MPC performance for hybrid GEOTABS buildings

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ABSTRACT

Hybrid GEOTABS buildings are buildings equipped with a ground source heat pump (GSHP), thermally activated building systems (TABS), a conditioned ventilation and, optionally, additional heating and cooling systems such as variable-air-volume boxes or radiators. GEOTABS can be very energy efficient but its controllability is limited and thermal comfort is therefore not always guaranteed. Hybrid GEOTABS systems have the potential to eliminate these problems, provided the different system components interact properly. In this paper, we investigate the performance of hybrid GEOTABS systems for an office building, a retirement home, a school and a block of flats when controlled by a current practice rule-based-controller (RBC). The study is based on detailed simulation models inspired by four existing buildings. The RBCs performance is then compared with the performance achieved by Model Predictive Controllers (MPC) which optimize both the heat flow rates to the TABS and to the supplementary systems, and the ventilation supply temperature. The study shows that while thermal comfort level cannot be guaranteed by RBC for all buildings, a very high thermal comfort is achieved when controlled by MPC. This means that hybrid GEOTABS systems can technically be successfully used for a wide variety of buildings (and occupancy) types when appropriate control is implemented. Moreover, the investigated MPCs can save between 30% and 50% of the energy cost of which 6% to 11% is obtained by optimizing both the TABS thermal powers and the ventilation supply temperature simultaneously instead of only the TABS powers.

1. INTRODUCTION

Hybrid *GEOTABS* buildings can be energetically very efficient but they are difficult to control due to the slow reaction of TABS (Henze, Felsmann, Kalz, & Herkel, 2008; Kalz, 2011; Bockelman, Plesser, & Soldaty, 2013) and their potentially conflicting behaviour with the fast reacting emission systems such as ventilation, radiators, etc. (Tian & Love, 2009; Sourbron & Helsen, 2013c). TABS control using a rule-based-controller (RBC) has been extensively studied in the past (Kalz, 2011; Tödtli, Gwerder, Lehmann, Renggli, & Dorer, 2009; Olesen, 2011). Despite the extensive research on TABS control, the potential of *GEOTABS* buildings cannot be fully used by existing RBCs, as they are not able to optimally exploit the thermal storage capacity of TABS or to fully exploit solar and internal gains as well as changes in thermal comfort constraints due to a variable occupancy. Optimal controllers such as Model Predictive Controllers (MPC) are therefore particularly suited for such buildings.

The energy use and energy cost saving potential of MPC in buildings has been widely studied and demonstrated, and several companies already propose commercial products (Qin & Badgwell, 2003). Hilliard, Kavgic, and Swan (2015) compared in their review paper 19 different case studies where MPC was applied. They concluded that 15 to 30% of the energy used to heat and cool the building could be saved when the building is controlled by MPC instead of a traditional RBC. Hilliard et al. (2015) distinguished several building features for which MPC has a high saving potential: high building inertia (heavy walls and floors) and possibilities for thermal storage, highly predictable loads (internal and solar gains, etc.), broad thermal comfort ranges, slow HVAC systems, and a low infiltration and a high building insulation level. *GEOTABS* buildings are typically characterized by these features.

