hybrid GEOTABS

Controlling the power of the ground by integration

D3.2

Report describing the mathematical formulation of different objective functions for hybridGEOTABS buildings MPC

Author(s): **KU Leuven, EK**

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Lead beneficiary: KUL (KU Leuven, Belgium)

Deliverable lead: KUL (KU Leuven, Belgium)

Author(s): KUL (KU Leuven, Belgium)

Iago Cupeiro Figueroa (iago.cupeirofigueroa@kuleuven.be)

Lieve Helsen

EK (Energoklastr, Czech Republic)

Jiří Cigler (cigler@feramat.cz)

Reviewer(s): KUL (KU Leuven, Belgium)

Damien Picard

UGent (Universiteit Gent, Belgium)

Eline Himpe

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Summary

This deliverable 3.2 "Report/paper describing the mathematical formulation of different objective functions for Hybrid GEOTABS buildings MPC", is part of the hybridGEOTABS project WP3 on the "Development of an MPC Toolchain for the hybridGEOTABS concepts". The aim of this deliverable is to describe the possible objective functions in the MPC formulation for the hybridGEOTABS concept.

Model Predictive Control implies the recurring use of an optimization problem in the discrete time which aims to minimize a cost or objective function. Applied to buildings, this objective typically minimizes the energy use and the occupants' discomfort. However, other formulations encountered in the literature are reviewed in this document.

It is found that different objectives can be optimized by MPC, among them: energy cost, (primary) energy use, indoor environmental quality, peak power, share of renewable energy sources, flexibility… as long as these objectives can be quantified in a mathematical way. To facilitate the integration of renewable energy sources (on a broader scale), connection of the MPC framework to energy grid(s) is realized by setting appropriate pricing schemes or communicating optimal load profiles. Thermal comfort is usually treated as a soft constraint, allowing a limited level of comfort violations, in order to keep the optimization problem solvable. Non-linearities make the optimization problem far more complex and are avoided when justified. There exists a lack in the literature regarding long-term objectives such as objectives to guarantee the thermal balance of the geothermal borefield, which is a key component of the hybridGEOTABS system. As a consequence, and in parallel to the hybridGEOTABS project, a methodology that includes a shadow-cost in the objective function to take into account the long-term effects that appear in the borefield, is developed.

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Nomenclature

Acronyms

CCA	Concrete core activation
COP	Coefficient of Performance
CO_2	Carbon Dioxide
DR	Demand Response
DSM	Demand Side Management
EER	Energy Efficiency Ratio
EU	European Union
GEOTABS	system combining TABS and geothermal energy using a heat pump
GHG	Greenhouse Gases
HVAC	Heating, Ventilation and Air Conditioning
IAQ	Indoor Air Quality
IEQ	Indoor Environmental Quality
KPI	Key Performance Indicator
MPC	Model Predictive Control
OCP	Optimal Control Problem
PMV	Predicted Mean Vote
PV	Photovoltaic
RBC	Rule-based Control
RES	Renewable energy sources
TABS	Thermally Active Building System

Symbols

J	objective term
G	set of constraints
N	number of prediction horizon steps
k	discrete time-step
$\dot{W}$	power [W]
$\dot{Q}$	heat transfer [W]
Q	quantity of heat [kWh]
T	temperature [K]
t	time [s]
c	cost factor [EUR/kWh]
e	emission factor [gCO_2/kWh]
s	slack variable
u	upper bound [K] or system input
l	lower bound [K]

Greek symbols:

Δ	difference prefix to be combined with other symbols
η	Efficiency [-]
α	Objective weighting term

Subscripts:

HP	heat pump
PC	passive cooling
SS	secondary system
BF	borefield
TABS	tabs
T	temperature
max	maximum
el	electricity
loc	local
zone	zone
e	energy
c	comfort
r	robustness
b	bound

1. Introduction

Model Predictive Control (MPC) is an optimal controller that can be used in a variety of applications, including the control of buildings. For controlling HVAC in buildings, it uses weather forecasts and a model of the building (called controller model) to predict the building energy needs and to optimize the control actions accordingly [1]. This control methodology is particularly interesting in (hybrid) GEOTABS buildings – i.e., buildings whose heat/cold supply system includes a geothermal heat pump and borefield (GEO) and whose emission system involves thermally activated building system (TABS) by means of concrete core activation (CCA) – since MPC is able to anticipate their high thermal inertia and thus harness their storage capabilities [2]. Nonetheless, to cope with the slow-reacting nature of TABS and geothermal borefields, a fast-reacting secondary supply and/or emission system is often installed, leading to the hybridGEOTABS concept [3]. The augmented complexity of such buildings with multiple (interacting) components enforces and motivates even more the necessity of MPC. Hence, a correct optimal control problem (OCP) formulation that takes into account the different components is of utmost importance to attain a desirable system behaviour.

