Preprints of the 21st IFAC World Congress (Virtual)
Berlin, Germany, July 12-17, 2020

Low-Complexity Hierarchical Control for Distributed Shopping Center HVAC ⋆

Joakim Børlum Petersen * **Jan Dimon Bendtsen** *
Andrew Alleyne ** **Jakob Stoustrup** *

* *Automation and Control, Department of Electronic Systems, Aalborg University (e-mail: {jbp, dimon, jakob}@es.aau.dk).*
** *Mechanical Science and Engineering Department, University of Illinois at Urbana - Champaign (e-mail: alleyne@illinois.edu).*

Abstract: In this paper we present a low-complexity hierarchical control approach to fan-coil-based HVAC systems, applicable to shopping centers as exemplified through a case study of a Danish shopping center. Although Model Predictive Control remains the optimal approach performance-wise, we show that we can recover 66 % of the performance with the proposed approach, when considering no model-mismatch for the Model Predictive Controller. The recovered performance comes with the added benefits of increased reusablity and operator transparency, given no dependence on an accurate dynamical model and lower complexity.

Keywords: Hierarchical control, MPC, building control, HVAC, energy management

1. INTRODUCTION

Buildings constitute one third of the energy consumption in Denmark (International Energy Agency (2017)) and while energy refurbishments of older buildings often consider the building envelop itself, there is a large potential for energy savings through updating Heating Ventilation and Air Conditioning (HVAC) equipment which – given an assumed lesser effort – can prove a better investment for building owners/operators. One way of going about this is through control applications.

Energy savings within building control have been studied extensively, with the majority of work revolving around Model Predictive Control (MPC) (Killian and Kozek (2016); Shaikh et al. (2014)) and with buildings exhibiting multi-zone characteristics, both distributed (Cai et al. (2016)) and decentralized (Chandan and Alleyne (2014)) predictive control have been investigated.

In Petersen et al. (2019) a setpoint-manipulating MPC for minimizing energy consumption, in a fan-coil-based shopping center HVAC system (see **Fig. 1**), was designed and evaluated through simulations. It was compared to a simulation with historical input data, in which setpoints were set manually by building operators. The general issue with manually setting setpoints is that in a large scale system, it can be difficult for operators to balance production and demand of cooling, leading to situations such as cooling air in fan coils, where energy has already been spent heating it in an Air Handling Unit (AHU). In Petersen et al. (2019), the MPC introduced the necessary coordination, but it was concluded that the problem could be solved using a simpler control method; i.e. with less

Fig. 1. From left; AHU, chiller unit and Building Management System (BMS) gateway for remote data acquisition and control, situated at Kolding Storcenter, a Danish shopping center.

complexity. The desire to consider less complexity is not rooted in computational issues, especially when considering building systems with large time constants, rather, the reasoning lies in control reusability and operator transparency. Control reusability is key, considering impact on energy savings when one control approach can be deployed among multiple buildings. However, using MPC requires an accurate system model, which severely diminishes the reusability and induces a high initial investment, as also demonstrated in Sturzenegger et al. (2016). This, together with availability of both data and processing power has sparked a significant interest in data-based and learning-based methods; both considering learning the model, as highlighted in the references treated in Afram et al. (2017) and learning the control itself, e.g. using reinforcement learning (Overgaard et al. (2019)). This does not, however, cater to the issue of operator transparency.

This work investigates the use of hierarchical control. In Pangborn et al. (2018) and Koeln et al. (2019), which deal with experimental validation of hierarchical control for thermal management, it is concluded that hierarchical control is especially suitable in complex thermal management

⋆ This reseach is funded by the SEBUT project under ForskEl/EUDP grant no. 2016-1-12555. URL: http://sebut.teknologisk.dk/.

systems, where a decentralized approach can result in poor performance, due to the general difficulty of managing couplings between subsystems.

We propose a low-complexity hierarchical control architecture to coordinate production and demand in a fan-coil-based HVAC system – avoiding heavy-use of a model in an effort to provide reusability and operator transparency. To the knowledge of the authors, this type of architecture does not appear in the academic literature.

In **Section 2** we present the class of HVAC systems considered, the proposed hierarchical control framework, and MPC as a reference approach. Following that, in **Section 3**, we present a Danish shopping center as a case study and in **Section 4** we present simulation studies, comparing the proposed hierarchical control to MPC. Conclusions are given in **Section 5**.

Notation-wise, vectors are denoted in lowercase bold, e.g. $\boldsymbol{x}$. Time-dependence of variables, $\boldsymbol{x}(t)$, is implied and will not necessarily be written explicitly. Derivative with respect to time is written as $\dot{\boldsymbol{x}}$.

