself allows energy balances for the electric consumption as well as the provided thermal energy. Furthermore, the gas consumed by the condensing gas boiler can be measured. Unfortunately, there is not enough space between boiler and tank to place a volume flow meter for balancing the thermal gains of only this heat generator. Yet, we are able to determine the thermal demands of both consumer circuits: Space heating and domestic hot water (DHW).

An experimental time frame of about 20 h (73900 samples) is used for the evaluation the presented calibrating method. The inlet and outlet temperature curves as well as the volume flow were already illustrated in figure 2. Besides these physical quantities, we also use the compressor power for performing the classification and additionally the first and the second derivatives of the inlet and outlet temperature for clustering. The derivatives are important in order to capture dynamic effects. Furthermore, a simple moving average filter with a window size of 500 seconds is used for the derivatives to reduce the influence of noise effects on the clustering. As already explained, for classification, the optimization is devided into a training and a test data set to avoid overfitting. Therefore, we use approximately 70 % of the data as training and 30 % as test data for cross validation, which is a common ratio in data science. In contrast to the cross validation for the decision tree classifier, we do not select the training and the test data randomly but ensure that both data sets are representative and contain all kinds of operating phases we identify.

Regarding the temperature curves in figure 2 we can manually identify three fundamentally different operating procedures that occur repeatedly: A heat-up phase, a heating and a cool-down phase. As one can observe, the heat up phase is comparably short while the cool down phase is clearly dominant in the considered experimental data.

The objective HP model is part of the open-source Modelica library AixLib (Müller et al. (2016)), which is available on https://github.com/RWTH-EBCC/AixLib. The model bases either on mathematical functions or tabulated data according to DIN-EN-14511 (2018). Besides this black box approach for the refrigerant circuit, the rest of the model is grey box. In particular this means that it comes along with thermal capacities, heat losses and pressure drop at both heat exchangers (condenser and evaporator). The thermal output is determined by a variable compressor speed signal. However, since the system controller regulates the particular HP, just with an on/off signal, we apply this control to the simulation model as well. The HP model uses a PT1 element to be able to represent heat-up and cool-down phases of the compressor. The total model consists of 86 submodels and a total of 384 scalar equations. For this study we consider the six parameters that describe performance scaling, heating losses and time delays.

**Results**

As already explained, mainly three classes can be distinguished manually by analyzing the inlet and the outlet temperature curves. Hence, in a first try we set number of centroids to three for the Mini Batch K-means method. The result of the clustering analysis is illustrated in figure 6. We recognize the three clusters found do not correspond to the ones initially expected. Although the Mini Batch K-means assigns over 90 % of measurements correctly, the beginning of the heat-up phase and the heating phase are recognized as only one cluster, whereas the algorithm assigns two clusters to the cool-down phase. The lower one of cooling phases sometimes even passes over into the heat-up phase.
sharper and we clearly identify the a priori expected clusters plus one additional within the cooling down phase at lower temperature levels.

Using 70% of the labeled data set for training of the decision tree classifier, we find that the classifier assigns about 99% of the measurements of training data correctly. This is also proven by a cross validation.

Since the reference to the automated method is a manual calibration method, we use the three a priori expected clusters for the sensitivity analysis and the optimization, whereas we sum up the two clusters of the cool down phase to only one for better comparability. This assumption is reasonable because, as already mentioned the cool down phase is modeled as only one PT1. The sensitivity analysis reveals that six investigated parameters have influence for the heat pump simulation model. Consequently, these parameters are set as variables for the optimization in the respective class, in which the sensitivity index is the highest.

The fitting accuracy is evaluated by using statistical measures that describe the model discrepancy like the RMSE and the coefficient of determination ($R^2$). Both are presented in table 1.

Table 1: Statistical evaluation of model discrepancy after calibration.

<table>
<thead>
<tr>
<th>Class</th>
<th>RMSE in K</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>heat-up</td>
<td>1.57</td>
<td>0.87</td>
</tr>
<tr>
<td>heating</td>
<td>1.03</td>
<td>0.72</td>
</tr>
<tr>
<td>cool-down</td>
<td>0.44</td>
<td>1.00</td>
</tr>
<tr>
<td>Total</td>
<td>0.65</td>
<td>0.99</td>
</tr>
</tbody>
</table>

Besides the statistical evaluation we use the diagrams shown in figure 8 and figure 9 for visualizing the discrepancy between the simulation and the measurement. We find that the trajectories of simulation and measurements are mostly congruent with only small deviation during the cool-down phase. This is mostly recognizable at the beginning of the cool-down phase. The second diagram also proves the absence of significant simulation errors.

Discussion

The clustering results show that the algorithm is only partly able to create classes, which represent the three physical effects we are able to distinguish manually.

Obviously, the heat-up and the heating phase are not delimited from each other while the cooling phase is divided into two different states. Consequently, the algorithm fails to entirely capture the physical effects entirely due to the similarity of the features for the heat up and the heating phase. However, the algorithm evaluates the difference between the two cooling down stages greater and thus, devides the decline based on the values for the first derivative of the supply and the return temperature. Increasing the number of clusters leads to the desired results, although the clustering algorithm still separates the cool down phase into two parts.

Since the algorithm does only neutrally interpret the provided statistical features without any deeper knowledge about the system, this effect can also be interpreted as lack of detail within simulation models that are not initially expected. Furthermore, this kind of cluster analysis can be further used in order to improve the model and for instance model the cool down as a two stage process or a PT2 instead of a PT1 element.

The sensitivity analysis works as expected. Although the Morris method is an rather simple method when compared to more advanced methods it works efficiently and leads to the desired results and enables a mapping of the investigated parameters to the individual classes with low computational effort. Although the method works fine within the scope of the presented use case future work may include the use of the median instead of arithmetic mean for better robustness against singularities. Additionally, for investigation of more complex models incorporating higher number of parameters other methods such as linear regression or Sobol as described by Menberg et al. (2016) may lead to better results. Although the computational effort may increase significantly.
The obtained results of the sequential optimization are promising when compared to non-decomposed calibration. Due to the automated decomposition into sub calibration processes, it was easier to find accurate model parameters for the overall system. Simultaneously, the computation time for the error minimization is shorter because the overall mathematical problem converges faster. However, the results depend on the order the individual suboptimizations are executed. Starting with heat-up provides the best results because the system is in equilibrium with its environment. Nevertheless, this order still needs to be automatized.

We mostly automated the individual steps of the overall calibration algorithm, which enables a comfortable way for the calibration of complex simulation models based on real data. Applying the method to MPC, it will be possible to support the automated implementation process. Furthermore, it will pave the way for adaptive MPC for BES that are able to react to changing boundary conditions of the real systems.

Conclusion

In this work, we presented an approach that enables an efficient and automated calibration of simulation models of BES. It is applicable for online model calibration within model based control algorithms for BEMS and is structured in three modular parts: First, an automated time series analysis consisting of a clustering of operation states using K-Means and an automated classification of measurements using a decision tree classifier. Second, a class specific sensitivity analysis of model parameters. Finally, a multi-stage parameter optimization.

For proof concept, we demonstrated the considered approach, using measurements from a HiL-test of a real heat pump. In a first approach we set the number of clusters to three, where we find that K-means identifies other clusters within the measurements than the three also manually distinguishable clusters that were initially expected. A cross-validation shows that about 76% of the measurements are clustered as expected. However, adding an additional cluster we find the expected operation phases plus one and significantly better identification accuracy. The following classification of measurements shows an accuracy of about 99%.

The cluster specific applied sensitivity analyses enables a mapping of the parameters to their relevant measurements. Therefore, we are able to split the optimization of model parameters into a multi-stage process, where we only optimize a reduced set of parameters per cluster. Hence, the overall optimization problem is simplified significantly and therefore the chance for convergence increases significantly. This is also proven by results of the demonstration, where we obtain a good accordance of simulation results and measurements with an RMSE of 0.65 K for the evaluated set of testing data.

Essentially, the algorithm performs as expected although the results may depend on the chosen settings. However, due to its modular design the interim results can be checked after each step, which leads to high level of reliability. Furthermore, it makes the calibration lucid to the user. Additionally, the multi-stage optimization leads to better convergence of the parameter optimization. Compared to a manual calibration the process automation reduces required time to a minimum, which makes the algorithm promising for real world applications for model based control systems. Nevertheless, future work will include better setting estimation and interface automation in between the modules. Also the extension of other sensitivity and optimization methods may be desirable. Furthermore, we will investigate the performance of the calibration for additional HVACR-systems based on possibly incomplete real energy monitoring data from buildings.

Acknowledgement

We gratefully acknowledge the financial support provided by the BMWi (Federal Ministry for Economic Affairs and Energy), promotional reference 0350018A.

Nomenclature

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>BES</td>
<td>building energy systems</td>
</tr>
<tr>
<td>BEMS</td>
<td>building energy management systems</td>
</tr>
<tr>
<td>DHW</td>
<td>domestic hot water</td>
</tr>
<tr>
<td>EE</td>
<td>elementary effects</td>
</tr>
<tr>
<td>HP</td>
<td>heat pump</td>
</tr>
<tr>
<td>HVACR</td>
<td>heating ventilation air conditioning and refrigeration</td>
</tr>
<tr>
<td>MPC</td>
<td>model predictive control</td>
</tr>
<tr>
<td>m_i</td>
<td>i-th measurement</td>
</tr>
<tr>
<td>opt</td>
<td>optimized</td>
</tr>
<tr>
<td>R^2</td>
<td>coefficient of determination</td>
</tr>
<tr>
<td>RMSE</td>
<td>root-mean-squared error</td>
</tr>
<tr>
<td>res</td>
<td>result</td>
</tr>
<tr>
<td>s_i</td>
<td>i-th simulation output</td>
</tr>
<tr>
<td>var</td>
<td>variable</td>
</tr>
<tr>
<td>x̄</td>
<td>parameter vector</td>
</tr>
</tbody>
</table>

References


DIN-EN-14511 (2018, 05). Air conditioners, liquid chilling packages and heat pumps for space heating and cooling and process chillers, with electrically driven compressors; german version.


Quantification and Characterization of Energy Flexibility in the Residential Building Sector

Adamantios Bampoulas\textsuperscript{1,2}, Mohammad Saffari\textsuperscript{1,2}, Fabiano Pallonetto\textsuperscript{1}, Mattia de Rosa\textsuperscript{1,2}, Eleni Mangina\textsuperscript{1,3}, Donal P. Finn\textsuperscript{1,2}

\textsuperscript{1}UCD Energy Institute, University College Dublin, Dublin, Ireland
\textsuperscript{2}UCD School of Mechanical and Materials Engineering, University College Dublin, Dublin, Ireland
\textsuperscript{3}UCD School of Computer Science, University College Dublin, Dublin, Ireland

Abstract
Demand response can enable residential consumers to take advantage of control signals and/or financial incentives to adjust the use of their resources at strategic times. These resources usually refer to energy consumption, locally distributed electricity generation, and energy storage. The building structural mass has an inherent potential either to modify consumption or to be used as a storage medium. In this paper, the energy flexibility potential of a residential building thermal mass for the winter design day is investigated. Various active demand response strategies are assessed using two flexibility indicators: the storage efficiency and storage capacity. Using simulation, it is shown that the available capacity and efficiency associated with active demand response actions depend on thermostat setpoint modulation, demand response event duration, heating system rated power and current consumption.

Introduction
Demand Response (DR) is considered as one promising measure to enhance the penetration of renewable energy resources (RES) and reduce carbon emissions. However, electricity cannot yet be stored economically, so the supply of and demand for electricity must be maintained in balance in real time. In addition to this, demand levels also can change quite rapidly and unexpectedly causing mismatches in supply/demand balance, which can threaten the integrity of the grid (SEDC, 2015). To securely and efficiently tackle the aforementioned problems, availability of larger energy flexibility assets is required for the management of the electricity system.

Energy flexibility can be defined as the modification of generation injection and/or consumption patterns, on an individual or aggregated level, in reaction to an external signal (price signal/network tariff activation etc.) or in order to provide a service within the energy system or to benefit the grid. (CEER, 2018). Demand-side is referred either as dispatchable flexibility that can be traded on the different energy markets by an aggregator (explicit) or as the consumer’s reaction to price signals (implicit) (SEDC, 2016). Regarding the energy flexibility of buildings, Jensen et al. (2017) define it as “the ability to manage its demand and generation according to local climate conditions, user needs and grid requirements. Energy flexibility of buildings will thus allow for demand-side management/load control and thereby demand response based on the requirements of the surrounding grids and on the availability of RES, in order to minimize the CO2 emissions”.

Buildings can be part of the solution in the evolving future smart grid, since they offer various storage potential options, either in their structural fabric (building envelopes) or by means of their HVAC systems (e.g., thermal storage tanks), electric vehicles, etc.. In addition, they can play a key role in the future smart grid as they account for approximately 40\% of the global energy consumption (Byskov and Lindberg, 2017). By equipping buildings with ICT-based solutions, their energy efficiency and flexibility can be controlled. In this context, the energy flexibility of buildings should be defined and assessed to enable these smart capabilities. Such capabilities can effectively contribute to more comfortable buildings tailored to the needs of the user and the utility with lower environmental footprint (Verbeke et al., 2018).

Despite the various approaches over time regarding energy flexibility indicators, to date, there are no common definitions and methodologies for assessing energy flexibility. This is because energy flexibility is not only the result of the available technologies in a building, but it greatly depends on how these technologies are controlled, their interaction with the utility, the occupants and other boundary conditions (Finck et al., 2018). The resulting time-varying flexibility profiles should be available to communicate and interpret between different stakeholders of the energy system (e.g. energy system designers and operators, aggregators and governments) (Jensen et al., 2017).

DR strategies can provide additional flexibility to meet the requirements of the utility and/or aggregators. These expectations are accompanied by the need to determine not only the quantity of the load to be added or reduced but also the time and the duration at which the DR should be activated. In order for utilities/aggregators to be aware of the above-mentioned characteristics, suitable control strategies are needed to adapt the building electrical demand to render the DR idea feasible for the energy business. These strategies must be able to dynamically control shiftable building without severely affecting occupant comfort (Christiantoni et al., 2016).

To exploit the energy flexibility potential of buildings, their structural thermal mass can be used as thermal storage capacity. The thermal mass of buildings is a
readily available energy storage medium which can be used with few additional investments, mainly by means of more sophisticated heating system controllers. Such controllers, if integrated within a building energy management system, can utilise the energy flexibility of the structural thermal mass, by responding to an external signal (Foteinaki et al., 2018). The energy flexibility potential depends on various factors such as the functional typology (commercial, residential building, etc.), the properties of the thermal envelope and the installed HVAC systems, as well as the building type (Reynders et al. 2017; Le Dréau and Heiselberg, 2016).

Unlike electric energy storage, the energy flexibility potential of the structural thermal mass is not constant but varies with the boundary conditions and use of the heating system. Specifically, the heat that can be stored or curtailed in the building fabric depends on various parameters such as the building thermal properties as well as occupant behaviour and climatic conditions. Consequently, energy flexibility is time-variant, and this attribute is also depicted in the definitions and the associated equations.

Background

The energy flexibility potential of the structural thermal mass of residential buildings has been thoroughly investigated in the literature. Specifically, Alibabaei et al. (2017) and Rodriguez et al. (2018) investigate the flexibility potential of the thermal mass by developing specific case studies of price-based control schemes. Foteinaki et al. (2018) and Le Dreau et al. (2016) assess the energy flexibility potential of residential buildings by using different energy flexibility indicators and by implementing DR actions with specific starting points and durations. A similar methodology is obtained by Reynders et al. (2016) but only for upward flexibility events. Finally, Reyders et al. (2013) couple the DR actions to investigate the energy flexibility potential of a residential building with the locally produced solar power.

Research Aim

The cited studies investigate the energy flexibility potential of the residential buildings thermal mass either by implementing DR actions at specific starting times or by developing control schemes for specific case studies. The main contribution of this paper is the evaluation of the energy flexibility potential through the daily energy flexibility profile of the structural thermal mass of a smart-grid ready residential building. The flexibility profiles are obtained for the available storage capacity as well as the associated storage efficiency for both upward and downward flexibility actions. This methodology is applied for various DR actions using suitable flexibility indicators. Special emphasis is put on the effect of rebound effects and boundary conditions. The obtained results indicate that the energy flexibility profile depends on thermostat setpoint modulation, demand response event duration, heating system rated power and the building heating demand during normal operation. Moreover, the daily profiles of storage capacity for various thermostat temperature setpoint modulations appear to exhibit a consistent trend, constrained by the heating system power limits.

Methodology

DR Events

In this section, the methodology followed to evaluate the energy flexibility potential associated with the building thermal mass is described. The reference case utilises a winter design day with a constant internal setpoint temperature of 20°C. The DR events are carried out as modulations of the living room thermostat temperature setpoint. These temperature changes can charge/discharge the thermal mass in case of a temperature setpoint increase/decrease. To evaluate these events, the difference $Q_{diff}$ between the modulated $Q_{mod}$ and the reference $Q_{ref}$ electrical demand is considered, as described in equation (1):

$$Q_{diff} = Q_{mod} - Q_{ref}$$

The temperature setpoint changes could be necessitated by different levels of RES production availability: e.g., a downward/upward flexibility strategy corresponds to a high/low-level availability of RES generation. To assess the performance of these modulations, various DR actions (indoor temperature setpoint changes) are implemented considering different starting times and durations ($L_{DR}$). Specifically, twelve independent two-hour and six four-hour DR events are considered for the heating design day. Thus, the starting times of the two-hour DR strategies are 0000 hr, 0200 hr, etc., while the four-hour DR strategies starting times are 0000 hr, 0400 hr, etc. These simulations will result in the formulation of the energy flexibility profiles. Two major modulations were tested as follows:

Downward flexibility: In this case, the living room thermostat setpoint is decreased by 1-3°C, which subsequently decreases the GSHP power consumption. In this case, heat is curtailed during the modulation period and it is restored later, in order for the building to return to the state before the DR action. As illustrated in Figure 1, the green area corresponds to the energy reduction during the DR event, while the red area corresponds to the rebound effect, i.e., the energy consumption required to restore the previous setpoint conditions.

![Figure 1: Energy reduction (DR action) / Energy Increase (Rebound).](image)

Upward flexibility: In this case, the thermostat setpoint is increased by 1-3°C, and heat is stored passively in the building fabric by the increase of thermostat setpoint. Examining Figure 2, the red area corresponds to the
energy used during the DR event, while the green area corresponds to the energy decrease (inverse rebound) related to this event.

Figure 2: Energy Increase (DR action) / Energy Decrease (Inverse Rebound).

Energy Flexibility Indicators

Flexibility indicators are useful to building owners and aggregators to exploit the available energy flexibility that the building can provide. In the literature, there is an abundance of methodologies to determine energy flexibility performance indicators (Finck et al., 2018). The flexibility indicators used in this study are the available structural storage capacity ($C_{ADR}$) and the storage efficiency ($\eta$). According to Reynders et al. (2017), “the available capacity for active demand response ($C_{ADR}$) is defined as the amount of energy that can be added to the storage system, without jeopardizing comfort, in the time-frame of an ADR-event and given the dynamic boundary conditions”. The $C_{ADR}$ is given by equation (2). To account for both upward and downward flexibility, the absolute value of the $Q_{diff}$ is considered.

$$C_{ADR} = \int_0^{t_{DR}} Q_{diff} dt \quad (2)$$

To account for the energy savings (Figure 4) and the rebound effect (Figure 5) in upward and downward flexibility, respectively, equation (3) is used. The infinity symbol in the integral is interpreted as the time when the $Q_{diff}$ term becomes insignificant.

$$C' = \int_{t_{ADR}}^{\infty} Q_{diff} dt \quad (3)$$

Regarding storage efficiency, it is defined as “the fraction of the heat that is stored during the ADR event that can be used subsequently to reduce the heating power needed to maintain thermal comfort”. In this study, the flexibility indicators as suggested by Kathirgamanathan et al. (2018) and Reynders et al. (2017) are used. Thus, the storage efficiency is given by different formulas for downward (equation (4)) and upward flexibility (equation (5)) as:

$$\eta_{DF} = 1 - \frac{\int_0^{t_{ADR}} Q_{diff} dt}{\int_0^{t_{ADR}} Q_{diff} dt} = 1 - \frac{Q'}{C_{ADR}} \quad (4)$$

$$\eta_{UF} = 1 - \frac{\int_0^{\infty} Q_{diff} dt}{\int_0^{t_{ADR}} Q_{diff} dt} = \frac{\eta_{DF}}{C_{ADR}} \quad (5)$$

In this study, consecutive and independent DR events are imposed to create a daily flexibility profile; the later can be used to select the most suitable DR strategy in terms of requested energy (to be curtailed or postponed) and energy cost associated with the DR action. The methodological steps of this study are summarised in Figure 3.

Building Model

The selected testbed is a single-storey detached house located in eastern Ireland. This dwelling represents 40% of the Irish building stock and is the most common single building category (Pallonetto et al., 2016). A picture of the building and the modelled geometry are shown in Figure 4. It was constructed in 1973 with increased thickness of insulation materials in its opaque elements compared to the contemporary standards.

As a result of its construction (two-leaf concrete wall with cavity insulation), it exhibits significant passive thermal energy storage capacity. The total surface area of the exterior walls is 187 m², excluding associated windows and doors. A slate roof has a surface area of 279 m². The roof does not have insulation, while the ceiling is covered with acoustic tiles to ensure both acoustic and thermal insulation. On top of the acoustic tiles, a 200 mm layer of fibreglass ensures high thermal resistance due to its low thermal conductivity (0.04 W/mK). The floor area is 208 m², and the overall window to wall ratio is 15%, with a 22% and 10% ratio on the south and north facades, respectively.

As illustrated in Figure 5, the house is comprised of twelve rooms and an unused attic space at roof level. Two temperature sensors were installed, one in the main living area and one in the corridor. The building walls, roof, windows, and floor have $U$-values of 0.21, 0.21, 1.7, and 0.21 W/m²K, respectively.
The space heating system is a 12 kW (thermal output) ground source heat pump (GSHP). For the provision of thermal energy storage, the heat pump was equipped with a hot water storage tank of 0.8 m$^3$. The system is illustrated in Figure 6.

The white-box model used to develop and analyse the DR control algorithms was created using EnergyPlus V. 8.9 and calibrated using monitored data from the building (Pallonetto et al., 2016).

