Model predictive control of indoor microclimate: existing building stock comfort improvement

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Abstract

We analyze how model predictive control (MPC) applied to microclimate control in buildings that cannot be substantially modified, can provide energy-efficient solutions to the problem of occupants’ comfort in a variety of situations principally imposed by external weather. For this purpose we define an objective function for the energy consumption, and we consider two illustrative cases: one building designed and built in recent times with modern HVAC equipment, and one designed and built several decades ago with poor thermal and ventilation characteristics. Our model includes various physical effects such as, e.g., air infiltration and indoor ”inertia mass”, and also accounts for the impact of human presence essentially as heat and CO\textsubscript{2} sources. Further, the influence of forecast horizons and that of uncertainties due to inaccuracies in the weather and room occupancy forecasts on the numerical results are analyzed. We solve the non-convex optimization problems using a linear and a nonlinear optimizer. Full MPC performance is compared to both linearized MPC and a standard on/off controller. The main advantage of MPC is its ability to provide satisfactory solutions for microclimate control at the least possible energy cost for both modern and old buildings. As old buildings are usually not properly ventilated, an inflow ventilation system installation is proposed as a quite advantageous so-
olution for significant air quality improvement in light of our simulation results.

Keywords: Model predictive control, Indoor comfort, Building energy simulation, Residential building

1. Introduction

Buildings designed and built during the 20th century and before form the largest part of those in use today. Their basic characteristics in terms of energy efficiency, environmental impact and comfort are de facto below par with the present standards driven by low-carbon policies, sustainability and features of modern energy systems. Furthermore, aging of buildings is accelerated by poor/harsh weather conditions [1, 2], favoring wall degradation because of, e.g., penetration of moisture in cracks and cavities of the walls and around windows, which in turn enhances heat leaks. In fact, buildings that host people in general, either public offices or dwellings, pose particular design and engineering challenges, as the human presence entails particular requirements in terms of comfort and use of energy.

Generally speaking, comfort is usually characterized by a variety of ranges of measurable quantities such as, e.g., temperature, humidity, concentration of CO₂ generated by occupants, other pollutants and particulate matter (PM), as well as lighting, and radiant heat. Given the complexity and interplay among these quantities, comfort constitutes an active field of research, which drives innovative design in the building sector by setting bounds on them [3]: indoor comfort temperatures typically lie between 19°C and 25°C, the relative humidity within the 45% to 65% range, and ideally CO₂ concentration should be kept to a minimum comparable to, e.g., the environmental level which is typically below 400 ppm [4]. Note that CO₂ concentration deserves particular attention: levels recorded in houses may reach values as high as 5000 ppm, which dramatically affects people’s behavior as recently shown in dedicated studies [5, 6]; in fact, even at moderate levels of concentrations, say 2500 ppm, routinely reached in classes and conference rooms, intellectual activities like strategic thinking,
initiative, information utilization, are negatively impacted.

Energy requirements of occupied buildings amount to 40% of primary energy consumption, 70% of electricity consumption, and 30% of greenhouse gas emission with most of the energy consumption being due to heating, ventilation and air conditioning (HVAC) systems operation. So, as traditional microclimate control solutions are very energy-intensive, a proper design and control of HVAC systems is crucial both from the energy saving and health viewpoints. Further, design of new buildings should account for their shape and the surface area of their envelope to minimize so that energy efficiency is enhanced. For the current large stock of existing buildings their shape is given and difficult to modify, so efficiency improvement can be reached only at moderate costs by the upgrading of the thermal insulation and the installation of recuperation systems for ventilation as well as the optimal control of microclimate. By doing so, the energy consumption can be minimized while maintaining an acceptable level of comfort. However, besides hardware (sensors, controllable actuators, information exchange between zones, computational facilities installed in every HVAC unit) the main challenges from the control viewpoint are many and include, e.g., model accuracy, stochasticity in internal heat sources, and poor forecast of external weather conditions.