1.1. MPC Formulation

MPC applied to buildings is usually based on multi-objective optimization, which involves two or more objective functions J_i in the OCP formulation. The objective function, or cost function, is the mathematical function that we desire to minimize/maximize. Solving the optimization problem consists on finding the optimization variables that minimize/maximize this function. In multi-objective optimization, the terms *k* of the objective function are generally conflicting (e.g., energy use of the building and thermal discomfort of the occupants) and they are often adjusted with weighting factors α_i to obtain a summed weighted objective function (see Equation (1)) . Thus, weighting factors implicitly give more priority to either the one or the other term and their adjustment becomes one of the important ingredients to achieve appropriate results. However, other approaches than weighting factors exist, such as lexicographic MPC, where one of the objectives is optimized in a prioritized way [4]. The formulation is subjected to m inequality or equality constraints G_j (Equation (2)), typically related to thermal comfort requirements and power limits of the components.

$$J = \sum_{i=1}^{k\geq 2} J_i \; = \alpha_1 J_1 + \alpha_2 J_2 + \cdots + \alpha_k J_k \tag{1}$$

s.t.

$$G_j \; \leq 0, \;\; j = 1, 2, 3 \ldots m \tag{2}$$

The cost function minimization can cover everything that can be quantified in a mathematical way within the model, hence it is a key feature to obtain the desired results. Energy use and thermal discomfort are the most common objectives to be minimized, but other objectives could be optimized as well, such as monetary costs, GHG emissions, use of renewable energy sources (RES), flexibility and demand response indicators, etc… Furthermore, several indicators exist to assess thermal comfort and indoor environmental quality (IEQ). Moreover, in practical implementations, extra terms could be included to improve robustness of the OCP. This paper gives a review of building MPC formulations and is structured as follows: Section 2 presents the typical formulation to reduce energy use. Section 3 discusses an OCP for users that prefer monetary savings. In contrast, Section 4 approaches the OCP from green users' point of view. Section 5 explains how to handle thermal comfort and IEQ in the MPC formulation. Section 6 analyses how to improve the robustness of the MPC in the OCP formulation. Conclusions are summarized in Section 7.

2. Minimization of energy use MPC

The (discrete) formulation of the MPC problem is presented by Equation (3). Note that we include the energy use term J_e only, the comfort term J_c is analysed in a further section. For hybridGEOTABS buildings, we need to take into consideration that we will have a heat pump, a ground source heat exchanger that can provide passive cooling (PC) and at least one secondary system.

$$\min \sum_{k=0}^{N-1} J_e = \min \sum_{k=0}^{N-1} \left[\frac{\dot{Q}_{HP}(k)}{COP(k)} + \frac{\dot{Q}_{PC}(k)}{\eta_{PC}(k)} + \sum_i \frac{\dot{Q}_{SS}(k)_i}{\eta_{SS}(k)_i} + \sum_j \dot{W}(k)_j \right] \Delta t \qquad (3)$$

s.t.

$$0 \leq \dot{Q}_{HP}(k) \leq \dot{Q}_{HP,max} \qquad (4)$$

$$0 \leq \dot{Q}_{PC}(k) \leq \dot{Q}_{PC,max}$$

$$0 \leq \dot{Q}_{SS}(k)_i \leq \dot{Q}_{SS,max,i}$$

$$0 \leq \dot{W}(k)_j \leq \dot{W}_{max,j}$$

The symbol k here represents the time-step of the controller. The cost function to be minimized contains a weighted sum of the heat and/or cold produced by the different supply systems $\dot{Q}$ over the prediction horizon of length N. The weighting factor is composed of the supply system efficiency. The *COP* is the coefficient of performance of the HP and it is a time varying parameter that depends on its operation conditions. Notice that if the heat pump is reversible, the *COP* would be substituted by the *EER* when operating in cooling mode. The second term refers to the passive cooling mode, of which the efficiency η depends mainly on the temperature of the soil. If passive cooling is continuously applied, the temperature of the soil will increase to a point where passive cooling is no longer possible. The third term includes the sum of all secondary supply systems in the building, if more than one. The last term includes the electric power due to the sum of all the necessary transport components, e.g. hydraulic pumps and fans. All these terms are subjected to power limiting constraints (Equation (4)(6)), depending on the component being used.

3. Economical MPC

The current structure of the final electricity price consists of multiple contributions that can be divided in fixed items and items related to the amount of energy used. The ratio between these two items depends on various factors, among them: voltage level, end consumer, yearly electricity consumption - the smaller the consumption and circuit breaker, the higher the fixed item payments.

Fixed items consist of a payment for reserved capacity based on the current main circuit breaker installed before the meter. The items related to the energy used can be split in a regulated part, which covers an electricity tax, the monthly fee, electricity transport and distribution fee, and the variable part that represents payment for the actual electricity consumption and additional services including fees for using the electricity grid. So, in total, the price for the electricity commodity can represent up to 30-50% of total costs of electricity.

With the mass implementation of smart meters, it becomes possible for end customers to select from a wider variety of electricity commodity payment options. Typically, the flat price or low-high tariff options were used in the past (and still today in many countries). Nowadays, it becomes possible to use hourly energy prices or in some EU countries even 15-minutes energy prices, which can be obtained from the energy supplier or aggregator companies, e.g. BELPEX in Belgium. A wide variety of options exists.

Intra-day wholesale market prices, which change from hour to hour, show the highest variability. A comparison with the daily electricity market is represented in Figure 3-1. Note that the price signals have the same scale, however for the sake of trade secret, the absolute values are not included.