2. METHODS

2.1 Shopping Center HVAC

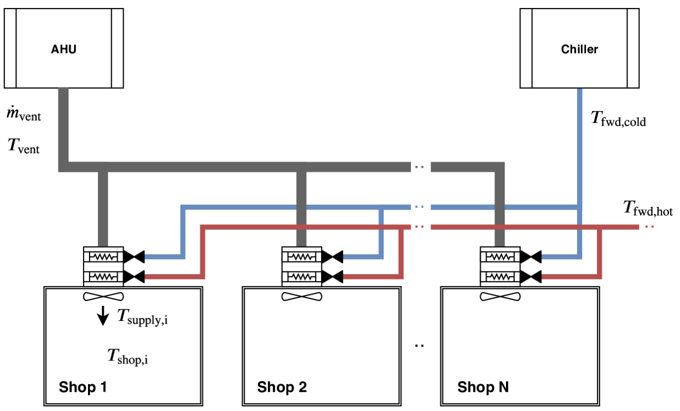

Fig. 2. Fan-coil-based shopping center HVAC layout. No return ducts/pipes are depicted to simplify the diagram.

In this paper we focus on shopping centers that employ fan coils for shop temperature control. The general HVAC system considered is depicted in **Fig. 2**. The system consists of:

- AHU supplying ventilated air with flow $\dot{m}_{\text{vent}}$ and at temperature T_{vent}.
- Chiller supplying chilled water at temperature $T_{\text{fwd,cold}}$ for cooling coils in fan coils.
- N shops with fan coils.

Hot water to heating coils in fan coils is supplied at temperature $T_{\text{fwd,hot}}$ by, e.g., district heating. Shop temperature, $T_{\text{shop,i}}$, for the i-th shop can be regulated by manipulating shop supply temperature, $T_{\text{supply,i}}$. This is done through heating and cooling valves in the fan coils. We consider a Constant Air Volume (CAV) setup for the fan coils; they are either ON or OFF.

We assume a decentralized control configuration, where each shop has its own temperature controller, manipulating valve openings to reach desired shop temperature, $T_{\text{shop,r,i}}$. The AHU is controlled through operator-given setpoints, $T_{\text{vent,r}}$ and $\dot{m}_{\text{vent,r}}$, and the chiller through the setpoint $T_{\text{fwd,cold,r}}$.

2.2 System dynamics

We present the main dynamics considered for the system described in **Section 2.1**. The model is based on the previous work done in both Petersen et al. (2018) and Petersen et al. (2019) where we employ a grey-box RC-equivalent modeling paradigm, treating each shop as a thermal zone with a lumped thermal capacitance.

Temperature dynamics Letting N denote the number of shops, the shop temperature dynamics of the i-th shop is given by:

$$C_{\text{shop,i}}\,\dot{T}_{\text{shop,i}} = \dot{Q}_{\text{FC,i}} + \dot{Q}_{\text{center,i}} + \dot{Q}_{\text{int,i}} \tag{1}$$

where $C_{\text{shop,i}}$ is the lumped thermal capacitance of shop i, $\dot{Q}_{\text{center,i}}$ is the heat flow to/from the surroundings, $\dot{Q}_{\text{FC,i}}$ is the fan-coil-supplied heat flow and $\dot{Q}_{\text{int,i}}$ models internal heat gain, e.g. from occupancy, lighting and appliances.

The supply temperature dynamics are modeled as:

$$C_{\text{supply,i}}\,\dot{T}_{\text{supply,i}} = \dot{Q}_{\text{AHU,i}} + \dot{Q}_{\text{cool,i}} + \dot{Q}_{\text{heat,i}} + \dot{Q}_{\text{recirc,i}} - \dot{Q}_{\text{FC,i}} \tag{2}$$

where $C_{\text{supply,i}}$ is a lumped thermal capacitance for the fan coils. $\dot{Q}_{\text{AHU,i}}$ is the heat flow supplied by the AHU, $\dot{Q}_{\text{cool,i}}$ is the heat flow supplied by the chiller and $\dot{Q}_{\text{heat,i}}$ is heat flow from heating. Some air is recirculated in the fan coils, modeled by the heat flow $\dot{Q}_{\text{recirc,i}}$.

Heat flows The heat flow supplied by fan coils to shops is given by:

$$\dot{Q}_{\text{FC,i}} = \dot{m}_{\text{FC,i}}\,c_{\text{p,air}}\,(T_{\text{supply,i}} - T_{\text{shop,i}}) \tag{3}$$

where $\dot{m}_{\text{FC,i}}$ is flow of air and c_{p} is specific heat capacity. Heat exchange with the surroundings, $\dot{Q}_{\text{center,i}}$, is given as:

$$\dot{Q}_{\text{center,i}} = \text{UA}_{\text{center}}\,(T_{\text{center}} - T_{\text{shop,i}}) \tag{4}$$

where UA is a heat transfer coefficient and T_{center} is a lumped shopping center temperature, modelling the temperature in the shopping center as a whole:

$$\dot{T}_{\text{center}} = \tau_{\text{extract}}\,(T_{\text{extract}} - T_{\text{center}}) + \tau_{\text{amb}}\,(T_{\text{amb}} - T_{\text{center}}) \tag{5}$$

where τ is a time-constant, T_{extract} is temperature of air extracted from shops by the AHU (return air) and T_{amb} is ambient temperature (outside). The heat flow supplied by the AHU to the fan-coils is modeled as:

