Distributed model predictive control of building energy systems coupled to geothermal fields

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Abstract. In building energy systems (BES), operation strategies are a key factor to exploit the full potential of renewable energy sources and thus to reduce the CO₂ emission and energy costs. However, advanced operation strategies like model predictive control require high engineering effort, which limits the applicability. To ease the implementation of model predictive control in BES, we present a flexible and robust distributed control framework. The framework supports the use of different model types and timescales for the various subsystems, allowing the user to tailor models from white to black modelling according to the available system knowledge. In a case study, we apply this framework to control a real-life industrial hall. We further simulate a case in which the hall is supplied by a geothermal field to investigate the sustainable long-term control of the field. We vary the temperature setpoint of the hall and adjust the thermostats in the office rooms. Since the set temperature of the hall and offices differs, the model predictive control framework finds an economic trade-off between the requirements of those two zones. Judging from these results, the approach and our implementation could be an important contribution to energy efficient operation of buildings with renewable energy sources.

1. Introduction
In the worldwide striving for an increased use of renewable energy sources, shallow geothermal energy could play an important role for heating and cooling of buildings: its low volatility, high availability and low operation cost are major benefits. However, the integration of geothermal energy into a building’s heat and cold supply demands a well-suited control to prevent long-term ground temperature changes and consequently decreased heating or cooling potential. Predicting the future behaviour of the coupled system consisting of building and geothermal field is an approach followed in several studies on geothermal energy. Moreover, model predictive control (MPC) was successfully applied by many research groups in the field[1][2][3]. Simulation and experimental investigations show that the use of MPC in building energy systems (BES) can lead to significant energy savings and improved thermal comfort[4][5]. However, many implementations require considerable effort for modelling and commissioning and are not transferable to generic systems. For that reason, we identified the need for a flexible MPC implementation for geothermal energy that can be tailored to the user’s system knowledge and allows for using various model types. In this paper, we outline our control approach and present our implementation. In comparison to other existing building MPC frameworks like TACO[4] our approach uses a distributed MPC formulation together with a brute force algorithm to ensure that the
global optimum is found.

In a case study, we investigate the suitability of the approach by applying it to a real-life building energy system and a model of a geothermal field. Based on the learnings from this study, we draw conclusions for the further development of this approach.

2. Related work

Conventional operation strategies for building energy systems coupled to geothermal fields are often rule-based. In [6], a mode-based strategy is applied to a geothermal field which is used for heating and cooling. In that case, the operation mode of the field depends on the ambient temperature and its outlet temperature. To prevent long term-ground temperature changes, the field is turned off if a certain temperature is exceeded.

A comprehensive predictive control strategy for a BES with a heat pump and a geothermal field is proposed in [1]. Compared to the benchmark, the model-predictive controller on integrated system level achieves 20 to 40% energy cost savings. A central MPC approach deploying linearized black, grey and low-order white box models is used in [3]. Simulations show that the presented controller could lead to energy cost savings of 30 to 50% underlining the potential of MPC applications in buildings. A white box model of geothermal fields combining both short (minutes) and long-term (decades) behavior of the field is presented in [7]. It consists of a short-term step response which takes local heat transfers into account and a long-term model to consider borehole interactions.

A real-life implementation of MPC in building energy systems is given in [2]. For this implementation, a bilinear high-level modeling approach was used, resulting in energy savings of 17%. Nevertheless, the authors emphasize that the modeling and engineering effort is too high to employ this approach in everyday building projects.

The influence of model uncertainty in MPC of building energy system is investigated in [8]. The study compares MPC, robust MPC and a rule-based controller. It is shown that the MPC approach performs best if the model uncertainty is below 30% and the robust MPC is uncertainty is between 30 and 67%. For higher model uncertainties, the rule-based controller should be used.

3. Method and implementation

We investigate the flexibility and generic applicability of control systems for buildings with geothermal fields by applying an agent-based control design: we split the total system model into small subsystems, namely the geothermal field and various building subsystem models such as the heat generation. Moreover, we assign an individual model and a control agent to each subsystem. The control agents are part of a control framework that we developed in previous works [9]. These agents use either data-driven or physical models or fuzzy logic to predict the behaviour of the subsystem they are assigned to. Consequently, if more sophisticated models are available, these may replace the above-mentioned simplified models in the framework. Furthermore, the agents exchange information on cost and temperature trajectories with neighboring agents in order to find a temporary control law for the total system. In the following, we outline our implementation and the model types we use. All code is available on GitHub 1.