MPC for *GEOTABS* buildings focuses on saving energy and improving thermal comfort by using the inertia of the building optimally. The thermal comfort range and the building inertia are used to shift thermal loads, to maximize the use of *free* energy sources like solar gains or passive cooling, and to use slow reacting HVAC systems like TABS in an efficient way. The energy use, energy cost and thermal discomfort saving potential of MPC for *GEOTABS* buildings has been investigated both in simulation environments and in real buildings. Oldewurtel et al. (2012) and Gyalistras and Gwerder (2009) investigated the MPC saving potential for office buildings by simulating different variants of a 12th order RC white-box model (different orientations, construction types, building standards, window area fractions, internal gains levels, HVAC systems and climates were considered). The MPC optimized the operation of blinds, the ventilation, the TABS and the supplementary emission system. They found that for about 50% of the investigated building variants, MPC could save more than 40% of the non-renewable energy use. These high energy savings are an over-estimation of the real possible savings as the controller and the building models were identical (no model mismatch and perfect disturbance prediction) and they were relatively simplified. Sturzenegger et al. (2013) used a similar white-box controller model to control the HVAC of a real office building of 6000 m^2 floor area. Field tests showed that the implemented MPC could save 17% of the energy use. The MPC optimization variables were the heating and cooling powers of the TABS, the solar transmission through the windows (blinds), the air flow through the recovery wheel or through its by-pass, and the flow through the ventilation heating and cooling coils. The resulting optimal control problem was bi-linear in both its inputs and its states. Váňa, Cigler, Širokỳ, Žáčeková, and Ferkl (2014) developed an MPC controlling the TABS of a 3000 m^2 real building. Experiments during the winter season showed energy savings of 17%. The controller model was an 8th order model representing three thermal zones (one per floor) and its parameters were obtained by means of system identification. As the controller model had been identified using only winter measurement data, the MPC was only used for the heating season. Prívara, Široký, Ferkl, and Cigler (2011) also proposed an MPC to control the TABS power of a large university building during the heating season. The controller model was obtained by subspace black-box model identification and savings between 17 and 24% were found.

To the author's best knowledge, no previous study has investigated the savings potential of MPC for different types of hybrid *GEOTABS* building and building occupancy while optimizing the TABS, the ventilation and the supplementary systems for heating and cooling simultaneously. All studies mentioned in the previous paragraphs focus on for office buildings. This paper demonstrates that *GEOTABS* concepts can be successfully used to condition an office, a retirement home, a school or a block of flats when proper control is used to control the TABS. The study is carried out on simulation models based on four existing Belgian buildings. This paper further investigates the energy use, energy cost and thermal discomfort savings obtainable by MPC for each of the four buildings. Different linear MPC formulations are developed which are able to simulaneously optimize the TABS heating and cooling powers, the ventilation supply temperature (while the on-off ventilation flow is defined by the hygienic building requirements), and the thermal powers of the supplementary systems (radiators, fan coil units) while taking into account the operating cost of the different heat and cold production units (gas boiler, heat pump, ...). Very accurate controller models for MPC are obtained by automatically linearising the building emulator models which ensures good control performance thanks to the low model mismatch. The study further quantifies the extra savings obtainable when not only the TABS but also the ventilation and the supplementary systems are optimized.

2. GOALS AND METHODOLOGY

This paper has three goals: i) to assess the feasibility and performance of (hybrid) *GEOTABS* systems in terms of thermal comfort, energy use and energy cost for different types of buildings and occupancy, ii) to assess the performance improvements that MPCs can achieve compared to current practice RBCs, and iii) to compare the results obtained when only the TABS are optimally controlled with the results obtained when the TABS, the ventilation and (optionally) the supplementary emission system are optimally controlled.

This study is based on the four detailed simulation models (the emulators) presented in (Picard & Helsen,

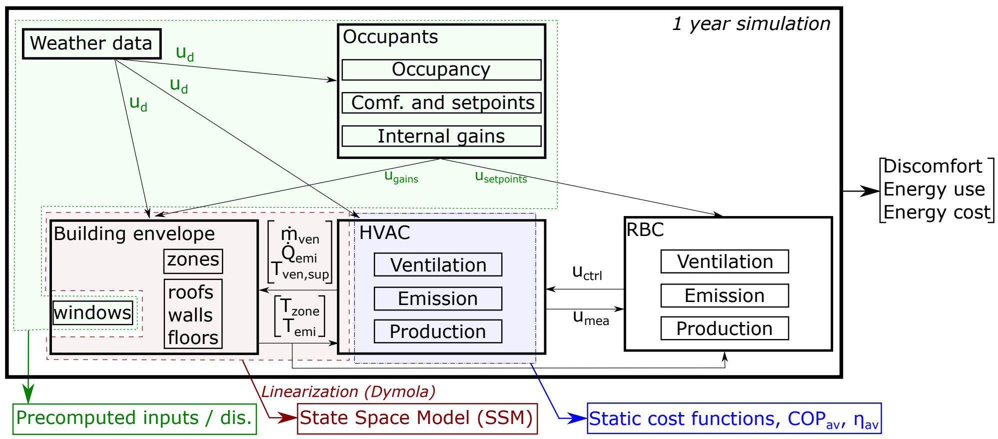

Figure 1: Graphical representation of the methodology used to evaluate the performance of the RBC and compute the MPC controller model (SSM), MPC disturbances (dis) and MPC cost function factors.