**Boundary Conditions**

The energy flexibility analysis in the current study is focused on the living room of the residential building testbed, considering a constant thermostat setpoint of 20°C. According to ASHRAE 2004b Standard 55 (2004), there is a maximum change in operative temperature allowed during a period, in order that the thermostat setpoint changes remain within the acceptable limits. Table 1 summarises DR durations and temperature restrictions applied in this study. For each DR action, the resulting operative temperature change is also tested to ensure that the thermal comfort is maintained. The upper limit of the integral in equation (4) changes, depending on the difference between modulated $\dot{Q}$ and $\dot{Q}_\text{ref}$ (stable time).

**Results**

**Reference Case**

In this section, the weather profile (ambient temperature and global solar irradiance) of the simulation day and the day after (Figure 7a), the total internal gains (Figure 7b) and associated GSHP power consumption (Figure 7c) under normal operation are presented. As seen in Figure 6c, the GSHP power decreases between 1800 and 2200 hrs. During this period, the ambient temperature decreases by 0.5°C while the solar irradiance remains zero. This happens because during that period the indoor air temperature increases due to the internal heat gains which include heat emitted from lighting, equipment, and occupants. These internal gains depend on the occupancy schedules over the simulation period.

![Figure 6: Heat system design and sensor metering (Pallonetto et al. 2014).](image)

![Figure 7: (a) Ambient temperature and global solar irradiance; (b) total internal gains; (c) GSHP power in the reference case.](image)

**Downward Flexibility**

The GSHP electrical power deviation for a thermostat setpoint change of -1°C, -2°C, and -3°C between 0600 and 0800 hrs is presented in Figure 8a and the change in the room operative temperature is illustrated in Figure 8b. Similar figures can be obtained for all the twelve two-hour DR events. This scenario is indicative and is selected to assess the applied methodology and the impact of different thermostat setpoint reductions on occupant comfort. The area between the time axis and the negative part of each curve equals $C_{\text{ADR}}$ and the area between the time axis and the positive part of each curve equals $C'$. Furthermore, as shown in Figure 8b, the operative temperature change is within acceptable limits ($\Delta T < 2.8°C$) as summarised in Table 1.

<table>
<thead>
<tr>
<th>Time Period</th>
<th>2 h</th>
<th>4 h</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max. Operative Temperature Change Allowed</td>
<td>2.8°C</td>
<td>3.3°C</td>
</tr>
</tbody>
</table>

The GSHP power for thermostat setpoint decreases of 1°C, 2°C, and 3°C between 0800 and 1000 hrs as well as 2000 and 2200 hrs are presented in Figure 9a and the electrical power deviation is illustrated in Figure 9b. It can
be observed that the higher the heating demand the higher the energy curtailment potential.

Figure 8: 2-hour down-flex DR action for temperature setpoint reductions of 1, 2 and 3°C, 0600-0800 hr: (a) GSHP power deviation; (b) operative temperature.

Figure 9: (a) GSHP power and (b) GSHP power deviation in down-flex between 0800-1000 and 2000-2200 hrs.

The storage capacity and the storage efficiency for each of the twelve two-hour DR events are illustrated in Figures 10a and 10b, respectively. $C_{ADR}$ is observed to follow a specific trend. Specifically, the storage capacity for a -2°C setpoint change is on average 77% higher than the storage capacity for a -1°C setpoint change. Likewise, the storage capacity for a -3°C setpoint change is on average 152% higher than the storage capacity for a -1°C setpoint change. It can be also seen that the available storage capacity is decreased between 1800 and 2200 hrs; in fact, the higher the temperature setpoint change, the more the storage capacity decreases. This is due to the heating consumption decrease during that period, and the resulting flexibility margin reduction (Figure 7c). The storage efficiency for a thermostat setpoint change of -1°C is greater since the rebound effects resulting from thermostat setpoint changes of -2°C and -3°C are more significant. Because of the reduced GSHP power during 1800 and 2200 hrs, the associated DR actions result in less significant rebound effects; thus, the storage efficiency for the DR events between 1800 and 2000 hrs as well as 2000 and 2200 hrs is greater. In Figure 11, the maximum operative temperature changes during the pertinent DR events are illustrated. It is evident that maximum operative temperature changes are within acceptable limits for all temperature setpoint changes considered. This is due to the high thermal mass of the building envelope.

Figure 10: Down-flex DR action for temperature setpoint reductions of 1, 2 and 3°C, 2 hours DR actions: (a) storage capacity; (b) storage efficiency.

The electrical power deviation for a four-hour DR action between 0800 and 1200 hrs is presented in Figure 12a and the change in the room operative temperature is illustrated in Figure 12b. As with the two-hour DR actions, 1°C, 2°C, and 3°C setpoint changes are evaluated. Similar figures can be obtained for all the six four-hour DR events. As shown in Figure 12b, the operative temperature change lies in acceptable limits ($\Delta T<3.3\,^\circ C$) as per Table 1. The storage capacity and the storage efficiency for all six four-hour DR events are illustrated in Figures 13a and 13b, respectively. The storage capacity over all DR events for all thermostat setpoint modulations (-1°C, -2°C, -3°C) appears to exhibit a consistent trend. The storage capacity associated with the -2°C and -3°C setpoint changes are on average 83% and 163% higher than the storage capacity for the -1°C setpoint change, respectively. The storage efficiency for a thermostat setpoint decrease of -1°C is constantly greater than the rest of the cases (thermostat setpoint decreases of -2°C and -3°C). This is due to the
significant rebound effects which accompany the thermostat setpoint decreases of -2°C and -3°C.

![Electrical Power Deviation (a)](image1)

![Operative Temperature Change (b)](image2)

**Figure 12:** 4-hour down-flex DR action for temperature setpoint reductions of 1, 2 and 3°C, 0800-1200 hr: (a) GSHP power deviation; (b) operative temperature.

![Storage Capacity (kWh)](image3)

![Storage Efficiency (%)](image4)

**Figure 13:** Down-flex DR action for temperature setpoint reductions of 1, 2 and 3°C, 4 hours DR actions: (a) storage capacity; (b) storage efficiency.

By comparing the storage efficiencies of the Figures 10b and 13b, it is shown that the efficiencies of the four-hour DR events are significantly lower than those of the two-hour DR events. This is due to the significant rebound effects resulting in from longer DR modulations, as well as greater associated energy losses from the building envelope. In addition, the operative temperature for all temperature setpoint modulations lie in acceptable limits changing by 0.5°C to 1.9°C.

**Upward Flexibility**

The GSHP power consumption and electrical power baseline deviation are presented in Figures 14a and 14b, respectively. Both DR events are independent and are for thermostat setpoint increases of 1°C, 2°C, and 3°C between 0800 and 1000 hrs and 2000-2200 hrs. The area between the time axis and the positive y-axis equals $C'$. It can be observed that the GSHP power demand is 2.1 kW. Thus, the greater the heating power difference during the DR event with the maximum GSHP power level, the greater the energy flexibility potential. Regarding the 0800-1000 hr DR event, temperature setpoint increases of two or more degrees result in similar power deviations, because the maximum GSHP power has been reached. On the contrary, during the 2000-2200 hr DR event, the GSHP power does not reach its maximum value and the heating power can increase even with a thermostat setpoint increase of 3°C.

From the above analysis, it is evident that the energy flexibility potential strongly depends on the GSHP characteristics and the potential of reducing its peak power demand. This is because energy flexibility in each case depends on the allowable power deviation. The power deviation depends on the difference between the current power consumption and the maximum GSHP power. Therefore, if the current power is already close to the maximum, the margin of energy flexibility is reduced.

![GSHP Power (a)](image5)

![Electrical Power Deviation (b)](image6)

**Figure 14:** (a) GSHP power deviation and (b) GSHP power in up-flex between 0800-1000 and 0800-1000 hrs.

For the scenario in Figure 14, the room air temperature and operative temperature change are illustrated in Figures 15a and 15b, respectively. It is evident that in all cases, the room temperature does not reach the pertinent setpoint and the resulting operative temperature change lies in acceptable limits.

The storage capacity and the storage efficiency for all twelve two-hour DR events are illustrated in Figures 16a and 16b, respectively. Even though the storage capacity for DR events of 1°C and 2°C of temperature increase is the same before 1800 hr, a differentiation is noticed between 1800 and 2200 hrs. This is due to the GSHP decreased consumption during this four-hour period which allows for a further power increase. Finally, there is not any evident pattern between the storage capacity curves (as noticed in downward flexibility) due to the upper power limit of the GSHP.

Because of the different definition of storage efficiency in upward flexibility, the storage efficiency for a thermostat setpoint decrease of 1°C is constantly lower than the rest...
of the cases (thermostat setpoint decreases of 2°C and 3°C). The storage efficiency is proportional to the energy savings and the latter are greater during thermostat setpoint decreases of -2°C and -3°C (inverse rebound).

In this work, the energy flexibility potential of the structural thermal storage capacity of a dwelling has been investigated using various DR strategies. A methodology has been presented to quantify and characterise the energy flexibility provided by a residential building through suitable energy flexibility indicators and various DR modulations.

These indicators provide a quantification framework for assessing the flexibility potential of a dwelling over a 24h scenario. By using these indicators, stakeholders gain insight into not only the energy amount that can be shifted but also the energy cost (i.e. energy losses) associated with the activation of the structural thermal storage of the building. The aggregation of all the results associated with the considered case studies leads to the daily mapping of energy flexibility. This mapping can be of benefit to aggregators for optimising the portfolio of buildings with which to contract.

In downward flexibility, the storage capacity associated with the -2°C and -3°C setpoint changes is on average 77/83% and 152/163% higher than the storage capacity for the -1°C setpoint change, respectively for two-hour/four-hour DR actions. In addition, smaller temperature modulations and shorter DR events prove to be more efficient because of associated minor rebound effects. In contrast to this, in upward flexibility, greater changes in the room temperature setpoint and longer DR events are more efficient, as a result of the increased inverse rebounds. Finally, the energy flexibility margin is reduced when the current GSHP power is already close to the maximum. Thus, the available storage capacity of the building strongly depends on the difference between the heating system under normal operation and the GSHP power limitations. Specifically, the higher/lower the heating system power consumption, the greater the energy flexibility potential in downward/upward flexibility events. The quantification and characterisation of the energy flexibility provided by the dwelling thermal mass storage.

Conclusions and future work

The storage capacity and the storage efficiency for all six four-hour DR events are illustrated in Figures 17a and 17b, respectively. As is the case with two-hour DR events, storage capacity curves for temperature increases of 2°C and 3°C coincide before 1600 hr and differentiate afterwards due to the GSHP power decrease. The storage capacities of all four-hour DR events are approximately equal to the storage capacities of the corresponding two-hour events, as in downward flexibility. By comparing the storage efficiencies of the Figures 16b and 17b, the efficiencies of the four-hour DR events are significantly higher than those of the two-hour DR events. This is due to the significant energy savings resulting in from longer DR actions (rebound effect). From simulations, the maximum operative temperature change during the four-hour DR events is 1°C.
depend on the heating system. Due to the presence of an integrated thermal storage system within the GSHP, the energy flexibility potential of the building could be also assessed by modulating the water tank temperature. In addition, the usage of phase change materials for passive thermal storage as well as the reduction of the rebound effects could be investigated. This methodology can also be extended to include other energy components of the residential testbed building.

In the current work, the demand response characteristics of the structural thermal storage were investigated by using suitable flexibility indicators. To evaluate the suitability and performance of these indicators, the proposed methodology was applied to a white box model developed on EnergyPlus. Nevertheless, wide-scale flexibility assessment by using building simulation tools was found to be impractical due to occupant behaviour variability, the detailed and often inaccessible information about the building geometry and thermal parameters, etc. Considering the large number of sites involved, the practical evaluation of energy flexibility would require the extension of the considered case-specific approach to a generic methodology. This methodology will aim to characterise and quantify energy flexibility by using data-driven methods, as described thoroughly in (Bampoulas et al. 2019).

Acknowledgement

This publication has emanated from research supported (in part) by Science Foundation Ireland (SFI) under the SFI Strategic Partnership Programme Grant Number SFI/15/SPP/E3125. The opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the Science Foundation Ireland.

References


Smart Energy Demand Coalition (SEDC) (2016). Explicit and Implicit Demand-Side Flexibility, Brussels.


Assessing the Impact of Control Algorithms in Direct Evaporative Cooling Systems in Mixed-mode Buildings
Charalampos Angelopoulos1, Malcolm J Cook1, Shukla Yashkumar2, Eftychia Spentzou1, Rajan Rawal2, Luciano Caruggi-De-Faria1, Dennis Loveday1, Sanyogita Manu2, Deepta Mishra2, Jayamin Patel2
1School of Architecture, Building and Civil Engineering, Loughborough University, United Kingdom 2CEPT University, Ahmedabad, India
*c.c.angelopoulos@lboro.ac.uk

Abstract
Direct evaporative cooling (DEC) is one of the most commonly used cooling systems in many parts of the world with mainly hot and dry climatic conditions. Various simulation-based studies have been conducted to explore the potential of direct evaporative cooling in buildings. However, current dynamic thermal simulation tools use a simplified on/off control approach and do not allow modelling of situations where advanced algorithms are used in controlling DEC units. This paper couples EnergyPlus with Dymola® to simulate and assess the benefits of sophisticated control strategies for DEC units in mixed-mode buildings. This is a novel simulation approach for investigating control of DEC units in buildings that provides great flexibility for investigating future advanced control algorithms. The simulated results suggested that using the proposed sophisticated control algorithms for DEC units it is possible to achieve energy savings up to 35% compared to the base-case scenario and achieve up to 92% comfort hours for Ahmedabad, India. Similar results were predicted for Gatwick, UK.

Introduction
Evaporative cooling operation is based on the processes of heat and mass transfer (Camargo et al., 2005). The two fluids that are used are air and water: when the water evaporates it absorbs energy from the air resulting in a cooling effect (Jain & Hindoliya, 2014). Direct evaporative cooling (DEC) occurs when the water and the air come into direct contact, and the transfer of energy from the air to the water takes place when the air has relative humidity less the 100% (Jain & Hindoliya, 2014). In a DEC system a fan forces the air through a wet surface for evaporation. The heat and mass transfer between air and water results in a decrease of the air dry-bulb temperature and increase of its humidity levels, and in an ideal case, this process is adiabatic (Watt & Brown, 1997). The minimum temperature that can be reached is determined by thermodynamics and is the wet-bulb temperature of the incoming air. Consequently, this process is more efficient when the levels of the relative humidity of the incoming air to the evaporative cooler are low. The effectiveness of a DEC is defined as (Jain & Hindoliya, 2014): Based on its characteristics, DEC is most suited to regions with hot and dry climatic conditions but it can be used in other climatic conditions too (Camargo et al., 2005; Jain & Hindoliya, 2014).

\[
\varepsilon_{\text{saturation, eff}} = \frac{T_{\text{in}} - T_{\text{out}}}{T_{\text{db}} - T_{\text{wb}}} 
\]

In countries with high demand for cooling, such as India, alternative cooling systems can provide thermal comfort that consume less energy compared to vapour compression mechanical cooling systems, such as split air-conditioning units.

The design of a DEC will depend on the material of the cooling pad. Common materials that are used are grass, aspen and khus (Jain & Hindoliya, 2014). Previous studies have examined the performance of DEC systems based on different pad materials. Barzegar, et al., (2012) used pad materials made by kraft and nscc corrugated papers and evaluated their performance experimentally. They concluded that cooling/saturation efficiencies can be improved by decreasing air velocity at the inlet of the cooling pad. Similarly, Jain & Hindoliya, (2014) examined different cooling pad materials, typically used in the Indian context, and found the performance of the DEC is inversely proportional to the mass flow rate of the inlet air. Depending on the pad material, the increase of the flow rate can result in up to 15% reduction on the performance of the DEC. Al-Sulaiman, (2002) predicted maximum efficiency for air velocities of 2.4m/s, whilst for higher air velocities the drop in the efficiency was substantial. Similarly, Wu, Huang, & Zhang, (2009) using a theoretical model based on the frontal air velocity and the thickness of the cooling pad, concluded that the most important parameter to determine the efficiency is the air velocity with the optimum value 2.5m/s.

Although several studies have highlighted the importance of optimum air velocity, there are no studies, to the authors’ knowledge, assessing the impact of sophisticated control strategies for a DEC system for simulation purposes. The use of sophisticated control strategies is important for controlling the air velocity and hence improving the efficiency of the DEC unit. Dynamic thermal modelling (DTM) tools, such as EnergyPlus, use a simplified On/Off control approach and often assume constant saturation efficiency of direct evaporative coolers. However, since the saturation efficiency varies with the mass flow, it is not accurate to assume constant saturation efficiency in the simulations (Jain & Hindoliya, 2014). The innovation of this research presented here lies in the proposed control strategies that utilise a variety of control algorithms that
control the fan speed and hence control the air velocity at the inlet of the cooling pad. The variation of the saturation efficiency also improves on the control approach currently being used by a wide range of DTM tools.

Using a co-simulation approach, this paper evaluates the benefits of using advanced control algorithms for DEC units in mixed-mode buildings, which are buildings operating in both mechanical and passive modes. To address this task, the following objective was followed: use of constant and variable fan flow to examine the impact of the variation of mass flow on the saturation efficiency and hence on the performance of the DEC unit. The benefits of advanced control algorithms are also assessed for two geographic location and climate zones.

**Methods**

Computer simulations were carried out to evaluate the performance of the different control strategies. EnergyPlus with Dymola® were used for the co-simulations and to assess the benefits of advanced control strategies for DEC systems in mixed-mode buildings. These were considered to be located in both Ahmedabad, India and London Gatwick, UK to represent different climates. EnergyPlus is used to design the building envelope, while Dymola is used to develop the control strategies. The focus of this paper is to evaluate and quantify the benefits of using more advanced control strategies for DEC systems compared to those that can be found in the majority of DTM tools. To eliminate the uncertainties associated with the building envelope, the BESTEST Case 600 (Henninger & Witte, 2011) was used to represent a single thermal zone building.

![Figure 1: Layout of the single thermal zone building](image)

### Table 1: Envelope characteristics and DEC input parameters

<table>
<thead>
<tr>
<th>Element</th>
<th>U-value</th>
<th>W/m²K</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wall</td>
<td>0.514</td>
<td></td>
</tr>
<tr>
<td>Roof</td>
<td>0.318</td>
<td></td>
</tr>
<tr>
<td>Floor</td>
<td>0.039</td>
<td></td>
</tr>
<tr>
<td>Window</td>
<td>2.721</td>
<td></td>
</tr>
<tr>
<td><strong>DEC Unit</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cooling pad area [m²]</td>
<td>0.18</td>
<td></td>
</tr>
<tr>
<td>Cooling pad depth [m]</td>
<td>0.1</td>
<td></td>
</tr>
<tr>
<td>Maximum air flow [m³/s]</td>
<td>0.25</td>
<td></td>
</tr>
</tbody>
</table>

The floor area of the building is 48 m² and has two south facing windows 3m² each (see Figure 1). The occupancy density was assumed to be 16 m²/occupant and the total internal electrical gains were 19.3W/m² as used in previous work investigating the performance of dynamic cooling setpoints for mixed-mode buildings (Angelopoulos et al., 2018). Table 1 summarizes the envelope characteristics employed and the input parameters for the DEC unit. Default weather files provided by EnergyPlus were used for this study (EnergyPlus WeatherData, 2018).

### Co-simulations

As mentioned in the Introduction, the majority of DTM tools use a simplistic On/Off approach to control a DEC. The reason for this is that the main focus of DTM tools is to perform annual energy performance simulations and not to design advanced control strategies for mechanical or passive systems (Nouidui, Wetter, & Zuo, 2014). Therefore, to improve the performance of the DTM tools, co-simulations have recently attracted great attention. The coupling of two or more simulation tools can be achieved using the Functional Mock-up Interface (FMI), which is a standardised method to couple different simulation tools (MODELISAR, 2017). The use of the co-simulations has the advantage of combining the strengths of each simulation tool.

![Figure 2: Variable exchange between the two simulation tools](image)

For this reason, the building envelope, the evaporative cooler (AIRLOOPHVAC object) and the cooling pad, as well as the schedules for the occupants and the electrical equipment usage, were developed in EnergyPlus (DOE, 2018), see figure 2. The control algorithms for the DEC system were developed in Dymola which is a commercial tool based on the Modelica language (DYMOLA, 2018). The EnergyPlus model was then exported in a Functional Mock-up Unit (FMU) and imported into Dymola. The exchange of variables occurred between the two simulation tools at each timestep (300 sec). Dymola handled the co-simulations and it was responsible for “calling” EnergyPlus at each timestep and to exchange the required information. This process is completely automated and occurred at each timestep throughout the simulation period. This simulation technique provides great flexibility since the same control algorithms can be used in different cases, if the case is imported to Dymola via the FMU.

### Control algorithms

To fully examine the effect of the variation of the fan speed, as well as the variation of the saturation efficiency based on the airflow rate, different control
algorithms were developed and simulated. Since the focus of this paper is to examine the benefits of using advanced control algorithms for DEC systems and not to investigate the actual performance of mixed-mode buildings, it is assumed that the windows will remain closed throughout the simulation period, which is from January to December (inclusive). The design of the control algorithms has focused solely on the control of the evaporative cooler and its components.

In the literature, there is not a common approach on how to operate or control a DEC unit. In EnergyPlus, you cannot assign directly a cooling setpoint temperature to the AIRLOOPHVAC system. For this reason, the cases that were simulated on EnergyPlus did not have a direct control of the temperature and the control of the DEC unit was based on the occupancy schedule. For the co-simulations, the adaptive comfort model from ASHRAE Adaptive Standard 55 (ASHRAE-Standard-55, 2013) was used to determine the heating and cooling setpoint. A 30-day running mean for the outdoor temperature \( T_{\text{out}} \) was used to calculate the heating and cooling setpoint temperatures for the 90% acceptability limits:

\[
T_{\text{HSP}} = 0.31 \ast T_{\text{out}} + 15.3
\]

\[
T_{\text{CSP}} = 0.31 \ast T_{\text{out}} + 20.3
\]

**Variation of control algorithms for co-simulations**

The design of the control algorithms has a gradually increasing complexity. The “basic” control algorithms use a similar methodology to the majority of the DTM tools. The control of the DEC systems is based on the On/Off approach of the evaporative cooler and the fan. When there is a need for cooling, the control algorithms turn on the evaporative cooler without any extra control over the fan speed. The fan operates at its maximum airflow, see table 1. The decision to operate or not the DEC takes place at the beginning of each timestep. When the unit operates, it runs at the full design air flow rate regardless of the required amount for cooling. This control method might not be optimal but it is similar to how most thermostats operate in real applications. To eliminate the short cycling of the DEC unit, a deadband of 0.5°C is used. The value of the deadband was selected by carefully adjusting it in trial simulations to ensure the maximum comfort conditions. The control algorithm, see figure 3A, uses as inputs the most recent value of the zone air temperature \( T_{\text{int,aver}} \) and the current cooling setpoint \( T_{\text{CSP}} \). This approach has a disadvantage of operating the DEC unit at full load at periods when there is no need for this amount of cooling. However, this is the most common control approach found in DTM tools.

