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NeuroCool: an adaptive, model-predictive control algorithm for ventilation and air conditioning systems

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Abstract
Energy used by air conditioning and especially cooling is steadily increasing, and modernization of the technical systems is critical. The standard controllers must be replaced by novel and more efficient controllers. In the present article a model-predictive controller (MPC) called NeuroCool is presented, which features a self-learning building thermal model. In this article an overview of the algorithm and associated simulation / testing environment is provided; simulation results are analyzed to assess the performance of the algorithm. It is shown that when benchmarked against a standard controller, exploitation costs can be reduced by about 11% under similar comfort. If the comfort is lowered, but maintained within the tolerable norms, exploitation costs can be further reduced by 75%.

Keywords – HVAC, MPC, ventilation, cooling

1. Introduction

The energy consumption in Switzerland for cooling increased by 8% in the last decade and an increase of 20% is foreseen for the next 20 years [1]. Similar values are expected in other European countries. Better management of cooling costs is becoming critical.

Currently, HVAC (Heating Ventilation and Air Conditioning) control relies mostly on PID controllers [2], which need to be properly tuned in order to achieve good performances [3, 4]. In order to further improve the comfort, multi-variable controllers have been proposed [5]. However, these controllers lack any forecasting capabilities. Such features can be incorporated in controllers based on fuzzy logic [6] or genetic algorithms [7]. Only MPC (Model-Predictive Control) appears able to efficiently combine the benefits of multi-variables and forecasting [8, 9].

Here we present a novel MPC based controller for HVAC systems. This paper is organized in two main sections. First, we introduce the simulation environment, the NeuroCool MPC, and the analysis methodology. Second, we analyze the simulation results to see how the MPC performs in two distinct simulation cases. The results are compared with a standard controller. The article concludes by summarizing the results and giving some future perspectives.

2. Method

a. Simulation environment

To develop and validate the NeuroCool algorithm, a simulation environment was built in MATLAB & Simulink. An overview is provided in Figure 1. The simulation environment is composed of three main blocks: technical systems (Air Handling Units (AHU)), buildings and controllers. In order to assess the efficiency of the algorithm, a reference simulation, with a standard state of the art controller, is also run with the same inputs. Note that for the reference simulation, the controller is included in the AHU block which explains why there is no separate controller block.

Figure 1: MATLAB & Simulink simulation environment.

The **AHU block** takes as input either the room temperature (if running in standard mode) or the desired pulsed air set-point (if running in NeuroCool mode) and the outdoor conditions (i.e. weather). Based on that data and its current status, the block outputs the corresponding pulsed air. In addition, for analysis reasons, the AHU block also computes the power consumption related to air treatment and fan operation.

The **building block** takes as input the outdoor conditions and pulsed air and computes the corresponding indoor temperature and humidity (computed at extraction level). The simulation model is based on a lumped resistor-capacitor model (RC). The RC values can be manually set, if all parameters are known. Since this is rarely the case, a calibration method was developed to find these parameters from a set of data measured on a real building.

Two **controller blocks** are available: 1) the standard controller, that corresponds to the one available by default (i.e. reference) and 2) the NeuroCool MPC controller that will be described in the next section. The reference controllers take as input the room temperature and, if available, the room humidity, and based on predefined comfort setpoints (with hysteresis) compute the desired pulsed air temperature (and humidity). These controllers normally operate at a fixed speed and are often schedule-based, in the sense that a timer prevents ventilation from operating during the night or over the week-ends.

b. NeuroCool model predictive controller

In order to optimize the energy expenditure of the AHU while at the same time ensure user comfort, we use a model predictive control (MPC) approach as depicted in Figure 2, i.e. an optimization is performed on a given, finite time-horizon, and only the first value returned by the optimization is used. MPC makes it possible to control a system while taking into account future events. While the length of the time horizon is configurable, in practice we perform the optimization every 5 minutes with a horizon of 2 hours.