$$\dot{Q}_{\text{AHU,i}} = \dot{m}_{\text{FC,i}}\,c_{\text{p,air}}\,(T_{\text{vent}} - T_{\text{supply,i}}) \tag{6}$$

$$\dot{Q}_{\text{AHU}} = \sum_{i}^{N} \dot{Q}_{\text{AHU,i}} \tag{7}$$

For heating and cooling, the heat flows are modeled as:

$$\dot{Q}_{\text{cool,i}} = \alpha_{\text{cool}}\,u_{\text{valve,cool,i}}\,c_{\text{p,w}}\,(T_{\text{fwd,cold}} - T_{\text{supply,i}}) \tag{8}$$

$$\dot{Q}_{\text{heat,i}} = \alpha_{\text{heat}}\,u_{\text{valve,heat,i}}\,c_{\text{p,w}}\,(T_{\text{fwd,hot}} - T_{\text{supply,i}}) \tag{9}$$

$$\dot{Q}_{\text{chiller}} = \sum_{i}^{N} \dot{Q}_{\text{cool,i}} \tag{10}$$

where α is a constant modeling both coil efficiency and valve characteristics and $u_{\text{valve,i}}$ is valve opening degree. Given the assumption that each shop has its own temperature controller, the valve openings are controlled by PI regulators included in the model. $\dot{Q}_{\text{recirc,i}}$ is modeled as a heat exchange with extract air:

$$\dot{Q}_{\text{recirc,i}} = \text{UA}_{\text{FC}} \left(T_{\text{extract}} - T_{\text{supply,i}}\right) \tag{11}$$

Finally, first order dynamics govern the control of both AHU and chiller:

$$\dot{T}_{\text{vent}} = \tau_{\text{AHU}} \left(T_{\text{vent,r}} - T_{\text{vent}}\right) \tag{12}$$

$$\dot{T}_{\text{fwd,cold}} = \tau_{\text{chiller}} \left(T_{\text{fwd,cold,r}} - T_{\text{fwd,cold}}\right) \tag{13}$$

2.3 Hierarchical control framework

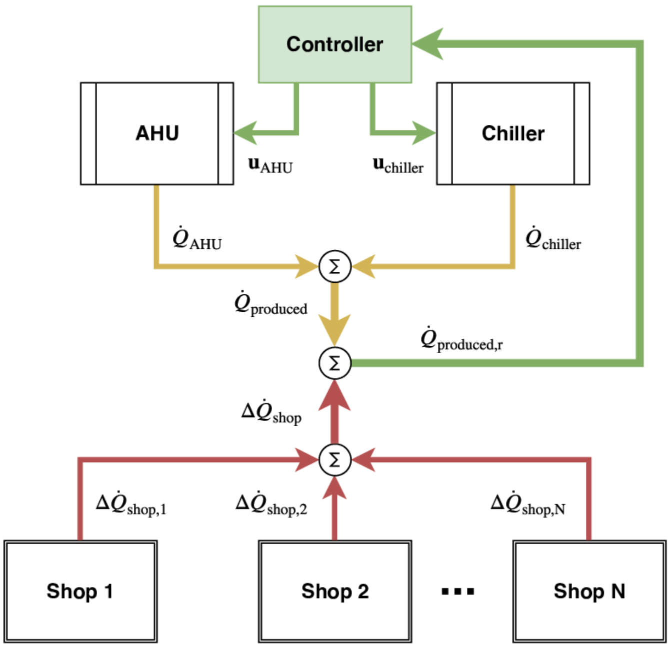

Fig. 3. Hierarchical control framework; separating *production* (AHU, chiller) from *demand* (shops).

To introduce the necessary coordination we consider a hierarchical control framework, depicted in **Fig. 3**.

Where:

- $\dot{Q}_{\text{AHU}}$ is the heat flow from AHU to the shops [1] .
- $\dot{Q}_{\text{chiller}}$ is the heat flow from chiller to the shops.
- $\boldsymbol{u}_{\text{AHU}} \in \mathbb{R}^{n_{\text{u,AHU}}}$ is control input affecting $\dot{Q}_{\text{AHU}}$.
- $\boldsymbol{u}_{\text{chiller}} \in \mathbb{R}^{n_{\text{u,chiller}}}$ is control input affecting $\dot{Q}_{\text{chiller}}$.

and where:

$$\dot{Q}_{\text{produced}} = \dot{Q}_{\text{AHU}} + \dot{Q}_{\text{chiller}} \tag{14}$$

$$\dot{Q}_{\text{demand}} = \dot{Q}_{\text{produced}} + \Delta\dot{Q}_{\text{shop}} \tag{15}$$

Here, $\dot{Q}_{\text{demand}} = \sum_i^N \dot{Q}_{\text{demand,i}}$, denotes the total demand for all the shops considered. When $\dot{Q}_{\text{produced}} = \dot{Q}_{\text{demand}}$, the system is balanced and the shops have enough heating/cooling capacity to meet the heating/cooling demand. In case $\dot{Q}_{\text{produced}} \neq \dot{Q}_{\text{demand}}$, then there is a discrepancy, given as:

$$\Delta\dot{Q}_{\text{shop}} = \sum_i^N \Delta\dot{Q}_{\text{shop,i}} = \dot{Q}_{\text{demand}} - \dot{Q}_{\text{produced}} \tag{16}$$

Note that $\Delta\dot{Q}_{\text{shop}}$ can be both positive and negative; positive in case of a heating demand and negative in the case of a cooling demand.