2017) and the toolchain developed in (Picard, Jorissen, & Helsen, 2015; Jorissen & Helsen, 2016) is used. For clarity reason, the methodology is here again illustrated in fig. 1 specifically applied to this study. Each building model with its RBC is firstly simulated for a full year using typical Belgian weather data (Meteotest, 2009) and the thermal discomfort, the energy use and the energy cost are evaluated (see fig. 1). Thermal discomfort is expressed as the number of hours during which the operative zone temperatures are lower (resp. higher) than ±0.5K the lower (resp. upper) thermal comfort bound defined by the occupancy model. In order to facilitate the comparison between different buildings which have each a different number of zones, the average thermal discomfort over the zones will be further used (i.e. the sum of the absolute value of discomfort of each zone divided by the number of zones), except where specified differently. The energy use is expressed in kilo-Watt-hour per year per square meter floor area (kWh/y/m^2) and it corresponds to the energy delivered to the emission systems. The energy to the emission systems is used instead of the energy used by the production units in order to limit the influence of the production unit sub-controllers on the results. Finally, the energy costs are computed using the variable efficiencies of the heat pump and the gas boiler and using the average electricity (P_{el}) and gas (P_{gas}) price of 2015 for Belgian buildings with an energy use between 20 and 500 MWh/year: 0.1466 €/kWh for electricity (computed as energy supply (0.0575 €/kWh) + network (0.0656 €/kWh) + taxes and levies (0.0235 €/kWh)) and 0.0464 €/kWh for gas (Eurostat, 2017, 2016). A fixed energy price is chosen as large buildings rarely use a day/night tariff.

The simulation results are then used to generate the MPC precomputed inputs (see green texts and frames in fig. 1): the (weather) disturbances u_d including the solar radiation through each window, the internal gains u_{gains}, and the setpoints $u_{\text{setpoints}}$ for thermal comfort, ventilation, etc. The yearly average heat pump coefficient of performance (COP$_{\text{av}}$) and gas boiler efficiency (η_{av}) are further computed to be used by the MPC cost function (see blue parts in fig. 1). Using average efficiencies is necessary to keep the MPC formulation linear and the suboptimality it introduces is limited as the efficiencies only slightly vary during the year. The MPC building controller model is obtained by linearising the building envelope into a linear time-invariant state space model (SSM) using the methodology described in (Picard et al., 2015) (see red parts in fig. 1 and see section 4.1).

In order to assess the MPC performances, the same building model is used as the one used for the RBC simulations except that the RBC is replaced by an MPC and that the HVAC system, which in the case of RBC simulations is composed of hydraulic components (pumps, fans, pipes and valves), production components (heat pumps, heat exchangers, gas boilers) and emission components (water circuits for TABS, radiators, fan coil units, ventilation), is here idealized. The MPC simulations assume thus perfect sub-controllers which convert the optimal emission thermal powers and ventilation supply temperature into mass flow rates and water supply temperatures for the different HVAC components such that the optimal control values are respected. The MPC is composed of the linear SSM obtained by linearisation as its controller model, of a linear cost function and linear constraints corresponding to the same system constraints as in the RBC simulations (see Section 4.2), and of an optimizer (see Section 4.3). The annual thermal discomfort and energy use are computed in the same way as for the RBC simulation. The energy costs are computed from the energy use using $\mathrm{COP}_{\mathrm{av}}$ and η_{av} as using the time varying efficiencies would lead to a non-linear MPC. In this study the linearity of MPC is kept in order to use efficient solvers capable of solving large optimization problems in tractable computational time (see (Jorissen & Helsen, 2016)). This approximation has the draw-back that peak powers (causing lower COP for GSHP) will not be penalized by the optimization. However, as the borefield of the building is generally oversized, the COP variation is expected to remain limited ($<$ 1% for short time scales and $<$ 5% for seasonal time scales in the RBC simulations, except for the block of flats where the COP ranges from 6 to 4.5). Finally, as the controller model originates from the linearisation of the building model and they therefore have the same states, no state observer needs to be used here. The MPC states can thus be updated at each control step using the virtual measurements from the building model (see section 4.3).

