Long-term Optimal Control of Hybrid Ground Source Heat Pump Systems. How far are we from the Optimum?

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Optimal control of buildings relies on predicting their behaviour using techniques such as mathematical modelling, data science or a combination of both. However, these predictions are typically limited to a few days. Consequently, in ground source heat pump systems, the controller is unaware whether abusive energy injection/extraction into/from the ground will deplete the source over the years. This article presents a simulation-optimization study that showcases the importance of accounting for the long-term behaviour of the ground towards the optimal operation of hybrid geothermal systems. Further theoretical energy use savings of 23.4% can be achieved compared to a baseline optimal controller that only accounts for the short-term future.

Over the last decade, intelligent building management and optimal control have demonstrated a large potential to mitigate the carbon footprint, energy use and monetary costs related to building operation [1]. Optimal control techniques found in buildings can be divided into model-based control approaches or Markov decision processes [2]. One common feature of both approaches is that they optimize towards future system behavior, typically for a few days.

However, the time constant of ground dynamics of the geothermal borefield is too large to be captured by the typical prediction windows used by these optimal control techniques. In that regard, it is uncertain in the long-term whether an optimal solution is being achieved or, even worse, the ground-source is being depleted. The borefield long-term dynamics can be well predicted using its characteristic thermal response function or g-function [3]. Thus, this article follows a physics-based Model Predictive Control (MPC) approach, eliminating the need for large training datasets.

Optimal control using MPC

MPC uses a mathematical model of the building envelope and its energy system. Using forecasted disturbances (i.e., weather, occupancy, appliances, etc.) and control inputs (temperature set-points, distribution signals, etc.), the model can predict the building's dynamic response and the energy system efficiencies. The mathematical model can be reformulated as an optimization problem to find the optimal control input sequence that minimizes a target or objective function (energy use, CO_2 emissions or monetary costs [4]) while at the same time a set of comfort constraints (thermal comfort, indoor environmental quality, etc.) is enforced. Due to the increasing uncertainty over time of the forecasts and the computational burden, the optimization is solved recursively at steps for the desired horizon.

We apply MPC to a building emulator depicted in Figure 1. The considered building is modelled as a 1200 m^2 single space using verified high-fidelity models from the IDEAS Modelica library [5]. The building is equipped with a ground source heat pump (GSHP) and a gas boiler for heat production (Q_{con}, Q_{boi}), and passive cooling from the geothermal borefield and an active chiller for cold production (Q_{pc}, Q_{chi}). The building can also choose between thermally activating the building structure (TABS) through embedded pipes (Q_{TABS}) and using air conditioning ($Q_{air,hea}$, $Q_{air,coo}$) as the slow and fast-reacting emission systems, respectively. Thus, the building case study is hybrid both at the production and emission sides. Still, the gas boiler and the chiller can only supply energy to the fast-reacting emission system, whereas the TABS are only fed by the GSHP or passive cooling heat exchanger. The performances of the GSHP and chiller are dependent on the borefield outlet and outdoor temperature, respectively. The system components are sized based on a previous dynamic simulation of this emulator, and the geothermal borefield is deliberately undersized due to the hybrid production system of the building. No occupant/appliances heat gains are considered to keep the building as a highly heating-dominated building. For the detailed model equations and design process, we refer to [6].

The building emulator equations are reformulated into a non-linear optimization problem using TACO [7]. This optimization problem is solved each hour recursively with a prediction horizon of one week and for a period