We can now formulate our primary control objective as minimizing $\Delta\dot{Q}_{\text{shop}}$, or equivalently as:

$$\dot{Q}_{\text{produced,r}} = \dot{Q}_{\text{produced}} + \Delta\dot{Q}_{\text{shop}} \tag{17}$$

$$\dot{Q}_{\text{produced}} \to \dot{Q}_{\text{produced,r}} \text{ for } t \to \infty \tag{18}$$

Assuming we have perfect tracking of $\dot{Q}_{\text{produced,r}}$:

$$\dot{Q}_{\text{produced,r}}(t) = \int_{t_0}^{t} \Delta\dot{Q}_{\text{shop}}(t)\, \mathrm{d}t + \dot{Q}_{\text{produced}}(t_0) \tag{19}$$

Revealing, that this approach is in fact an integral controller – integrating the demand to form the reference production.

The primary control objective can be met in many different ways if not considering the characteristics of either AHU or chiller – and can also be met by manually operating the setpoints of the AHU and chiller, as the capacities just have to be *large enough* to not saturate the fan coil valves for longer durations. Instead, it is more interesting to introduce a secondary control objective, to also minimize the cost of $\dot{Q}_{\text{produced}}$.

2.4 Hierarchical Controller

We propose a controller with the objectives presented in **Section 2.3** that does not require a dynamical model of the system; instead we only consider static model equations for the heat flows taken into account, namely $\dot{Q}_{\text{AHU}}$ and $\dot{Q}_{\text{chiller}}$, which in this case are given by (7) and (10) in **Section 2.2**.

For $\Delta\dot{Q}_{\text{shop}}$, we could let it be based on the heat flows considered for the shop temperature dynamics. This choice will however be very model-dependent. Instead, we propose to estimate $\Delta\dot{Q}_{\text{shop}}$ as:

$$\Delta\dot{Q}_{\text{shop}} = \dot{m}_{\text{vent,nom}}\, c_{\text{p,air}} \sum_i^N e_i \tag{20}$$

where $\dot{m}_{\text{vent,nom}}$ is the nominal air flow from the AHU and e_i is the error signal for the i-th shop temperature controller. If we let C be the cost (e.g. power consumption) of supplying $\dot{Q}_{\text{produced}}$, we can formulate an optimization problem, which seeks to minimize $\Delta\dot{Q}_{\text{shop}}$ and C_{produced}:

$$\boldsymbol{u} = [\boldsymbol{u}_{\text{AHU}}, \boldsymbol{u}_{\text{chiller}}]^T \tag{21}$$

$$\min_{\boldsymbol{u}} J = q_d \left(\dot{Q}_{\text{produced,r}} - \dot{Q}_{\text{produced}}\right)^2 + q_c\, C \tag{22}$$

$$\text{subject to:} \quad \boldsymbol{u}_{\min} \leq \boldsymbol{u} \leq \boldsymbol{u}_{\max}$$

where $\dot{Q}_{\text{produced}}$ is given as a function of $\boldsymbol{u}$, q_d and q_c are tuneable weights and $\leq$ is taken element-wise.

In **Fig. 3** we only consider an AHU and a chiller. The method would however also handle any other given cooling unit or heating unit, as the production is abstracted away

[1] Or more specifically, the fan coils.

behind $\dot{Q}_{\text{produced,r}}$, which can potentially be both positive when considering heating and negative when considering cooling. In the case of an economizer – or any passive cooling or heating unit – its contribution could be directly handled as a disturbance added to $\dot{Q}_{\text{produced}}$. Due to the proposed demand estimate being based on error signals it is however handled transparently, as we only act on deviations.

2.5 Reference Controller: MPC

For comparison purposes, we present a MPC with the same objectives as for the hierarchical controller in **Section 2.4**. This reference controller will require a dynamical model and here we use the model described in **Section 2.2**. We let the dynamics be given by:

$$\dot{\boldsymbol{x}} = \boldsymbol{f}(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{u}_{\text{ex}}, \boldsymbol{p}) \tag{23}$$

where $\boldsymbol{x} \in \mathbb{R}^{n_x}$ is the state, $\boldsymbol{u} \in \mathbb{R}^{n_u}$ is controllable inputs, $\boldsymbol{u}_{\text{ex}} \in \mathbb{R}^{n_{u,\text{ex}}}$ is exogenous inputs and $\boldsymbol{p} \in \mathbb{R}^{n_p}$ are parameters. Then we pose an optimal control problem to be solved with a receding horizon:

$$\min_{\boldsymbol{u}} J_{\text{MPC}} = \int_{t_0}^{t_f} J \, \mathrm{d}t \tag{24}$$

subject to:

$$\dot{\boldsymbol{x}} = \boldsymbol{f}(\boldsymbol{x}(t), \boldsymbol{u}(t), \boldsymbol{u}_{\text{ex}}(t), \boldsymbol{p}) \quad \text{(dynamics)}$$
$$\boldsymbol{u}_{\min} \leq \boldsymbol{u} \leq \boldsymbol{u}_{\max}$$

and subject to constraints on states as well.