In the present work, we are interested in indoor comfort through a proper control of the smart systems setting the indoor microclimate with a focus on both high- and low-efficiency buildings. To that end, we use a model predictive control approach. We aim to see how a sizable decrease of energy consumption may be efficiently achieved under various conditions: building characteristics, occupancy, and weather, while a decent level of comfort is maintained. More precisely, we consider a state-of-the-art 100 m² conference room located in a modern office building near Moscow (test case 1) and the typical urban Russian panel building series P44 (test case 2). Most of Russian buildings are heated by district heating (DH) systems. If no access to DH exists, individual gas boilers are used. Some radiators are equipped with valves that can be manually tuned to control the heating level. Air conditioners are widely used in regions
with warm summers and are controlled mainly by setting a desired temperature on on/off controllers. Natural ventilation dominates in dwellings which implies that windows must be opened even in winters despite its inefficiency and loss of comfort. Commercial buildings are equipped with air handling units (AHU) mostly based on constant air volume (CAV) technology resulting in uncontrollable ventilation rate. More efficient variable air volume (VAV) systems are used less often due to higher price.

Test cases 1 and 2, the detailed characteristics of which will be detailed in the main text, correspond to buildings submitted to harsh weather conditions during winter, so their comparison provides quantitative information on the actual added value of the state-of-the-art technology and design, and also on the HVAC model predictive control approach we adopt. The article is organized as follows. In Section 2 we briefly review the main methods which can be applied to microclimate control, and discuss our choice for MPC in the context of the present work. In Section 3, we present our approach to the comfort and energy saving problem in buildings, based on the linear and model predictive control methods. In section 4, we implement numerically our approach to two illustrative test cases, and analyze and discuss the obtained results. The article ends with concluding remarks.

2. Overview of the main control methods

Different control methods have been developed for HVAC systems, including rule-based, model predictive control [14], PI/PID and artificial neural networks-based approaches [15, 16, 17]. In Russia, on/off controllers are usually used in dwellings, while rule-based ones are used in commercial buildings.

2.1. Rule-based control

Rule-based control is widely used for temperature control on building scale and also taken as industry standard. Set temperature values are taken from engineering scenarios at building level and then on/off control of thermostats
implements the feedback control of the temperature for every thermal zone. No matter which other devices (ventilation, blinds etc.) are involved, all control inputs are taken from rules of the kind “if condition then action”\[18]. Experienced engineering intuition helps to fit various specifications. Good performance is a result of proper rules and associated parameters. The main drawback is that it needs tuning during operation with conditions changing to provide optimality. Unfortunately, this type of control may lead to temperature overshoots or synchronization effects\[19] and hence may not provide optimal solutions from energy consumption viewpoint. Rule-based control strategies do not use predictions to perform better control actions.

2.2. PI and PID controllers

Various controllers for thermostats improve transient dynamics to reach the objectives set. Classical proportional-integral (PI), proportional-integrative-derivative (PID) controllers as well as fuzzy, adaptive, neural network controllers\[20] are capable to ensure that the desired temperature is reached and to exploit HVAC for providing demand response services\[21]. But the controllers performance is sensitive to the choice of the gains. Having tuned controller parameters for a particular objective, e.g. following a certain temperature, the designer loses the ability to reach other objectives, e.g. minimization of an energy consumption, as well as to find a compromise among them. Besides, as the control goal is to maintain the prescribed air characteristics, comfort requirements dominate energy saving objectives. In other words PI and PID controllers cannot ensure optimal control or stability.

2.3. Model predictive control

Model predictive control\[22] provides a suitable framework for microclimate control as it ensures optimality using an appropriate strategy. Instead of operating on an infinite time horizon as in classical optimal control, MPC yields optimal results for finite prediction horizons. At each time-step, MPC solves an optimal control problem over a given prediction horizon and obtains the control
parameters and states that satisfy both the dynamics and constraints. Finally, it synthesizes a feedback control signal that minimizes objective functions (operation cost, energy consumption) and satisfies comfort constraints. Existing methods for predicting the energy consumption of households, commercial, industrial and municipal consumers, using mostly regression models, do not take into account the new technological capabilities of consumers and do not allow to predict a demand response in the event of a significant change in pricing policy. From a control perspective, MPC is capable to face all the requirements and possesses additional useful features such as: ability to use occupancy profile and incorporate weather forecast, moderating trade-off between preferences that may vary between thermal comfort and energy efficiency covering all intermediate solutions.

