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Smart Buildings (Predictive & Neuro-Fuzzy Control)

Development of a generic model-assisted control algorithm for building HVAC systems

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Abstract

Universally applicable building automation and control systems could contribute largely to reducing both the environmental impact and the operation costs of buildings. We present a building HVAC control algorithm that excites small subsystems and uses the system responses to calibrate prefabricated Modelica models. It uses these models for distributed model-assisted online control. We demonstrate and evaluate the algorithm in simulations and real-life experiments on a central air handling unit. Results show that the algorithm is capable of controlling the systems. Its performance is comparable to the reference scenario based on PI controllers.

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1. Introduction

Every building energy system (BES) has unique characteristics. It requires a suitable building automation and control system (BACS) to provide a comfortable indoor climate for the users and deliver other energy services such as process heat in an efficient way. Due to the unique features of BES, the BACS are often custom-made in a long and costly design and commissioning phase [1]. Especially the practical implementation of advanced optimization-based control approaches causes high labor cost during the implementation phase because they require manual calibration by experts [2].

Currently, many researchers are concerned with the question of how to develop BACS that automatically adapt to the characteristics of the building they are implemented in. Baldi et al. [2] developed an adaptive optimization algorithm. Huber [3] demonstrated a multi-agent system on a test bench based on an air handling unit (AHU). Zhou [1] presents a framework that features auto-recognition of temperature sensors in an AHU. All authors call their approaches “plug and play” to underline the very limited requirement for manual configuration.

Besides Baldi et al. [2], other authors are turning towards the use of BPS tools such as EnergyPlus, TRNSYS or Modelica. Compared to the widely used linear models, the main advantages of BPS tools are a better approximation of the building dynamics and complex phenomena [4]. There are open-source libraries of models created by experts in the field, such as Fuchs et al. [5]. The complication is that we often have to apply derivative-free optimization algorithms to use these models directly [2]. Algorithms such as the genetic algorithm are limited in performance when it comes to complex systems with many manipulated variables. Another issue reported is the high computational time [2].

Many research efforts have already focused on the operation optimization of energy systems. However, according to Dounis and Caraiscos [6], difficulties with implementing the novel strategies lead to the current situation in which most BACS are still built on rule-based control strategies. We thus identified the need to develop an approach that is suitable for practical implementation without causing high development or commissioning costs. In order to do so, we propose an approach based on continuous system identification and distributed optimization. For information on these fields of research, refer to [7] and [8].

According to [4], model predictive and model assisted control (MAC) approaches have many advantages compared to other approaches and especially with regard to rule-based control. Afram and Janabi-Sharifi [9] give an overview of the various model types that we can select for setting up a MAC.

In this paper, we present a possible approach for automatic generation of automation software for building energy systems. It is structured as follows. We introduce the algorithm, which consists of an identification and a control part. As a proof-of-concept, we apply the algorithm on a central AHU. We present simulation and real-life implementation results to quantify the performance of the algorithm and to draw conclusions on the suitability of the approach for implementation in generic BES.

2. Methodology

2.1. Model-assisted distributed control

Our approach is based on grey box models of elementary modules that occur in every BES. The idea is that the components already available in open-source BPS libraries such as AixLib [5] can cover a large part of the components in the built environment. The complication arises from the facts that we have to adapt the model parameters and that there are many possible combinations of these components. The generation of a detailed model of the real system is time consuming and error-prone. Even worse, the model validity often deteriorates in time because characteristics of BES change due to wear and tear. Since, in building automation, labor costs play an important role, we consider this one of the reasons why grey-box-based control approaches have not yet found their way into practical implementation. If we find a method to adapt the model parameters automatically to the real component and find a way around assembling all the subsystem models to a complex system model, this could pave the way for model-based and even plug-and-play control in BES.

We thus develop a control algorithm for building HVAC supply chains, which automatically calibrates elementary subsystem models. It simulates the models for various boundary conditions and finds the most suitable

control decision for each set of boundary conditions. We consider both the cost in each subsystem and in the downstream subsystems. We published an early version of the algorithm in [10]. This so-called neighbor communication is often used for distributed model-based control, e.g. by Jalal and Rasmussen [11].