3. CASE STUDY: KOLDING STORCENTER

As a case study, we consider *Kolding Storcenter*, a Danish shopping center. Kolding Storcenter is divided up into clusters of shops; each cluster featuring a fan-coil-based HVAC layout as described in **Section 2.1**. A demo-area has been established for the Smart Energy Shopping Centers (SEBUT) project, consisting of one cluster of shops – and the rooftop AHU and chiller supplying the fan coils of these shops. The AHU can both heat and cool, using a built-in heat pump and direct expansion coils.

Instrumentation has been established for the demo-area using a 'piggyback'-approach, by interfacing with the existing BMS through a *communication gateway unit* [2]. This allows extraction of measurement data and allows for manipulation with exposed setpoints. **Table 1** presents an overview of the, for this paper, considered inputs and outputs of the BMS, which can be manipulated and measured.

3.1 Model parameterization

Parameters for the model described in **Section 2.2** have been identified using a combination of:

- Manual flow measurements from fan coils
- Measurements from BMS
- Shop dimensions and table-lookup

The parameters that could not be identified directly (e.g. lumped time constants) were identified by posing and solving a Least Squares Estimation problem. No heat

[2] Neogrid Technologies. URL: https://neogrid.dk

Table 1. BMS I/O

Name	Description	Type
	AHU	
T_{vent}	Supply temperature	Output
$T_{\text{vent,r}}$	Supply temperature setpoint	Input
T_{extract}	Extract temperature	Output
$\dot{m}_{\text{vent}}$	Supply air flow	Output
$P_{\text{AHU,cool}}$	AHU power consumption (cooling only)	Output
	Chiller	
$T_{\text{fwd,cold}}$	Forward temperature	Output
$T_{\text{fwd,cold,r}}$	Forward temperature setpoint	Input
P_{chiller}	Chiller power consumption	Output
	Shops	
$T_{\text{shop,i}}$	Shop temperature	Output
$T_{\text{shop,r,i}}$	Shop temperature setpoint	Output
$T_{\text{supply,i}}$	Fan coil supply temperature	Output

interaction between shops is considered as internal heat gains have been found to dominate the energy balance, given the quantity of display lighting. We can therefor consider $\dot{Q}_{\text{int,i}}$ constant during opening hours. Note that shops are not exposed directly to sunlight and thus no heat gain from solar load is considered.

Parameters (for a single shop) are given in **Table 2** and a comparison of shop temperature between a simulation and measurements is presented in **Fig. 4**, simulating 8 days; 4. September to 12. September – the model is deemed accurate enough for both control purposes and simulation studies.

Table 2. Model parameters (single shop)

Area	C_{shop}	C_{supply}	$\dot{Q}_{\text{int}}$
250 m^2	2.0 MJ K^{-1}	1.0 MJ K^{-1}	4.0 kW
$\text{UA}_{\text{center}}$	UA_{FC}	α_{cool}	α_{heat}
2.0 kW K^{-1}	2.0 kW K^{-1}	0.1 kg s^{-1}	0.1 kg s^{-1}
τ_{AHU}	τ_{chiller}	τ_{extract}	τ_{amb}
1 h	1 h	1 h	6 h
	$\dot{m}_{\text{vent,nom}}$	$T_{\text{fwd,hot}}$	
	3.3 kg s^{-1}	55 °C	

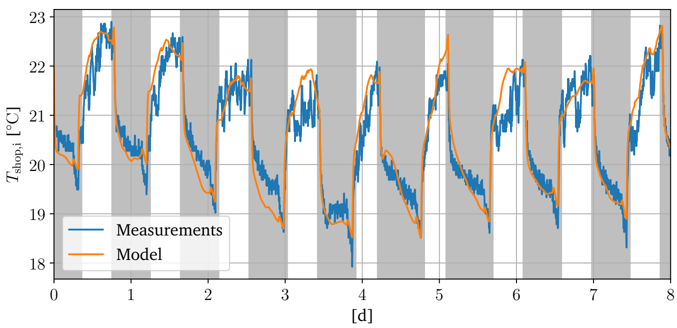

Fig. 4. Comparing simulation of model to measurements extracted from BMS. Shop temperature for a single shop. Shaded areas indicate that the shop is closed.

3.2 Estimating power consumption

In order to not only balance production and demand but also meet the objective of minimizing cost, a measure for cost is needed; here we consider power consumption for both AHU and chiller.

For the chiller, we estimate power consumption as a function of $\Delta T = T_{\text{amb}} - T_{\text{fwd,cold}}$, where T_{amb} is the ambient temperature. The best fit was found by assuming the function to be a 3rd degree polynomial. The results are given in **Fig. 5**.