In its classical formulation, MPC is a centralized algorithm and hence a proper identification of the building model is crucial [23, 24, 25]. One needs to know the model and have computational facilities to run the underlying optimization problem at building level. The computational burden increases with the number of zones and the model complexity. That is why linearized physical models are widely used for MPC: they provide rather acceptable solutions at lower computational cost. However, linear MPC (LMPC) obviously cannot capture the nonlinear dynamics of actual buildings and consequently provides suboptimal solutions.

Bilinear models capture the airflow effect of ventilation: the heat flux is proportional to the mass flow rate (control variable) and the temperature difference (state variable). Sequential linear programming [26] solves bilinear optimization problems fast enough (say below 1 mn for the execution time on a standard computer). The MPC approach has been implemented successfully for several problems pertaining to microclimate control in, e.g., office buildings and in green houses, including energy storage [27, 28, 29]; the approach may incorporate weather forecast, which leads to stochastic model predictive control [13].
2.4. Decentralized and distributed control Schemes

For a successful MPC implementation, state measurements should be collected in a central computer that performs all the necessary calculations. In order to reduce the computational burden and communication time, the system can be decomposed into several control systems. Local subsystems may operate autonomously (purely decentralized scheme) or exchange information between neighboring zones (distributed scheme) and send limited information to the higher-level system. This is the hierarchical (hybrid) approach with MPC operating as high-level supervisory control \[30\]. Note that purely decentralized schemes ignore coupling effects that lead to suboptimal behavior.

Distributed implementation of MPC is discussed in Ref. \[19\]. Being equipped with its own computational facilities and using microclimate parameters from adjacent zones, each controller synthesizes a control law in a distributed way. Real-time decentralized and distributed control schemes for temperature control do not necessarily need to be in the form of MPC. In Ref. \[31\] the primal-dual gradient descent method provides a distributed control of flow rate for every thermal zone equipped with an independent variable air volume box. This control aims to regulate the temperature within prescribed limits while minimizing energy consumption, but optimality is due to convergence to optimal steady-state rather than predictive approach.

3. Formulation of the problem

In the present work, we apply MPC to microclimate control first in a standard room equipped with DH radiators, air conditioners supplied by electricity and an inflow ventilation. Our method, summarized on the flowchart on Fig. \[11\] is based on a physical model \[28, 32\] describing the microclimate dynamics. The model takes into account the heating/cooling effects, ventilation, room occupancy, weather and thermal inertia of the building.
3.1. Physical model of a room microclimate

The most crucial part of the method is the microclimate physical model, which provides the time evolution of, e.g., the temperature and CO2 concentration from the knowledge of the current state and action. In turn, this allows us to take into account the microclimate dynamics in optimal actions calculation which is the main advantage of MPC. From the principles of mass and energy conservation, we obtain the following set of differential equations:

\[
\begin{align*}
mc_p \frac{dT}{dt} &= U(T - T_{\text{out}}) + U^*(T^* - T) + W_{\text{oc}}N_{\text{oc}} \\
&\quad + W_{\text{hc}} + C_p Q_{\text{in}}(T_{\text{in}} - T) + C_p m R(T_{\text{out}} - T) \quad (1) \\
m^*c_p^* \frac{dT^*}{dt} &= -U^*(T^* - T) \quad (2)
\end{align*}
\]

where \( t \) is the time, \( m \) is the mass of air in the room, \( C_p \) is the specific heat capacity of air at constant pressure, \( U \) is the linear heat transfer coefficient between the indoor and outside air at temperatures \( T \) and \( T_{\text{out}} \) respectively, \( R \)
is the rate of air replaced by infiltrated air per one hour, \( m^* \) is the “inertia mass”, i.e. the accumulated mass of the walls, floor, ceiling and furniture of the room with \( T^* \) being its effective temperature and \( C^* \) being its effective average heat capacity, \( U^* \) denotes the linear heat transfer coefficient between the inertia mass and the air in the room, \( N_{oc} \) is the number of persons occupying the room, each being a source of heat of average power \( W_{oc} \). The system of equations (1) and (2) are nonlinear because of the variation of the mass value \( m \) over time and the presence of the term responsible for a heat exchange due to ventilation \( C_p Q_{in}(T_{in} - T) \). In order to numerically integrate the equations, a first-order explicit method is used to discretize Eqs. (1) and (2):