In this paper, we focus on the subsystems of a central AHU. Since the subsystems are coupled by the air stream, the algorithm optimizes each subsystem for a couple of discrete combinations of the temperature and the absolute humidity of the entering airflow (coupling variables). Beginning at the last system in the supply air chain, the algorithm optimizes all subsystems sequentially and stores the results in look-up tables. These enable each subsystem to estimate the effect that its control decisions will have on the downstream systems. The last system in the chain ensures that the AHU supplies the desired temperature and humidity by penalizing deviations from the respective set points with additional cost.

We use the AHU because of its modular structure, which makes it especially suitable for demonstrating the combined identification and control capabilities. In future work, we will apply the algorithm to an entire BES.

2.2. Tools

For reasons of simplicity, we implement both the identification and the control algorithm in Matlab. In order to be able to set up the framework in other environments such as Python, we do not use any specialized function or toolbox in Matlab. Instead, we use the open-source optimization tool GenOpt and select the available pattern search algorithm. This tool works with compiled simulation models and uses text files for exchanging data. However, for our purposes it is also possible to employ a functional mockup unit (FMU) instead. It is our goal to develop a generic control approach, which can be implemented as a plug-and-play system. In the future, manufacturers may provide models of their components. These could easily be loaded into the existing framework.

2.3. Identification algorithm

The identification algorithm serves mainly as demonstration of how identification approaches can be used for universally applicable control systems. We use a simple excitation, namely a stair signal with long steps covering the entire operating range. We choose this excitation because our control algorithm simulates the subsystems with constant inputs and long enough to reach a steady state. Moreover, the models do not account for many dynamic effects. In future work, we will use models that are more detailed and a dynamic excitation signal. However, one advantage of the stair signal is that we can apply it to some subsystems during normal operation because the downstream subsystems can react to this slowly changing disturbance sufficiently fast. Other subsystems such as the last heat exchanger in the supply chain have to be excited during times when no user is affected by the identification. This facilitates the continuous repetition of the identification to account for aging effects.

The inputs that the user has to provide are the name of the component, the experiment time and the performance metric. Afram and Janabi-Sharifi [9] give an overview of performance metrics. For this work, we chose the goodness of fit (GOF). A value of 100 indicates the best fit.

We use the name of the component to access a pre-defined mapping of the sensor and actuator data points. This mapping is a task that the system integrator has to carry out during the implementation in the real building. The user initiates the identification run manually. In future implementations, we will add a periodic trigger. For example, experiments could be repeated every three months.

2.4. Cost functions

The algorithm can switch between two different cost functions. On the one hand, we can select the monetary costs of the supply water and the electricity entering the respective subsystems. We use cost factors that depend on the thermodynamic states of supply and return flow to account for variable efficiencies of the supply system. On the other hand, we can use the sum of exergy destruction and loss. Equation (1) is the objective function comprising the penalty terms and the monetary cost related to the flow rate of the supplied (water or steam) mass m_i .

$$\phi = \sum_{i=1}^2 \alpha_i \cdot \left((\max(x_i - x_{i, \text{set}} - \Delta x_i, 0))^2 + (\max(x_{i, \text{set}} - x_i, 0))^2 \right) + \sum_{j=1}^n c_j \dot{m}_j \quad (1)$$

The controlled variables and their set points are denoted by x and x_{set} , respectively. We use a tolerance Δx and a weighting factor α . The specific cost c depends on the thermodynamic state of the supplied mass flow rate.

3. Case Study

We study a central AHU that supplies laboratories. A scheme of the unit is depicted in Fig. 1. It is equipped with a water-based heat recovery system and can be used for adiabatic cooling as there is a liquid water humidifier on the exhaust airside. Moreover, it contains a steam humidifier, a cooler and two heaters. We can thus heat up or cool down the air using two different modules, respectively. The supply temperature on the waterside of the heaters is approximately 80 °C and thus comparatively high.

We consider each of the heat exchangers plus the connected valve and pump one subsystem. The steam humidifier is the last system in the supply chain. In each heat exchanger subsystem, we identify five grid points of the characteristic curve of the valve, the nominal thermal conductance of the heat exchanger and a static pressure difference. Thus, the characteristic curve of the valve does not only incorporate the characteristics of the valve itself but also represents the control behavior of the pump.