For each building, different MPC formulations are evaluated (see section 4.2). It should be stressed that as the MPC controller models are obtained by linearisation of the building emulator models, as no measurements, weather and heat gains prediction errors are considered, as perfect state update is used and as ideal subcontrollers are assumed, the saving potential found for the MPCs are upper bounds for more realistic cases. The results, however, are very instructive about the physical capabilities and constraints of (hybrid) *GEOTABS* buildings when controlled by optimal controllers. The study allows the isolation of the physical limitations of the building from their limitations due to non-optimal control. Furthermore, the fact that the controller models are an accurate representation of the building models which are themselves modelled using a detailed BES tool, avoids the sub-optimality that many MPCs encounter due to their simplified controller model and this, without simplifying the building emulator model used for the performance evaluation.

3. BUILDING DESCRIPTION

In this paper, four existing Belgian hybrid *GEOTABS* buildings are considered as described in (Picard & Helsen, 2017): a school (S), an office building (O), a retirement home (R), and a block of flats (F). This section briefly repeats the most important features of the different buildings and compares them to help the reader to understand their main differences.

All buildings have a high insulation level, a limited window-to-wall ratio and a good air tightness. The office building is further equipped with solar blinds which automatically shade the windows when the solar radiation on a horizontal plane exceeds 150 W/m^2. The school is composed of two parts: an old existing building and a newly built part. Figure 2 shows the hydraulic scheme of each building. All these buildings use TABS and all (except the block of flats) have a ventilation system composed of a heat recovery wheel with by-pass, a heating and cooling coil, a supply and an extraction fan. The ventilation system creates a constant air flow prescribed by the design hygienic requirements during the occupancy periods (see fig. 3). The ventilation system of the block of flats is composed of an extraction fan, window slits and it is on/off controlled according to the occupancy. The RBC of each building is similar: based on the 7-days (or 3-days in the case of the office building) running mean average ambient temperature, the HVAC is in *heating*, *neutral*, or *cooling mode*. During the *neutral* mode, the TABS are not used. The water supply temperature changes according to a heating/cooling curve tuned for the specific building. For the office building, the water is circulated in the TABS at the start of each hour for 10 minutes after which the temperature difference between the supply and the return is measured. Depending on that value, water is recirculated for a given amount of time. For the other buildings, a PI-controller keeps the TABS return temperature equal to the thermal comfort lower / upper temperature plus / minus an offset for respectively the heating and cooling modes. For all buildings with a conditioned ventilation, the by-pass, and the heating and the cooling coils are controlled by PI-controllers such that the supply air temperature equals the lower thermal comfort temperature. The different production units and circulation pumps are also controlled by PI-controllers or on/off.

The thermal comfort temperatures, internal gains and ventilation flow rates have a large influence on the