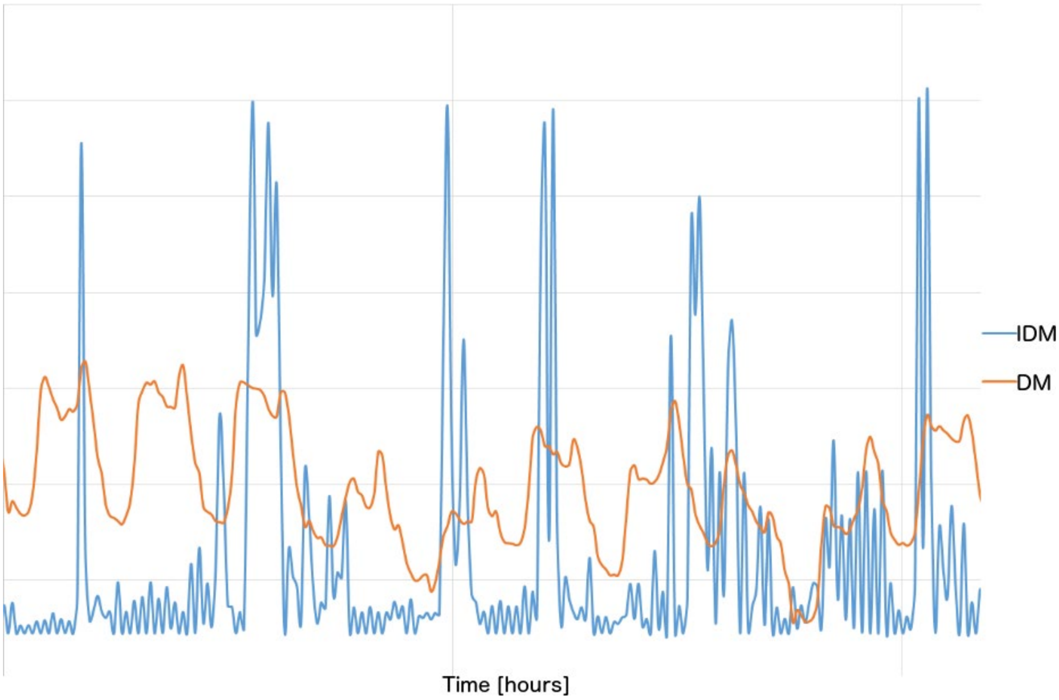


Figure 3-1: Difference between prices on daily market (DM) and intra-day market (IDM)

The economical MPC formulation is presented. The formulation is analogue to the minimization of the energy one, but including the cost of the energy vector used *c*, which corresponds to the price signal forecast obtained from the different suppliers (Equation (5)). The idea behind this formulation is that the electricity-driven components power is controlled based on the electricity price signal. Furthermore, if the secondary production system of the building is a traditional oil-, gas- or biomass-fired boiler, the associated cost term must be adapted to include the monetary cost associated to the use of oil, gas or wood. These combustibles have also time variant prices, although not at a relevant level for MPC, so price could be considered fixed for each step. They are typically stored in storage tanks, however gas is usually supplied by the gas grid.

$$\min \sum_{k=0}^{N-1} J_e = \min \sum_{k=0}^{N-1} \left[c_{el}(k)\frac{\dot{Q}_{HP}(k)}{COP(k)} + c_{el}(k)\frac{\dot{Q}_{PC}(k)}{\eta_{PC}(k)} + \sum_i c_{SS}(k)_i \frac{\dot{Q}_{SS}(k)_i}{\eta_{SS}(k)_i} + c_{el}(k)\sum_j \dot{W}(k)_j \right] \Delta t \qquad (5)$$

s.t.

$$0 \le \dot{Q}_{HP}(k) \le \dot{Q}_{HP,max} \qquad (6)$$

$$0 \le \dot{Q}_{PC}(k) \le \dot{Q}_{PC,max}$$

$$0 \le \dot{Q}_{SS}(k)_i \le \dot{Q}_{SS,max,i}$$

$$0 \le \dot{W}(k)_j \le \dot{W}_{max,j}$$

3.1. Demand response

Power from RES is highly variable and unpredictable, which can lead to unforeseen peaks that may cause instability and congestion of the electricity grid, ultimately leading to RES curtailment. Integration of RES into the electrical distribution grid comes thus along with higher requirements on control of the supply side. As the amount of electricity produced from RES has been growing significantly in EU in recent years, it becomes evident that the electricity grid stability cannot be achieved only by appropriate control on the production side, and active participation of end electricity consumers is also required. The active participation is usually achieved by so called demand-side management (DSM) that includes both demand response (DR) and energy efficiency. The reasons for actions taken by DSM are versatile, namely: i) avoiding RES power curtailment, ii) maximizing auto consumption, iii) minimizing procurement cost of electricity, iv) minimizing imbalance costs or cost of ancillary services…

The proposed economical MPC improves stability of the electricity grid as the system uses electricity mainly when there is a power surplus in the grid (which leads to lower costs). As such the energy is delivered in a cost-optimal way within both time and availability in the grid. Moreover, while the MPC drives the customer to use primarily the cheapest energy on the market, the provider saves money by having information about the amount of required energy during the next period at hand. If the grid operator asks to limit the electricity use, one way to proceed would be to include a variable constraint for the sum of the maximum power of the electricity-based supply systems. The MPC would then use the aforementioned predictions to shift the load to harness the thermal mass of the building. However, this would require that all local MPCs in the grid are interconnected. For example, if price drops between 8:00 AM and 9:00 AM, all heat pumps in the grid would turn on at this time, potentially creating a huge demand. So local MPCs which do not communicate with each other would probably not stabilize the system.