The “advanced” control algorithms used a more detailed approach to control the DEC unit and the fan. For the “advanced” control algorithms a variable speed fan, with 3 fan speed levels (33%, 66% and 100% of its maximum air flow), was used instead of a constant volume fan that was used in the previous cases. This control method uses a more sophisticated approach to modulate the fan speed based on the required cooling load at each timestep. At each timestep, part load fraction (PLF) is calculated. PLF is the cooling load that is required for the zone is calculated in Dymola, divided by the maximum value of the cooling load that the DEC unit is capable of providing. To avoid running the DEC unit at periods when there is no need for cooling, a deadband 0.5°C value for the temperature is used. This control approach eliminates the cases where the unit is turned on and off constantly. Then the sensible cooling provided by the unit \( Q_{\text{Fulloput}} \) is calculated and compared against the cooling load of the zone \( Q_{\text{C OOLING LOAD}} \) as presented in figure 3B.

The power consumption of the variable speed fan was calculated by calculating the required mass flow for each timestep \( \dot{m}_{\text{timestep}} \) and then calculating the flow fraction\( f_{\text{flow}} = \frac{\dot{m}_{\text{timestep}}}{\dot{m}_{\text{design}}} \), where \( \dot{m}_{\text{design}} \) is the maximum flow. Then the total power consumption was calculated by using the formula:

\[
P_{\text{total}} = RT F \left[ \frac{\dot{m}_{\text{timestep}} \Delta P}{\dot{P}_{\text{F L}}} \right]
\]

where \( RT F = \frac{f_{\text{flow}}}{\dot{P}_{\text{F L}}} \) and \( \Delta P \) is the fan design pressure increase in Pascals.

**Detailed modelling of saturation efficiency**

The default selection for most DTM tools is to use a cooling pad with a constant saturation efficiency. The efficiency is determined by manufacturers’ data and the modeller can only decide what would be the area and the thickness of the pad.

Then by using equation (1) the dry-bulb temperature of the outlet air can be calculated. As equation (1) shows, the calculation of the outlet temperature is not related to the mass flow of the inlet air which contradicts findings from the literature suggesting, that the saturation efficiency is highly affected by the air frontal velocity (Jain & Hindoliya, 2014; Sheng & Nnanna, 2011). EnergyPlus has also an object that provides the flexibility to the user to include an equation to vary the saturation efficiency based on the frontal air velocity. Jain & Hindoliya, (2014) examined a variety of pad materials that are typically used in the Indian context. For the purpose of this research it was assumed that palash fibers were used as the cooling pad material and based on experimental observations by Jain & Hindoliya, (2014) the correlation between the saturation efficiency and the frontal air velocity for this material is given by equation (4):

\[
\varepsilon_{\text{satur,effic}} = 1 - e^{-\frac{606}{m_{\text{out}}}}
\]

where \( m_{\text{out}} \) [kg/h] is the mass flow of the air entering the cooling pad. For this paper, both cases, with constant and variable saturation efficiency, were used to compare whether this influences the total thermal performance of the DEC unit.
Control Strategies
The simulations are divided into the base case scenarios, where only EnergyPlus was used (scenario 1 & 2) and to the cases where co-simulations were performed to incorporate the advanced control strategies proposed in this paper, see table 2. For all the simulation scenarios (1-10) it was assumed the DEC unit is available between March-October (inclusive) and only when the house was occupied. For the base case scenarios (scenario 1 & 2), the operation of the DEC unit was based on the occupancy schedule. When occupants were present between March-October, DEC was modelled to turn on without any extra control algorithm whilst for the rest of the scenarios the advanced control algorithms were used, see table 2.

Results analysis and Discussion
This section presents whether there is any impact as a result of i) different control strategies and ii) different methods to model the evaporative cooler, constant or variable saturation efficiency, on the thermal performance of the DEC unit and hence on the overall energy consumption. Additionally, it analyses the comfort hours that could be achieved under the different simulation scenarios.

As expected, the absence of sophisticated control algorithms, figure 4B, resulted in internal temperature outside the comfort limits. Specifically, on average the internal air temperature was 2~4°C higher than that recommended by the thermal comfort models. The lack of a control algorithm to maintain the air temperature within the comfort limits affected the performance of the DEC unit even during periods when the external temperature was low. As figure 4B shows, during February and September, the internal air temperature was lower than the lowest acceptable comfort limit. The reason for this is that the external temperature (figure 4C) was low at these periods and the control logic did not include temperature control hence the heating system was not able to meet the heating demand. As these results suggested, the use of very simplistic control algorithms, base case, results in uncomfortable internal conditions. It is essential therefore to include more advanced control algorithms that incorporate temperature control in their logic (co-simulation scenarios 3-10). By incorporating the temperature control logic, the thermal performance of the DEC unit was improved significantly compared to the base case scenarios, figure 4A. The use of a deadband temperature was deemed important to improve the performance of the DEC unit. The periods of the year that the DEC unit is available can be seen, as indicated in figure 4D. The inclusion of temperature control logic into the control algorithms had a positive impact on both cooling and
heating energy consumption. As it can be observed, the predicted air temperature is always equal to or higher than the lower band for thermal comfort in contrast with the base case where the uncontrolled operation of the fan resulted in internal air temperatures lower than that suggested by the thermal comfort model.

The use of a variable fan speed improved the thermal performance of the DEC unit over the use of a constant volume fan (figure 5B and figure 5A respectively). By calculating the required cooling load and modulating the fan speed based on this, it was possible to improve further upon the overall improved thermal performance. The fluctuations of the predicted temperature were smaller compared to the case of the constant volume fan due to the operation of the fan at different speeds. As figure 5 suggests, the control of the variable fan speed based on the sophisticated control algorithms suggested in this research (figure 5B) could ensure that the internal air temperature will be maintained within the comfort limits for most of the period.

The variation of the saturation efficiency based on the mass flow of the air had a higher positive impact on the On/Off fan, see figure 6B. As suggested in figure 6B, the thermal performance of the DEC unit improved substantially between April to September compared to the constant saturation efficiency scenario (figure 6A). For the variable speed fan, the improvement of the thermal performance based on the temperature predictions is less because, even with the constant saturation efficiency, the DEC unit was still very effective.

DEC units can increase the levels of relative humidity (RH). Hence, it was important to examine how each scenario impacts the levels of RH in the zone. The levels of RH inside the zone are high, especially during the months of the year that the DEC unit operates. An additional check was made in the control algorithm regarding the level of the internal RH. When RH was equal to or less than 70%, the DEC unit was available, otherwise it remained off. Figure 7 shows the variation of the internal air temperature when the RH was used as a control parameter (figure 7B). The inclusion of the RH as the control parameter slightly improved the levels of the internal RH but it resulted in less hours of operation of the DEC unit and, as a result, the internal air temperature was higher. Furthermore, due to high internal air temperature when the DEC unit was turned off, the system could not reach the setpoint temperature when it was in operation. Due to the high levels of external RH in addition to the internal RH, it is not feasible to maintain the internal RH or the internal air temperature within the limits without the use of mechanical systems. The inclusion of the RH as part of the control logic is important for all the cases when DEC units are used. As the analysis showed however, during the periods of the year that the levels of outside RH were high, the internal RH was found to be high as well. Hence, from a practical point of view, mechanical systems to maintain the RH within the desirable limits

Figure 4: Predicted internal air temperature for Ahmedabad for scenario 3 (fig 4A), and scenario 1 (fig 4B); outdoor air temperature (fig 4C) and DEC availability (fig 4D).

Figure 5: Predicted internal air temperature for Ahmedabad for scenario 3 (fig 5A), and scenario 7 (fig 5B); and DEC availability (fig 5C).

Proceedings of the 16th IBPSA Conference
Rome, Italy, Sept. 2-4, 2019
throughout the year deem essential. However, the purpose of this paper is not to include any additional mechanical systems, but to investigate how intelligent control algorithms can improve the thermal performance of the DEC unit.

Figure 6: Predicted internal air temperature for Ahmedabad for scenario 3 (fig 6A), and scenario 5 (fig 6B); and DEC availability (fig 6C).

It is very important to present the hours of the year that the proposed control algorithms could maintain a thermally comfortable internal environment. To calculate the comfortable hours, two different approaches were used. In this research the comfortable hours were measured i) firstly using the operative temperature (ASHRAE-Standard-55, 2013), and ii) secondly using the operative temperature and the levels of RH. For RH values above 70%, irrespective of the internal operative temperatures, these periods did not count as comfortable hour. Table 3 summarizes the results for the comfortable hours for each scenario. It should be mentioned that the percentages are referring to the periods when the space was occupied between March-October (both months included) and not to the whole year. The inclusion of the RH as a parameter resulted in less comfortable hours which is expected as the levels of RH were very high, but it does not overestimate the comfortable hours as in the case where only the operative temperature is used. In Gatwick, the simulations predicted overall higher hours of comfortable internal conditions compared to Ahmedabad. This is due to the lower levels of RH in Gatwick in addition to the relatively smaller demand for cooling. Hence the DEC unit was able to meet the demand for cooling for longer periods compared to Ahmedabad. Significant differences were predicted in

To calculate the energy consumption, the consumption of the fan and the evaporative cooler (AIRLOOPHVAC object). As expected, the base case scenarios resulted in the higher energy demand predictions among the rest of the scenarios. The use of the very simplistic control algorithms for the DEC unit, based on the occupancy schedule (scenario 1-2), resulted not only in very high internal air temperatures and hence in thermally uncomfortable internal environments, but also in very high energy consumption. The control of the fan based on the On/Off approach (scenario 3-6) resulted in higher energy saving potentials for both Ahmedabad and Gatwick compared to the variable fan speed (scenario 7-10). This can be explained because the On/Off fan operated for fewer hours compared to the variable fan speed. In instances where the On/Off fan was off, the variable fan speed operated at lower speed to meet the setpoint temperature. This resulted in slightly higher energy consumption, but also a higher percentage of thermally comfortable hours. When using both the air temperature and RH as a control parameter in the control algorithms, the co-simulations predicted higher energy saving potential compared to the rest of the scenarios. This can be explained because the DEC was turned off when the internal RH was above the limit. However, in those scenarios the analysis showed that the percentages of the comfortable hours were significantly smaller. Table 4 summarizes the energy savings and comfort hours for the different scenarios.
Table 3: Summary table for percentage of comfortable hours. In the brackets are the numbers of comfortable hours.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Saturation efficiency</th>
<th>Volume fan</th>
<th>Control parameters</th>
<th>Operative temperature as parameter</th>
<th>Operative temperature and RH as parameter</th>
<th>Operative temperature and RH as parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Constant</td>
<td>Constant</td>
<td>--</td>
<td>50.2% [2161]</td>
<td>47.6% [2049]</td>
<td>89.4% [3848]</td>
</tr>
<tr>
<td>2.</td>
<td>Variable</td>
<td>Constant</td>
<td>T_zone,_air</td>
<td>48.1% [2070]</td>
<td>45.3% [1950]</td>
<td>77.3% [3327]</td>
</tr>
<tr>
<td>3.</td>
<td>Variable</td>
<td>Constant</td>
<td>T_zone,_air &amp; RH</td>
<td>82.6% [3555]</td>
<td>61.5% [2647]</td>
<td>85.7% [3689]</td>
</tr>
<tr>
<td>4.</td>
<td>Constant</td>
<td>Constant</td>
<td>T_zone,_air &amp; RH</td>
<td>77.1% [3318]</td>
<td>57.2% [2462]</td>
<td>79.6% [3426]</td>
</tr>
<tr>
<td>5.</td>
<td>Variable</td>
<td>Constant</td>
<td>T_zone,_air &amp; RH</td>
<td>87.6% [3770]</td>
<td>66.2% [2849]</td>
<td>89.7% [3861]</td>
</tr>
<tr>
<td>6.</td>
<td>Variable</td>
<td>Constant</td>
<td>T_zone,_air</td>
<td>80.2% [3452]</td>
<td>62.4% [2686]</td>
<td>83.5% [3594]</td>
</tr>
<tr>
<td>7.</td>
<td>Constant</td>
<td>Variable</td>
<td>T_zone,_air &amp; RH</td>
<td>85.2% [3667]</td>
<td>65.2% [2806]</td>
<td>87.6% [3770]</td>
</tr>
<tr>
<td>8.</td>
<td>Variable</td>
<td>Variable</td>
<td>T_zone,_air &amp; RH</td>
<td>82.1% [3534]</td>
<td>61.2% [2634]</td>
<td>85.2% [3667]</td>
</tr>
<tr>
<td>9.</td>
<td>Variable</td>
<td>Variable</td>
<td>T_zone,_air</td>
<td>92.3% [3973]</td>
<td>72.1% [3103]</td>
<td>95.4% [4106]</td>
</tr>
<tr>
<td>10.</td>
<td>Variable</td>
<td>Variable</td>
<td>T_zone,_air &amp; RH</td>
<td>85.6% [3684]</td>
<td>67.8% [2918]</td>
<td>90.2% [3882]</td>
</tr>
</tbody>
</table>

Figure 8: Predictions of the cooling and heating consumption for the different scenarios

Table 4: Summary table of energy savings and comfort hours

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Ahmedabad</th>
<th>Gatwick</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fan speed control</td>
<td>61.2-92.3%</td>
<td>25.0-30.9%</td>
</tr>
<tr>
<td>Temp control</td>
<td>57.2-82.6%</td>
<td>30.5-35.2%</td>
</tr>
</tbody>
</table>

Conclusions
The research presented in this paper aims to develop and test control algorithms for DEC units for mixed-mode buildings in different climatic conditions and to quantify their energy saving potential using co-simulations. The development of improved simulation tools to achieve this is also described and presented. The most important findings are:

- The use of co-simulations can improve the thermal performance of DEC systems over the
- use of DTM tools and the proposed control algorithms can be used for co-simulations with any software that has the FMU import function;
- The use of advanced control algorithms in conjunction with constant fan speed and constant saturation efficiency cooling pad
increased the number of comfortable hours by approximately

- 1000h in Ahmedabad compared to the basic control algorithms used by the DTM tools;
- The use of variable saturation efficiency cooling pads improved the thermal performance for energy consumption of the DEC unit between 2-8% for all the scenarios.
- The use of RH in the control logic of the control algorithms resulted in 2-5% lower internal RH compared to the scenarios without RH control.
- The DEC unit in combination with the proposed control algorithms can be used as the sole cooling system to maintain comfortable internal conditions for almost 95% of the time that was available in moderate climates such as Gatwick.
- The use of the internal RH to assess the comfortable hours is essential to enable more accurate predictions of the comfortable hours when a DEC unit is used.

Current DEC units, in the residential market primarily, rely on the users to adjust fan speed as well as water pump operations. Further, these DEC units do not modify their operations automatically, based on the prevalent temperature or relative humidity in the space. As this research highlighted, the proposed control strategies have the potential to reduce the energy consumption of DECs while achieving better comfort in the space.

**Future work**

The following work is proposed to improve even further the current study:

- Expand the control algorithm to include the control of the windows/dampers and ceiling fan.
- Include a dehumidifier as part of the control algorithm to mitigate the risk of uncomfortable internal conditions due to high levels of RH;
- Validate the thermal performance of the proposed control algorithms using a full-scale environmental chamber; and
- The cost implications of incorporating sophisticated controls and variable speed fan may also need to be studied further for real implementation.

**Acknowledgement**

This research was financially supported by the Engineering and Physical Sciences Research Council (EPSRC) via the London-Loughborough Centre for Doctoral Training in Energy Demand (LoLo) (grant EP/L01517X/1) and via the research project Low Energy Cooling and Ventilation for Indian Residences (LECaVIR) (grant EP/P029450/1).

**References**


Coupling of Modelica Domestic Hot Water Simulation Model with Controller

Elisa Van Kenhove1,*, Lien De Backer2, Marc Delghust3, Jelle Laverge4
1,2,3,4 Ghent University, Faculty of Engineering and Architecture, Department of Architecture and Urban Planning, Research Group of Building Physics
*Elisa.VanKenhove@UGent.be

Abstract
The energy needed for Domestic Hot Water (DHW) represents an important share in the total energy use of well-insulated and airtight buildings. One of the main reasons for this high energy demand is that DHW is produced at temperatures above 60°C to mitigate the risk of contaminating the hot water system with Legionella pneumophila. However, this elevated temperature is not necessary for most DHW applications, and has a negative effect on the efficiency of hot water production units. A Modelica simulation model has been developed that proposes an alternative to this constant 60°C by predicting the L. pneumophila concentration dynamically throughout the DHW system. Based on this knowledge, the topic of this paper is coupling the simulation model with a virtual DHW controller prototype. The DHW controller sets a comfortable DHW set point temperature in combination with heat shocks. The simulation model algorithm predicts the concentration of L. pneumophila present in the system, as this concentration cannot be measured in real time. When this predicted concentration passes a predefined threshold level, the controller will increase the set point temperature of the boiler (heat shock) in order to lower the concentration of L. pneumophila present until the predicted concentration is below a predefined boundary level. The energy savings by implementing the heat shock regime instead of the constant 60°C regime can be predicted with the simulation model. This new DHW controller is expected to become an important alternative for the current, energy intensive, constant high temperature tap water heating systems.

Introduction
Motivation
The energy needed for production, storage and distribution of Domestic Hot Water (DHW) represents an important share in the total energy use of well-insulated and airtight buildings. One of the main reasons for this high energy demand is that hot water is produced, stored and distributed at temperatures above 60°C to mitigate the risk of contaminating the hot water system with Legionella pneumophila, a bacteria that can cause an acute respiratory disease or severe pneumonia which can be fatal. At 60°C, L. pneumophila growth is stopped and the remaining bacteria are killed. However, this elevated temperature is not necessary for most DHW applications, taking a shower and washing our hands requires a temperature of only 30-40°C. The disparity between 60°C and 40°C doubles the temperature difference between hot water system and environment (around 20°C) which has a negative effect on the storage and distribution losses and on the efficiency of hot water production units (such as heat pumps).

Research question
A simulation model has been developed that proposes an alternative to this constant 60°C by predicting the L. pneumophila concentration dynamically throughout the hot water system [1]. Based on this knowledge, a hot water controller is coupled to the simulation model that sets a lower hot water comfort temperature in combination with heat shocks when a predefined concentration limit has been reached. Simulation results of such a controller show savings of more than 35% on the hot water distribution energy use in an apartment building, without increasing contamination risk [2]. Additional production energy use savings, by implementing the controller in three different production units, namely an electric boiler, a heat pump boiler and a heat pump boiler with solar collectors, are going from respectively 14% to 64%.

A theoretical proof of concept has been reached based on these simulation results. However, it is not sure whether the simulation model algorithms can run on a real controller (e.g. Arduino). The first steps in achieving this ultimate goal are investigated in this paper. An elaboration on the future steps will also be given.

Background L. pneumophila
The 60°C temperature limit has been established by investigating the growth dynamics of L. pneumophila bacteria in laboratory conditions and studying infection cases [3], [4], [5]. At these temperatures the DHW system is considered to be safe. Similarly, the Domestic Cold Water (DCW) temperature should be kept below 20°C to be considered L. pneumophila safe.

At temperatures below 20°C, the bacteria become dormant but remain viable for months. The bacteria grow best at temperatures between 20°C and 45°C with an optimum around 35°C-41°C. Beyond 45°C, pasteurization starts and higher temperatures will
eventually kill the organisms [6]. This can be seen on Figure 1A. On the x-axes, the water temperature in degrees Celsius can be seen and on the y-axes, in Figure 1B, the time to double the number of L. pneumophila (mean generation time) and, in Figure 1C, the time to reach 90% reduction in cells (decimal reduction time). Figure 1B is based on data from Yee and Wadowsky [7] from experiments on unsterilized tap water and Figure 1C is based on data from laboratory experiments [3], [4], [5], [8], and is consistent with field data [9]. Figure 1B shows that the time to double the number of L. pneumophila cells in water is less than half a day at 41°C and in Figure 1C it can be noted that at 70°C, 90% of L. pneumophila in water gets killed in less than a minute.

The hardware of the controller will set the prototype of the controller will be compared with a heating thermostat, but instead it is a communicating thermostat (switch) and it can consequently only be adjusted manually on the heating element itself, the own developed controller will replace the existing control. In the other case, the boiler has the possibility to communicate with the own developed controller. In that case, the developed controller will set the water temperature using the communicating protocol. The communication protocol can be OpenTherm in certain cases or an alternative. OpenTherm is a standard which is not manufacturer-specific, enabling the straightforward coupling of the controlling device to different heat production appliances (e.g. boiler of type X, heat pump of type Y, solar boiler of type Z).

Algorithm predicts the concentration of L. pneumophila present at the taps (e.g. shower, kitchen sink), as this concentration cannot be measured real time. When this predicted concentration passes a predefined threshold level, the controller will increase the set point temperature of the boiler in order to lower the concentration of L. pneumophila present until the predicted concentration is below a predefined boundary level. An energy use optimisation process is part of the simulation model.

The focus of this paper is preparing for building the prototype of the controller. The hardware of this controller prototype will consist of a microprocessor unit (e.g. Arduino) running the algorithms on site, with potentially some additional peripherals (e.g. storage and communication modules for data collection during the testing phase or online updates).