\[
m_i C_p \frac{T_{i+1} - T_i}{\Delta t} = U(T_i - T_{out,i}) + U^*(T^*_{i} - T_i) + W_{oc} N_{oc,i} + W_{h/c,j} + C_p Q_{in,j}(T_{in} - T) + C_p m R_{oc}(T_{out,i} - T_i) \tag{3}
\]

\[
m_i^* C^* \frac{T^*_{i+1} - T^*_{i}}{\Delta t} = -U^*(T^*_{i} - T_i) \tag{4}
\]

where \( i \) denotes the current time step, \( i + 1 \), the next time step, and \( j \) the control step. The integration time step \( \Delta t \) is chosen to be 1 min so that solution is not changed with its further decrease. The control time step is the interval where controlled parameters, i.e. \( (W_{h/c}, Q_{in}) \) are fixed. For the test cases we present in the next section, the control time step is 1 hour, while the control horizon at which an objective function is minimized is varied: it is set to capture the microclimate dynamics sufficiently accurately while permitting the computation of the optimization problem solution in a reasonable time on a standard computer (less than one minute).

3.1.1. Weather and occupancy forecasts

One of the main advantages of MPC is its ability to take into account foreseeable exogenous factors for microclimate dynamics simulations. For the particular cases we address in the present work, these factors are the occupancy of rooms and the external weather. The room occupancy for the test cases is drawn from our knowledge of buildings usage (Fig. 2): office building occupancy
statistics and private house usage based on general understanding of how apartments are used. The weather forecast can, for example, be downloaded from weather forecast websites. Examples of temperature profiles used are shown on Fig. 3 and correspond to generic cold, normal, and hot days. Note that the cold days correspond to those of a typical Russian winter.

![Figure 2: Occupancy forecast.](image1)

![Figure 3: Outside temperature forecast.](image2)

3.2. Constraints

Constraints impose the range of HVAC operational regimes and comfort. The lower limit of $W_{h/c}$ represents the air conditioner maximum power (with
a negative sign for an energy sink), and the upper limit, the heating maximum power. The ventilation upper limit corresponds to the air handling unit maximum performance. The lower limit depends on the room occupancy: for a fixed number of occupants \( N_{oc} \) one need to provide a minimum ventilation rate \( Q_{in}^{\text{min}} \) in order not to exceed a certain comfort limit of CO\(_2\) concentration \( \nu_{\text{CO}_2}^{(\text{max})} \).

From the mass balance equation for the CO\(_2\) fraction of air, we obtain:

\[
Q_{in}^{\text{min}} = \frac{N_{oc} \tilde{Q}_{\text{CO}_2}}{\nu^*_{\text{CO}_2} - \nu_{\text{CO}_2}^{(\text{max})}}
\]  

(5)

where \( \tilde{Q}_{\text{CO}_2} = 0.000012 \text{ kg/s} \) is the CO\(_2\) mass exhausted by one person each second, \( \nu^*_{\text{CO}_2} = 400 \text{ ppm} \) is an average CO\(_2\) concentration in the environment and \( \nu_{\text{CO}_2}^{(\text{max})} \) is taken to be 1000 ppm as a maximum comfort value.

Temperature limits are also important for the comfort: when there are no occupants inside, the lower and upper limits are 15°C and 25°C respectively. During daytime the limits are \( T^* - 1 < T < T^* + 1 \) (in °C). The comfort temperature equals \( T^* = 22°C \) in our cases.