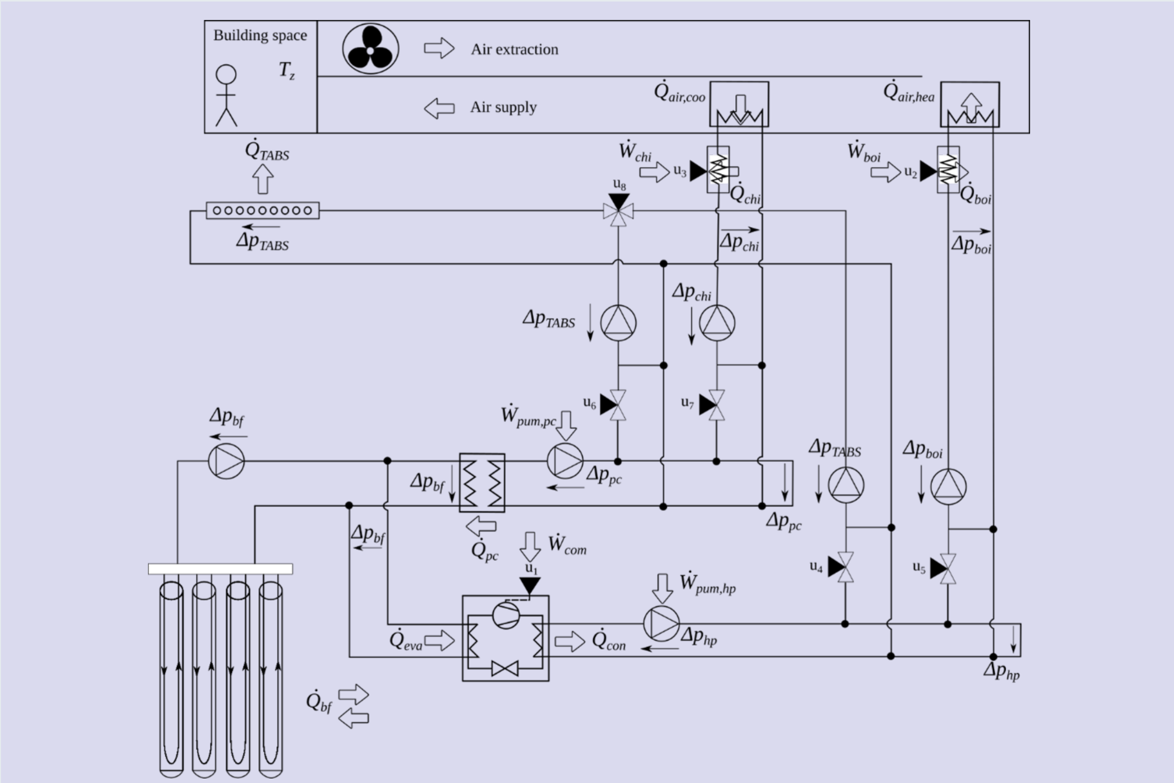

Figure 1. Schematic presentation of the considered building emulator, main energy flows and fluid network pressure drops.

of 5 years. The first set of inputs from the optimization is used to advance the simulation which starts at the beginning of the heating season, hence closing the loop. Weather forecast is considered to be perfect and deterministic. The optimization problem aims at minimizing the energy use of the installation while keeping thermal comfort in the space. Comfort is achieved when the space operative temperature is between 21°C and 25°C. A night-setback widens these bounds by ±5°C during the night.

The control input variables include the control of the production systems: u_1 for the GSHP, u_2 for the gas boiler and u_3 for the chiller; the valve openings that control the mass flow rates (and, in consequence, the heat/cold supply) to the different emission systems u_4, u_5, u_6 and u_7 and the 3-way valve that determines the TABS mode u_8. Since non-linear optimization problems do not accept binary inputs, this 3-way mixing valve needs to be considered as modulating in the simulation study. However, in practice, this valve is expected to be on/off to choose between heating or cooling mode in TABS. All pumps and fans work at a constant pressure head, although the pressure drops (Δp) they need to overcome can vary depending on their respective valve opening and, as a consequence, their energy use.

The energy distribution results over the 5 years simulation are shown in Figure 2a. Since the performance ratio between the GSHP and the gas boiler is around 5:1, MPC prefers the use of the GSHP to cover the heating energy needs of the building as much as it cans. However, the gas boiler energy shares increase each year due to the accumulated thermal imbalance in the borefield. This feature, in turn, favors passive cooling as the only cooling system being used in the building.

...but, how far are we from the true optima?

To answer this theoretical question, an Optimal Control Problem (OCP) is set up using the same building emulator equations and formulation. The only difference now is that the optimization is solved for a period of 5 years instead of recursively for 1 week at each control timestep. Computationally, solving this optimization problem is expensive and in the same order of magnitude as the full MPC simulation. Hence, a full OCP is non-applicable in real installations at the moment but serves as a theoretical benchmark.

The energy distribution results of the OCP can be observed in Figure 2b, revealing that the energy use of the building can be further decreased. To achieve this, the OCP increases the amount of cooling produced by passive cooling, thus reducing the thermal imbalance of the borefield and unlocking further use of the GSHP for the next heating season. This is possible thanks to the defined comfort bounds (instead of a fixed set-point), which confers freedom to the optimization. Figure 3 shows that the OCP keeps the building at the lower comfort bound during the summer season, whereas the MPC minimizes the short-term energy use and the space temperature is at the upper comfort bound.