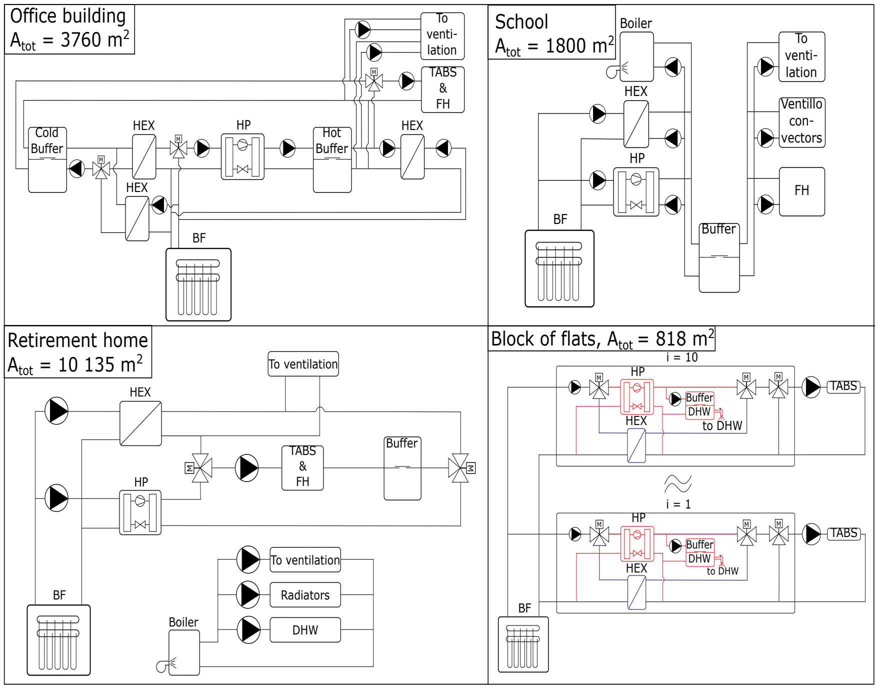

Figure 2: Hydraulic scheme of the different buildings. The components are borefields (BF), heat exchangers (HEX), buffers, a heat pump (HP), TABS, floor heating (FH), fan coil units, radiators, domestic hot water (DHW) tap, circulation pumps and threeway valves.

total heat and cold demand of the building. Figure 3 shows them for each building for a week in January (the convective and radiative gains are summed in fig. 3). Humidity is not modelled and latent gains are therefore not included in the models. For a detailed description per building, see Picard and Helsen (2017).

4. MODEL PREDICTIVE CONTROL FRAMEWORK

The building emulator models developed with the Modelica Library `IDEAS` are not suited for optimization. Even though Modelica is an equation-based language and it can be used directly for gradient-based optimization by using JModelica (Åkesson, Årzén, Gäfvert, Bergdahl, & Tummescheit, 2010), the complexity of the building models cannot yet be handled by the JModelica compiler. This has been recently tackled by the tool TACO (Jorissen, Boydens, & Helsen, 2018) which was however, not available at the time of this study. Nevertheless, gradient based optimization is preferred here over other methods such as *genetic* or *particle swarm* algorithms in order to keep the computation time tractable (Wetter, Bonvini, & Nouidui, 2016). In this paper, only the building envelope is dynamically included in the controller model as its time constants are much larger than those of the HVAC system (days/hours compared to minutes) and a linear model is used to enable the use of an efficient solver which ensures a global optimum. As the control time steps of the implemented MPCs vary between 20 and 60 min which is more than twice longer that the largest time constant of the HVAC components and as the constraints of the HVAC system are taken into account by the MPC, it is expected that the HVAC system and its control will be able to reach the set points computed by MPC. However, not including the HVAC system dynamically might conceal unexpected system failures (e.g. oscillatory behaviour of PID controllers for particular reference trackings, etc.) and it also prevents the computation of time-varying efficiencies (e.g. heat pump COP, etc.).

This section describes the controller model (section 4.1) and the cost function and constraints of each MPC (section 4.2) as well as the optimization parameters (section 4.3).