In case the DHW set point temperature is controlled by a non-communicating thermostat (switch) and it can consequently only be adjusted manually on the heating element itself, the own developed controller will replace the existing control. In the other case, the boiler has the possibility to communicate with the own developed controller. In that case, the developed controller will set the water temperature using the communicating protocol. The communication protocol can be OpenTherm in certain cases or an alternative. OpenTherm is a standard which is not manufacturer-specific, enabling the straightforward coupling of the controlling device to different heat production appliances (e.g. boiler of type X, heat pump of type Y, solar boiler of type Z).


**Methodology**

The aim of this paper is coupling a Modelica system simulation model with a virtual DHW controller prototype (Figure 2A). The operation of the controller can be compared with a heating thermostat, but instead it is controlling the set point temperature of the DHW boiler and in some cases the flow rate of the circulation pump of the DHW recirculation circuit. The simulation model is straightforward to couple the controlling device to different heat production appliances (e.g. boiler of type X, heat pump of type Y, solar boiler of type Z).

In this paper, the controller is still driven from a computer. In future research, the algorithms of the simulation model will be simplified in order to be implemented in a real Arduino to test the operation of the controller. Subsequently, the prototype of the controller will be
implemented in a basic setup of a DHW system, that will be built in laboratory conditions, to test the performance of the controller to achieve a technological proof of concept (Figure 2B).

Before performing the study in real conditions, a simulation study has been performed, that is part of this paper. Three simulation models of the test rig DHW systems have been developed. The difference between the three models is the DHW heat production unit. With these models a dynamic calculation has been performed, in order to test the algorithms on the microprocessor unit before building the hardware of the controller prototype. The controller should be able to control the temperature in the systems with a time based heat shock regime.

The development of the controller consists of different steps (Figure 3). In the first step, the hydraulic system is built in Modelica with the biological library. All the technical characteristics of the real boiler were used as input for the Modelica boiler component. This step is described in [10].

In the second step (Figure 4), the virtual Arduino component from the Arduino library is used. This allows to implement the temperature control algorithms in a sketch file, which will be used later in the real controller. The virtual controller receives the temperature from a temperature sensor. For this, a Modelica component is developed that converts the temperature to an electrical signal. The L. pneumophila concentration calculation still happens in Modelica. In case the L. pneumophila concentration increases above the threshold value of 100CFU/L, a signal is sent to the virtual controller (pin D4) raising the set point temperature of the boiler to 65°C. The output signal of the virtual Arduino is a 5V signal. Since the Arduino operates at 5V, it cannot control the higher voltage immersion heater directly. Therefore, a 5V relay is used to switch to 230 volt.

In the third step, the L. pneumophila concentration is no longer calculated in Modelica, but it is calculated in the sketch file of the virtual Arduino component. Meaning that the virtual controller has only one input, the water temperature in the bottom layer of the tank predicted by the temperature sensor component. A simplified function is used to predict the L. pneumophila concentration. This function is derived from the growth and starvation equation for L. pneumophila in water, as described in [1], in which a third degree piece-wise polynomial fitting technique (cubic hermite spline) is chosen to calculate the growth and death rate as is shown Figure 1. A separate spline function for L. pneumophila growth and starvation is developed. The predicted temperature in the bottom layer of the storage tank is used as input for this function. In future research, this function will be further optimised by finding a balance between the accuracy of the L. pneumophila concentration prediction, the calculation time and the limitations of the controller (RAM).

In step 4, that is part of future research, the real controller will be used. In a first step, it will also have only one input,
i.e. the measured water temperature in the bottom layer of the tank.

Modelling environment
The Modelica language and Dymola (Dynamic Modelling Laboratory) environment is used to develop the models. The Modelica language is suitable for modelling various kinds of physical systems. It can handle large, complex multi-engineering models and is open to add user defined model components, such as the biological components that are required here. To model the hydraulic system, the Modelica 3.2.2 library, the Buildings 5.0.1 library [11] and IDEAS 2.0.0 library [12] has been used. To calculate the *L. pneumophila* concentration, a custom developed, by the authors, biologic library [2] has been used that makes it possible to predict the *L. pneumophila* growth. The virtual Arduino library [13] has been applied to build the virtual controller.

Simulation model of three test rig DHW systems
First of all, a Modelica model has been made of the complete laboratory system (Figure 5).

![Figure 5: Test rig DHW system with heat pump boiler with solar collectors as production unit.](image)

For all three production units, a different simulation model is made, including the distribution circuit and two distal pipes connected to two tap profiles corresponding with typical DHW kitchen and shower profiles of a single family household. In the next paragraphs, the different test rig DHW system components are being discussed.

Production units
Each production unit consists of a storage tank with a volume of 200L. The internal height of the tank is 1.5m and the internal width is 0.4m. The tank is insulated with 10cm of mineral wool with a thermal conductivity value of 0.04W/(m·K). The water outlet is situated at the top. The water inlet (of return and cold water) is situated at the bottom of the tank. The thermostat to control the water temperature is located at the bottom layer of the storage tank. To model the temperature in the storage tank, a one dimensional model is used that divides the height of the tank into several volumes (multi node approach), allowing to calculate the occurring temperature stratification. This is necessary because the growth of *L. pneumophila* is temperature dependent. By neglecting the stratification in the boiler, the death rate of the bacteria would be too high, leading to an underestimation of the corresponding health risks. The storage tank component used in the case study DHW system simulation model consists of eight layers. The six middle layers have a height of 0.1725m. The top (layer 1) and bottom layer (layer 8) have a height of 0.086m.

As mentioned before, three different DHW production units are compared. The base component used to model the storage tank will be the same. However, depending on the type of production unit, an additional heat exchanger and/or resistor has been added to the storage tank model. The power of the boiler is 3000W, in the first case this is provided by an electric immersion heater.

The component model used to simulate the storage tank is extended from the StratifiedEnhanced tank model, available in the Buildings 5.0.1 library. This component, as it is used in this paper, is updated by the authors in three ways [1].

- Addition of the possibility to vary the height of each volume segment.
- Addition of the possibility to choose different insulation thicknesses for the top, side and bottom of the tank.
- Addition of *L. pneumophila* growth equations to the thermohydraulic model.

Distribution pipes
The recirculation loop, connected to the tank, is 40m long and consists of insulated multilayer pipes (Alpex). Characteristics of the pipes are retrieved from the technical ATG data sheet from the manufacturer [14].

*Table 1* shows the characteristics of the recirculation loop and the distal pipes. The mass flow rate of the recirculation loop is calculated in such a way that a maximum temperature difference of 5°C between the
supply and return temperature is achieved. This depends on the heat losses of the distribution system. With the 65-60°C temperature regime and a constant environmental temperature of 15°C (in shafts), this results in a mass flow rate of 0.14kg/s. Accordingly, with a regime of 50-45°C, this is 0.08kg/s.

**Table 1: Length and diameters of the distribution pipes.**

<table>
<thead>
<tr>
<th>Supply recirculation pipe</th>
<th>Length [m]</th>
<th>18.6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outer diameter [m]</td>
<td>0.032</td>
<td></td>
</tr>
<tr>
<td>Thickness pipe [m]</td>
<td>0.003</td>
<td></td>
</tr>
<tr>
<td>Insulation [m]</td>
<td>0.015</td>
<td></td>
</tr>
<tr>
<td>Heat loss coefficient [W/m·K]</td>
<td>0.23</td>
<td></td>
</tr>
<tr>
<td>Return recirculation pipe</td>
<td>Length [m]</td>
<td>21.4</td>
</tr>
<tr>
<td>Outer diameter [m]</td>
<td>0.016</td>
<td></td>
</tr>
<tr>
<td>Thickness pipe [m]</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td>Insulation [m]</td>
<td>0.015</td>
<td></td>
</tr>
<tr>
<td>Heat loss coefficient [W/m·K]</td>
<td>0.17</td>
<td></td>
</tr>
<tr>
<td>Correction factor for thermal bridges [%]</td>
<td>20</td>
<td></td>
</tr>
<tr>
<td>Distal pipes</td>
<td>Length of one distal pipe [m]</td>
<td>5.5</td>
</tr>
<tr>
<td>Insulation [m]</td>
<td>0.006</td>
<td></td>
</tr>
</tbody>
</table>

**Taps**

The required comfort temperature at the tap is 45°C. This temperature can be reached with a mixing valve (three-way-valve) in case the production unit produces water at or above 60°C or by direct withdrawal if water with a temperature around 45°C is produced.

*Table 2* shows the daily tap profile schedule used in the simulation model. The total tapped daily water volume is 211.40L. The volume flow rate at the taps (at 60°C) is calculated based on DIN 1988-300 [15].

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>6:59</td>
<td>Purge of the shower/kitchen pipe</td>
<td>9.00</td>
<td>10</td>
<td>1.50</td>
</tr>
<tr>
<td>7:00</td>
<td>Shower</td>
<td>9.00</td>
<td>355</td>
<td>53.25</td>
</tr>
<tr>
<td>7:10</td>
<td>Shower</td>
<td>9.00</td>
<td>393</td>
<td>58.95</td>
</tr>
<tr>
<td>8:00</td>
<td>Shower</td>
<td>9.00</td>
<td>296</td>
<td>44.40</td>
</tr>
<tr>
<td>12:00</td>
<td>Kitchen faucet</td>
<td>4.20</td>
<td>6</td>
<td>0.42</td>
</tr>
<tr>
<td>12:30</td>
<td>Kitchen faucet</td>
<td>4.20</td>
<td>20</td>
<td>1.40</td>
</tr>
<tr>
<td>13:45</td>
<td>Kitchen faucet</td>
<td>4.20</td>
<td>30</td>
<td>2.10</td>
</tr>
<tr>
<td>18:15</td>
<td>Children’s bath</td>
<td>9.00</td>
<td>311</td>
<td>46.65</td>
</tr>
<tr>
<td>19:00</td>
<td>Kitchen faucet</td>
<td>4.20</td>
<td>6</td>
<td>0.42</td>
</tr>
<tr>
<td>19:15</td>
<td>Kitchen faucet</td>
<td>4.20</td>
<td>3</td>
<td>0.21</td>
</tr>
<tr>
<td>20:00</td>
<td>Kitchen faucet</td>
<td>4.20</td>
<td>30</td>
<td>2.10</td>
</tr>
</tbody>
</table>

**Controller components**

**Development board**

The first controller will be made with the development board Arduino Uno (*Figure 6*), this is an open-source microcontroller electronic platform based on the ATmega328P, featuring 14 digital input/output pins (of which 6 can be used as PWM outputs), 6 analogue inputs, a 16 MHz quartz crystal, a USB connection, a power jack, an ICSP header and a reset button [16], [17]. Arduino executables can be a stand-alone process or can communicate with other processes, i.e. running processes on a PC.

*Figure 6: Arduino Uno Rev3 [17].*

An Arduino library had been built for Modelica to test the Arduino virtually before configuring the hardware. With the Modelica Arduino library it is possible to simulate sketches (unit of code that is uploaded to and run on an Arduino board) on a virtual Arduino Uno, without the need for hardware, and connect the Modelica models to a real-world DHW system using the Firmata protocol [18]. Firmata is a generic protocol for communicating with the Arduino microcontroller from software on a host computer. The Arduino Uno model is driven by an ExternalObject that contains the compiled sketch and an implementation of the Arduino API. The external object is synchronized at every sample step with the Modelica model. When a model that contains the Arduino Uno block is translated the external object is automatically rebuilt [18].

**Power supply**

The Arduino Uno board will be powered with an external power supply (DC 5V).

**Immersive temperature Sensor (DS18B20)**

To measure the temperature, a 1-wire temperature sensor is used (*Figure 7*). This type of sensor provides calibrated digital temperature readings and is more tolerant of long wires between the sensor and the Arduino board [19]. The chip will be powered in normal mode.

*Figure 7: Immersive temperature sensor.*

**Solid state relay**

In an electric boiler, the thermostat is built in and no communication port is present to overwrite this thermostatic control. Therefore, the original controller will be removed and replaced by the newly developed controller. This newly developed controller directly controls the immersion heater by a solid state relay (240VAC/25A) (*Figure 8*).
Results

In a first step, the simulation models of the hydraulic system consisting of a boiler, pump, pipes and taps have been made (Figure 9). A virtual Arduino controller component is made in Modelica Dymola and added to the simulation model to test the controller in simulations (Figure 10).

As can be seen in Figure 10, the effect of the temperature controller based on the predicted L. pneumophila concentrations is shown for step 1, 2 and 3. As expected, in step 2, the virtual controller behaves nearly the same as in step 1. The really small differences between step 2 and step 1 are due to the model of the temperature sensor in step 2, which transform the temperature of the storage tank into a voltage signal that can be interpreted by the Arduino. This difference in temperature causes also a difference in the predicted L. pneumophila concentration. The biggest error occurs during the heat shock. However, this small error in L. pneumophila concentration is almost zero after the heat shock due to the strong decrease of the L. pneumophila concentration during this heat shock.
In the third step, the heat shocks do not take place at exactly the same time as in step 1 and step 2. As can be observed in Table 3 and Figure 11, this leads to a larger Absolute Error (AE). The difference in time is due to the predicted L. pneumophila concentration that is no longer calculated in the Modelica model, but with a function based on the temperature in the bottom of the storage tank (layer 7) and the growth equation for L. pneumophila. This function is a simplification of the hydraulic model in Modelica, and it is chosen to overestimate, rather than underestimate the real concentration of L. pneumophila present as a safety precaution. Consequently, the threshold value of 100CFU/L will be exceeded faster than in step 1 and step 2.

Table 3: Comparison of RMSE, MBE and CV(RMSE)
L. pneumophila concentration values of step 1, 2 and 3.

<table>
<thead>
<tr>
<th></th>
<th>RMSE [CFU/L]</th>
<th>MBE [%]</th>
<th>CV(RMSE) [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1 (base case)</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Step 2 versus Step 1</td>
<td>2.83</td>
<td>0.23</td>
<td>10.08</td>
</tr>
<tr>
<td>Step 3 versus Step 1</td>
<td>18.89</td>
<td>10.59</td>
<td>74.22</td>
</tr>
</tbody>
</table>

Discussion
In a future step, it can be useful to use the predicted concentration of L. pneumophila in the distal pipes to regulate the controller. To make this possible it is necessary to send a signal to the controller when a tap occurs.

Conclusion
In this study, the possibility of a DHW controller prototype has been studied. This controller prototype includes an algorithm that predicts the L. pneumophila concentration present in the system, as this concentration cannot be measured in real time. Comparing the results of step 1, 2 and 3 shows that it is possible to run the algorithm on the virtual Arduino. The third step, which will be investigated further, shows similar predictions for temperature and L. pneumophila concentration as those of the first and second step, although a shift in time can be noticed, i.e. the threshold value of 100CFU/L is reached faster. This new DHW controller is expected to become an important alternative for the current, energy intensive, constant high temperature tap water heating systems.

Future research
In future, the algorithms in the hydraulic Modelica Dymola simulation model will be simplified and replaced with C++ code in order to be implemented in a real Arduino to test the operation of the controller. In this case the Arduino will predict the L. pneumophila concentration instead of the simulation model. The possible levels of simplification of the hydraulic simulation model will need to be analysed.

Subsequently, the prototype of the controller will be implemented in a basic setup of a DHW system, that will be built in laboratory conditions, to test the performance of the controller to achieve a technological proof of concept.

Acknowledgement
Funding details: This work is supported by the Industrial Research Fund (IOF) of Ghent University. The work that is the basis for this work (development of biological Modelica library) was supported by the Agency for Innovation by Science and Technology-Belgium (IWT/VLAIO) under Grant 141608.
**Nomenclature**

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AE</td>
<td>Absolute Error</td>
</tr>
<tr>
<td>DCW</td>
<td>Domestic Cold Water</td>
</tr>
<tr>
<td>DHW</td>
<td>Domestic Hot Water</td>
</tr>
<tr>
<td>L. pneumophila</td>
<td>Legionella pneumophila</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root Mean Square Error</td>
</tr>
</tbody>
</table>

**References**


Energy Savings of Occupancy-Based Controls in Office Buildings

Weimin Wang¹, Jian Zhang², Michael Brambley², Benjamin Futrell¹

¹University of North Carolina at Charlotte, Charlotte, NC USA
²Pacific Northwest National Laboratory, Richland, WA USA

Abstract

Variable-air-volume (VAV) systems are used in many office buildings. The terminal’s minimum air flowrate set point is an important parameter that has significant impact on energy consumption and indoor air quality. Conventional controls usually have the terminal’s minimum air flowrate at a constant, irrespective of the occupancy status. Such practice may cause energy waste, ventilation and thermal comfort problems. This paper examines the potential of energy savings by occupancy-based controls (OBCs). The sensed occupancy information, either presence or the people count, is used to determine the air flow rate of terminal boxes, the thermostat set points, and the lighting as well. Using EnergyPlus, energy savings of OBC strategies are evaluated for representative existing medium office buildings in the U.S. Simulation results show that for the location of Baltimore, MD, the use of air-side economizer or not does indeed have significant impact on the comparison between the two OBC strategies. The OBC based on the occupant presence has about 13% whole-building energy savings no matter whether the air-side economizer is used in the AHU operation. However, for the OBC based on the people count, the percentage of energy savings increases from 13% for the case of not using air-side economizer to 23% for the case of using air-side economizer.

Introduction

VAV systems are widely used in commercial buildings. According to the recent commercial building energy consumption survey (EIA 2016), buildings with VAV systems represent 41% of all U.S. commercial building floor space and account for 51% of the commercial sector primary energy use. In a VAV system, outdoor air (OA) enters the air-handling unit (AHU) through an outdoor-air damper and is then mixed with the air returned from the space. The mixed air sequentially passes through a filter, a heating coil (if present), and a cooling coil, which are used to maintain the supply air at a predefined temperature set point in the supply duct downstream of the supply fan. In addition to AHUs, VAV terminal boxes are an integrated part of the VAV system. A terminal box usually serves a building zone (which can be a single room or multiple rooms) by controlling the air flowrate to the zone and reheating the air if it is too cool for the zone served. Terminal boxes are sized to address the design thermal load (usually the cooling load). The terminal’s minimum air flowrate set point is an important parameter that has significant impact on energy consumption and indoor air quality. In principle, this parameter value needs to be determined by the maximum flow to satisfy the heating load and the ventilation requirement. However, in practice, control system integrators and installers often set the terminal minimum air flowrate between 30% and 50% of its maximum flowrate (Cho and Liu 2009; Stein 2005). The minimum setting is maintained as a constant during system operation, which potentially leads to two major issues related to ventilation. First, the rule-of-thumb setting cannot guarantee to meet space ventilation requirement, as will be demonstrated later in the paper. Second, because building occupancy varies dynamically over time, setting a constant minimum air flowrate may result in over ventilation during times when space has less than the maximum occupancy or is unoccupied at all. The over ventilation causes energy waste and even discomfort for occupants in some spaces (e.g., conference rooms) from over-cooling (Taylor and Stein 2004; Zhu et al. 2000).

To cope with the variations in occupancy, the ASHRAE Standard 62.1 on ventilation for acceptable indoor air quality (ASHRAE 2016) allows dynamic reset of the outdoor air flowrate in response to the change of zone population. The standard also lists four example approaches that can be used to account for occupant information: 1) direct count of people; 2) presence of people; 3) time-of-day schedule; and 4) CO₂-based occupancy estimation. Many occupancy-based control (OBC) strategies have been proposed and evaluated in literature (e.g., Lin and Lau 2014; Taylor 2006). According to the information requirements and complexity, OBC strategies can be classified into two categories: rule-based control and model predictive control. Rule-based control requires instantaneous occupancy measurements (presence/absence or number of occupants) to calculate the control inputs. The sensed occupancy information together with other measurements (e.g., space air temperature) are used as feedback signals to override the control settings. For example, Balaji et al. (2013) leveraged the occupants’ mobile devices to detect which rooms are occupied. The thermostat set points are relaxed for 1.1°C if the room is unoccupied. Based on one-day experiment in a university campus building, they obtained 17.8% electrical energy savings for HVAC systems from the application of occupancy-based controls to 23% zones in that building. Goyal et al. (2013) used the
measured occupancy instead of the design occupancy to calculate the minimum air flowrate of the occupancy-associated VAV terminal box. Meanwhile, the temperature set points are relaxed if a zone is unoccupied. Based on the MATLAB simulation for a single zone in three typical days (i.e., cold, hot, and mild), Goyal et al. obtained 50% HVAC energy savings for that zone relative to the baseline terminal control with a minimum air flow fixed at 40% of its design flow rate. This rule-based OBC strategy was further tested in a campus building (Brooks et al. 2015) in Gainesville, FL. The field test was performed on 12 fully actuated zones (i.e., each zone is served by a single terminal unit) for six days in April. The experimental results showed that the rule-based OBC achieved 37% HVAC energy savings, 30% of which came from heating.

Model predictive control (MPC) requires predictions of occupancy (presence/absence or the number of occupants) at future times and solves an optimization problem to determine the control inputs. These control inputs are implemented at the current time $t_k$ and their corresponding outputs are measured. Using the measured outputs, the control inputs at the next time $t_{k+1}$ are calculated by solving the optimization problem again for the next $k$ time steps. The entire process is repeated at the time $t_{k+1}$. To solve the optimization problem, MPC requires a dynamic model and predictions of exogenous inputs such as weather and occupancy. Oldewurtel et al. (2013) compared various types of MPC strategies for the control of lighting, window blinds and HVAC in office buildings. Their simulation results showed that the MPC based on perfect prediction over a 3-day time horizon had a savings potential of up to 34% if five out of 15 days are vacant on the average. A large portion of this savings potential can be captured by using the default occupancy schedule as prediction and adjusting lighting and ventilation to instantaneous measurements of occupancy status. Similar observations were made in another study (Goyal et al. 2013), where the MPC controller using perfect occupancy prediction over a 24-hour time horizon led additional 1-13% energy savings relative to the rule-based controller.

In this paper, we extend the previous work by Zhang et al. (2013) to estimate the energy savings of rule-based OBC strategies using the whole building simulation program EnergyPlus. The sensed occupancy information, either presence or the people count, is used to determine the air flow rate of terminal boxes, the thermostat set points, and the lighting as well. We hereinafter refer the detection of occupancy presence (occupied or unoccupied) as common occupancy sensors and the detection of the number of people as advanced occupancy sensors. Occupancy-based control (OBC) strategies based on the above two kinds of sensors are proposed and evaluated using building simulation. Their results are compared with the baseline of not using occupancy-based controls.