Demand response programs can earn back up to 15% of the electricity bill [5]. To exploit this potential demand response systems (DRS) should be set up to: i) remotely control electrical loads and ii) effectively use batteries and thermal energy storage. Heat pumps can play an important role in this context as they can be controlled in order to achieve load shifting or peak shaving. The energy storage capabilities of GEOTABS buildings make them important players. Furthermore, non-electrical based secondary systems available in hybridGEOTABS buildings present an extra degree of freedom.

4. MPC minimizing GHG emissions

The price profile does not necessarily coincide with the GHG emissions profile, as shown by Figure 4-1a. While the former is dependent mainly on the electricity supply and demand, the GHG emission factor varies with the generation systems active at the moment considered. In Figure 4-1b we can see that the peaks in the electricity generation (green) are approximately the same, in contrast to what happens in the CO_2 emissions profile (orange in Figure 4-1a). In this particular case, this was caused due to a major availability of wind energy on the 25th of January. Thus, minimization of the operational costs of heating and cooling systems does not lead automatically to the lowest GHG emissions, while the latter is one of the principal objectives of the environmental policies developed by the different EU countries.

The minimal GHG emission MPC formulation in Equations (7) and (8) is similar to the economic MPC formulation with time varying electricity prices, but the prices are replaced by emission factors *e* that can be provided or estimated through generation schedules by the grid operators (e.g. Elia in Belgium, Red Eléctrica Española in Spain or ČEPS in Czech Republic). These emission factors can change the way a hybridGEOTABS building anticipates the disturbances and harnesses the thermal inertia of the building and the borefield. Several setups are possible, which differ in the complexity of the formulation.

$$\min \sum_{k=0}^{N-1} J_e = \tag{7}$$

$$= \min \sum_{k=0}^{N-1} \left[e_{CO2,el}(k)\frac{\dot{Q}_{HP}(k)}{COP(k)} + e_{CO2,el}(k)\frac{\dot{Q}_{PC}(k)}{\eta_{PC}(k)} + \sum_{i} e_{CO2,SS}(k)_i \frac{\dot{Q}_{SS}(k)_i}{\eta_{SS}(k)_i} + e_{CO2,el}\sum_{j} \dot{W}(k)_j \right] \Delta t$$

$$0 \le \dot{Q}_{HP}(k) \le \dot{Q}_{HP,max} \tag{8}$$

$$0 \le \dot{Q}_{PC}(k) \le \dot{Q}_{PC,max}$$

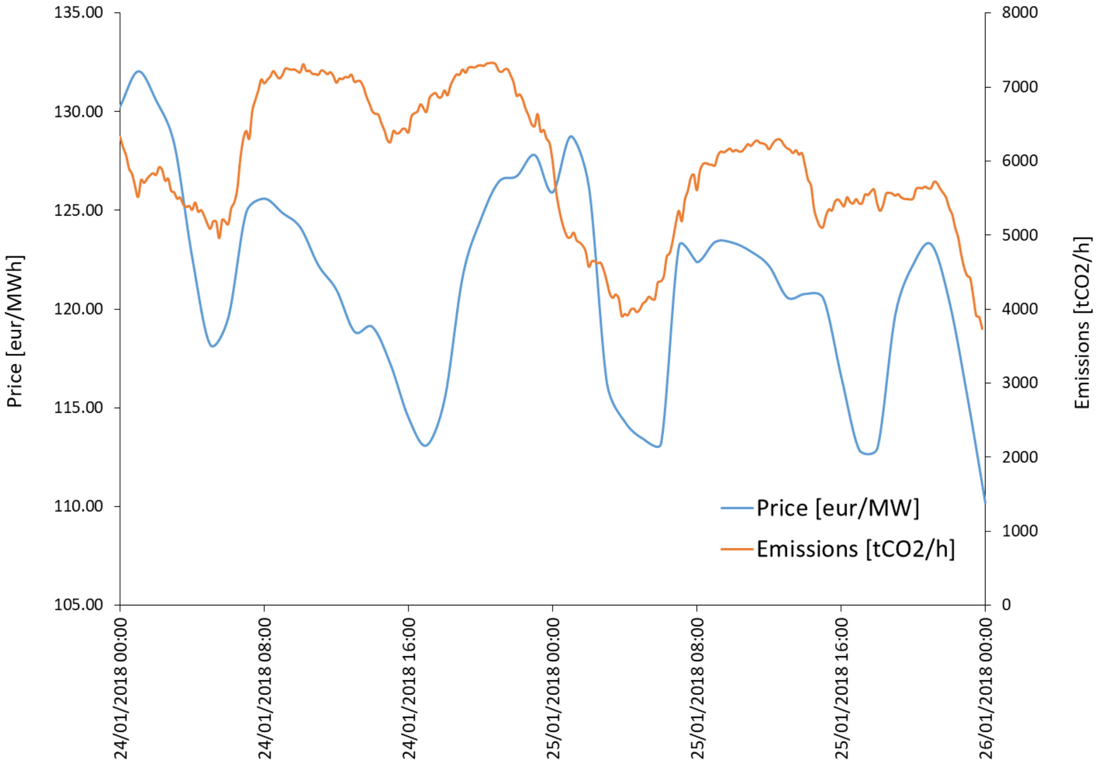
$$0 \le \dot{Q}_{SS}(k)_i \le \dot{Q}_{SS,max,i}$$