In the case of the AHU, we have measurements of power consumption for cooling. As such, the power consumption of the fans is *not* included and, given the ambient conditions, active heating is not present for the time period under consideration. A naïve approach would be equivalent to that of the chiller, estimating power consumption as only dependent on a $\Delta T = T_{\text{amb}} - T_{\text{vent}}$. However, recirculation and heat recovery plays a significant role for the AHU introducing a dependence on T_{extract}. Thus, for the AHU we formulate a 2nd degree polynomial dependence on both $\Delta T_{\text{amb}} = T_{\text{amb}} - T_{\text{vent}}$ and on $\Delta T_{\text{extract}} = T_{\text{extract}} - T_{\text{vent}}$, yielding:

$$\begin{aligned}\hat{P}_{\text{AHU,cool}}(\Delta T_{\text{amb}}, \Delta T_{\text{extract}}) = \\ a_0\ \Delta T_{\text{amb}}^2 + b_0\ \Delta T_{\text{amb}} + \\ a_1\ \Delta T_{\text{extract}}^2 + b_1\ \Delta T_{\text{extract}} + c\end{aligned} \tag{25}$$

Results are given in **Fig. 5**, as both a time series comparison and a histogram of the error between measurement and estimation. There are improvements to be made in the case of the AHU, as either filtering, the inclusion of dynamics or perhaps a faster sampling time of the data will provide better results. Both fits are deemed convincing enough to be used in a control setting.

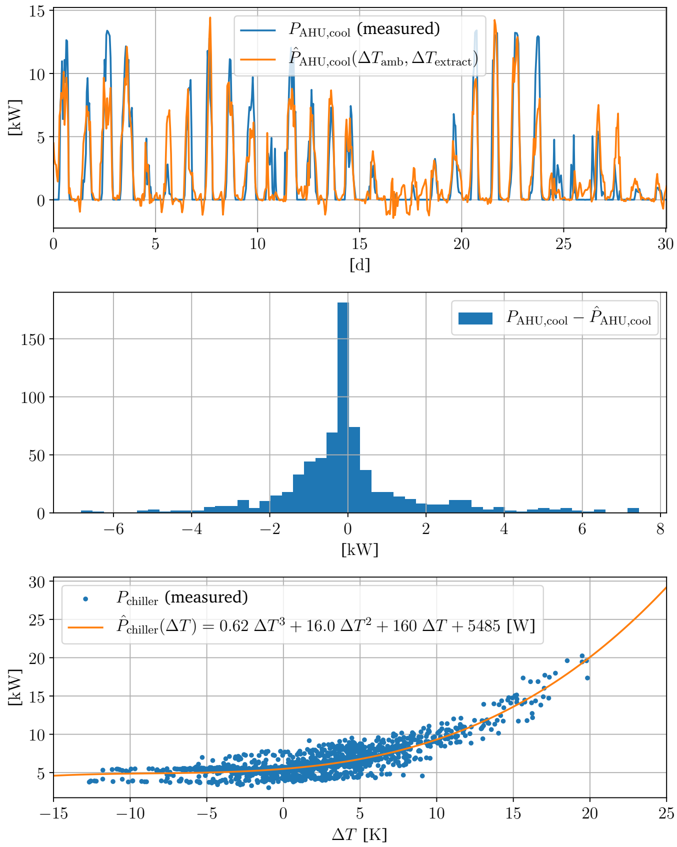

Fig. 5. Power consumption estimation for both AHU and chiller, for demo-area in Kolding Storcenter. Coefficients for the AHU fit found as: $(a_0, b_0, a_1, b_1, c) = (131.0, 1741, -69.85, 114.0, 5750)$. Data used was from 15. August to 8. October, with T_{amb} from 2 °C to 30 °C and $T_{\text{fwd,cold}}$ from 11 °C to 14 °C.

4. SIMULATION STUDIES

Simulation studies have been conducted to evaluate the performance of the proposed hierarchical controller, compared to both a reference controller, MPC, and to a simulation with historical inputs – a nominal case. All simulations have been done using *CasADi* (Andersson et al. (2019)) through Python, where the nonlinear system dynamics have been formulated. Given that measurements from the BMS are obtained with a sampling time of 5 min, this has also been chosen as sampling time for all simulations.

As a measure of cost, C, we use the power consumption estimates given in **Section 3.2**:

$$C = \hat{P}_{\text{tot}} = \hat{P}_{\text{AHU,cool}} + \hat{P}_{\text{chiller}} \tag{26}$$

and as controllable inputs we choose:

$$\boldsymbol{u} = [T_{\text{vent,r}}, T_{\text{fwd,cool,r}}]^T \tag{27}$$

We use $q_d = 2$ and $q_c = 1$ in all cases.