**Building model description**

The medium office building model originates from the commercial reference building models developed by the U.S. Department of Energy (Deru et al. 2011). The reference building models offer three vintages: new construction in compliance with ASHRAE Standard 90.1-2004, existing buildings constructed in 1980s, and existing buildings constructed before 1980. According to the latest commercial building energy consumption survey conducted in 2012 (EIA 2016), the median age of medium office buildings (floor area between 2,300 m² and 18,500 m²) in the U.S. was approximately 32 years. Assuming that this median age has not changed appreciably between 2012 and 2019, the median year in which currently-standing medium office buildings were built is 1987. Ideally, the building modeled to estimate likely energy savings from retrofit with OBC would be the average medium office building built in 1987 but in its present 2019 condition. Such a requirement, however, cannot be met by none of the three vintage models of reference buildings. Thus, an alternate procedure (Zhang et al. 2013) is used to define a representative medium office building for this study. Starting with the reference medium office building model for new construction, adjustments were made to bring the model closer to the characteristics that might be expected for a building constructed in 1987 but has been upgraded over the last 32 years. The changes (see Table 1) were selected mostly based on the professional judgment of the authors of this paper because no data sufficient to support specification of such changes were found to be available.

The resulting model represents a three-story office building with approximately 5000 m² of total floor area. Figure 1 illustrates an axonometric view of the building and its floor zoning. The building has 1.2 m plenum spaces above each floor and a continuous band of windows for a total window-to-wall fraction of 33%. Perimeter zones are delineated by the orientation of each façade. Each perimeter zone is 4.6 m deep. On each floor, perimeter zone 1 (Figure 1) is used as the conference room while the other three perimeter zones are private offices and the core zone is for open-plan offices. According to ASHRAE Standard 62.1, the occupant density is modelled as 5 and 50 people per 100 m², respectively for the offices and conference rooms; the OA ventilation rate is 0.0025 m³/s per person and 0.0003 m³/s per m² space area for both offices and conference rooms. Three packaged direct-expansion rooftop VAV air-handling units with gas furnaces serve the medium office building, one for each floor. The units have a rated energy efficiency ratio of 10.1 for cooling and rated thermal efficiency of 0.8 for heating. Persily et al. (2005) conducted a ventilation field study in U.S. office buildings and found that for those AHUs without economizers 1) the mean ratio of the design OA flowrate to the supply air flowrate is 0.19; and 2) the mean ratio of the measured OA intake to the design intake is 1.37. This means the mean measured OA fraction is 26%. Therefore, the AHUs in the model have their OA dampers...
at the minimum position to maintain OA intake at a fixed 25% of the supply air unless in the air-side economizing mode. Pressure-independent VAV terminal boxes are used in the model. The maximum air flow rate of each VAV box is autosized by EnergyPlus according to the thermal load. Following the common practice and design recommendations (Pang et al. 2017), all terminal boxes have hot-water reheat and the single-maximum control logic. The minimum air flow rate is set at 30% of the maximum for terminal boxes serving offices and at 50% for those serving conference rooms. The scheduled maximum for terminal boxes serving offices and at 50% have hot-water reheat and the single-maximum control recommendations (Pang et al. 2017), all terminal boxes thermal load. Following the common practice and design VAV box is autosized by EnergyPlus according to the used in the model. The maximum air flowrate of each mode. Pressure-independent VAV terminal boxes are down. During these operation hours, the zone thermostat set points are 23.9°C for cooling and 21.1°C for heating. A 5.6°C set back or set up is used during scheduled system off hours.

The Page occupancy model simulates the patterns of presence of each occupant individually. To obtain the occupancy pattern for a zone, each occupant in that zone is simulated separately and the produced patterns of presence are then summed together. For example, the peak number of occupants in Zone 2 (Figure 1) is calculated to be 7. The page occupancy model needs to be ran 7 times to obtain that zone’s occupancy profile. The outcome of occupancy modelling includes the occupancy patterns for all 15 zones, which are different from each other. All occupancy patterns have a time step of 15 minutes, instead of one hour as used in the average occupancy profiles. The generated annual occupancy corresponds to a fraction of the design maximum occupancy. The weekday and weekend daily profiles are repeated across the entire year for all occupants in all spaces (e.g., offices and conference rooms). Using this simplified approach to study occupancy-based controls has the following weaknesses. First, the temporal variation of occupancy pattern is neglected although late arrivals, early departures, and unpredicted presence on weekends are not uncommon in office buildings. Second, the spatial variation of occupancy pattern is neglected although the reality is that different offices and conference rooms may have their own schedules. To address the problems of using repetitive occupancy profiles, the stochastic model for simulating occupant presence from Page et al. (2008) is employed in this work. The Page occupancy model considers occupant presence as an inhomogeneous Markov chain with probabilities of transition $T_{ij}(t)$, defined as:

$$T_{ij}(t) = P(X_{t+1} = j | X_t = i)$$

where, $X_t$ is the random variable for the state of occupant presence at time step $t$, and $i$ and $j$ take values 0 (absent) or 1 (present).

Based on the profile of probability of occupant presence and a parameter of mobility $\mu$, the time-dependent conditional probability in Eq. 1 can be further expressed as (Page et al. 2008):

$$T_{01}(t) = \frac{\mu - 1}{\mu + 1} P(t) + P(t + 1)$$

(2)

$$T_{11}(t) = \frac{P(t)}{P(t)} \left[ \frac{\mu - 1}{\mu + 1} P(t) + P(t + 1) \right] + \frac{P(t+1)}{P(t)}$$

(3)

In Equations 2 and 3, $P(t)$ and $P(t + 1)$ are the probability of presence respectively at time step $t$ and $t+1$. Their values are from the predefined occupancy profiles as illustrated in Figure 2 and Figure 3. The occupancy profile for offices is from Wang et al. (2005) while the profile for conference rooms is from Hart (2012). The parameter of mobility $\mu$ is defined as the ratio between of the probability of change of the state of presence over that of no change. Page et al. (2008) suggested to define constant values for three levels of mobility (low, medium, and high), but the values were not given. This paper used a value of 0.25 for the parameter $\mu$, which is the mean value used in (Gunay et al. 2015) when comparing different occupancy models.

The Page occupancy model simulates the patterns of presence of each occupant individually. To obtain the occupancy pattern for a zone, each occupant in that zone is simulated separately and the produced patterns of presence are then summed together. For example, the peak number of occupants in Zone 2 (Figure 1) is calculated to be 7. The page occupancy model needs to be ran 7 times to obtain that zone’s occupancy profile. The outcome of occupancy modelling includes the occupancy patterns for all 15 zones, which are different from each other.

**Occupancy modelling**

Realistic modelling of occupancy is critical to the evaluation of the impact of OBC strategies. The most common approach of considering occupancy in building energy simulation programs is by using occupancy profiles. Daily occupancy profiles are usually defined differently on weekdays and weekends for office buildings. A daily profile (either for a weekday or weekend) consists of 24 hourly values, each of which...
patterns are used as the inputs of the EnergyPlus simulation program for both control strategies to be discussed below.

![Figure 2: The probability of occupant presence in offices.](image)

![Figure 3: The probability of occupant presence in conference rooms.](image)

**Control strategies**

We now describe the baseline control and the two occupancy-based control strategies (one is for conventional occupancy sensors that detect presence only and the other is for advanced occupancy sensors that detect the number of people). These control strategies differ in the following aspects: 1) the minimum air flowrate settings of terminal boxes, 2) the thermostat set points, and 3) the lighting control.

**Baseline control**

The baseline control does not rely on occupancy information at all. Thus, the terminal box has a constant minimum air flowrate settings of terminal boxes, the thermostat set points, and conference rooms, the minimum air flowrate is kept the same as the baseline control because the probability of being unoccupied in large open-plan offices is relatively low.

**Conventional OBC**

The conventional OBC modifies the baseline control depending on the space type and the space occupancy status. Major changes relative to the baseline control include the following:

- **Minimum terminal air flow setting.** For private offices and conference rooms, the minimum air flowrate is reset to zero when no people is detected in any of the spaces served by the terminal box. Accompanying the change of minimum terminal air flowrate, the dual-maximum control logic replaces the single-maximum control logic used in the baseline. This means that the thermal load can drive a higher terminal air flowrate than the minimum setting. It is worth noting that setting the minimum air flowrate to zero violates the current ventilation standard that requires the area outdoor air rate during scheduled building operation hours even if the space is unoccupied. This problem could be addressed by setting the minimum air flowrate according to the area ventilation component, but we use zero setting to explore the potential savings from conventional OBC. For open-plan offices, the minimum air flowrate is kept the same as the baseline control because the probability of being unoccupied in large open-plan offices is relatively low.

- **Thermostat set points.** For conference rooms, the thermostat set points are reset to 25°C for cooling and 20°C for heating if the space is unoccupied. Although some time delay (say 15 minutes) is generally needed in the field to reset thermostat set points after the space is detected to be unoccupied, it is not considered in the simulation at the current stage. The thermostat set points are not reset for offices.

- **Lighting control.** Conventional OBC for lighting turns lights on when occupants enter a room and off following a delay after all occupants leave the room. Delay times of approximately 15 minutes are usually used to help ensure that lights are not turned off while occupants are still in the room. In the conventional OBC, lighting controls are applied in conference rooms and private offices. Von Neida et al. (2001) investigated the potential of lighting energy savings in different
space types by applying occupancy-based lighting control with varied delay times. About 24% lighting energy savings were obtained for both conference rooms and private offices for a time delay of 15 minutes. To consider the occupancy-based control for lighting in the simulation, we revised the lighting schedule during building operation hours (8:00 am to 10:00 pm) using the following equation:

\[ LtgSch_{OBC,i} = LtgSch_{base,i} \times (1 - SavingPer) \]  

(4)

where, \( LtgSch_{OBC,i} \) and \( LtgSch_{base,i} \) refers to the lighting schedule at hour \( i \) for the case of occupancy-based lighting control and the baseline control, respectively. The \( SavingPer \) takes the value of 24% for conventional OBC. As an example, Figure 4 shows the baseline lighting schedule being 0.9 from 8:00 to 17:00 during weekdays. The lighting schedule is changed to \( 0.9 \times (1 - 0.24) = 0.684 \) for the conventional OBC simulation.

**Advanced OBC**

The advanced OBC improves further from the conventional OBC based on the number of occupants detected in spaces. Major differences relative to the conventional OBC are highlighted in the following:

- Minimum terminal air flow setting. The zone outdoor air requirement at any time (\( V_{o2,t} \)) is calculated as:

\[ V_{o2,t} = \frac{R_pP_{z,t} + R_aA_z}{E_z} \]  

(5)

where, \( R_p \) and \( R_a \) represents the OA rate required per person and per area; \( A_z \) is the zone floor area in \( m^2 \); \( P_{z,t} \) is the zone population at time \( t \); and \( E_z \) is the zone air distribution effectiveness. In this work, the value of \( i \) is used for \( E_z \) in the simulation.

The zone primary air flowrate (\( V_{p2,t} \)) needed to meet the ventilation requirement is then calculated as:

\[ V_{p2,t} = \frac{V_{o2,t}}{Z_p} \]  

(6)

where, \( Z_p \) indicates the zone primary outdoor air fraction. For single-duct VAV systems as used in this work, \( Z_p \) is the same as the OA fraction at the AHU.

Under the advanced OBC, \( V_{p2,t} \) calculated from Eq. 6 is used as the minimum air flowrate for terminal boxes. The actual number of people is used in conference rooms and open-plan offices, where a single large space is served by one or more terminal units (one terminal per zone assumed in the simulation model). For a terminal unit serving multiple spaces such as private offices, the number of people is zero if none of the offices in that zone is occupied; otherwise, the design zone population is used in Eq. 6 if any of the offices in that zone is occupied. In comparison with the conventional OBC, the advanced OBC always satisfies zone ventilation requirement during building operation hours even if the space is not occupied. Certainly, \( V_{p2,t} \) can by no means exceed the maximum terminal air flowrate.

- Thermostat set points. This aspect of control is similar to that used for the conventional OBC. The only difference is that the spaces for resetting thermostat set points are expanded to include both conference rooms and private offices.

- Lighting control. Considering that the advanced occupancy sensors have the (potential) ability to precisely identify when a room is vacated, the delay time between all occupants leaving the room and turning off lights is significantly reduced from 15 minutes to 5 seconds (Zhang et al. 2013). Again, occupancy-based lighting control is applied to conference rooms and private offices only. The approach to lighting control simulation is identical to the one used for conventional OBC. However, because Von Neida et al. (2001) did not provide lighting energy savings for a time delay of 5 seconds, a linear regression was made to correlate the lighting energy saving and the time delay based on available data. The regression equation was then employed to estimate the lighting energy saving corresponding to the time delay of 5 seconds, which was 50.9% for conference rooms and 34.9% for private offices. More details about the regression can be found in Appendix A-3 of the report (Zhang et al. 2013).

**Simulation results and discussions**

The medium office building model is simulated in EnergyPlus. We selected Baltimore, MD as the location for energy simulations because it represents a mixed climate (i.e., cold winter and hot summer) in the U.S. Percentages of energy savings from the OBC strategies are presented against the original baseline model.

In the original baseline model, terminal boxes are autosized by EnergyPlus according the zone thermal loads at design conditions. AHU OA fraction is maintained at 25% unless air-side economizer is used and the weather condition is favourable for economizing. Using air-side economizer or not is expected to affect the results because the minimum terminal air flowrate for the advanced OBC depends on the OA fraction (see Eq. 6). Thus, the baseline model and the two OBC models are simulated for two scenarios: no air-side economizer and with air-side economizer. If air-side economizer is used, differential dry-bulb is the control option.

The baseline has an energy use intensity of 647 MJ/m² for the case of not using economizer and 625 MJ/m² for the case of using economizer. Figure 5 shows the annual energy savings of the two OBC strategies relative to the original baseline, where “Con-OBC” and “Adv-OBC” represent conventional OBC and advanced OBC, respectively. The numbers above the bars indicate the percentage of whole-building energy savings. Figure 5 leads to the following observations:

- Using air-side economizer or not does indeed have significant impact on the comparison between the two OBC strategies. If air-side economizer is not used in the AHU operation, the two OBC strategies have minor difference in energy savings: 85 MJ/m² per year for the
conventional OBC vs. 89 MJ/m² per year for the advanced OBC. However, if air-side economizer based on differential dry-bulb control is used, there is much higher difference in energy savings: 78 MJ/m² per year for the conventional OBC vs. 146 MJ/m² per year for the advanced OBC. This phenomenon can be explained by Eq. 6, which indicates the larger value of OA fraction ($Z_p$), the smaller value of the minimum terminal air flowrate. Because the use of air-side economizer potentially increases $Z_p$ from 25% to 100%, the minimum terminal air flow under advanced OBC can be much lower than that under conventional OBC, thereby leading more energy savings.

- All energy savings come from four energy end uses (i.e., cooling, fan, lighting, and heating) but with different levels of contributions. Detailed calculations indicate that across the four control cases, 10%~18% of annual energy savings is due to cooling, about 5% due to fan, 11%~18% due to lighting, while 61%~74% due to heating. The heating energy here can be understood solely as terminal reheating energy as the central heating energy used by AHUs are negligible, let alone its difference across different control cases.

Under the conventional OBC strategy, the minimum terminal air flowrate is unchanged from the baseline if any of the spaces in the zone is occupied. However, the minimum air flowrate is reset to zero for the terminal units serving conference rooms and private offices whenever all spaces in that zone are totally unoccupied. Both the baseline and the conventional OBC control strategy do not guarantee the satisfaction of ventilation standard when the zones are in the modes of heating, deadband and low cooling. On the contrary, the advanced OBC guarantees the satisfaction of ventilation during all occupied hours. Therefore, we selected the top floor zones to provide a conservative comparison between the advanced OBC and the other two cases. Of all time steps that the zones are occupied, Figure 6 shows the distribution of four ventilation situations according to the differences between actual provided OA and OA requirement calculated from Eq. 5. The green bar indicates that the zone ventilation meets the requirement while the blue, orange and red bars indicate the zone ventilation is below the requirement by less than 10%, between 10% and 20%, and more than 20%, respectively. Figure 6 shows that the advanced OBC meets the ventilation requirement for all zones. Both baseline and the conventional OBC have many hours not meeting the ventilation requirement, which is especially the case for perimeter ZN 1 (conference room) and the core zone. The core zone’s ventilation requirement was not met for more than 80% of the time across the whole year when the open-plan office is occupied.

![Figure 5: Annual energy savings of different end uses from occupancy-based controls.](image)

**Figure 5: Annual energy savings of different end uses from occupancy-based controls.**

![Figure 6: Ventilation comparison of top floor zones for different control cases.](image)

**Figure 6: Ventilation comparison of top floor zones for different control cases.**

### Conclusions

Many commercial products are available on the market to detect whether a space is occupied or not. Advanced occupancy sensors for people counting are also available although they are expensive at the moment. With these two different kinds of occupancy sensors, it is important to devise occupancy-based control (OBC) strategies and estimate their potential benefits. A model that represents a currently-standing medium office building constructed in late 1980s was used in this OBC research. Major conclusions from this work include:

- For the climate conditions in Baltimore, MD, the conventional OBC can save whole building energy use by 13% while the advanced OBC can save energy up to 23%.

- The percentage of energy savings due to the advanced OBC depends on whether the baseline AHUs have air-side economizer controls. Using air-side economizers or in general increasing the AHU OA fraction will lead to more energy savings. Most of the energy savings come from the reduction of terminal reheating.

- In addition to energy savings, the advanced OBC satisfies the zone ventilation during all occupied hours across the whole year. However, neither the conventional OBC nor the baseline guarantees the satisfaction of zone ventilation requirement.

In this paper, the advanced OBC strategy has a major focus on terminal box controls via the change of terminal minimum air flowrate. Since AHU OA fraction has a significant impact on the energy savings of the advanced OBC, it is worthwhile to combine the terminal air flow...
control and the AHU OA flow control together for the purpose of system optimization. The second avenue of future research lies in the occupancy modeling. Although a stochastic occupancy model was used to consider the temporal and spatial variation of occupancy patterns. The model does not consider the movement of occupants from one zone to the other. Therefore, it is worthwhile to consider more sophisticated occupancy models such as the occupancy simulator by Chen et al. (2017) in future work. Lastly, the simulation assumes that all sensor and actuators work perfect (e.g., no air leakages when the terminal damper fully closes and the occupancy sensor can detect the occupancy status or the number of occupants accurately), it would be interesting to investigate the impact of sensor and actuator uncertainty on the results.

References


Table 1: Changes to the medium office reference model to create a building model that approximates a medium office building constructed in 1987 as it would exist in 2019 and the rational for each change.

<table>
<thead>
<tr>
<th>Category</th>
<th>Change</th>
<th>Rational</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zone description</td>
<td>Specific space types (conference room, private office, and open-plan office) are assigned to the thermal zones.</td>
<td>The use of distinct space types i.e., conference rooms, private offices and open-plan offices, enables evaluation of the savings associated with OBC based on the unique occupancy patterns and ventilation requirement of different spaces.</td>
</tr>
<tr>
<td></td>
<td>The occupancy profiles are modified for private offices, open-plan offices, and conference rooms to consider spatial and temporal variations.</td>
<td>To address the problem of using an average weekly occupancy profile to represent all occupants for all times.</td>
</tr>
<tr>
<td>HVAC sizing</td>
<td>Terminal-box size (flow rate and reheat) sizing factor is increased from 1.0 to 1.2.</td>
<td>The larger size for the terminal boxes more realistically represents a late 1980s office building.</td>
</tr>
<tr>
<td></td>
<td>Lighting peak load power density (LPD) is scaled to 133% of the LPD required by Standard 90.1-2004 for HVAC sizing.</td>
<td>The HVAC system in a late 1980s building would have been sized for the less efficient lighting of the era. Lamps and lighting fixtures are assumed to have been replaced with more efficient ones since building construction in 1989, but retrofit of HVAC components, primarily the terminal box, is assumed to have been considered too expensive to have been replaced in most buildings.</td>
</tr>
<tr>
<td></td>
<td>Peak plug load density is scaled to 140% of the Standards 90.1-2004 prototype plug load density for HVAC sizing.</td>
<td>The HVAC system in a late 1980s building would have been sized for a higher plug load densities of that era. Expensive HVAC system replacement, such as for terminal boxes, are less likely to have been done.</td>
</tr>
<tr>
<td>Outdoor air flowrate at air-handling units</td>
<td>The outdoor air flowrate is changed from a constant (sum of zone outdoor air requirements) to 25% of supply air flowrate.</td>
<td>Outdoor-air flow station is not commonly used in the field.</td>
</tr>
<tr>
<td>Terminal box settings</td>
<td>The minimum air-flow rate for conference rooms is changed from 30% to 50% of the design peak flow rate.</td>
<td>Implementation of this procedure is based common practices with for conference room minimum damper positions presented by Yu et al. (2007) and Stein (2005).</td>
</tr>
<tr>
<td></td>
<td>The control of maximum discharge air temperature is added.</td>
<td>Discharge air temperature from terminal boxes should keep below a certain limit to avoid stratification and short circulation of conditioned air.</td>
</tr>
</tbody>
</table>
A Multidisciplinary Model to Couple Power System Dynamics and Building Dynamics to Enable Building-to-Grid Integration

Yangyang Fu\textsuperscript{1}, Sen Huang\textsuperscript{2}, Yuan Liu\textsuperscript{2}, T. E. McDermott\textsuperscript{2}, Draguna Vrabie\textsuperscript{2}, Wangda Zuo\textsuperscript{1}
\textsuperscript{1}University of Colorado, Boulder, USA
\textsuperscript{2}Pacific Northwest National Laboratory, Richland, USA

Abstract

Interactions between power systems and buildings are usually ignored or over-simplified by existing modeling and simulation tools. This limits how system modeling can support Building-to-Grid integration activities. In this paper, we developed a multidisciplinary model for motor-driven building devices to consider the interactions. This multidisciplinary model considers both mechanical dynamics and electrical dynamics of the motor-driven building devices. It characterizes the motor behavior, in response to disturbances from both power systems and buildings. We validated this model by comparing its simulation results, in terms of the response to a varying voltage signal, to those from a commonly-used power modeling tool. To demonstrate the usage of the developed model, we integrated the developed model into a simulated building cooling system. We then studied how this simulated system responses to changes in the supply voltage and the thermal load.