$$0 \le \dot{W}(k)_j \le \dot{W}_{max,j}$$

4.1. Building supplied by green electricity

In this case, the building owner or tenants have a contract with an electricity supplier who guarantees that electricity will be supplied from RES (PV, wind farms, hydropower plants, etc…). In this case, there is nothing to optimize assuming these RES have zero GHG emission.

a)



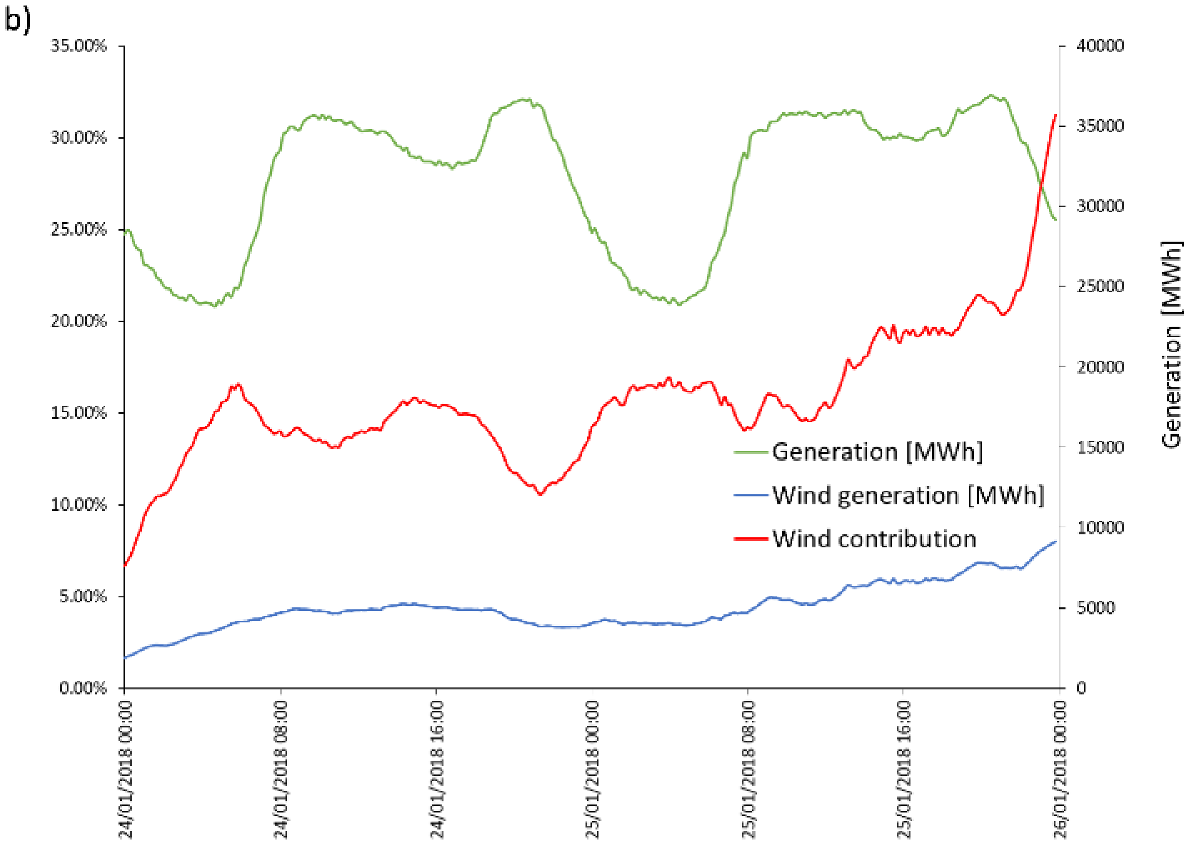


Figure 4-1: (a) Comparison between electricity prices (regulated market) and CO_2 emissions associated to electricity generation and (b) electricity generation between 24/01/2018 and 25/01/2018 in Spain. Data extracted from [6].

4.2. Building without local RES, no green electricity from grid

Here we consider the case where the electricity supplier delivers electricity from the grid without the guarantee that it originates from RES, and the building has no local electricity production from RES. Then it is important to take into account the emission factors. In general, the emission factors for the specific location are time varying – e.g., the actual value of the emission factor will differ between summer and winter if a lot of PV electricity is injected in the grid.