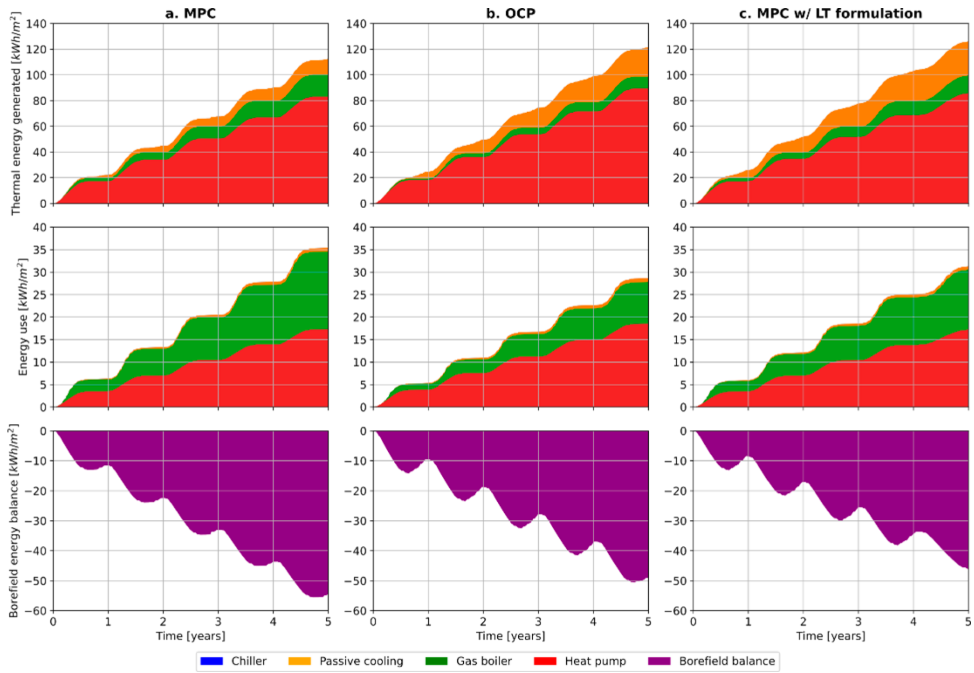

Figure 2. Energy distribution of the building HVAC components.

This behaviour is repeated for every year. The "short-term" MPC is not achieving its full potential in hybrid geothermal systems.

Can we do better than a "short-term" MPC?

Not many authors have proposed formulations that account for the borefield long-term dynamics. Typical approaches include a penalty term in the objective function to penalize the use of the borefield on the dominant energy side [8,9]. However, the determination of such a penalty relies upon trial-and-error. Imposing yearly cyclic conditions to the borefield by, for example, constraining the surrounding ground temperatures [10], can guarantee the sustainable use of the ground source. Still, the approach can be sub-optimal since (i) a yearly thermal imbalance can be allowed depending on the borefield size and (ii) it also limits the freedom of MPC to take optimal actions.

More recent research proposes extending the MPC objective function using a shadow-cost or cost of opportunity [11]. In summary, the shadow cost comprises the energy use of the building over a long-term horizon and can be computed using a set of prescribed predictions of the building heating and cooling needs (for example, using the building heating or cooling degree-days) and adding a set of static energy balance equations to the optimization problem. The short- and long-term optimizations are coupled by the load history of the borefield model, which in turn determines the predictions of the borefield outlet fluid temperature. Therefore, the actions of the short-term MPC optimization problem slightly influence the long-term optimization. Compared to the short-term MPC, the computational burden of the approach is increased, but still feasible towards real implementation.

The "short-term" MPC is extended by adding this shadow cost term to the objective function, estimating the energy use of the building emulator over one year. The building energy needs are estimated from the previous MPC simulation. The energy distribution results of this long-term MPC (MPC-LT) strategy are shown in Figure 2c, whereas the space temperatures are shown in Figure 3. It can be observed that the long-term MPC formulation overperforms the short-term MPC following a similar strategy as the OCP. Still, it cannot reach the full potential benchmarked by the OCP.

Several factors cause this loss of optimality. First, by imposing the use of fixed predictions coming from the short-term MPC, we mislead the long-term MPC during the mid-season when no heating is required by the short-term MPC, as shown in Figure 3. Therefore, the long-term MPC does not know that it needs a few days of extra heating per year. In addition, the long-term MPC drives the overuse of passive cooling since the beginning of the summer season at low pump speeds, whereas the OCP waits until the middle of the season using a higher pump speed. This results in a lower borefield energy imbalance, but it is not translated into a lower energy use probably due to (i) the effect of the loads farther in time having a lower effect on the borefield fluid temperatures and (ii) thermal losses into the ground.