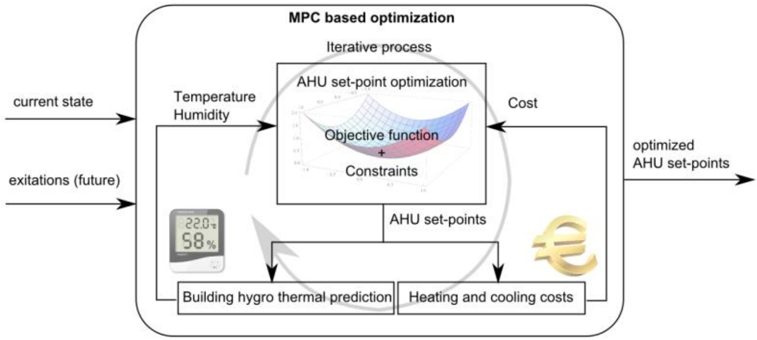

Figure 2: MPC based approach for AHU optimization.

The control variables of the AHU system we are optimizing are the pulsed air's:

- temperature over the horizon
- humidity over the horizon
- flow rate over the horizon

The objective function of the optimization problem is composed of two terms (as shown in the equation below):

- <u>Energy costs</u>: We rely on a thermodynamic model of the heating and cooling systems and the Mollier diagram to predict the energy costs of the AHU.
- <u>User comfort</u>: The user comfort is defined as the averaged squared error from the room temperature and humidity setpoints. In order to compute this error, an adaptive model of the temperature and humidity inside the building (a so-called building hygro-thermal model) was developed.

The balance of these two terms can be controlled by a regularization parameter λ, as highlighted below.

Formally, the optimization problem can be stated as:

Minimize: $AirTreatmentCost(x, w) + \lambda \cdot \|p(x, w, r_c) - d\|^2$
Subject to: $p(x, w, r_c) \leq b$

Where:

- x^1: is the AHU air (temperature, humidity and flow)
- w^1: is the outdoor air (temperature and humidity)
- r_c: is the room current status (temperature and humidity)
- d^1: is the ideal temperature/humidity in the room (defined by the comfort norms)
- b^1: are the comfort boundaries (defined by the comfort norms)
- λ: is the weighting coefficient given to the comfort (0: optimize cost only)
- *AirTreatmentCost(x,w)*[1]: computes the cost associated to treating the outdoor air
- $p(x,w,r_c)$[1]: building thermal model, computes the indoor conditions

The optimization problem incorporates the following constraints:

- **Comfort norm constraint**: In order to guarantee that the comfort norm are respected, we constrain the temperature and humidity in the room to be in a range given by the European norm EN 15251. Typically, the temperature in the room has to be between 20°C and 24°C in winter, and between 23°C and 26°C in summer, while the relative humidity has to be in the range 25% to 60%. Note that this constraint is nonlinear because it depends on the temperature and humidity prediction model, which is nonlinear.
- **Variations constraint**: in order to model the dynamics of the AHU system which can only change "smoothly" the values of the air temperature, humidity and flow rate, we constrain these optimization variables to have a maximum and minimum derivative in time. This constraint is linear.
- **100% relative humidity constraint**: The air coming outside of the AHU should not reach the limit of 100% relative humidity. In order to avoid this case, we implement a constraint to guarantee that the air humidity variable is always less than 100% of relative humidity. This constraint is nonlinear because the conversion from absolute humidity to relative humidity is nonlinear.

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[1] These elements are vectors or return vectors of the length defined by the optimization horizon (96 elements with the used settings).

Our optimization approach relies on a smooth local nonlinear optimization solver. We used the MATLAB optimization toolbox with its interior point solver and we provided, to the solver, the gradient (computed explicitly from the model equations) of the objective function and the nonlinear constraints. Note that it would be possible to let MATLAB evaluate numerically the gradient but explicitly providing the gradient sped up the optimization by a factor 30 in our case.

c. Analysis methodology

The performance of the two controllers should be compared in terms of both comfort and cost of operation. For this purpose, some preprocessing of data is done. The training period of the building model, during which the NeuroCool controller is not operating, is discarded. To make sure the transition between the controllers is not taken into account, we discard also the data concerning the day following the transition.

In order to compute a comfort, we need to define the optimal comfort level. For this purpose, we refer to the European norm EN15251 which defines comfort boundaries in terms of temperature and humidity, depending on the season. In winter, indoor temperatures should be in the range 20-24 °C while the relative humidity should be between 25% and 60%. In summer, the temperatures should lie within 23-26°C and relative humidity between 25-60%. The "optimal comfort level" is defined as the center of the rectangle defined by these boundaries.