### 3.3. Objective functions

Optimization problems require objective functions \([34, 35]\). In the present work, the objective function \( f_{ec} \) represents the energy consumption for a room heating/cooling, ventilation air heating and propulsion:

\[
f_{ec} = \sum_{t=1}^{t_{\text{max}}} \left[ |W_{h/c}(t)| + C_p Q_{in}(t)(T_{in} - T_{out}(t)) + (Q_{in}(t))^2 / 2S_p \right]
\]

(6)

where \( S_p \) is the cross section area of the air inflow device’s pipe. The function \( f_{ec} \) yields values given in kWh. Here \( W_{h/c}(t) \) and \( Q_{in}(t) \) are control actions at the control time step \( t \), \( t_{\text{max}} \) is the control horizon, and the control time step is 1 hour. It is worth noticing that the function can easily be modified to correspond to a primary energy, total energy or price via multiplication of the function term by a specific constants or functions responsible for pricing, efficiency etc.
3.4. Optimizer

For our purpose here, we use two optimizers, linear and nonlinear, to solve non-convex problems.

3.4.1. Nonlinear non-convex optimization

The first controller, nonlinear MPC, is based on the nonlinear physical model given by Eqs. (3) and (4), and requires a nonlinear non-convex optimization algorithm for an optimal control vector calculation. The main advantage of the method is its accuracy provided by the model.

3.4.2. Linear optimization

In practice, linear optimization is used to limit the computational burden, so we also developed a linear MPC version of our approach to check its relative accuracy and value as a tool for our work. This naturally entails the linearization of the physical model, Eqs. (1) and (2); to this end, both the mass $m$ of air in the room and the effective temperature $T^*$ are taken as constants at each control time step, assuming that it is sufficient to describe the slow air temperature dynamics, and for the ventilation control, we set $Q_{in}(t) = Q_{in}^{\text{min}}(t)$. As a relative change of mass is rather small and the ventilation should work at the minimum possible power to decrease heat exchange with the environment we do not expect a significant decrease of the model accuracy due to the model linearization. An explicit first-order time-stepping is then used with an integration time step equal to the control time step, and we obtain a linear equality constraints matrix that can be used for optimization computation.

3.5. Rolling horizon

We perform rolling horizon calculations to assess the efficiency of the MPC implemented according to the following sequence of steps:

1. Initial values for $T$ and $T^*$ are chosen;
2. MPC code is run to obtain control vectors at a set control horizon;
3. The first control values are used to simulate $T$ and $T^*$ in 5 to 15 min;
4. The obtained $T$ and $T^\star$ are used as initial values for MPC, and the procedure restarts from step 1.

4. Test cases

The MPC performance is tested on two cases with the predefined occupancy profiles shown on Fig. 2. We evaluate the efficiency of MPC by comparison with a standard on/off controller:

1. State space for heating/cooling and ventilation is discretized so that HVAC devices can work at regimes from 0 (switched off) to 10 (maximum power);
2. Setpoints for temperature correspond to comfort limits used in MPC;
3. Setpoint for CO$_2$ concentration is 900 ppm with a deadband region of 100 ppm;
4. When no people are inside in hot and normal days the heating/cooling equipment is switched off.

For each test case we plot the time evolution of the temperature, heating/cooling, and ventilation utilization.

4.1. Test case 1: Skoltech campus room

We consider a 100 m$^2$ room which is a standard lecturing room at the Skolkovo Institute of Science and Technology. The relevant physical parameters are derived using the room model assembled in TRNSYS [36] and are listed in Table 1. The building has a high thermal inertia. When the room occupancy is higher than 20-25 people during lectures, the air quality may deteriorate fairly quickly because of insufficient ventilation. In addition, during a large part of a typical daytime, when no student nor staff is inside, the ventilation system works on its nominal regime thus spending energy, which rather could be saved. MPC can utilize the capacity for shaving peaks in demand via pre-cooling or pre-heating the room at off-peak hours. Distributed MPC of a set of rooms with moderate thermal coupling is also tested.
| Parameter                | Test case 1 | Test case 2 | Test case 2 + breezer |
|--------------------------|-------------|-------------|-----------------------|
| $U$ [W/K]                | 55          | 15          | 15                    |
| $U^*$ [W/K]              | 200         | 200         | 200                   |
| $m^*C^*$ [MJ]            | 107         | 20          | 20                    |
| $V$ [m$^3$]              | 540         | 105         | 105                   |
| $R$ [1/h]                | 0.1         | 0.2         | 0.2                   |
| $T_{t=0}$ [$^\circ$C]   | 21          | 21          | 21                    |
| $T_{t=0}$ [$^\circ$C]   | 21          | 21          | 21                    |
| $W_{\text{min}}^{h/c}$ [kW] | -15        | -2          | -2                    |
| $W_{\text{max}}^{h/c}$ [kW] | 5          | 0.95        | 1.1                   |
| $W_{oc}$ [kW]            | 0.12        | 0.12        | 0.12                  |
| $Q_{\max}$ [kg/s]       | 0.55        | -           | 0.05                  |
| $T_{in}$ [$^\circ$C]    | 21          | -           | 21                    |
| $S_p$ [cm$^2$]           | 500         | -           | 120                   |