4.1 Hierarchical Controller setup

We employ the hierarchical controller outlined in **Section 2.4** and in the expression for $\dot{Q}_{\text{produced}}$ we assume steady-state, letting $T_{\text{vent}} = T_{\text{vent,r}}$ and $T_{\text{fwd,cold}} = T_{\text{fwd,cold,r}}$. In calculating $\dot{Q}_{\text{produced,r}}$, we consider two approaches:

Mean over last hour Let $\Delta t = 1$ h; then:

$$\dot{Q}_{\text{produced,r}}(t) = \frac{1}{\Delta t} \int_{t-\Delta t}^{t} \dot{Q}_{\text{produced}}(t) + \Delta \dot{Q}_{\text{shop}}(t)\ \mathrm{d}t \tag{28}$$

We denote this version **H-1h**

Mean over next hour Exploiting the inherent periodic behavior, with period time $T_d = 24$ h (see **Fig. 4**), we use yesterdays data to predict and calculate the next reference, again with $\Delta t = 1$ h:

$$\dot{Q}_{\text{produced,r}}(t) = \frac{1}{\Delta t} \int_{t-T_d}^{t-T_d+\Delta t} \dot{Q}_{\text{produced}}(t) + \Delta \dot{Q}_{\text{shop}}(t)\ \mathrm{d}t \tag{29}$$

We denote this version **H-23h**.

4.2 Reference Controller (MPC) setup

Using CasADi allows for also posing, discretizing and solving optimal control problems using (in this case) a multiple-shooting approach; this has been applied for the reference MPC design. The sample time is as for the simulation, 5 min and the prediction horizon chosen to be 2.5 h. Given that we do not know exogenous inputs in advance, we also here exploit the periodic behavior and use inputs from the previous day (delayed 24 h). Note that we consider $\dot{\boldsymbol{u}}$ as our control input.

4.3 Simulation setup and results

We only consider 2 shops for this simulation, with slightly different consumption profiles, given by their different shop temperature references:

$$\boldsymbol{T}_{\mathbf{shop,r}} = [21.5\,°\mathrm{C},\ 22.0\,°\mathrm{C}]^T \tag{30}$$

Simulating 8 days, 4. September to 12. September, using historical data we compare the four cases:

- Nominal (Purely historical inputs)
- Hierarchical Controller (H-1h)
- Hierarchical Controller (H-23h)
- MPC

Given that actuation (fan coils ON) is limited to operator set schedules, control authorithy is limited to these schedules; not exactly opening hours but resembling working hours of staff. The results are presented in **Fig. 6**, with shaded regions depicting when fan coils are turned OFF. Common between the three control strategies attempted, is that they all use the chiller to a lesser extent than in the nominal case, as visible in the response of $T_{\mathrm{fwd,cold}}$. The main difference lies in the use of the AHU, where the MPC almost avoids using it, the **H-23h** uses it to some extent and the **H-1h** even more. Tracking performance is very similar, as visible from both the response of $\Delta\dot{Q}_{\mathrm{shop}}$ and T_{shop}. The results also show, from looking at the excitation of the valve openings, how both hierarchical control and MPC end up using the heating valve to a lesser extent, as air from the AHU is delivered at a higher temperature; avoiding first spending energy cooling the air in the AHU and the heating it up again in the fan coils. Performance-wise, we compare the four cases on three metrics:

1. Root-Mean-Square Error (RMSE)

$$\bar{e} = \bar{\boldsymbol{T}}_{\mathbf{shop,r}} - \bar{\boldsymbol{T}}_{\mathbf{shop}} \tag{31}$$

where $\bar{a}$ denotes mean value.

2. Energy consumption

$$E_{\mathrm{tot}} = \int_{t=0\,\mathrm{d}}^{t=8\,\mathrm{d}} \hat{P}_{\mathrm{tot}}\ \mathrm{d}t \tag{32}$$

3. Simulation time as a measure of complexity; this is time taken for the entire simulation to run, for each case considered. Measured on the same hardware.

Note that we only consider RMSE and energy consumption for the times when the fan coils are ON.

These results are presented in **Table 3**. Comparing RMSE values, the MPC is best and **H-23h** worst; but the difference is 0.004 K – and, as such, a fair conclusion is that the comfort performance is almost identical. Comparing energy consumption, the MPC is again best with **H-23h** second; the MPC amounting to a 44 % reduction compared to the nominal case, where **H-23h** reduces energy consumption by 29 %. As such, the MPC wins on performance. However, comparing simulation time the MPC falls short of the other methods. Here, the proposed hierarchical controllers are 17 times faster – and this is when only considering $N = 2$ shops.

Table 3. Performance metrics

Metric	Nominal	H-1h	H-23h	MPC
RMSE	0.481 K	0.480 K	0.483 K	0.479 K
E_{tot}	918 kW h	754 kW h	649 kW h	520 kW h
t_{sim}	2 s	20 s	20 s	340 s

5. CONCLUSIONS

We have proposed a low-complexity hierarchical control approach to fan-coil-based HVAC systems, exemplified by the case study of a Danish shopping center. The hierarchical controller is designed to avoid the dependence on a dynamical model, while still introducing the necessary coordination for energy efficient operation, by balancing production and demand using only steady-state model information and an empirically-based model for power consumption.