Introduction

Power systems and buildings interact in a dynamic and coupled manner. For example, the supply voltage was found to dramatically affect the instantaneous energy efficiency of the building systems. (Hood (2004); Bichik et al. (2015); Lee (2014)). The operation of building systems, on the other hand, influences the transient performance of the power system, such as the voltage stability (Wu et al. (2006); He et al. (2012); Li et al. (2017)). Therefore, it is necessary to consider those interactions when designing and operating power systems or buildings in order to avoid undesirable side effects. When it comes to the Building-to-Grid (B2G) activities, this necessity becomes even more urgent since more interactions are expected to be introduced by the B2G activities.

Modeling and simulation is an effective way to investigate the interactions. However, when simulating power systems or buildings, the interdependent influences tend to be ignored. One major reason is that existing models and simulation tools were developed from a single disciplinary perspective and thus have difficulties in capturing the multidisciplinary interactions. For example, in the power system modeling, it is quite common that power factors of the building system are assumed to be constant (Chassin et al. (2008a)). In the building system modeling, usually the influence from power systems is ignored by implicitly assuming the supply voltage to be constant (Crawley et al. (2001)).

There were efforts to consider the interactions between buildings and power systems (Chassin et al. (2008b); Bokhari et al. (2014); Clarke (2015)). For example, a ZIP coefficient model (Bokhari et al. (2014)) was proposed to approximate the influences of the voltage on the building device using a polynomial function. However, they over-simplify those interactions, and thus may not be able to support larger-scale applications. The ZIP coefficient model, for instance, is a static model and ignores the transient dynamics. Thus, it may not be used for the dynamic analysis purposes.

Under specific circumstances, we remark that, ignoring or simplifying those interaction may be acceptable. For example, when resistive devices (such as the electric heater) dominate the power usage in buildings, we can assume the power factor is constant without sacrificing the accuracy too much (Gilbert (1965)). Furthermore, for the static or semi-dynamic analysis on the power system, the ZIP coefficient model can still provide reasonably good approximation on the response from the load side (Hatipoglu et al. (2012)). Nevertheless, ignoring or simplifying those interactions would generate significant errors in some applications, especially the B2G activities, such as optimizing the supply voltage to maximize power saving in a building (Arriffin et al. (2017)). In those applications, obviously, ignoring the interaction or only considering the one-directional impacts from power system to buildings may lead to unrealistic or even incorrect conclusions.

To support broader applications, we discussed how to consider those interactions in the building system modeling (Fu et al. (2019)). We also performed a proof-of-concept by developing models for motor-driven building devices. Those models, however, were designed primarily to support qualitative analysis and based on simplified mathematical descriptions of the motor operation. Therefore, they may not be able to be used directly in a real application.
In this paper, we developed a new multidisciplinary model for motor-driven building devices to better represent the interactions between power systems and buildings. This multidisciplinary model considers both mechanical dynamics and electrical dynamics in the motor-driven building devices. It characterizes the motor behavior, in response to disturbances both from power systems and buildings. We validated this model by comparing its simulation results, in terms of the response to a varying voltage signal, to those from a commonly-used power modeling tool. To demonstrate the usage of the developed model, we integrated the developed model into a simulated building cooling system. We then studied how this simulated system responses to the changes in the supply voltage and the thermal load.

The rest of the paper is organized as below: we first describe the studied motor-driven building devices, and then elaborate how their dynamic behaviors are modeled. After that, we validate the model by comparing its simulation results with that from a commonly-used power analysis tool. We then perform a case study to demonstrate the usage of the developed model. At last, we discuss the simulation results and future works.

Motor-driven Building Devices

Typical motor-driven building devices include fan, pump, chiller, etc. They are the major consumers of the electricity in buildings (Webster et al. (2000)). As shown in Figure 1, a typical motor-driven building device consists of three major components:

- **Variable frequency drive (VFD)**
  The VFD is used to adjust the input frequency and voltage for the motor. It is connected with the components (such as transformers) in power systems and transports the electricity power to the motor. It is noted that VFDs are generally optional. In absence of VFDs, the input frequency and voltage of the motor depends on the power system operation directly.

- **Motor**
  Induction motors are the commonly used type of motors in buildings. A typical induction motor consists of several sub-components: coil, magnet, stator, and rotor. The coil and stator are connected with the electric circuit from the VFD and generates induced magnetic field. The generated magnetic field from the coil and the stator interact with the rotor, and produces an electromagnetic torque around the rotor’s axis. The torque forces the rotor to rotate at a constant or varying speed.

- **Transitional device**
  The transitional device links the shaft in the rotor with that in a mechanical counterpart. It transfers the torque from the rotor to the mechanical device. A commonly used transitional device is belt.

- **Mechanical devices**
  The mechanical device converts the torque into mechanical works. In buildings, they usually interact with other systems indirectly via different fluid loops. For example, for supply air fans, the mechanical device circulates the air between the air conditioning system and the room, so that the cooling and heating energy can be delivered from the former to the latter. Usually feedback controls are utilized to guarantee that the mechanical system can deliver a desired amount of mechanical works. Those feedback controls monitor the controlled variable and send the frequency signal to the VFD in order to modulate the input frequency of the motor.

The operation of the motor-driven building devices are affected by both power systems and other systems in buildings. In that sense, motor-driven building devices act as an interface to connect power systems and buildings. Specifically, the impact of power systems to the buildings is reflected by the supply voltage and the frequency, which affects the actual voltage of the power system. Therefore, modeling the motor-driven building devices is the key to consider the interactions between power systems and the buildings.

System models

In this section, we elaborate how the motor-driven building device are modeled at the component level.

- **Variable frequency drive (VFD)**
  The VFD model basically has three inputs: input voltage, \( V_{in,i} \), input frequency, \( f_{in} \), and frequency signal, \( f_{sig} \), and two outputs: output voltage, \( V_{vfd,out,i} \), and output frequency, \( f_{vfd,out} \). In this study, the VFD is assumed to be ideal, in other words,

\[
    f_{vfd,out} = f_{sig} \quad (1)
\]
\[
    V_{vfd,out,i} = V_{in,i} \quad (2)
\]

where the subscript \( i \) denotes the phases of the power system.

- **Motor**
  We considered a three-phase induction motor with unbalanced supply. It has two major inputs: the input frequency, \( f_{motor,input} \), the input voltage for each phase, \( V_{motor,input,i} \), calculated...
Figure 1: Motor-driven building devices.

by:

\[ f_{\text{motor,input}} = f_{\text{vfd,out}} \] (3)

\[ V_{\text{motor,input},i} = V_{\text{vfd,out},i} \] (4)

The outputs include the apparent power of the motor and the generated electromagnetic torque, \( \tau_e \), obtained by solving a series of differential equations that represent the electrical dynamics and magnetic dynamics of motors (Stankovic et al. (2002)).

- **Transitional device**

Regarding the transitional device, the inputs include the \( \tau_e \) and the load shaft power, \( P_{\text{shaft}} \), while the outputs include the load speed, \( \omega_r \) and the load torque, \( \tau_L \). One major parameter for the transitional device is the load moment inertia \( J_L \). The \( \tau_L \) is calculated by solving the following equations:

\[ \tau_L = \frac{P_{\text{shaft}}}{\omega_r} \] (5)

\[ \frac{d\omega_r}{dt} = \frac{\tau_e - \tau_L}{J_L} \] (6)

- **Mechanical device**

The major input of the mechanical devices is the mechanical work they provide, \( w \). For the device such as fans or pumps, the mechanical work is calculated by:

\[ w = \Delta p Q \] (7)

where \( \eta_{\text{shaft}} \) are the shaft efficiency. For fan or pumps, \( \eta_{\text{shaft}} \) can be expressed as a quadratic equation as

\[ \eta_{\text{shaft}} = (b_0 + b_1 \left( \frac{Q}{r} \right) + b_2 \left( \frac{Q}{r} \right)^2) r^2 \] (9)

where the normalized speed \( r \) can be calculated based on the rotation speed \( \omega_r \) and the nominal rotation speed \( \omega_{r,0} \), and is shown as

\[ r = \frac{\omega_r}{\omega_{r,0}} \] (10)

It is noted that all the above formulas, including both algebraic equations and deferential equations, shall be solved simultaneously since some of them are coupled. To simplify the implementation process, we use Modelica (Fritzson and Engelson (1998)) as the modeling tool. Modelica is an equation-based modeling language which allows describing the systems with implicit equations. Therefore, differential equations can be directly implemented in Modelica without any modification. Figure 2 is the diagram of the generated Modelica model for one type of motor-driven device: fan/pump.

**Validation**

In this section, we validate the developed Modelica model against PSCAD (Woodford (2003)), a widely used power modeling tool. In this validation, we considered a scenario where there are sudden changes in the supply voltage of a motor-driven device, due to a fault occurs in the power grid. We then modeled the above scenario with both the developed Modelica model and the PSCAD. For the Modelica models, we simulate it with a solver called DASSL, provided by a commercial software Dymola (Bück et al. (2002)). The solver DASSL supports variable time steps, and...
the minimum and the maximum time step in the Modelica model during the simulation are 0.0154 µs and 0.282 s, respectively. For the PSCAD model, we select a fixed time step as 50 µs and use the trapezoidal algorithm for integration.

Figure 3 illustrates the simulation results. We can see that, at the 5 s, the voltage ramps down to 0.3 p.u., i.e., decreasing by 70%, in 0.02 s, then stays at 0.3 p.u. for 0.3 s. At t=5.32s, the voltage ramps up to 1 p.u. in 0.02 s, and finally keeps at 1 p.u. till the 8 s. The two models can generate approximately close results in general.

The simulated rotor speed, real power, and reactive power from the two models, in response to the voltage change, are close in terms of general patterns. There are some relative large differences, however, in the period from the 0 s to the 3 s, this is because the initial values for state variables are different for the two models. Due to the limitations of the simulation environment, we are not able to force the two models to have the same initial values. Based on the above results, we believe that the developed model provides reasonable representation on the system dynamic behaviors, in response to the voltage change, for the studied motor-driven device.

Case Study
To demonstrate how the developed Modelica models can help to capture the interactions between power systems and buildings, we conducted a case study. In this case study, we integrated the developed model with a simulated building cooling system. We then investigated how the model responses to the disturbances in both power systems and buildings.

This section starts with a brief description on the studied building cooling system; it then elaborates the simulation scenarios and simulation results.

**Studied system**
We considered a simplified building cooling system in this study. As shown in Figure 4, this simplified system contains a water loop and an air loop. The water loop consists of an ideal cooling source, a pump, an air handler, and a two-way valve and the air loop contains an air handler and a load. In the water loop, the ideal cooling source maintains the temperature of the leaving water to be 7 °C and the pump circulates cold water between the cooling source and the air handler. In the air loop, the cold supply air from the air handler then removes the heat from the load with a constant air flow rate. In addition, there are some interactions between the water loop and the air loop. The water flow rate is modulated by adjusting the opening position of a two-way valve to maintain the cold air leaving the air handler to be around 16 °C. In addition, the frequency of the pump is adjusted to maintain a constant pressure difference in the pipe across the air handler when the water flow rate varies.

We then modeled the studied system with Modelica Buildings library. When generating the system models, we considered two options as well. In the first option (named as “proposed”), the pump is modeled with the developed model while in the second option (“conventional”), the pump is modeled with a module called “Buildings.Fluid.Movers.SpeedControlled, “ from Modelica Buildings library (Wetter et al. (2014)). “Buildings.Fluid.Movers.SpeedControlled” doesn’t consider the interactions between the power system and pumps, and thus is used as a reference to better understand the performance of the proposed model. For both options, the rest components of system besides the pump were modeled with components from the Modelica Standard library (Fritzson and Engelson (1998)) and the Modelica Buildings library.

**Testing scenarios**
In this case study, we considered two scenarios. In the first scenario, we studied how disturbances in power systems affect the studied system by introducing a step change in the supply voltage from the grid and assuming that the thermal load keeps constant. In the second scenario, we studied how disturbances in buildings affect the studied system. Similar to the first scenario, we introduced a sudden increase of the thermal load and keep the voltage unchanged.

In both scenarios, the simulations are conducted from 0 s to 1600 s, and the signal changes are implemented at the 800s. We use the above simulation time settings to make sure the system has sufficient time to become steady before and after the signal changes. This can allow us to study both the dynamic and the steady state responses of the system to the changing signals.
Figure 3: Validation results of the Modelica model.

Figure 4: The studied cooling system.

Results

Figure 5 illustrates the simulation result for scenario 1. The step change in the voltage from 1.0 p.u. to 0.5 p.u. is introduced at 800 s. In response to the sudden change of the voltage, in the “proposed” option, the real power oscillates dramatically between -10 kW and 15 kW in a very short time (less than 0.2 s). The real power becomes negative because this rapid voltage change could force the motor to be in a generator mode and generates some real power during the contingency. After that, the real power become relatively steady at around the 801 s. The steady state values of the real power changes slightly before and after the voltage dip: from 4.15 kW to 4.29 kW. However, in the “conventional” option, there is no change in the real power as the voltage is not considered as an input for the pump operation. In addition, the “proposed” option shows that the reactive power of the pump experiences an oscillation as well: from around -17.00 kVAR to around 3.00 kVAR in 0.2 s. The steady value of the reactive power also changes slightly, from 2.94 kVAR to 2.83 kVAR.

As shown in Figure 6, the primary reason for the oscillations is that the speed controller of the pump tries to maintain a constant pressure difference. When the voltage decreases, the electromagnetic torque produced by the motor drops. As a result, the motor speed, driven by the electromagnetic torque, also decreases, leading to a lower head pressure. To maintain a constant pressure difference in the pipe across the air handle, the speed controller of the pump generates a higher frequency signal to increase the motor speed. The increased motor speed then generates a higher head pressure and forces the speed controller to reduce the frequency signal. The above process repeats until the frequency signal becomes steady. The oscillations influence significantly the power consumption by the pump. Before the dip, the pump consumes 4.15 kW. During the rebalancing process, the pump can consume as much as 13.5 kW, which increase the demand by about 2.25 p.u. However, those oscillations don’t dramatically affect the building operation performance. For example, as shown in, the change of the static pressure is less than 0.03 kPa. This is because the mechanical inertial prevents the load torque changes as the same pattern as the electromagnetic torque.

Figure 7 illustrates the simulation results for scenario 2. At t=800 s, its thermal load increases by 0.5 p.u. As a consequence, more chilled water need to pass through the air handler, which then decreases the pressure difference. The frequency of the pump is then increased by the pump controller to maintain a constant pressure difference.
Figure 5: Simulation results of the scenario 1.

Figure 6: Detailed simulation results of the scenario 1.
In the “proposed” option, similar to scenario 2, the pump control contributes mostly to the significantly oscillations in the real power. We can see that the real power changes from around 4 kW to around 10 kW in just 0.1 s. In addition, there is a significant oscillation in the reactive power as well.

However, in the “conventional” option, we observe no oscillations since “Buildings.Fluid.Movers.SpeedControlled’y” doesn’t consider the mechanical inertia in the motor and the transitional device. Therefore, the change of the frequency signal is much smoother than that in the “proposed” option.

**Conclusion**

In this paper, we developed a Modelica models to allow considering the interactions between buildings and the power system. We validated the developed model by comparing its simulation outputs to those from a power modeling tool. The validation results suggested that the developed models can predict reasonable responses of the motor-driven devices to the studied changing voltage. To demonstrate the usage of the developed model, we conducted a case study with a simplified building cooling system. The case study results suggest that the proposed model provides more realistic representation on how the studied system responds to the disturbances from the supply voltage and the thermal load, compared with the existing models.

In the future study, we will perform a more realistic case study by including power systems into the simulation scope rather than treating it as a boundary condition. By doing that, we can better understand how the buildings and power grids interact in a coupled manner. In addition, we will also apply the proposed model in the B2G activities to support the design or the evaluation of the relevant controls.

**Acknowledgement**

This work has been supported by the the Building Technologies Office of the U.S. Department of Energy’s Office of Energy Efficiency and Renewable Energy.

This research is supported by Colorado Energy Research Collaboratory (Award No. 22-2018). 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 demonstrate a BIM/GIS and Modelica Framework for building and community energy system design and operation.

**References**


Impact of Realistic Controls on Building Energy Consumption and Comfort

Rohini Brahme¹, Aswath Mukundan², Rakesh Goel¹
¹Lennox International Inc., Texas, USA
²Lennox India Technology Centre, Chennai, India

Abstract
Increasingly, the control logic of HVAC system plays a significant role in defining the system’s operational efficiency and ability to establish and maintain the desired indoor conditions. Whole building performance simulation tools (EnergyPlus, eQuest, etc.) can be used to evaluate the impact of various control strategies, with the caveat that most of these strategies are predefined, with limited options for customization. These tools assume ideal control logic and cannot predict the impact of equipment cycling accurately. In this paper, co-simulation of building model (in EnergyPlus) with equipment and control model (in Matlab) is used to study the impact of cycling and of control parameter on comfort and HVAC energy consumption, to understand the significance of actual control logic for building performance simulation. Preliminary analysis of few cases shows that this setup allows for a better prediction of cycling losses. It allows one to study the impact of control parameters on annual energy consumption and comfort indices. More importantly, this setup opens up the analysis of any number of enhancements to typical control strategies which are pre-defined in whole building simulation tools.

Introduction
HVAC systems operate to establish and maintain conditions comfortable for human occupancy in the buildings. However, these systems consume a significant portion, around 40-45%, of the total energy used in the building (DoE 2010). Therefore, it is essential to improve the performance of the HVAC system in different ways possible. HVAC system consist of different components and one of the ways to improve the overall system performance is by improving the design of the individual components like enhancing the heat transfer efficiency of the heat exchangers viz. the condenser and the evaporator, improved compressor efficiency etc.

Apart from the design of individual components that constitute a HVAC system, the efficiency of the HVAC system is also influenced by operating thermal conditions i.e. dry bulb temperature and relative humidity of ambient and thermal zone served by the HVAC system. The ambient condition varies widely from place to place and the desired indoor conditions depend on the occupant and can vary drastically too. However, in this work the desired indoor conditions are assumed to be the same for different simulation cases. Thus it is possible that identical HVAC systems, i.e. those which include components of same design, may end up operating with different performance in different locations.

In such cases, the control logic governing the operation of the system may have an influence on the system performance. Understanding the influence of control parameters on performance of HVAC system requires the simulation of the actual operation cycle of the HVAC system. Building performance simulation tools simulate different energy interactions in a building and can predict the cooling load profile against which the HVAC system has to operate. In this study, two building types have been considered – a small office building and a typical single family residence. Both the models are taken from the reference building prototype models developed by PNNL (PNNL Commercial and PNNL Residential).

- A 35 kW (10 ton) two stage roof top air conditioning unit serves a zone in a small office building. This unit can operate in different modes, namely part load and full load, depending on the indoor requirements and outdoor conditions.
- A 10.5 kW (3 ton) variable speed split system serves the single family residence.

The dynamics of HVAC system controls can change in timescale of minutes or less. In this study, the time step of one minute is used for the annual simulations, since that is the minimum time step possible in Energyplus, and it also works reasonably well for understanding the impact of control parameters. Further, the control logic provided in EnergyPlus is different from the actual system and therefore co-
simulation is used here, modelling the building in EnergyPlus and the equipment and control in Matlab. The transition between different stages of HVAC equipment is very different from steady state operation at these stages in terms of the cooling capacity and energy consumption of the HVAC system. Both ideal and actual transitions between the operating modes have been considered in annual simulation of the office building to understand the impact of the realistic controls. For the single family residence, only the steady state simulations are used currently. On the controls side, the effect of minimum on time, minimum off time, low stage run time, and PI gains, are studied to understand the impact of PI control logic on energy consumption and comfort.

**Method**

Annual building energy simulations were carried out for a small office building consisting of two zones viz. Office Space Main and Office Space 1 with area of 444 m² (4779 ft²) and 67 m² (721 ft²) respectively. To study the impact of the realistic controls, a two stage roof top unit of 35 kW (10 ton) cooling capacity is considered for meeting the cooling demands of Main Office Zone. The cooling demand of the zone Office Space 1 is considered to be met by an ideal HVAC system (using EnergyPlus’ system definition). The thermostat cooling set-point for the zones is always at 23.89 °C (75 °F).

The building is modelled in EnergyPlus 8.6.0 and includes the building geometry, envelope construction and material, infiltration, occupancy, lighting and equipment schedules. The ideal HVAC system is modelled using Ideal Loads Air System object in EnergyPlus. To simulate the real time operation of the HVAC system for the Office Space Main, the equipment is modelled using performance curves based on lab test data and its control logic is implemented in Matlab. The performance curves are generated for both steady state operation (when the system is in Stage 1, in stage 2, or OFF) as well as transient state (the transition between ON to OFF, OFF to ON etc.) The steady state performance curves are similar to what is used commonly in energyplus, and can be generated from manufacturer’s published data. The performance curves for transient state modelling need data from lab testing.

The single family residential building consists of a 2 storey conditioned zone and an unconditioned attic zone with floor areas of 223 m² (2400 ft²) and 111.5 m² (1200 ft²) respectively. The thermostat cooling set-point is at 23.88 °C (75 °F) with a setback to 26.67 °C (80 °F) during the day time, the period of reduced occupancy between 8:00 and 18:00 hours.

The building model in EnergyPlus and equipment model in Matlab are connected using MLE+ for co-simulation. MLE+ is an open-source Matlab/ Simulink toolbox developed by Nghiem, Truong X (2010) et al. at mLAB, the Real Time Embedded Lab at the University of Pennsylvania. MLE+ integrated and adapted source code from the BCVTB and provides a more direct coupling between Matlab and EnergyPlus (from discussion with Michael Wetter at LBNL).

The simulation setup is as shown in Figure 1. It broadly consists of an EnergyPlus input file, a Matlab script file and a variable configuration file. For each time-step, EnergyPlus performs the zone heat balance considering the ambient conditions from weather data, internal loads and system parameters and finds the resulting zone thermal conditions. The zone and ambient conditions namely, temperature and relative humidity, are sent to Matlab at each time-step. The
control logic in Matlab determines the operating mode of the system, i.e. stage 1 or stage 2 and transient or steady state operation, and accordingly the equipment capacity and its power consumption for that time-step are determined. From these values, the system air flow rate, temperature and relative humidity are calculated and together with the zone thermostat set-point are sent back to EnergyPlus for zone heat balance in the subsequent time-step. On an average, the annual simulation runs took 15 to 20 minutes for completion.