Table 1: Test cases parameters.

Rolling horizon simulations are performed for linear and nonlinear MPC. Here, the nonlinear physical model, Eqs. (1) and (2) is used to predict the evolution of the microclimate both for the linear (L) and nonlinear MPC. For the LMPC only heating is controlled while the ventilation mass flow ensures that the CO$_2$ concentration is less than 1000 ppm. This is confirmed by the nonlinear MPC simulations, where the optimal ventilation mass flow equals the minimum given by Eq. (5).

4.1.1. MPC vs. LMPC and on/off controller

For a 24-hour time horizon, the optimization of the vector consisting of $24 \times 3$ variables is performed. Here the variables are the temperature, heating/cooling power and ventilation flow for MPC, and the temperature, heating and cooling power only for LMPC to exclude the nonlinearities in the physical model, Eqs. (3) and (4).

On Fig. 4 one can see from the temperature time evolution, that MPC
allows a proper comfort level for harsh conditions while the LMPC underestimates the necessary heating level. For both control methods the ventilation flow equals the lower limit. From the results displayed in Table 2, one can conclude that MPC is the most efficient in terms of energy spent for microclimate with the on/off controller being the worst among the tested approaches.

4.1.2. Forecast horizon influence

To obtain the optimal time horizon for MPC, simulations of MPC with different horizons are performed. In practice the power of heating/cooling systems is limited and hence one cannot rapidly heat/cool the room to a desired level. Therefore heating/cooling equipment should be switched in advance. For example, the numerical results depicted on Fig. 5 are obtained for a cold weather with maximum heating power limited to 3.5 kW. Here, the control corresponding to the minimum of the objective function starts from horizon = 4 hours and no further change of control is observed. The corresponding objective functions are 184 kWh for horizon = 2 hours, 181 kWh for 3 hours and 180 kWh for other horizon values.

4.1.3. Uncertainty influence

In practice, as occupancy and weather forecasts are not perfectly accurate, errors in future states estimations are unavoidable. To account for this problem at every rolling horizon step, stochastic errors are added to occupancy, outside temperature, and room temperature at the initial MPC/LMPC time step. Sim-

| Day type | Heating (+)/Cooling (-) [kWh] | Ventilation [kWh] |
|----------|-------------------------------|------------------|
|          | MPC  | LMPC | on/off | MPC  | LMPC | on/off |
| Cold     | 36.8 | 34.6 | 62.0   | 61.7 | 61.7 | 70.4   |
| Normal   | -2.8 | -3.9 | -6.1   | 2.0  | 2.0  | 2.4    |
| Hot      | -11.4| -13.9| -16.1  | 18.7 | 18.7 | 21.7   |

Table 2: Energy consumption for 24 hours of operation for the test case 1: MPC vs. LMPC vs. on/off control.
Figure 4: Comparison of LMPC and MPC for different weather conditions.
Figure 5: MPC control with different prediction horizons under cold weather. Maximum heating power = 3.5 kW.
Simulations are performed with MPC and LMPC for a normal day (see Fig. 3). Different discretization time steps in rolling horizon are used: 1 hour, and 6 minutes. From the results displayed on Fig. 6 one can see that in general both MPC and LMPC provide rather good control in terms of comfort. But LMPC violates comfort boundaries more than MPC due to the loss accuracy of the physical model used.

Figure 6: Temperature evolution with uncertainty: normal weather. MPC (lines) and LMPC (dots).