Through simulation studies the proposed hierarchical controller was compared to MPC; using the same cost function but having the benefits of accurate model dynamics, as no model-mismatch is considered. Using MPC would amount to a 44 % reduction in energy consumption compared to a simulation with historical inputs (no advanced control). Using the hierarchical controller and relying only on measurements from the last hour of operation, the reduction was only 18 %; a significant reduction but not comparable to the MPC. However, exploiting the periodic behavior of the HVAC system and allowing the system to use yesterdays data to predict consumption for the next hour, the reduction was increased to 29 % – recovering 66 % of the MPC performance.

This is a promising reduction in energy consumption when considering that the hierarchical controller does not rely on model dynamics. Without the dependence on model dynamics and with the demonstrated lower computational overhead, it is concluded that this low-complexity method has the potential to provide both less initial costs, less operator training overhead and thus higher reusability. This is key for energy savings, when considering the deployment among multiple buildings.

ACKNOWLEDGEMENTS

The authors would like to thank the SEBUT team; in particular Neogrid Technologies for providing their BMS gateway and cloud solution, including invaluable support.

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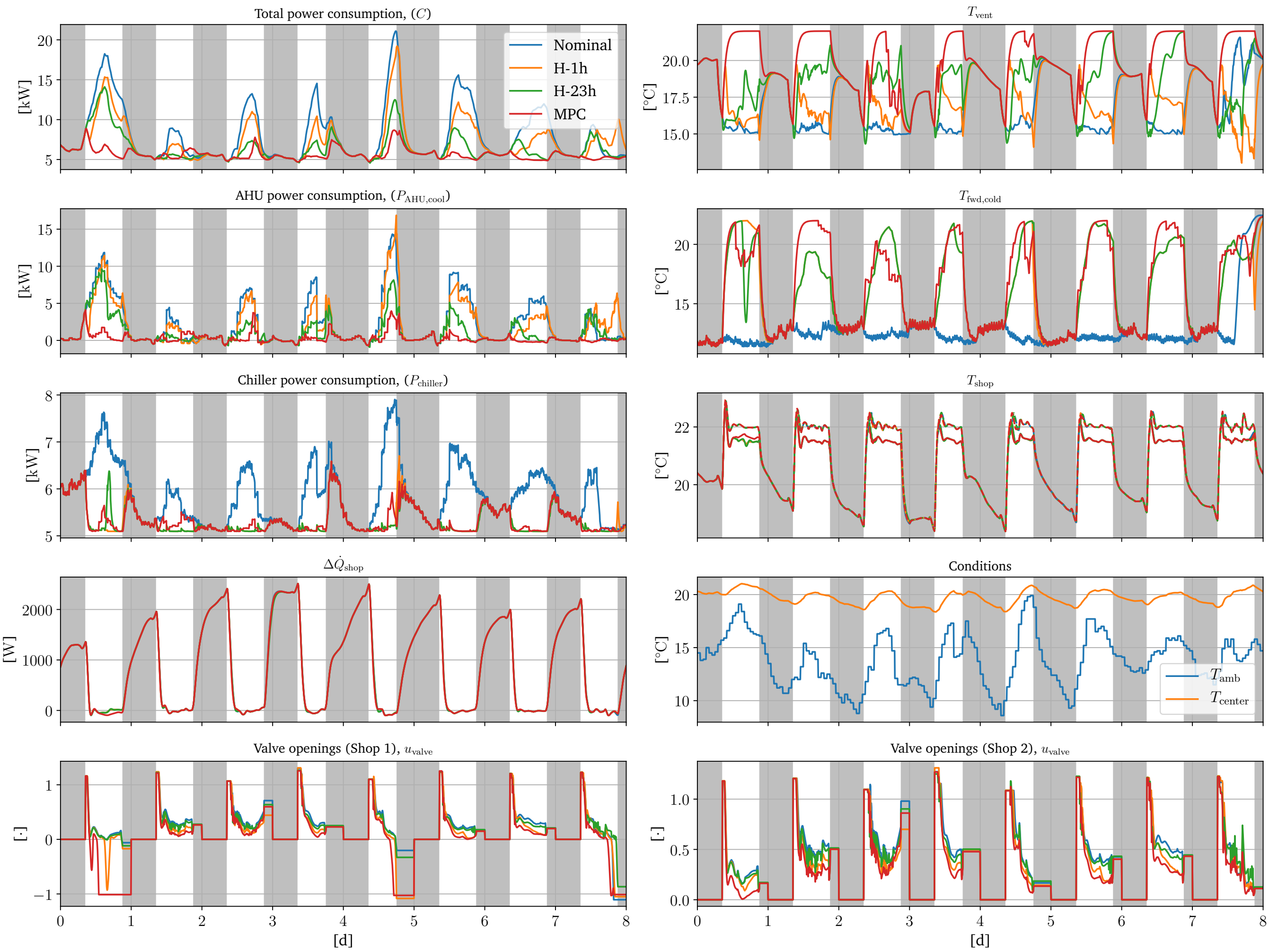

Fig. 6. Simulation results from 8 d simulation, comparion nominal case to three different control strategies. Shaded area indicates no control authority. Shop temperature, T_{shop} is depecited as a solid line for *Shop 1* and a dashed line for *Shop 2*. Valve opening signals, u_{valve}, combines signal for both heating valve (> 0) and cooling valve (< 0).

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