In order to test the algorithm, we apply it on a simulation model so that we have ideal system knowledge. The fresh air temperature follows a sine wave with a period duration of 7200 s and an amplitude of 10 K, which is a strong disturbance compared to real AHU applications. The relative humidity of the fresh air is constant 70 %, so the steam mass fraction also resembles a sine wave. The valve openings of the four heat exchangers and the steam mass flow rate of the humidifier are the decision variables. To benchmark the performance, we apply two reference control strategies on the same system. One is the same algorithm with the same settings but using the total system model. The other one is based on PI controllers. The controlled variables are the supply air temperature and the relative humidity. The MAC algorithms work at a sample rate of 120 s and optimize every 600 s using a prediction horizon of 3600 s. We simulate all scenarios for 10 hours.

In the real-life demonstration, we control only the heat exchangers and disregard the humidity. In the first part, we vary the temperature set point. In the second part, we overwrite the cooler valve opening to create disturbance.

4. Results

4.1. Results of identification test

Fig. 1 shows the air temperature behind the heater in the real AHU, which is excited with a double stair signal, and the temperature trajectory produced by the BPS model. The GOF is 70 % and thus satisfactory. However, as we are still in the process of developing the algorithm, three months passed between the identification and the control experiment. In the meantime, the characteristic curve changed drastically, probably due to clogging. By manual recalibration, we found out that the control range had narrowed to 58–67 % of the nominal opening. This reveals the importance of continuous repetition of the identification runs. It could also be beneficial to increase the number of grid points of the characteristic curve to enable the identification algorithm to cover such small ranges. For the real-life demonstration, we thus use the manually recalibrated heater model and the automatically calibrated models of pre-heater, cooler and heat recovery system.

4.2. Results of the simulation studies

Fig. 2 shows the trajectories of the temperature and the relative humidity of the supply air as well as the fresh air temperature. The algorithm manages to keep the supply air temperature close to the set point of 23 °C. The supply air humidity, however, deviates from the set point of 50 %. Table 1 includes key performance indicators (KPIs). The difference between the arithmetic mean of the temperature and the set point is 0.18 K and thus lower than in the two reference scenarios. The tracking error, which corresponds to the root mean squared error with regard to the set point, is 0.53 K and thus slightly higher than in the scenario in which we use the PI controllers.

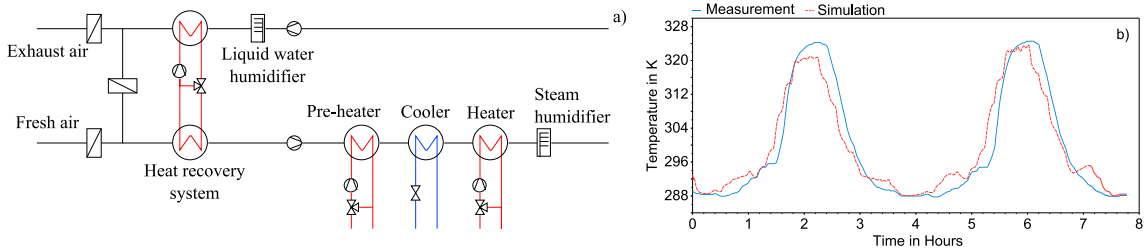


Fig. 1. (a) Scheme of the air handling unit test bench; (b) measured and computed air temperature during heater identification run.

Regarding cost, the distributed control algorithm outperforms the scenario based on PI controllers. The cost is, however, higher than in the scenario based on the total model.

In addition to these indicators, we calculate the weighted sum of the normalized KPIs for each scenario. To normalize, we divide each indicator by the mean value of each line in Table 1. We also include the weight factors and the mean values in Table 1. A lower value indicates a better performance. According to the index, the algorithm and the PI-controllers have a comparable performance and outperform the algorithm based on the total model, whereas the computational time required for one optimization using the subsystem models is approximately 10 minutes. We would like to remark, however, that we use well-tuned PI controllers. In practical implementations, PI controllers are often not well tuned. In addition to that, they have to be embedded in control logics. Our distributed MAC algorithm functions without any logic – at the cost of higher computational effort.

Table 1. Key performance indicators of control strategies used in simulation case study.