4.3. Building with local RES, no green electricity from grid

This case has the highest complexity, since it is important to take into account both the forecast of other electricity consumers and the electricity production by the local RES (PV, wind, etc...) denoted by P_{loc}. If the local RES produces more electricity than needed by the building (heat pump and other consumptions), then the carbon footprint is zero. If the production of local RES is not sufficient, then some electricity must be obtained from the grid and the correct emission factor has to be taken into account. Figure 4-2 depicts an example of the cost function trend for a heat pump system, being $f_1 = \frac{Q_{HP}(k)}{COP(k)} - P_{loc}$ and f_2 the cost function. If $f_1 < 0$, then more energy is produced by the local RES and therefore the cost function is zero. Otherwise, this cost function is proportional to f_1 by an emission factor e_{CO_2}. Note that this type of cost functions can be formulated and optimized with the aid of slack variables, further explained in Section 5 .

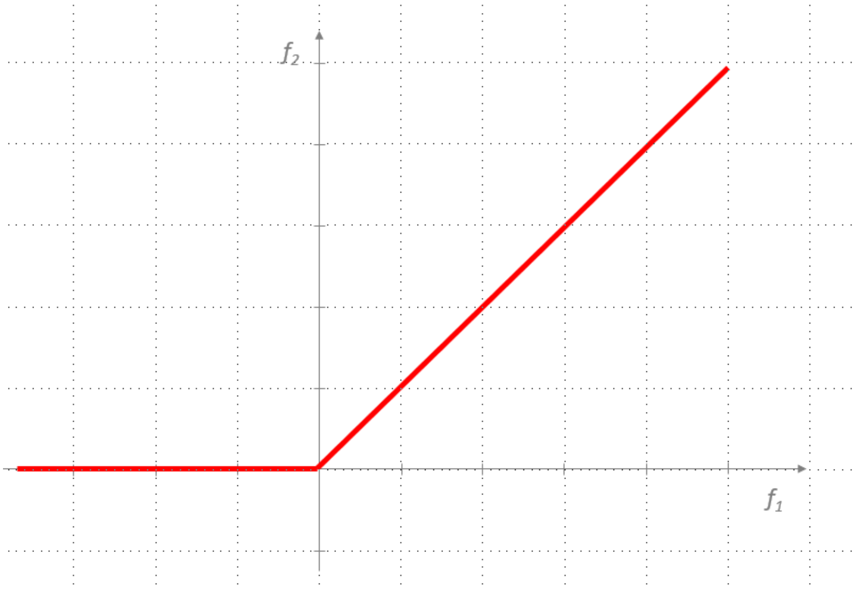


Figure 4-2: Cost function trend

4.4. Building with conventional fossil energy source heating systems

If the secondary system of the building is a traditional oil- or gas-fired boiler, an additional term should be added to the objective function that takes into account the GHG emissions of oil or gas combustion. Typical values for these emission systems can be found at Table 4-1, based on EN ISO 52000-1:2017.

Table 4-1: CO_2 emission factors for different combustibles [7]

Combustible	CO_2 emission factor [g/kWh]
Natural Gas	220
Fuel oil	290
Wood	40

5. Thermal comfort and indoor environmental quality

The main purpose of designing heating, cooling and ventilation systems in buildings is to achieve a good level of thermal comfort and indoor air quality (IAQ) for the occupants. Enhanced indoor environmental quality (IEQ) can improve occupants productivity by 5 to 10% [8], which may be a significant cost saving especially in office buildings. Furthermore, elderly people prefer warmer thermal conditions [9], a factor to take into account in elderly care homes. Thus, it is clear that this aspect has to be included somehow in the OCP. In sections 2 and 3, we have analysed the term corresponding to energy use J_e without taking into account thermal comfort J_c. Some MPC formulations [10] have included the latter as temperature bounds within hard constraints, however this formulation could lead to unfeasibility issues, which need to be tackled by the introduction of slack variables. Moreover, if slack variables are used to track a determined set-point, this would limit the freedom of the MPC and may result in higher energy use [11]. Therefore, temperature bounds are desirable combined with a penalization for crossing the bounds.

Several thermal comfort standards exist to define the upper and lower temperature (and other comfort parameters) bounds of a building, such as ISO7730, EN15251, ASHRAE55 and ISSO74, extensively discussed by Sourbron and Helsen [12]. These models are either based on thermal comfort bounds or on the PMV model of Fanger [13]. However, the non-linear nature of the latter makes it computationally more expensive, leading to the use of simplified versions of this model [14]. These are not the only thermal comfort models found in the literature, for more details the reader is referred to Enescu [15]. Some studies recommend an adaptive thermal model that involves acclimation of people, which may improve people's health by increasing their thermo-neutral zone [16].