3.1. Model types

According to our approach, the user shall be able to select the model type for a certain subsystem that fits best, depending on the available system knowledge, the dynamics and non-linearity and requirements regarding computational time. Currently, we use a brute-force algorithm for an

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1 [https://github.com/RWTH-EBC/pyDMPC](https://github.com/RWTH-EBC/pyDMPC)
explorative search and the SLSQP solver from SciPy for refining the search. It is part of the future work to introduce different solver types to allow the selection of the most suitable solver for a certain model type. The algorithm computes the optimal costs for each subsystem by applying a cost function in the form

$$C = a_1 \cdot (T - T_{set})^2 + a_2 \cdot c_{op} + a_3 \cdot c_{neigh}$$

where $a_1 - a_3$ are weighting factors, $T$ is the temperature, $c_{op}$ is the operation cost and $c_{neigh}$ is the cost in the neighboring subsystem.

**Modelica simulation model** The most complex type of model we implement is the Modelica simulation model. Modelica is an object-oriented modeling language that is commonly used in building performance simulation but seldom in model predictive control.

**Multi-layer perceptron** The MLP is a data-driven model that is often used for time series regression. Once trained, the computation is orders of magnitude faster than the computation of a Modelica model. This type can be used if sufficient training data is available, either in systems with extensive measurement equipment or if a thoroughly validated simulation model is available that shall be replaced by an MLP and can generate the training data. We use the MLP implementation of scikit-learn.

**Linear model** The user implements the required equations of the linear model in Python. Due to the fast computation and the wide variety of excellent solvers for linear systems, the linear model is a very important model type. However, it requires a lot of expert knowledge to assess if the modeled subsystem has linear characteristics or to perform a linearization.

**Fuzzy logic** If the user has very limited system knowledge, especially of disturbances, fuzzy logic can be a simple but powerful approach. It is very intuitive as it derives a set of rules from expert knowledge. We use the implementation Scikit-fuzzy.

3.2. Systems with large inertia

The subsystems in BES can have very different time constants, ranging from seconds in pressure controlled systems to days in thermo-activated building systems (TABS) and even years in geothermal fields. To account for these differences, each subsystem in our framework has its individual prediction horizon and optimization interval. In order to obtain a suitable prediction of the disturbances, we use weather predictions from a weather API for TABS and standard load profiles for geothermal fields. In the case study, we elaborate further on these predictions.

3.3. Case Study

In order to investigate the applicability of our approach, we apply it to a real-life building energy system. Its schematic is depicted in figure showing the architecture of the system as well as the model types we use for each subsystem. It is an industrial hall with 700 m$^2$ net floor area (zone 1) that also comprises office rooms (zone 2). The hall, except the offices, is equipped with a TABS for base load heating and a central air handling unit (AHU) for mixing ventilation. The two different zones are equipped with reheaters and recoolers. However, these are not considered in this study for the sake of simplicity.
The control task is to determine a suitable flow temperature set point for the TABS and a supply air temperature set point for the AHU. This temperature set point is a trade-off between the requirements of the hall and the offices. In future work, the reheaters and recoolers will also be considered and thus a proper selection of the supply air temperature avoids unnecessary simultaneous heating and cooling.

Actually, the building is connected to a district heating and a district cooling network. However, in this study, we assume the building was connected to a geothermal field and contained a heat pump that supplies heat and cold to the building. In order to allow sustainable operation of the field, we assume further that the building was equipped with an auxiliary chiller as well as a re-cooling system and that the overall cooling demand was higher than the heating demand. Sustainable operation is ensured if the soil’s end temperature after a long-term simulation over multiple years is equal to the start temperature of the soil before the simulation. In order to predict the long-term behavior of the field temperature, the heating and cooling load of the building have to be approximated. The load profiles are converted into a corresponding flow temperature, while peak loads are covered by the chiller, compare figure 2. The long-term simulation (3 years) is repeated with various contributions of the chiller until an ideal flow temperature is found.

As a starting temperature, the soil temperature has to be estimated based on monitoring data or the results of a geothermal response test (GRT). The GRT result is equal to the undisturbed ground temperature. Therefore, we include an additional term into the cost function of the energy conversion subsystem, which penalizes or rewards deviations of the ideal flow temperature into the geothermal field. According to our assumption that the overall cooling demand is higher than the heating demand, a reward will be granted if the flow temperature is lower than the soil temperature, which means a regeneration of the soil.

In our implementation, the subsystem agents responsible for the rooms use a fuzzy logic controller to determine the temperature set point depending on the current room temperature and the setting of a thermostat that is positioned in each room. The thermostat setting is a floating point number between -4 and +4, whereas -4 indicates the lowest and +4 the highest temperature set point. We thereby account for our limited knowledge of the user preferences and disturbances in the room. By contrast, the hall agent uses a Modelica model to calculate the long-term behavior of the TABS, integrating an outdoor air temperature prediction obtained from a weather API. Both in the hall and the offices, the cost in each subsystem corresponds to the difference of a predicted actual air temperature and the corresponding set point. Additionally, we
add a cost term in the hall subsystem that depends linearly on the TABS set point. Analogously, we assume the AHU cost depends linearly on the supply air temperature set point. Therefore, we use the linear model type for the AHU. As we only determine the set point and send it to the AHU controller in the real-life building, we do not require a physical AHU model.