4.2. Test case 2: Single-room apartments

The second test case corresponds to a typical single-room apartment (Table 1). Buildings series P44 were the most popular panel house type build in 1980-
Figure 7: MPC control for TC2: baseline case and breezer effect.
1990, and up to date they are among the most widespread in some cities. One of the main drawbacks of these and most of other apartments is the absence of a proper ventilation system which together with low infiltration leads to inappropriate growth of carbon dioxide concentration when occupants are inside for a long period of time, e.g. at night (see Fig. 7, the baseline case). To avoid this, one can open a window to increase air infiltration. But this also causes noise and particulates penetration in megacities like Moscow, as well as excessive heat leakage. Moreover, the solution generates uncontrolled air flows in a flat and can cause health problems.

| Configuration             | Heating(+) Cooling(-), [kWh] | Ventilation, [kWh] |
|--------------------------|------------------------------|--------------------|
| MPC on/off               |                              |                    |
| Cold day, with breezer   | 12.2                         | 18.8               |
| Cold day, no breezer     | 11.1                         | –                   |
| Normal day, with breezer | 0                            | 0.6                |
| Normal day, no breezer   | 0                            | –                   |
| Hot day, with breezer    | -3.8                         | <0.1               |
| Hot day, no breezer      | -1.7                         | –                   |

Table 3: Energy consumption for 24 hours of operation for the test case 2: MPC vs. on/off control.

One may also use one of the solutions for house ventilation called “breezer”: a small box installed over an orifice on the wall that includes a compressor, filters and a heater. The maximum power of these devices is normally 1.5 kW, most of which being spent for the inflow air heating. They also are equipped with a filtering and disinfecting system. On Fig. 7 (breezer effect) one can see that the solution requires higher heating/cooling power available but allows to limit carbon dioxide concentration at a desired level. Its advantages over windows opening are controlled fresh air mass flow rate that is needed for particular indoor conditions, air cleaning and noise reduction. As seen from table 3, in the present test case MPC does not seem to be a necessary control solution as it
neither allows to save energy nor is able to improve the comfort level. However, if energy storage is going to be utilized or significant change in prices for energy (both electric and thermal) are to be introduced MPC can become the solution able to significantly improve a microclimate efficiency.

5. Concluding remarks

The scope of our work is timely: as the majority of dwellings are highly dependent on fossil fuels for the provision of energy, either a thorough renewal of the housing stock or even their complete renovation up to nowadays best standards are prohibitive in terms of costs. Further, in a context where renewable energy sources cannot yet be seen as full substitutes for fossil fuels, even the strategies which promote low-power consumption and environment-friendly technologies (or “best available technologies” - BAT) have a major drawback known as the rebound effect: as these BAT multiply to satisfy the ever-growing public demand, the toll on standard energy sources is becoming unsustainable, especially when indoor comfort acquires a central role in people’s daily life. Therefore on a short to mid-term time scale, only smart technologies can answer the challenges of quality indoor microclimate at a reasonable cost through home automation systems and control.

In this article, we studied how to control comfort and efficiency of energy utilization in buildings. MPC simulations for the modern building case study show the significant advantage that nonlinear MPC has over both linear MPC and standard on/off controller in providing comfort with lower energy consumption, coupled with the ability to operate the HVAC equipment in advance in order to prepare the desired microclimate at a given time. In particular, for hot and cold seasons MPC allows to provide significantly higher levels of comfort than LMPC solutions. In addition, solutions which provide a good indoor environment also mitigate the detrimental effects of harsh weather conditions.

With the second test case corresponding to an old building, we showed that this type of apartments requires a ventilation system to be installed as, under
standard conditions of use, the air quality is rather poor with, in particular, \( \text{CO}_2 \) concentrations much higher than what is advised by comfort norms. MPC for the HVAC control here, does not appear to provide acceptable solutions as we observe no significant reduction of energy consumption. This implies that direct application of one type of solutions, successful in some cases, is not a valuable strategy as the specific characteristics of buildings must be assessed and solutions adapted; this conclusion is in line with recent work putting forth the need for suitability assessment \[38\]. Further, contextual factors influence the investment strategy for building or house management \[39\]. Nevertheless, MPC can be a promising solution if a storage device is utilized as part of the whole system.

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