Moreover, appropriate thermal comfort does not ensure a good IEQ since this depends on additional factors, such as indoor air quality (IAQ), lighting quality, visual and acoustic comfort… We focus on IAQ to improve the overall IEQ, which is usually enhanced by ventilation strategies. New evidence exists that mechanical ventilation systems lead to an overall improvement of the IAQ and reduction of reported comfort and health related problems [17]. If the building is equipped with an air handling unit and CO_2 sensors, efficient control can contribute to enhanced IAQ. However, MPC needs an occupancy model to predict the ventilation needs, e.g. based on statistical data or on available measurements [18]. These occupancy models are also important to predict internal gains and thus improve thermal comfort (in the end, humans are walking radiators), and when correctly implemented they can further save up to 30% energy [19]. On the other hand, it is important also to keep the TABS supply temperatures within a certain range to avoid discomfort due to a high gradient between the surface and air temperatures or condensation in the case of cooling. The proposed formulation includes therefore a slack term for thermal comfort s_T and another for IAQ s_{CO_2}. α_T and α_{CO_2} are the weighting factors that represent the "price" the final user is willing to pay to have more or less comfort, l_b and u_b represent the lower and upper bound for the chosen thermal comfort model and CO_2 levels. The TABS supply temperatures are kept as hard constraints to avoid technical problems such as condensation or pipe degradation.

$$\min \sum_{k=0}^{N-1} J_c = \min \sum_{k=0}^{N-1} [\alpha_T(k)\, s_T(k) + \alpha_{CO2}(k) s_{CO2}(k)]\, \Delta t \tag{9}$$

s.t.

$$l_{b,T} - s_T \le T_{zones} \le u_{b,T} + s_T \tag{10}$$

$$l_{b,CO2} - s_{CO2} \le CO_{2_{zones}} \le u_{b,CO2} + s_{CO2}$$

$$l_{b,TABS} \le T_{TABS} \le u_{b,TABS}$$

The hybrid GEOTABS concept can improve both thermal comfort and IEQ. TABS can provide an ideal vertical temperature gradient, and due to the small temperature differences between the surfaces and the space, the system can benefit from the self-regulating effect and provide a stable thermal environment [20]. However, TABS have difficulties to deal with sudden changes in heating or cooling loads of a room (e.g. due to sudden changes in solar or internal gains) due to their limited average heat flux and high thermal inertia [21]. Therefore the GEOTABS systems are inherently hybrid. Buildings with mechanical ventilation units can use these units as the fast-reacting secondary system by pre-heating or pre-cooling the air before injecting it in the building zones. The presence of TABS significantly reduces the size of the ventilation system (and corresponding fan power) to provide acceptable IAQ or the necessary heating or cooling at peak times, in systems where the ventilation is oversized to cover all heating/cooling needs. As a consequence, IEQ is also improved: less draught and noise from fans, no visible heating/cooling devices…

6. Additional robustness in the formulation

Perfect predictions would lead to a smooth behaviour of the MPC. However, in real implementations MPC has to deal with several uncertainties, i.e. (in)accuracy of predictions, measurement errors, model mismatch... Additional features to improve MPC robustness can be included in the OCP formulation. One example has already been mentioned in section 4: thermal comfort bounds are included as slack variables in the objective function to avoid unfeasibility problems.

Another problem that can appear is oscillatory behaviour. If the constraints are not very tight, the control actions result into either idle (no energy) or deadbeat control (full power), thus in control actions that need post-processing. This behaviour causes issues, especially in closed-loop performance, where the control actions can have a very oscillatory behaviour. These oscillations can be eliminated by introducing constraints in the rate of change of the delivered energy to the building [11]. The introduced constraints should be soft constraints to avoid problems with cases were full power is really required (e.g. after a long holiday period). Terms such as minimizing the maximum rate of change (Equation (11)) or the curvature of the delivered inputs (Equation (13)) can be included in the objective function.

$$J_r = \alpha_r |u(k) - u(k-1) - p(k)|_2^2 \tag{11}$$

s.t.

$$\underline{\Delta u} \leq p(k) \leq \overline{\Delta u} \tag{12}$$

$$J_r = \alpha_r |u(k-2) - 2\,u(k-1) + u(k)|_2^2 \tag{13}$$

Where α_r is the weighting factor for the robustness term, u is the considered input (e.g., the power delivered by a system or its input signal) and $\underline{\Delta u}, \overline{\Delta u}$ are the admissible rate of change limits for the considered input action.

However, these terms may curtail a bit the freedom of the MPC. **Error! Reference source not found.** shows an MPC with the objective to minimize the energy use (blue), and an MPC which adds the curvature minimization term. It can be seen from the plot that the second MPC has a more smooth handling of the supply temperatures. However, when analysing the energy use, the second MPC has lower energy use, with similar comfort violations in absolute terms. If the first MPC has only the objective of minimising the energy use, how is it possible that the second MPC achieves lower energy use? The answer could be on uncertainties within the state update of the model or model mismatch. Including terms that limit this oscillatory behaviour seems a good temporary solution, but they might limit the freedom of the MPC and can cause also problems after vacation periods such Christmas. The research to improve robustness should go towards minimising uncertainties and model mismatch, and it will be tackled in Task 3.5 of this project.