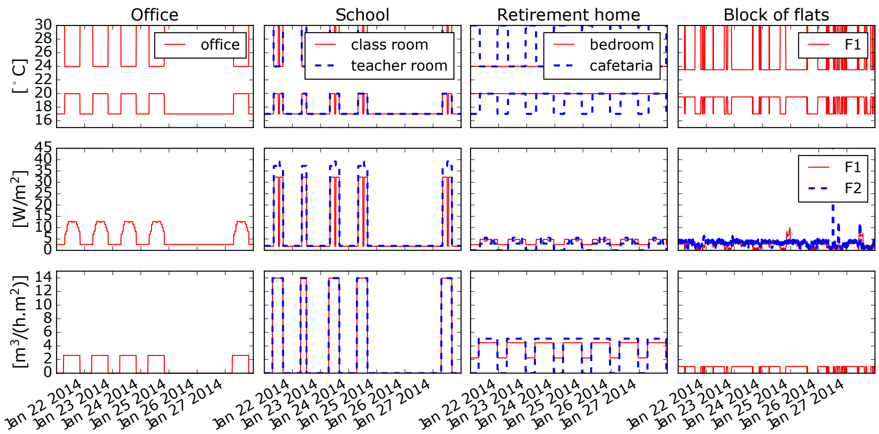

Figure 3: Top: thermal comfort ranges, middle: total internal heat gains (convective + radiative) and bottom: ventilation flow rate for a winter week (Tuesday to Monday).

4.1 Controller model

The controller models are obtained automatically from the building emulator models by using the linearisation method described in (Picard et al., 2015). The number of states of the resulting SSMs is 700 for the office building, 920 for the school, 941 for the retirement home and 732 for the block of flats.

4.2 Cost function and constraints

Due to the lack of space, this paper does not include the complete mathematical description of the different MPC formulations of each building. We refer the interested reader to chapter 9 of Picard (2017). The different formulations are the following. `MPC:T` minimizes the cost related to the TABS energy use while the ventilation is controlled by RBC and the auxiliary systems are not used. `MPC:T+V` is similar to `MPC:T` but here the cost related to the heating and cooling of the ventilation is simultaneously minimized by optimizing the unique air supply temperature to the building while the air volume flow rate is prescribed. (Picard, 2017) describes the tricks used such that the cost function and constraints formulation remain linear while the prescribed volume flow rate changes with time (e.g. day ventilation differs from night ventilation). Finally, the `MPC:T+R` formulation minimizes the cost related to the TABS and radiator energy use while the ventilation is controlled by RBC and `MPC:T+V+R` minimizes the cost related to the TABS, ventilation and radiator costs.

The linear MPC formulation introduces some approximations and assumptions. Firstly, no constraints on simultaneous heating and cooling could be formulated while none of the real building HVAC systems are able to simultaneously heat and cool through the TABS and only the retirement home can heat with its radiators and its ventilation while the TABS are cooling. This causes an overestimation of the MPCs capabilities. However, simultaneous active heating and cooling is rarely optimal and the effect of this approximation is thus limited. The approximation error increases when different zones have strong different thermal needs, e.g. cooling for the south zones while the north zones still need heating. Secondly, the different MPCs optimize the heating and cooling powers of each TABS circuit, radiator, and fan coil unit and the unique ventilation supply temperature. It assumes that as long as its power and temperature constraints are respected, the production units are able to deliver the required power perfectly (see section 2). However, despite the fact that all powers computed by MPC are constrained by the subsystem nominal values, this assumption can lead to an overestimation of the MPC performance as several TABS circuits are usually fed by a single circulation pump and they can therefore not be individually controlled in reality. Finally, the ventilation optimization takes into account the recovery wheel and the fraction of return ventilation air flow but it does not include the by-pass as the authors could not easily formulate its behaviour by linear equations.

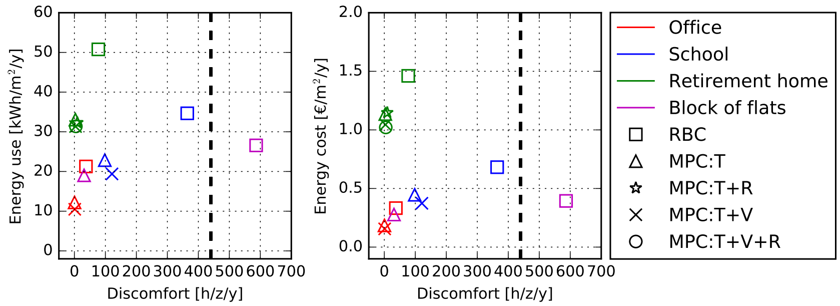

Figure 4: Comparison of the thermal discomfort, energy use and energy cost achieved by the RBCs and the different MPCs for the four buildings. The dashed line presents the acceptable limit of thermal discomfort according to EN 15251 (Technical Committee CEN/TC 156, 2007).