Table 1: Variables for co-simulation.

<table>
<thead>
<tr>
<th>Source</th>
<th>EnergyPlus Object Type</th>
<th>Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>EnergyPlus</td>
<td>Output: Variable</td>
<td>Site Outdoor Air Dry Bulb Temperature</td>
</tr>
<tr>
<td>EnergyPlus</td>
<td>Output: Variable</td>
<td>Site Outdoor Air Relative Humidity</td>
</tr>
<tr>
<td>EnergyPlus</td>
<td>Output: Variable</td>
<td>Zone Air Temperature</td>
</tr>
<tr>
<td>EnergyPlus</td>
<td>Output: Variable</td>
<td>Zone Air Relative Humidity</td>
</tr>
<tr>
<td>Matlab</td>
<td>ExternalInterface: Actuator</td>
<td>Ideal Loads Air System Air Mass Flow Rate</td>
</tr>
<tr>
<td>Matlab</td>
<td>ExternalInterface: Actuator</td>
<td>Ideal Loads Air System Air Temperature</td>
</tr>
<tr>
<td>Matlab</td>
<td>ExternalInterface: Schedule</td>
<td>Heating Setpoint Thermostat Schedule</td>
</tr>
<tr>
<td>Matlab</td>
<td>ExternalInterface: Schedule</td>
<td>Cooling Setpoint Thermostat Schedule</td>
</tr>
</tbody>
</table>

Results and Discussion

Office Building Simulation

Air conditioner cycling is generally modelled using average performance degradation effects of cycling over a given time step rather than modelling individual on-off cycles. Cyclic losses are accounted for by increasing the required air conditioner runtime to meet the building load. The runtime factor is a function of degradation coefficient (CD), the factor of efficiency loss due to the cycling of the unit (ASHRAE Standard 116-1995). The degradation coefficient CD for cooling cyclic operation is calculated as follows.

\[
CD = \left\{1 - \frac{EER_{cyc}}{EER_{ss}}\right\} / (1 - CLF)
\]  

The value of CD is typically between 0.05 (lower cycling loss) and 0.25 (higher cycling loss); Modern, single-stage air conditioners tend to have CD values around 0.07. From the results in the paper, we can see that the energy losses are almost similar to CD, so it is reasonable to conclude that the increase in energy consumption due to cycling losses is in the same range as CD – i.e. from 5% to 25% (Boothen, Christensen and Winkler, 2014). More often, during whole building simulations, a typical number for CD is used for all scenarios that are analysed – which results in a constant % increase in energy consumption due to cycling.

Analysis between steady state (does not include cycling impacts) vs. transient state (this state considers the impact of cycling) shows that the cycling losses differ significantly, depending on the conditions in which the unit is operating. Two different locations, Miami and Phoenix, have been considered in this study. Table 2 summarizes the results of steady state and transient state annual simulation of the building at these locations. Miami shows a 4% increase in energy consumption due to cycling losses. This is in line with the typical 7% energy consumption increase for a modern single-stage air conditioner. The unit in the study is 2-stage unit, so we can expect the cycling losses to be less. On the other hand, Phoenix shows a 15% increase in energy consumption due to cycling. It shows that the increase in runtime, which is 3% more in Phoenix compared to Miami, translates to an 11% more increase in energy consumption due to inclusion of transients in the simulation. Considering indoor zone conditions, the impact on humidity is more pronounced due to inclusion of the transient performance curves - which model the re-evaporation of condensate on the evaporator coil (Figure 3).

Table 2: Comparison of annual steady state and transient simulation for Phoenix and Miami.

<table>
<thead>
<tr>
<th>Location</th>
<th>Simulation Type</th>
<th>Total Energy [kWh]</th>
<th>Hours when Indoor RH &gt; 60 %</th>
<th>Hours when Indoor Temperature &gt;24.2 °C (75.5 °F)</th>
<th>Total Operating Hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>Miami</td>
<td>Steady State</td>
<td>25218</td>
<td>1152</td>
<td>452</td>
<td>4958</td>
</tr>
<tr>
<td></td>
<td>Transient State</td>
<td>26138</td>
<td>2137</td>
<td>364</td>
<td>5715</td>
</tr>
<tr>
<td>Phoenix</td>
<td>Steady State</td>
<td>24250</td>
<td>0</td>
<td>629</td>
<td>4215</td>
</tr>
<tr>
<td></td>
<td>Transient Stat</td>
<td>28405</td>
<td>0</td>
<td>661</td>
<td>5042</td>
</tr>
</tbody>
</table>

*These simulations were run with the following control parameters.
  i. Minimum off time & Minimum on time : 3 minute
  ii. Low stage time setting : 15 minute
The simulation of realistic control allows one to consider the impact of control parameters on energy consumption (Minimum on time, Minimum off time, Low stage time setting in the case of on-off control logic; Minimum on time, Minimum off time Cycles per hour, Proportional and Integral gains in case of PI control logic).

Table 3 summarizes the results of annual simulation for the office building at Miami with different values for the HVAC system control parameters. Table 4 summarizes the results of annual simulation for the office building at Phoenix with different values for the HVAC system control parameters. In both cases the transients are included.
Comparing the combinations that result in minimum energy value vs. the maximum energy value, the difference in energy consumption is about 1% to 2%. At first, this does not appear significant, but if we consider the impact on humidity, 4% (7% of System ON hours) less hours are outside the humidity comfort criteria for Miami. Similarly, for indoor temperature, looking at the Figure 4 and 5, we can see that changing the min-on/off time increases the amplitude of temperature. One would need to consider this parameter depending on how tight the control of temperature is required. On the other hand, in this study, for the limited number of options considered, the minimum time for a stage does not have much impact on comfort, so one could select this parameter based on just energy criteria, if it makes a difference.

### Table 3: Annual energy consumption and temperature set-point unmet hours at Miami at different control settings.

<table>
<thead>
<tr>
<th>Min. On Time [min]</th>
<th>Min. Off Time [min]</th>
<th>Low Stage Time Setting [min]</th>
<th>Total Energy [kWh]</th>
<th>Number of hours when Indoor RH &gt; 60 %</th>
<th>Number of hours when Indoor Temperature &gt;24.2 °C (75.5 °F)</th>
<th>Total Annual Operating Hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>3</td>
<td>10</td>
<td>26090</td>
<td>2157</td>
<td>378</td>
<td>5679</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>12</td>
<td>26137</td>
<td>2142</td>
<td>368</td>
<td>5696</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>15</td>
<td>26138</td>
<td>2137</td>
<td>364</td>
<td>5715</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>20</td>
<td>26123</td>
<td>2110</td>
<td>360</td>
<td>5735</td>
</tr>
<tr>
<td>4</td>
<td>4</td>
<td>10</td>
<td>26030</td>
<td>2314</td>
<td>478</td>
<td>5691</td>
</tr>
<tr>
<td>5</td>
<td>5</td>
<td>10</td>
<td>25983</td>
<td>2462</td>
<td>587</td>
<td>5676</td>
</tr>
<tr>
<td>6</td>
<td>6</td>
<td>10</td>
<td>25939</td>
<td>2529</td>
<td>639</td>
<td>5672</td>
</tr>
<tr>
<td>4</td>
<td>4</td>
<td>20</td>
<td>26087</td>
<td>2145</td>
<td>451</td>
<td>5758</td>
</tr>
<tr>
<td>5</td>
<td>5</td>
<td>20</td>
<td>26044</td>
<td>2183</td>
<td>570</td>
<td>5769</td>
</tr>
<tr>
<td>6</td>
<td>6</td>
<td>20</td>
<td>26023</td>
<td>2233</td>
<td>648</td>
<td>5772</td>
</tr>
</tbody>
</table>

### Table 4: Annual energy consumption and temperature set-point unmet hours at Phoenix at different control settings.

<table>
<thead>
<tr>
<th>Min. On Time [min]</th>
<th>Min. Off Time [min]</th>
<th>Low Stage Time Setting [min]</th>
<th>Total Energy [kWh]</th>
<th>Number of hours when Indoor RH &gt; 60 %</th>
<th>Number of hours when Indoor Temperature &gt;24.2 °C (75.5 °F)</th>
<th>Total Annual Operating Hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>3</td>
<td>10</td>
<td>28326</td>
<td>0</td>
<td>709</td>
<td>4918</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>12</td>
<td>28348</td>
<td>0</td>
<td>670</td>
<td>4991</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>15</td>
<td>28405</td>
<td>0</td>
<td>661</td>
<td>5042</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>20</td>
<td>28389</td>
<td>0</td>
<td>676</td>
<td>5087</td>
</tr>
<tr>
<td>4</td>
<td>4</td>
<td>10</td>
<td>28340</td>
<td>0</td>
<td>825</td>
<td>4887</td>
</tr>
<tr>
<td>5</td>
<td>5</td>
<td>10</td>
<td>28728</td>
<td>0</td>
<td>900</td>
<td>4843</td>
</tr>
<tr>
<td>6</td>
<td>6</td>
<td>10</td>
<td>28965</td>
<td>0</td>
<td>956</td>
<td>4804</td>
</tr>
<tr>
<td>4</td>
<td>4</td>
<td>20</td>
<td>28386</td>
<td>0</td>
<td>798</td>
<td>5078</td>
</tr>
<tr>
<td>5</td>
<td>5</td>
<td>20</td>
<td>28646</td>
<td>0</td>
<td>859</td>
<td>5053</td>
</tr>
<tr>
<td>6</td>
<td>6</td>
<td>20</td>
<td>28821</td>
<td>0</td>
<td>886</td>
<td>5027</td>
</tr>
</tbody>
</table>

### Single family residence simulation

The single family residence simulation uses PI control logic. In addition to minimum on/off time and cycles per hour parameter used in on/off control, PI control has additional parameters related to proportional and integral gains. Figure 6 shows the comparison between indoor temperature for various typical combination of proportional and integral gains, keeping the other parameters constant. As can be seen, the cycling varies quite a bit based on the parameters used, and also results in 5-7% (7% for no setback scenario – not detailed in the paper) HVAC energy consumption increase (~2-4% energy consumption at the whole building level). To put the data in perspective, a typical retrofit involving window upgrades (in both residential and commercial buildings) show negligible savings (2-5% range at the
whole building level) and in almost all cases not cost-effective (Sam Cohen, Charles Goldman and Jeff Harris, 1991).

Conclusions
This paper describes the advantages of simulating actual control logic in conjunction with building simulation. From a control logic developer’s standpoint, this allows him to consider the validity of the control parameters for all conditions that the equipment would be subjected to, instead of considering a few common scenarios. As the results related to cycling losses analysis show, in some cases, the savings and indoor conditions outcome is very different from what would have been obtained by traditional whole building simulation methodology. Similarly, even though the energy savings by loosely optimizing on the control parameters is not huge, when compared to typical retrofit savings, it gives similar savings, at no-cost.

In conclusion:

a. This setup allows better prediction of cycling losses.
b. It allows one to study the impact of control parameters on annual energy consumption and comfort indices.

c. It helps in avoiding rule of thumb / assumptions related to control strategies, cycling, parasitic losses, etc.

d. More importantly, this setup opens up the analysis of any number of enhancements to typical control strategies which are pre-defined in whole building simulation tools.

Acknowledgments
We would like to acknowledge the contributions by Jason Hou and Jie Ma (Purdue University) in implementing the control logic in Matlab; and Yanfei Li (University of Alabama) in setting up the connection between EnergyPlus and Matlab to allow for co-simulation.

Nomenclature
BCVTB: Building Controls Virtual Test Bed
CPH: Cycles per hour
CLF: Cooling Load Factor
EERcyc: Cyclic Energy Efficiency Ratio
EERss: Steady State Energy Efficiency Ratio
KISS: Integral Steady State Gain
KPSS: Proportional Steady State Gain
PI: Proportional Integral
PNNL: Pacific Northwest National Laboratory
RH: Relative Humidity

References

Methods of testing for rating seasonal efficiency of unitary air conditioners and heat pumps (ASHRAE Standard 116-1995).


PNNL - Commercial Prototype Building Models,
https://www.energycodes.gov/development/commercial/prototype_models

PNNL - Residential Prototype Building Model,
https://www.energycodes.gov/development/residential/iecc_models

Figure 7: Variable configuration file snippet.

```xml
<xml version="1.0" encoding="ISO-8859-1"?>
  <!DOCTYPE BCVTB-variables SYSTEM "variables.dtd">  
  <BCVTB-variables>

    <!-- The next two elements receive the outdoor and zone air temperature from E+ -->
    <variable source="EnergyPlus">
      <EnergyPlus name="ENVIRONMENT" type="Site Outdoor Air Drybulb Temperature"/>
    </variable>
    <variable/>

    <variable source="EnergyPlus">
      <EnergyPlus name="ENVIRONMENT" type="Site Outdoor Air Relative Humidity"/>
    </variable>
    <variable/>

    <!-- The next two elements send the set points to E+ -->
    <variable source="Ftoley">
      <Ftoley actuator="Reset_Zone_SA_Flow"/>
    </variable>
    <variable/>

    <variable source="Ftoley">
      <Ftoley schedule="CSP"/>
    </variable>
    <variable/>

  </BCVTB-variables>
```

Figure 8: Matlab code snippet – Start co-simulation and collect inputs from EnergyPlus.

```matlab
%% Create an mlepProcess instance and configure it
% installMlep;
ep = mlepProcess;
VERNUMBER = 2; % version number of communication protocol (2 for E+ 7.2.0)
%% Start EnergyPlus cosimulation
[status, msg] = ep.start;
if status ~= 0
  error('Could not start EnergyPlus: %s.', msg);
end
[status, msg] = ep.acceptSocket;
if status ~= 0
  error('Could not connect to EnergyPlus: %s.', msg);
end

%% The main simulation loop
for kStep=1:MAXSTEPS
    % Read a data packet from E+
    packet = ep.read;
    if isempty(packet)
        error('Could not read outputs from E+.
    end
    % Parse it to obtain building outputs
    % ep_outputs_to_Matlab contains: [outdoor_air_temp, zone_air_temp, zone_air_humidity]
    [flag, etime, ep_outputs_to_matlab] = mlepDecodePacket(packet);
    if flag ~= 0, break; end
    OAT(kStep) = ep_outputs_to_matlab(1);
    saflow_ep(kStep) = ep_outputs_to_matlab(2);
    zoneTemp(kStep) = ep_outputs_to_matlab(3);
    RH_room(kStep) = ep_outputs_to_matlab(4);
    GARH(kStep) = ep_outputs_to_matlab(5);
end

%% Write to outputs of E+
    etime = mod(etime, 86400); % time in current day
    onoff_ctrl = [...];
    matlab_outputs_to_ep = [saflow_ep(matlab_outputs_to_ep), DATF, ...]
    ep.write(mlepEncoderRealData(VERNUMBER, 0, (kStep-1)*sim_timestep, matlab_outputs_to_ep));
end

%% Stop EnergyPlus
ep.stop;
% disp(['Stopped with flag ' num2str(flag)]);
```

Figure 9: Matlab code snippet – Send outputs to EnergyPlus and stop co-simulation.
A Simplified Building Controls Environment with a Reinforcement Learning Application

Vasken Dermardiros¹, Scott Bucking², Andreas K. Athienitis¹
¹ Centre for Zero Energy Building Studies, Department of Building, Civil and Environmental Engineering, Concordia University, Canada
² Department of Civil and Environmental Engineering, Carleton University, Canada

Abstract
This paper has two contributions: (1) it describes the design and implementation of a thermal network based building zone emulator environment suitable for control applications with inputs and outputs matching those of the OpenAI Gym environments; and (2) the use of the environment to train a proximal policy optimization (PPO) reinforcement learning (RL) agent to maintain comfort for a house while minimizing the HVAC system energy consumption. The building controls environment can be extended to many other cases including training agents that can be mass-applied, studying the behaviour of communities and studying occupant behaviour and comfort. The trained RL agent was compared to conventional bang-bang and proportional-integral controllers. Given the penalty weights, the RL agent was more adept at minimizing equipment cycling thus improving equipment longevity and efficiency.

Introduction
As more decentralized renewable energy sources are introduced onto the grid, utility level load balancing is becoming an issue. Photovoltaics can potentially create local generation peaks when the loads are low and thus the grid may not be able to absorb this production. Wind turbines rely on wind which fluctuates. Recently, Google DeepMind is in talks with UK’s National Grid to help balance their electricity demand due to their larger reliance on energy from intermittent renewable sources (Thomas, 2017).

Regulation can occur on the utility side through modulating power plants or using large scale storage solutions, or on the consumption side through incentives and direct links with intelligent thermostats. Intelligent buildings and homes can aid the utility by relying on energy flexibility concepts such as optimally controlling their thermal and/or electrical storage systems (Denholm and Hand, 2011; Jensen et al., 2017; Morales et al., 2014).

Nest (Nhede, 2018) reports being able to save its US customers 12% in heating and 15% in cooling costs by shifting the usage period from peak times to when energy demand is lower and cheaper. Ecobee (Ecobee, 2018) another smart thermostat manufacturer, has a “donate your data” program where customers can share anonymized data to help researchers develop more energy efficient control strategies by having a statistical representation of the population. Even with an added layer of smartness, the underlying control algorithms in these thermostats are conventional and reactive. They condition the space based on a setpoint error: amount of heating or cooling is proportional to a difference in a desired and measured temperatures, with a deadband to reduce excessive cycling of the equipment. There is seldom reliance on the use of weather or occupancy predictions and on the use of the building characteristics itself. There is work on applying model-based predictive controls (MPC) on buildings, but it requires an accurate model of the system to be controlled which can be cumbersome to build (Shaikh et al., 2014).

Artificial intelligence (AI) techniques can be used to learn a surrogate model of the building using a black-box machine learning (ML) approach (Gaussian process regression models, support vector regression, random forests, neural network models) or using a grey-box Bayesian regression method (applied to a generalized linear model or other) where the learned parameters are physically interpretable. These learned models would then be used in a model-based predictive control (MPC) framework to control the system by minimizing its cost function. Alternatively, the model can be learned internally by a reinforcement learning (RL) agent which then uses it to apply actions to maximize its rewards. The learned model remains within the agent’s brain and is not accessible by other external programs. The RL case is presented in this paper.

RL has received tremendous attention lately after having defeated the world’s strongest Go player trained purely by self-play (Silver et al., 2017) and performing at a professional level in an imperfect information game of Dota 2 (OpenAI, 2018), and more recently, beat professional players in the real-time-
strategy game StarCraft II\textsuperscript{1}. Contrary to IBM’s Deep Blue chess program, these methods are not domain specific and the training methods can be generally applied to any problem that can be formulated as a Markov decision process – with care, this assumption can be relaxed. In a nutshell, an RL agent interacts with its environment to come up with a policy – what action to take when in a certain state – to maximize its sum of future discounted rewards. There exist many learning schemes and high-quality implementations are made available online through open source libraries such as OpenAI Baselines (Dhariwal et al., 2017) and Tensorforce (Schaarschmidt et al., 2017). These libraries plug their agents into standardized environments like those found in OpenAI Gym. By creating an environment that matches these requirements, we can directly leverage cutting-edge advances in RL into our building engineering and controls domain by using these libraries instead of having to re-implement the logic.

To briefly overview the RL process, an agent is placed in an environment where it observes the state it’s in and decides on what action to take based on its policy. Given the action, the environment responds and returns an updated state and, optionally, a reward, see Figure 1. This process continues until the end of the episode, after which, the environment is reset and the process is run again. Every episode is independent of one another. The agent’s task is to apply actions as to maximize its discounted future returns. During training, the agent is encouraged to explore the environment in an attempt to maximize its returns. As training continues and nears its end, exploration is forgone for exploitation of reward maximizing actions via an optimized policy. One of the major assumptions in RL is that the information contained in the current state is sufficient to drive a decision – Markov property.

Most reinforcement learning tasks are Markov decision processes (MDPs) and usually have a finite state and action spaces – called finite MDPs. A finite MDP is defined by its state and action sets and by the one-step dynamics of the environment. Given any state \( s \) and action \( a \), the probability of each possible pair of next state \( s' \) and reward \( r \), is denoted (Sutton and Barto, 2017, see Sec. 3.6):

\[
p(s', r|s, a) \doteq Pr\{S_{t+1} = s', R_{t+1} = r \mid S_t = s, A_t = a\}. \tag{1}
\]

The reader is encouraged to consult Sutton and Barto’s "Reinforcement Learning: An Introduction" textbook (Sutton and Barto, 2017) for a thorough introduction to the field. In this paper, the probability of getting to the next state \( s' \) is based on deterministic equations – it is a deterministic state transitional model.

Compared to MPC, RL methods map a state to an action learning a model of the environment internally whereas MPC takes in a model with the current state plus certain predictions and uses optimization to determine the best actions. Once trained, an RL agent will perform faster than an MPC scheme and with a smaller software footprint; however, training the agent to be robust is difficult and remains an open research question.

The second objective of this paper is to conduct a preliminary study to see if RL – on-policy, model-free – can be applied to buildings. Since we do not have a test building to experiment on, we have implemented a general thermal network model framework to emulate a building environment specifically for controls. Future work will consider applying RL to higher fidelity building simulation engines like EnergyPlus – Spawn-of-EnergyPlus (Spawn) with the Functional Markup Interface (FMI) seems to be a promising path, a beta version is expected in 2020 to 2021 (USDOE, 2019) –, TRNSYS or OpenModellica, and finally on an actual building or experimental setup. In all cases, the simulation models\textsuperscript{2} or experiment’s inputs and outputs should be mapped to match the formatting of OpenAI Gym to ease integration.

The contribution of this work is to demonstrate the development and use of a building emulator RL environment. This work is made publicly available\textsuperscript{2} where users can develop, implement and then upload their own features.

The advantage of the emulator herein versus higher fidelity models is, firstly, speed. Second, having a test bed where the controller does not see the underlying building model offers a more realistic testing environment since in most controller cases, especially in smaller buildings, there is scarce information about the characteristics of the space or its service systems besides the actuation levels. Having a common test bed, various algorithms and control methodologies can be compared, as well as model-learning algorithms (Kalman filters, Gaussian regression models, optimization-based methods) where the learned model will be used, for example, in MPC.