Indicator	Weighting	Subsystem alg.	PI controllers	Total system alg.	Mean of the index
Cost of energy in €	1/3	4.654	5.405	3.148	4.402
Average temperature deviation in K	2/9	0.177	0.259	1.486	0.641
Average relative humidity deviation in %	1/9	0.111	0.188	2.386	0.895
Tracking error of temperature in K	2/9	0.533	0.503	1.499	0.845
Tracking error of relative humidity in %	1/9	7.840	2.809	10.228	6.959
Comparative index in %		68.778	69.684	160.538	

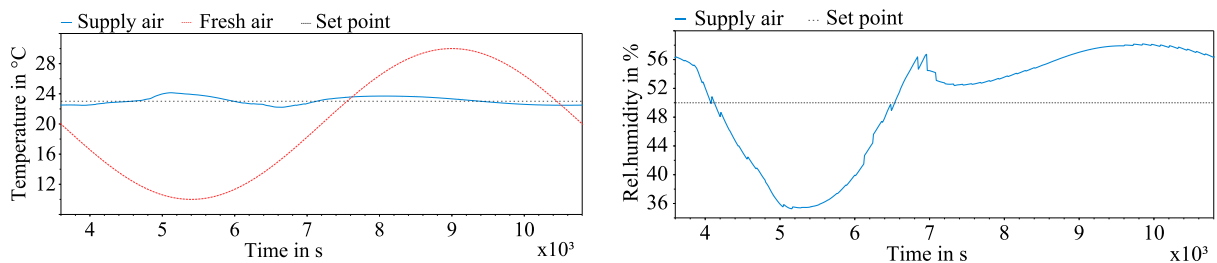


Fig. 2. (a) Fresh and supply air temperature; (b) Relative supply air humidity in simulation case study.

4.3. Results of the real-life demonstration

Fig. 3 shows the supply air temperature set point and the actual temperature that the MAC algorithm achieved when we applied it on the real AHU. The fresh air temperature changed very little so we created additional disturbance after four hours. Before, we varied the temperature point. As Fig. 3 reveals, the algorithm finds mainly plausible solutions, opening the cooler valve only when the set point is 18 °C. Simultaneously, it closes the pre-heater valve to 40 %, which corresponds to zero flow. Moreover, it mostly uses the heat recovery system at full capacity and decreases the recuperation when the set point is low. However, a better solution would be shutting off

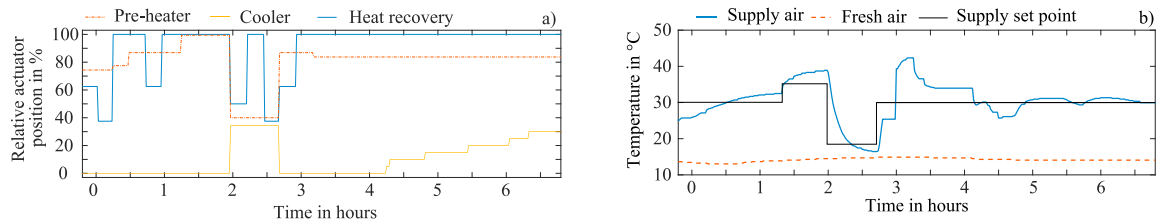


Fig. 3. (a) Relative actuator positions; (b) Fresh and supply air temperature measurement and temperature set point in real-life demonstration.

recuperation completely, which corresponds to a valve opening below 25 %.

It is obvious that the air temperature deviates strongly from the respective set points. These deviations result from imprecise models, which lack hysteresis and dead times, and the approximations we make when the algorithm estimates the mutual interactions of the subsystems. However, the algorithm does succeed in balancing the disturbance using the main heater.

5. Conclusion

We presented a model-assisted control algorithm, which excites modules of central AHUs to calibrate pre-fabricated building performance simulation models. It uses these models to optimize the control decisions. Starting at the end of the supply chain, it optimizes the subsystems sequentially and considers the mutual interactions using look-up tables. In simulation, the algorithm achieves lower cost and similar control performance compared to a control strategy based on PI-controllers. The real-life demonstration shows the practical feasibility but also the need to improve the model identification. The workload for setting up the control system is much lower than in conventional building automation and control systems. We thus consider the algorithm a suitable solution for generic control that can be further developed to become a plug-and-play control system for building energy systems.

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