4.3 Optimization parameters

The MPCs prediction horizon is 6 days in order to take the TABS (and building) inertia correctly into account. Due to the long horizon, an adaptive step size is chosen in order to keep a reasonable time accuracy without increasing the problem size excessively. For the cases of the retirement home and the block of flats the horizon is divided into 24 control steps consisting of 4 groups of 6 steps of equal size each. The different sizes are 3600, 7200, 14400 and 57600 seconds and the horizon steps can thus be written as: (3600, 3600, ... , 7200, ... , 14400, ..., 57600, ... , 57600) seconds. For each step, the average value of the disturbances is taken. For the office building and the school where the thermal comfort bounds switch sharply between day and night, 6 control steps of 1200 seconds each are added to the horizon steps array. In order to avoid sub-optimality, the MPC states are updated at each control time step.

5. RESULTS

This section compares the total thermal discomfort, the energy use and the energy cost achieved by the RBC and MPCs for the different buildings. Figure 4 compares the energy use and the energy cost as a function of the thermal discomfort achieved by the RBCs and the MPCs for the four buildings and the dashed line gives the acceptable thermal discomfort limit according to EN 15251. Each color represents a different building type and each marker a different controller.

Thermal comfort: For the block of flats, fig. 4 shows that its RBC does not achieve an acceptable thermal comfort as it has an average of 589 hours of thermal discomfort per zone per year and up to 1055 hours for one of the flats despite the individual tuning of each flat heating/cooling curve. The slow reaction of TABS is often insufficient to compensate for the intermittent cold flow from the non-conditioned ventilation, for the solar gains through the unshaded windows and for the highly variable internal gains. However, when controlled by MPC, the average thermal discomfort drops to 31 h/z/y which corresponds to a thermal discomfort saving (i.e. a thermal comfort improvement) of 94.7% compared to RBC. This indicates that the HVAC system is physically capable of providing thermal comfort and that the bottleneck of the system is its control.

For the school, thermal comfort is not guaranteed for all zones when controlled by the RBC and the average thermal discomfort is relatively high (364 h/z/y). This is mainly due to the zones with fan coil units which are not well insulated and which would still need heating during the neutral and during the cooling season. On the contrary, the renovated zones with floor heating (FH) show overheating during the neutral regime and some parts of the heating season (see figs. 3.9 and 3.10 from Picard and Helsen (2017)). As both the fan coil units and the floor heating are connected to the same buffer tank (see fig. 2) which is used both for heating and cooling, the simultaneous need for heating and cooling cannot be met by the production system. This illustrates that supplying different emission system types in rooms with different insulation levels by using a single production system leads to an insufficient controllability of the system. For the MPC simulations, no linear constraints could be formulated to avoid simultaneous cooling with floor cooling and heating with fan coil units. The MPC simulations for the school assume therefore that heating and cooling can be provided at any time during the year. Using this system improvement, the MPCs can significantly improve thermal comfort for each zone (thermal comfort improvement of more than 66%). The remaining thermal discomfort is mostly occuring in the zones with fan coil units (average thermal discomfort between 186 and 400 K/h/y compared to 1.5 to 20 K/h/y for the zones with FH). This is due to the model mismatch between the MPC controller model and the building emulator model which becomes significant when the air of the zone is strongly excited (high fan coil unit power), often causing undercooling at the start of the day. The effect is worsened by the relatively coarse controller time step of 20 minutes.

For the retirement home, fig. 4 shows that the thermal comfort realized by the RBC is very high. However, this high thermal comfort comes at the cost of the active use of radiators during the cooling season which compensates the undercooling of some zones (see fig. 2.12 from Picard and Helsen (2017)). This undercooling cannot be avoided by a better tuning of the RBC heating/cooling curves because some other rooms show overheating at the same time and because the RBC, as implemented in the model, controls the average water mass flow rate to the TABS instead of each TABS circuit individually. In contrast to RBC, the different MPCs are able to optimize the heat flow rate in each TABS circuit individually which results in an almost perfect thermal comfort (thermal comfort improvement of more than 87%). The radiators are barely used anymore.