---

\textsuperscript{1}https://deepmind.com/blog/
alphastar-mastering-real-time-strategy-game-starcraft-ii/

\textsuperscript{2}https://www.github.com/vderm/
SimplifiedBldgControlEnv
Review

The building controls must be robust to sensor measurement noise and to errors in weather and occupancy predictions to plan the best route or control sequence to apply.

There is a large library of papers modelling buildings for various types of control algorithms and very many on general reinforcement learning problems (20,000 new publications in 2018). However, we were able to identify only a handful that applies reinforcement learning to space conditioning. In their paper, Yamaguchi et al. (2015) have employed Q-Learning RL to an office space with multiple users. The thermal sensations of users were mapped as fuzzy ranges of hot, cold, or other. The ranges represent our ability to adapt to small temperature changes or to adjusting our clothing levels. The RL policy would try to minimize the overall dissatisfaction of the users. The action space consists of 3 power levels of heating and 3 for cooling. Different methods of comfort aggregation were used for rooms with many occupants. Lastly, they added a penalty for excessive use of cooling but the paper fails to report if it resulted in energy savings or improved comfort. The thermal model seems to be based on Fourier’s Law of Heat Conduction.

In Nagy et al. (2018), the authors have not simplified comfort to be hot or cold but cause a penalty as a function of how far the space temperature is relative to the comfort bounds. The authors claim the equation was based on thermal user comfort literature. The action space in their paper is a discrete set of values between full-off and full-on the agent can select. Overall, the agent is able to maintain a comfortable environment and is able to save 5-10% energy compared to a rule-based approach. They note further improvements can be made. Recently, Moriyama et al. (2018) have applied RL – trust-region policy optimization (TRPO) learning algorithm – on a data centre to minimize energy use while satisfying temperature constraints. The data centre is modelled in EnergyPlus and EnergyPlus’s Energy Management System (EMS) is used to supply external commands while the simulation is running. The inputs (continuous-domain temperatures) and outputs (continuous-domain temperature setpoints and airflow rates) are mapped to match that of OpenAI Gym. The RL reward function is designed to keep the centre’s temperature at a fixed setpoint by having small penalties around this value and linearly larger outside a threshold. This would attract the RL agent towards the setpoint by providing a smooth penalty. The authors picked EMS over the FMI since their application was simple enough and EMS was sufficient. The authors have published their source code online and by changing a few files, their framework can be used for other EnergyPlus models. Compared to a simpler equation-based method, EnergyPlus will be slower to train.

Method

For our environment, we use a general thermal network based approach. The user can describe their thermal network following the methodology shown in the "Finite Difference Heat Transfer Model" Appendix or simply use one of two predefined network models. The first is a 1st-order model which could represent simple spaces like a condo, a small house or a single office (see Appendix). The second is a 2nd-order model where the heating/cooling is applied to a thermal node that can be different from the occupied space node, such as the case of a radiant slab system. For control purposes, research has shown that simplified models are often suitable to represent the behaviour of a system (Candanedo and Athienitis, 2010; Athienitis and O’Brien, 2015). Our environment implementation is general and allows users to define a building in as much detail as required. A small house can be modelled with a simple model while a sizable office building with varying uses requires more detail.

The environment can run a curriculum of cases to ease learning going from synthetic simple weather and internal loads to more realistic weather read from EnergyPlus "*.epw" weather files. Future work is required to add in realistic and dynamic occupancy behaviour. The states can simply be what a smart thermostat observes plus noisy weather predictions where the further the prediction, the more (Gaussian) noise is added. The uncertainty of weather predictions is based on collected prediction data and compared to what actually happened. These predictions would represent what can readily be obtained from online weather sources. See Figure 2 and last section of the Appendix for simulation parameters, state descriptions and RL agent settings.

The action space is discrete: go cooler, stay, go warmer. This way, the agent can learn to either increase or decrease the amount of heating/cooling instead of picking a discrete action over all HVAC settings and translates more to how we tend to explain
our comfort, e.g., if a person feels cold, he/she will want the heating increased, if they are still cold, heating should be increased again.

For the rewards and penalties (negative rewards), the higher HVAC settings impose a stronger penalty than the low settings. Having the HVAC off is free. The HVAC level penalties do not change during the day, i.e., time-of-use energy pricing is not included, however it could be. To limit excessive cycling of equipment, especially to limit going from heating to cooling within a few timesteps, a rate-of-change penalty is added. When it comes to thermal comfort, the agent needs to maintain the room temperature within the setpoint bands otherwise a linear penalty is applied. The comfort penalty function of Nagy et al. (2018) was also implemented but not used as the linear penalty yielded better results. No terminal reward is given at the end of the episode. Details in Table 5 in the Appendix.

The agent selected in this paper uses the proximal policy optimization (PPO) method of learning. PPO was developed by OpenAI (Schulman et al., 2017) and in a blog post, they say "[PPO performs] comparably or better than state-of-the-art approaches while being much simpler to implement and tune" and is now one of the go-to algorithms in RL. Table 3 in the Appendix describes all parameter settings. PPO is a policy gradient method and it maps states to actions directly instead of going through a value or action-value function; we suggest the reader to consult the chapter about policy gradient methods in Sutton and Barto’s book (chapter 13 as of the date of this publication).

The environment is customizable. The reward or penalty schedule can be changed to correspond to time-of-use electrical pricing, or a demand response signal, or to improve on-site consumption of renewable energy generation. The HVAC system can have as many operating modes as desired, but they need to be input in ascending order of power. Temperature limits can be adjusted and adapted based on occupant feedback or adaptive models. The agent can also be swapped for another.

Results

To compare the performance of the reinforcement learning agent, we propose a bang-bang and proportional-integral (PI) controller that correspond to what is currently present in most homes. The bang-bang controller will have two stages for heating and one stage for cooling. In a heating application, if the temperature drops below a set temperature, stage 1 will be activated until the room temperature passes a threshold and then it will turn off to reduce cycling of the equipment. If the temperature of the room instead keeps dropping, a second threshold is used to activate a second stage of heating. Cooling is applied in a similar manner but for when the space is hot.

The PI controller will supply heat proportional to the setpoint error $e(t)$ – the difference between the current and setpoint temperatures. The integral term is used to correct for oscillatory behaviour. In our case here where the HVAC system works in discrete stages, the HVAC stage that comes closest to the output from the PI controller will be used with an additional deadband to, again, reduce cycling of the equipment. The PI output is given by:

$$\text{output}(t) = K_p e(t) + K_i \int_0^t e(t')dt'$$  

Where $K_p$ and $K_i$ are the proportional and integral factors that are selected to improve response and limit oscillatory behaviour. These factors were chosen based on heuristic rules and iteratively. Bang-bang and PI controller parameters are given in Table 4 in the Appendix.

The reinforcement learning agent is trained on the environment for 2500 episodes, 200 on synthetic cases, 1600 of which on random days of the year and the remainder on random weeks of the year. To test learning, the weather file can be changed to assure memorization is not occurring. Also, the neural network brain of the agent is not deep enough to truly memorize the weather file. In this paper, a typical house in Montreal is considered without and with a radiant floor system; Montreal weather data is used.

The agent’s learning can be tracked by looking at its accumulated rewards per episode as training progresses, see Figure 3. Here, we observe an increase in the collected rewards until it seems to plateau and training is stopped to reduce over-fitting. After 1800 episodes, the learning curriculum is switched and we observe a strong but brief decline in the rewards. As a cautionary note, over-training an agent on simple and synthetic cases can lead to a collapse in the weights of the neural network brain and learning irreversibly ceases; the agent needs to be then reinitialized.

Heating Scenario

Beginning with the heating cases. We have selected a very cold week in winter (see bottom-left subplot of Figure 5 for the ambient temperature), to compare how conventional controls compare to the RL agent. As can be seen from Figure 4, left, the bang-bang and
PI controllers try to maintain the lower limit temperature (setpoint was 20.5-21°C), the applied actions are representative of their design. The PI temperature over time is slowly moving upwards due to the integral portion of the controller. The RL controller, due to the set penalties, tries to maintain the temperature within the comfort boundaries and minimizes toggling of the HVAC system. The penalty weights can be tuned to instead reduce energy consumed and the room temperature would hover nearer to the lower limit. A grid-search or Bayesian optimization can be performed to determine parameter values to fine-tune the RL controller performance to users’ needs.

**Cooling Scenario**

In the cooling case, a hot summer week is selected (see bottom-right subplot of Figure 5). Compared to the conventional controllers, the RL case performs worst (see Figure 4, right). During the first day, the RL agent keeps the cooling off to minimize its HVAC toggle penalty which led to warmer space temperatures. The following days, it recovers and maintains comfort, but tends to hug the lower comfort boundary which requires more cooling energy.

**Radiant Floor System**

In the previous two cases, the 1st-order model was used where the HVAC system supplies the space directly. To study if the RL agent makes use of the future weather predictions returned by the environment, a case where the heating or cooling is supplied indirectly such as heating or cooling a hydronic radiant floor slab should be analysed. We have trained the RL agent on the 2nd-order model to see if it will utilize pre-heating and pre-cooling strategies. Results shown in Figure 5 for both winter and summer cases. Model parameters are listed in Table 2 in the Appendix.

We do see the temperature being maintained between the setpoints. Looking closely at the HVAC states and the ambient temperature — the bottom two subplots — we see pre-cooling for the summer case at around the 84th and 104th hours. The cooling is turned on before the peak temperature. The heating is turned on briefly at the 144th hour. A stronger penalty can be incorporated to ensure the HVAC system does not go from cooling to heating within a few hours; there is only a toggling penalty at this moment to avoid the use of both heating and cooling during the same day. In the winter heating case, the exterior ambient temperature is rather flat throughout the day and there is no advantage in pre-heating; heating should be supplied continuously.

**Discussion and Future Work**

In this study, we fixed the emulator model parameters to be more or less a typical house in Montreal based on our prior experience. In an application, the environment parameters that characterize the building itself can in fact be estimated and updated overtime using a Kalman filter approach based on the response of the building (Radecki and Hencey, 2012). The RL agent would then rely on the updated environment to train and would send commands to the actual building. This approach would effectively be closer to a model-based method and offers a low-disruptive control application. The reward function penalizes HVAC toggles, however, for a house in winter, having both heating and cooling on the same day should be disallowed by strongly penalizing this behaviour. For an office space, heating and cooling in the same day is possible.

As mentioned earlier, Ecobee has a "donate your data" program (Ecobee, 2018). This anonymized dataset can be used to determine environment parameters — one set per house. We can use these parameters and create a building environment instance per house. We can then train an agent on many different houses to come up with a "good enough" policy that can be mass-deployed on every intelligent thermostat. This policy would then be specialized to its house over time and discomfort reward signals would come directly from the occupants. Each person having a different thermal preference, the agent would eventually adapt to their comfort requirements.

Additionally, having a large set of building environment instances, we can essentially simulate the behaviour of a neighbourhood and perform community energy strategies/studies, e.g. Bucking and Dernadiros (2018). These simulated communities can help utilities test out various incentives and load management strategies.

One of the limitations of RL is that it tends to require an enormous amount of episodes and data to learn an optimal strategy/policy. This is because the RL agent not only needs to understand the environment it is in — effectively creating an approximate representation of the environment — but to also apply optimal actions. Action selection in itself is a difficult task. Recent work applies MPC in RL to improve action selection and/or to create an approximate physics-based model of the environment, e.g. Kamthe and Deisenroth (2017). Having introduced more structure to the problem, the agent can learn the optimal policy with greater ease which translates to a more effective use of episodic experience and in robust actions.

**Conclusion**

The main contribution of this work is the development of an open-source Python emulator with structure matching that of the OpenAI Gym environments. By relying on a standardized environment, cutting-edge reinforcement learning based methods can be directly applied to building service system controls. From the point of view of the controller,
the emulator corresponds to a model-less test bench where various control strategies and model-learning algorithms can be tested and compared. The emulator is based on a thermal network model representation. Two predefined models are included and a generic model where the user can design their system with as much detail as required. The emulator uses standard EnergyPlus "*.epw" weather files which can be swapped. Dynamic and realistic occupancy behaviour remains as future work. Another future work would be to partially train the agent on our environment and then move it to a more realistic/detailed model following the EnergyPlus EMS OpenAI Gym wrapper methodology proposed by Moriyama et al. (2018).

As a second contribution and case study, a PPO RL agent was trained on the environment on a curriculum of cases: random days in a year and random weeks in a year. The trained agent was compared to conventional bang-bang and proportional-integral controls. The RL agent tries to apply control actions to maximize its rewards. Here, comfort and toggling the HVAC equipment had a relatively large attributed penalty compared to energy use and so the resulting agent would minimize toggling the equipment and having the space temperature fluctuate within the comfort bounds. Given this learned behaviour, equipment life is likely to be extended compared to bang-bang and PI controllers.

The emulator environment and examples are uploaded to our GitHub repository\textsuperscript{4}.

**Acknowledgements**

We would like to acknowledge the input from Doina Precup, Pierre-Luc Bacon and Maziar Gomrokchi from McGill’s Reasoning and Learning Lab. We would also acknowledge Tawfeeq Jawwar for multiple discussions. And finally, we are thankful for all the high quality open source resources made avail-

\textsuperscript{4}https://www.github.com/vderm/SimplifiedBldgControlEnv
able online, be it Sutton and Barto’s RL textbook, RL frameworks such as OpenAI Gym and Baselines, Tensorforce, thorough blog posts and the rich library of Python libraries.

Vasken Dermardiros would like to acknowledge the financial support received from the NSERC Alexander Graham Bell Doctorate Scholarship, the Hydro-Quebec Engineering and Computer Science (ENCS) Entrance Scholarship, the Professor Hugh McQueen Award of Excellence, and the Concordia Faculty of ENCS Graduate Scholarship.

Appendix

Finite Difference Heat Transfer Model

For this project, the implicit finite difference approximation (first-order backward in time Taylor approximation) to Fourier’s heat transfer equations was used. Generalizing for a system, the equation can be written in a matrix form as shown in Equation 3 where, \( nN \) is the number of nodes, and, \( nM \) is the number of nodes with known temperatures (boundary condition).

As an example where \( i = 1 \), we can draw the thermal network in Figure 6. Where, \( U_{ij} \) is the conductance between nodes \( i \) and \( j \) equal to \( \frac{kA}{dx} \) for conductance, \( h_{conv}A \) for convection and \( h_{rad}A \) for radiation, \( \frac{W}{K} \); \( C \) is the capacitance of node \( i \) equal to \( \rho c_pAdx \), \( \frac{J}{K} \); \( \dot{Q} \) is the heat flow into the node, \( W \); and, \( \Delta t \) is the timestep, s.

1st and 2nd-Order Pre-Defined Models

In the experiments reported in this paper, we have relied on a simple 1st-order pre-defined model called "F1C1", see Figure 7. Its effective capacitance and conductance values are based on typical values for a reasonably well-insulated single family home in Montreal – based on experience, see Table 1.

We have also successfully tested the environment using higher order models such as the case of having the heating/cooling system applying energy on a different node than that of where the thermostat is measuring, e.g., a space heated and cooled using a radiant slab system, or via a thermal storage source. Table 2 summarizes the 2nd-order model parameters.

Simulation and RL Agent Settings

Table 3 summarizes the reinforcement learning agent parameter settings. Table 4 describes the bang-bang and PI controller settings. Table 5 summarizes the simulation parameter.

---

### Table 1: 1st-order model "F1C1" parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( C, \text{ effective, } J/K )</td>
<td>( 12 \cdot 10^6 )</td>
</tr>
<tr>
<td>( U, \text{ effective, } W/K )</td>
<td>250</td>
</tr>
<tr>
<td>( \Delta t, s )</td>
<td>900</td>
</tr>
</tbody>
</table>

### Table 2: 2nd-order model "F1U1C2" parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( C, \text{ room, } J/K )</td>
<td>( 2 \cdot 10^6 )</td>
</tr>
<tr>
<td>( C, \text{ slab, } J/K )</td>
<td>( 10 \cdot 10^6 )</td>
</tr>
<tr>
<td>( U, \text{ to exterior, } W/K )</td>
<td>250</td>
</tr>
<tr>
<td>( U, \text{ slab to room, } W/K )</td>
<td>2775</td>
</tr>
<tr>
<td>( \Delta t, s )</td>
<td>900</td>
</tr>
</tbody>
</table>

---

For this project, the implicit finite difference approximation (first-order backward in time Taylor approximation) to Fourier’s heat transfer equations was used. Generalizing for a system, the equation can be written in a matrix form as shown in Equation 3 where, \( nN \) is the number of nodes, and, \( nM \) is the number of nodes with known temperatures (boundary condition).

As an example where \( i = 1 \), we can draw the thermal network in Figure 6. Where, \( U_{ij} \) is the conductance between nodes \( i \) and \( j \) equal to \( \frac{kA}{dx} \) for conductance, \( h_{conv}A \) for convection and \( h_{rad}A \) for radiation, \( \frac{W}{K} \); \( C \) is the capacitance of node \( i \) equal to \( \rho c_pAdx \), \( \frac{J}{K} \); \( \dot{Q} \) is the heat flow into the node, \( W \); and, \( \Delta t \) is the timestep, s.

1st and 2nd-Order Pre-Defined Models

In the experiments reported in this paper, we have relied on a simple 1st-order pre-defined model called "F1C1", see Figure 7. Its effective capacitance and conductance values are based on typical values for a reasonably well-insulated single family home in Montreal – based on experience, see Table 1.

We have also successfully tested the environment using higher order models such as the case of having the heating/cooling system applying energy on a different node than that of where the thermostat is measuring, e.g., a space heated and cooled using a radiant slab system, or via a thermal storage source. Table 2 summarizes the 2nd-order model parameters.

Simulation and RL Agent Settings

Table 3 summarizes the reinforcement learning agent parameter settings. Table 4 describes the bang-bang and PI controller settings. Table 5 summarizes the simulation parameter.
\[
\begin{bmatrix}
\sum_{j} U_{ij} + \sum_{k} U_{ik} + \frac{C_j}{\Delta t} - U_{i2} & \cdots & -U_{inN} \\
\vdots & \ddots & \vdots \\
-U_{nN1} & -U_{nN2} & \cdots & \sum_{j} U_{nNj} + \sum_{k} U_{nNk} + \frac{C_{nN}}{\Delta t}
\end{bmatrix}
\begin{bmatrix}
T_1 \\
\vdots \\
T_{nN}
\end{bmatrix}
= 
\begin{bmatrix}
\dot{Q}_1 + \sum_{k} (U_{1kk} T_{kk}) + \frac{C_1 T_1^2}{\Delta t} \\
\vdots \\
\dot{Q}_{nN} + \sum_{k} (U_{nNk} T_{kk}) + \frac{C_{nN} T_{nN}^2}{\Delta t}
\end{bmatrix}
\]

(3)

Table 3: Reinforcement learning agent parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value or Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agent type</td>
<td>Proximal policy optimization (PPO)</td>
</tr>
<tr>
<td>Library</td>
<td>Tensorforce v.0.4.3</td>
</tr>
<tr>
<td>Agent network</td>
<td>Dense 64 units + LSTM 64 units</td>
</tr>
<tr>
<td>Optimizer</td>
<td>ADAM, learning rate: 1e-3</td>
</tr>
<tr>
<td>Other settings</td>
<td>As per Quickstart tutorial,</td>
</tr>
<tr>
<td></td>
<td>link: <a href="https://bit.ly/2Tgi21i">https://bit.ly/2Tgi21i</a></td>
</tr>
</tbody>
</table>

Table 4: Bang-bang and PI controller parameters; Heating Stage 1 and 2 correspond to HVAC Setting 2 and 3. Cooling is HVAC Setting 0.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Controller</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heating</td>
<td>Bang-bang</td>
<td>ON, Stage 1</td>
<td>20.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>OFF, Stage 1</td>
<td>21.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>ON, Stage 2</td>
<td>19</td>
</tr>
<tr>
<td></td>
<td></td>
<td>OFF, Stage 2</td>
<td>21</td>
</tr>
<tr>
<td>PI</td>
<td>Setpoint</td>
<td>21</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Kp</td>
<td>5000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Ki</td>
<td>20</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Deadband</td>
<td>2000W</td>
<td></td>
</tr>
<tr>
<td>Cooling</td>
<td>Bang-bang</td>
<td>ON</td>
<td>25</td>
</tr>
<tr>
<td></td>
<td></td>
<td>OFF</td>
<td>23.5</td>
</tr>
<tr>
<td>PI</td>
<td>Setpoint</td>
<td>24</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Kp</td>
<td>3000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Ki</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Deadband</td>
<td>1000W</td>
<td></td>
</tr>
</tbody>
</table>

Table 5: Simulation parameters.

<table>
<thead>
<tr>
<th>Env. Perturbations</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Curriculum, episodes</td>
<td>200 synthetic + 1600 daily random + 700 weekly random</td>
</tr>
<tr>
<td>Temperature, boundary</td>
<td>Montreal *.epw” file</td>
</tr>
<tr>
<td>Int. gains, episode</td>
<td>Uniform(100, 800)</td>
</tr>
<tr>
<td>Solar gains</td>
<td>&quot;*.epw” file + 0.5 (occlusion)</td>
</tr>
<tr>
<td>Env. Settings</td>
<td>Description</td>
</tr>
<tr>
<td>T° initial, °C</td>
<td>N(22.5,0.5...2.0)</td>
</tr>
<tr>
<td>T° comfort limits, °C</td>
<td>Low: 20, high: 25</td>
</tr>
<tr>
<td>HVAC setting 0</td>
<td>-3000W (cooling), cost: -2</td>
</tr>
<tr>
<td>HVAC setting 1</td>
<td>0W (off), cost: 0</td>
</tr>
<tr>
<td>HVAC setting 2</td>
<td>5000W (heating), cost: -2</td>
</tr>
<tr>
<td>HVAC setting 3</td>
<td>10,000W (heating), cost: -4</td>
</tr>
<tr>
<td>HVAC initial setting</td>
<td>Setting 2, off</td>
</tr>
<tr>
<td>HVAC cost multiplier</td>
<td>0.2</td>
</tr>
<tr>
<td>Action toggle penalty</td>
<td>-0.8</td>
</tr>
<tr>
<td>Reward, termination</td>
<td>0</td>
</tr>
</tbody>
</table>
References