4. Results and discussion
As a proof of concept, we vary the temperature set point of the hall and the setting of the thermostats in two offices. For reasons of simplicity, we assume the common extract air temperature of the hall and two office rooms to be the actual temperature in the respective rooms. Moreover, we selected the same thermostat settings for both offices. Figure 3 b) depicts the development of the set point and the thermostat settings. Figure 3 d) depicts the selected supply air temperature set point. Both figures show the resulting actual extract air temperature. In the beginning, the set temperatures are reached by an increase of the supply air temperature. When the set point decreases, the extract air temperature decreases as well. The results could be improved, i.e. the set point could be reached faster if predictions of the set points were considered. In this simple approach, only the current set point is used.

However, the supply air temperature remains above the set point. This is due to the fact that the thermostats still have a high setting. It is only when the thermostats are set to negative values that the supply air temperature and the extract air temperature decrease further. This behavior is the expected trade-off of the requirements of the two different zones – at least in this rather simplified setup, in which we do not have reheaters and recoilers. If they were used, the trade-off would be more in favor of the hall, which has a much higher volume than the offices.

Figure 3 a) shows the flow and return temperature of the geothermal field. The maximum cooling load extracted from the field has an optimal limit of 43 %, resulting in a stable temperature trajectory. There is still a slightly positive trend, that will be considered in future work.

Figure 3 c) shows the predicted outdoor air temperature development as obtained from the weather API and the predicted hall temperature as calculated by the hall subsystem model, given the optimized TABS setting.

In order to evaluate the performance of the algorithm, we perform a simulation and compare the results to the currently implemented control strategy in the real building, which keeps the supply air temperature of the AHU at constant 22°C and sets the TABS flow temperature according to a linear heating curve. The root mean squared error of the office and the hall zone decreases by 11 % and 45 %, respectively. The energy consumption decreases by 4 %.

5. Conclusion and Outlook
We contributed to the energy-efficient and sustainable operation of coupled building energy systems and geothermal fields by proposing an approach for model-based control that can be tailored to the user’s system knowledge and allows using various model types and time scales. In contrast to rule-based operation, our approach pursues control to an optimum where the cost of the system is minimized, while the distributed model predictive control simultaneously reduces the computational effort. A proof of concept showed that the various subsystems and their models are orchestrated successfully and that a real-life building could be controlled using our approach. Our future activities will focus on integrating the presented control strategy into a demonstrator building with a coupled geothermal field consisting of 41 individually controllable probes. To control the single probes efficiently and predict the ground water influence, a more detailed model of the geothermal field will be created. The cost function will be extended to enable demand side management and reduce the consumed electricity by the hydraulic pumps.
Figure 3: Results of the proof-of-concept in a real-life building: a) Flow and return temperature of the geothermal field (3-year-simulation) b) Temperature set point, thermostat settings and actual extract air temperature c) Predicted outdoor and hall temperature d) Supply air temperature set point and actual extract air temperature

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References
[1] Verhelst C 2012 Model Predictive Control of Ground Coupled Heat Pump Systems for Office Buildings Ph.d thesis KU Leuven
[2] Sturzenegger D, Gyalistras D, Morari M and Smith R S 2016 IEEE Transactions on Control Systems Technology 24 1–12 ISSN 1063-6536
[3] Picard D and Helsen L 2018 MPC performance for hybrid GEOTABS buildings International High Performance Buildings Conference ed Purdue University
[4] Jorissen F, Boydens W and Helsen L 2019 Journal of Building Performance Simulation 12 180–192 ISSN 1940-1493
[5] Afram A and Janabi-Sharifi F 2014 Building and Environment 72 343–355 ISSN 0360-1323
[6] Bode G, Fütterer J and Müller D 2018 Energy and Buildings 158 1337–1345 ISSN 03787788
[7] Picard D and Helsen L 2014 Advanced Hybrid Model for Borefield Heat Exchanger Performance Evaluation, an Implementation in Modelica Proceedings of the 10th International Modelica Conference, March 10-12, 2014, Lund, Sweden Linköping Electronic Conference Proceedings (Linköping University Electronic Press) pp 857–866
[8] Maasoumy M, Razmara M, Shahbakhti M and Vincentelli A S 2014 Energy and Buildings 77 377–392 ISSN 03787788
[9] Baranski M, Fütterer J and Müller D 2018 Energy and Buildings 175 131–140 ISSN 03787788