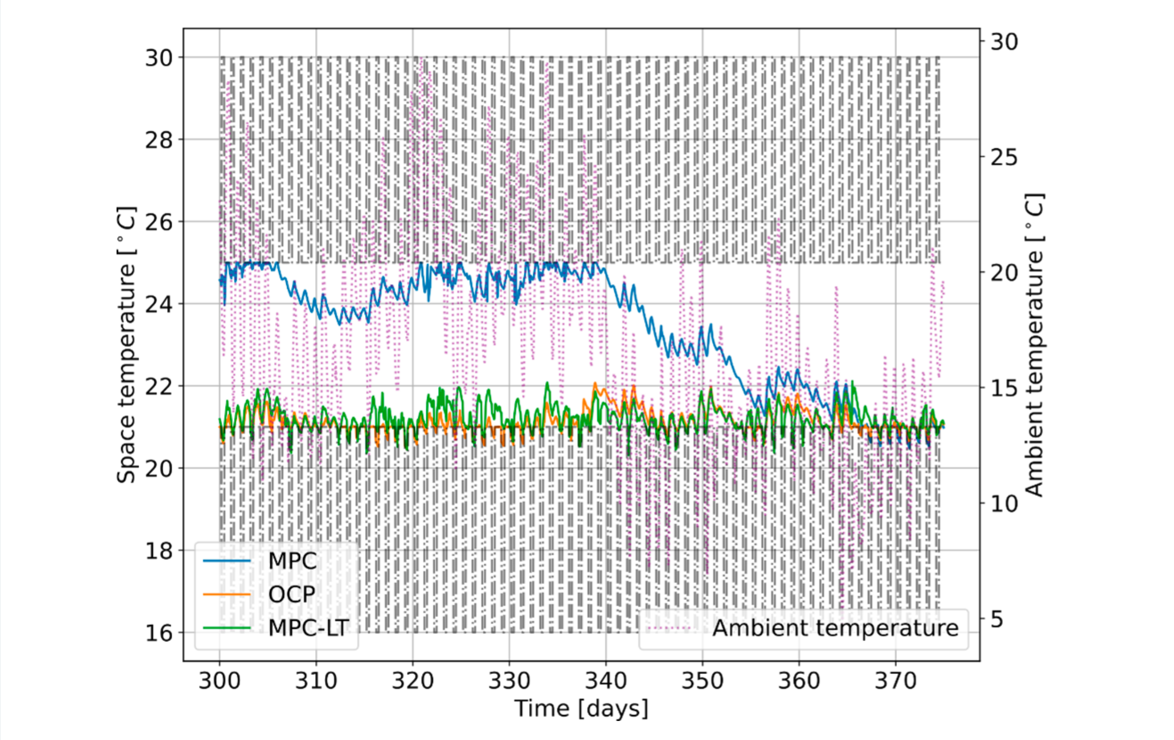

Figure 3. Temperature evolution of the building space at the end of the cooling season.

Table 1. Energy use comparison between the OCP and the MPCs with and without shadow cost

Energy use [kWh/m²]	OCP	MPC		MPC-LT	
		Absolute	Relative	Absolute	Relative
Heat pump	18.54	17.34	-6.4%	17.43	-6.0%
Boiler	9.28	17.26	+86.0%	13.33	+43.6%
Passive cooling	0.88	0.83	-5.6%	0.80	-9.1%
Chiller	0	0	0	0	0
Total	28.70	35.43	+23.4%	31.56	+10%

Conclusions

This study presents a simulation-optimization study of a heating-dominated building equipped with a hybrid geothermal system and whose borefield is deliberately undersized. MPC is applied to the building and benchmarked against an equivalent OCP for a period of 5 years. Then, the MPC is modified by introducing a shadow cost into its objective function.

The main numerics of the comparison are summarized in Table 1. Further theoretical energy savings of 23.4% can be achieved according to the OCP benchmark. The long-term MPC can reduce this gap down to 10%. If we define MPC efficiency as the ratio between the OCP and MPC energy savings, the short-term MPC is at 81.0% of its full potential, whereas the long-term MPC is at 91.0%.

This simulation study clearly shows that there is further potential in the optimal control of hybrid geothermal systems by accounting for the ground's long-term dynamics. If well formulated, the shadow-cost methodology can mitigate this performance gap. Still, further research should tackle the challenges regarding the quality and accuracy of the long-term predictions.

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