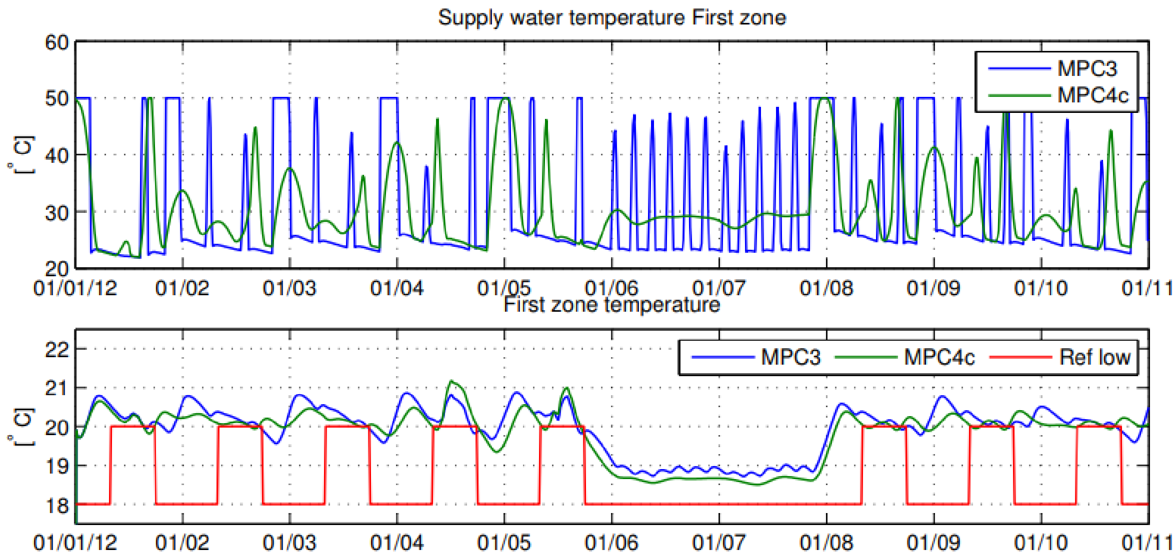


Figure 6-1: Comparison of behaviour between MPC with minimizing energy formulation and MPC with additional curvature term formulation. SOURCE [11]

MPC predicts over a chosen prediction horizon, which cannot be taken too long (maximum in the order of weeks) since this would lead to a too high number of optimization variables. As a consequence, it is difficult to incorporate in the MPC the effect of seasonal energy storage in the borefield. However, to avoid thermal depletion of the borefield, a thermal balance in the ground should be ensured on the long term. To this end, only author [2] has included a long-term cost in the objective function, that penalizes the use of the borefield at specific moments thereby inviting the system to use the secondary production unit. Equation (14) shows this long-term cost, where α_r is the weighting factor and $\dot{Q}_{BF}$ is the borefield heat flow (positive if injection, negative if extraction). This weighting factor has to be tuned depending whether the building is heating or cooling dominated. For example, in a cooling dominated building one would like to penalize the heat injection. Alternative ways to deal with this issue will be investigated in Task 2.3 (see D2.4). The thermal conductivity of the ground plays a crucial role in this thermal ground balance. For grounds with low thermal conductivity additional exploitation of seasonal thermal energy storage in the borefield may become economically beneficial. This switching point depends on the efficiency of the secondary (heat/cold) production units in relation to the heat pump and passive cooling COP. Storing energy always leads to losses [22].

$$J_r = \alpha_r \, \dot{Q}_{BF} \tag{14}$$

Design of hybrid GEOTABS systems is often based on static methods (described in standards). However, both TABS and borefield are usually in transient states due to their large thermal inertia. Therefore, using a dynamic controller model in the MPC is very important.

7. Conclusions

Several OCP formulations have been proposed based on the hybridGEOTABS buildings properties and literature review. Most of the formulations include multi-objective optimization based on the trade-off between energy use and thermal comfort. However, the way these terms are weighted is diverse and should be adapted to the final user needs. Energy use can be converted to energy cost by using price profiles or converted to GHG emissions by using CO_2 generation profiles. Thermal comfort can be adapted to satisfy the users' subjective comfort and enhance overall IEQ. Robustness of performance of the MPC can also be increased by incorporating additional terms that deal with oscillatory behaviour and ensure thermal balance of the ground.

Perspectives regarding the selection of the objective function in the hybridGEOTABS project will vary between the the buildings and between real demonstrators and emulator models. In the demonstration buildings, the objective function will be chosen by the building owner and according to his/her needs several simulations can be carried out for each function. The chosen objectives by the different owners are documented in Deliverable 3.6 and 4.11. The complexity of changing such formulation is low. For the emulator models in the virtual test-beds in Work Package 4, starting point is the minimization of the energy use, and the comparison between the different considered baselines is done based on this objective. Thermal comfort models use the comfort bounds as proposed in Deliverables 4.7 and 4.9, which were investigated as part of Tasks 5.1 and 5.2 of the project. Robustness terms in the formulation are avoided such as this issue will be more focused towards minimization of uncertainties in the state update, disturbances prediction and sensor accuracy.

Finally, in this literature review, a lack of long-term objectives that guarantee the thermal balance of the ground in the borefield is found. Due to this, and in parallel to the project, a methodology that includes a shadow-cost in the objective function to take into account the long-term effects that appear in the borefield is developed [23]. The shadow-cost is computed for a given longer-term horizon using an estimation of the building heating and cooling needs. The borefield model used in this methodology is further simplified for its use in the optimal design and optimal control exercise in Deliverable 2.3.

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