Finally, the office building shows a good thermal comfort when controlled by RBC and nearly no thermal discomfort when MPC is used instead (thermal comfort improvement of more than 96%).

Energy use and energy cost: While thermal comfort is considered as a (soft) constraint in the MPC formulation, the actual objective is to minimize the energy cost. Energy *use* differs from energy *cost* due to i) the different efficiencies of the production units and the different energy prices for electricity and gas, ii) the cooling energy is considered to be for free as only passive geothermal cooling is used (which leads typically to a very high EER), and iii) for HVAC with a hybrid production system, the same amount of heat or cold can be produced by different units. Notice that, as passive cooling is almost for free but it is still preferable to minimize the used cooling energy (seasonal storage is here not considered), a fictive cost is still attributed to it.

Figure 4 shows that when all emission systems are controlled by MPC, the energy cost savings range from 29.4% for the block of flats to 53% for the office building while thermal comfort is significantly improved and energy use decreased. The obtained savings are significantly higher than those found in the literature (15-25%), both when evaluated using building energy simulation (BES) software and in real buildings (see section 1). These substantial savings are mostly due to the ability of MPC to work at the thermal comfort boundaries while RBC is obliged to play safe and as a consequence to remain in the middle of the upper and lower thermal comfort temperature bounds. TABS have indeed a too long reaction time to use a feedback controller such as a PID controller and operating closer to the comfort bounds would result in regular overheating or undercooling. When the building controllability is low and the gains and occupancy are highly variable, using MPC can be a necessity to ensure thermal comfort as it is the case for the block of flats where thermal discomfort was reduced from 589 h/z/y to 31 h/z/y. It is interesting to note that thermal comfort improvement did not imply an energy cost increase (the cost was actually reduced from 0.39 to 0.28 €/m^2/y). MPC can further exploit the benefits of hybrid systems. Moreover, fig. 4 shows that optimizing both TABS and ventilation (`MPC:T+V`) increases the cost savings with 6% to 11% compared to `MPC:T` where TABS is optimized but the ventilation is controlled by the RBC algorithm. In the case of the school where the heat pump and the gas boiler can be used in parallel, `MPC:T+V` uses 25 times less the boiler than `RBC`.

6. CONCLUSIONS

This paper had three goals: i) to assess the feasibility and performance of (hybrid) *GEOTABS* systems for different types of buildings and occupancy, ii) to assess the thermal comfort, energy use and energy cost savings that MPCs can achieve compared to current practice RBCs, and iii) to compare the results obtained for pure *GEOTABS* buildings where only TABS are optimally controlled with hybrid *GEOTABS* buildings where simultaneously TABS, ventilation and (optionally) supplementary emission systems are optimally controlled. This study is carried out using simulation models based on four existing Belgian buildings: an office, a retirement home, a school and a block of flats. To reach these goals, a framework was developed that allows investigating the saving potential of MPC for different building types while optimizing all systems for heating and cooling simultaneously.

For all buildings, a very high thermal comfort was achieved when controlled by MPC. This means that (hybrid) *GEOTABS* systems can technically be successfully used for a wide variety of building (and occupancy) types when appropriate control is implemented. When a traditional RBC is used, a too low controllability of the building, such as the block of flats with unconditioned ventilation, or a too large difference of thermal needs between the different zones, such as the investigated school, leads to a low thermal comfort satisfaction. If *GEOTABS* is installed in such a building, MPC might be necessary to meet the thermal comfort requirements. The investigated MPCs could further save between 30% to 50% of the energy cost. These high savings contrast with the values found in the literature (between 15% to 25%) both when evaluated in building energy simulation software and in real buildings. This is probably due to the excellent predictions of the controller model compared to approaches using a black-box, a grey-box or a low order white-box controller model where significant model mismatch leads to sub-optimality. The implemented MPCs further optimize TABS and ventilation (and the supplementary system) simultaneously which improves the energy savings with 6 to 11 % compared to the savings obtained by the MPC optimizing TABS only.

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