The comfort achieved by the two controllers is then evaluated in terms of root mean squared error between the room conditions and the optimal comfort level. Another metric, which can be used for comparison, is the Predicted Mean Vote (PMV) [11]. This metric, originally developed by Fanger and later adopted by ISO, establishes the indoor comfort according to six factors: metabolic rate, clothing insulation, air temperature, radiant temperature, air velocity and relative humidity. The PMV should be kept between –0.5 and +0.5 to insure thermal comfort in a conditioned space. For our analysis, we set the air velocity to a constant value, since the considered system is a constant air volume one, we approximate the radiant temperature using the ambient temperature and we define the values of metabolic rate and clothing insulation to constant levels, such that the PMV is equal to zero when the temperature and humidity correspond to those defined as optimal by European norms. This yields the following parameters: (insert here the values for the PMV factors in summer and winter).

Finally, the cost of operation of each controller is computed. This is given by multiplying the consumption of each element of the HVAC system by the associated cost (in €/kWh). In a real building, these tariffs will be defined by the building manager, but in this simulation we used the following:

- 0.1 €/kWh for heat production;
- 0.2 €/kWh for cold production;
- 1.06 €/kWh for humidification;
- 0.2 €/kWh for fans.

3. Simulation results and analysis

The NeuroCool controller will be deployed on several real test sites. These can be broken down in two main categories:

- AHU with air heating and cooling only
- AHU with air heating, cooling, humidification, and dehumidification

Consequently, two distinct simulation cases have been considered.

a. Simulation case A: AHU with air heating/cooling and humidification/dehumidification

The zone that is controlled has a volume of about 42 m^3.

The AHU is capable of the following air treatment:

- Air flow: fixed at 540 m^3/h
- Pulsed air temperature: 15 to 40 °C
- Pulsed air absolute humidity: 10 to 18 g/kg

The comfort and regulation settings are the following:

- Minimum / maximum temperature in the zone in summer: 23 – 26 °C (average: 24.5 °C)
- Minimum / maximum relative humidity in the zone: 25 – 60 % (average: 42.25 %)
- Air flow: constant at 540 m^3/h
- Scheduler: none (i.e. the above settings are maintained all the time)

The default controller has a continuous air flow and tries to maintain the temperature and humidity at the average values provided above (i.e. 24.5 °C and 42.25 %).

The climate corresponds to Geneva in Switzerland (year 2014), the simulation lasts 100 days and starts at day number 130. This corresponds to May 10^{th} to August 18^{th}.

In order to assess the functionality of the developed MPC controller, tests with various comfort settings (i.e. λ in the objective function) have been performed.

The effect on the comfort within the zone can be directly observed in Figure 3. The comfort boundaries and the measured temperature / humidity within the zone are provided for a “low” and a “high” level of comfort.

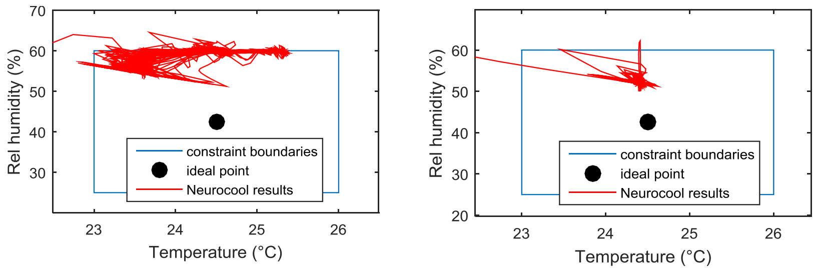

Figure 3: Simulation results (case A), measured room temperature and humidity for low (left) and high comfort (right)

In order to evaluate the impact of the comfort level on the operational costs and benchmark it against the default controller, the PMV (as defined in Section 2.c) is computed. This is shown in Figure 4. It can be observed that for a better PMV (-0.045 instead of 0.0667) the MPC solution cost 2774 CHF instead of 3055 CHF for the reference controller, corresponding to a cost decrease of ~10%. PMVs up to ± 0.5 are usually admitted, which suggests that lower values for λ in the objective function of the MPC controller can be used. For a PMV of -0.35, for example, the savings with respect to the default controller are of ~15%.

It is worth noting, that higher savings can be obtained if the local controller of the AHU itself is improved. Indeed, it can be shown that even though the MPC desires a specific air temperature / humidity to be output, the AHU is slightly off. This leads to switching between humidification and dehumidification which is energetically unfavorable. It can be shown that by modifying the local controller of the AHU, for a similar PMV the savings are increased to 20 to 30%.

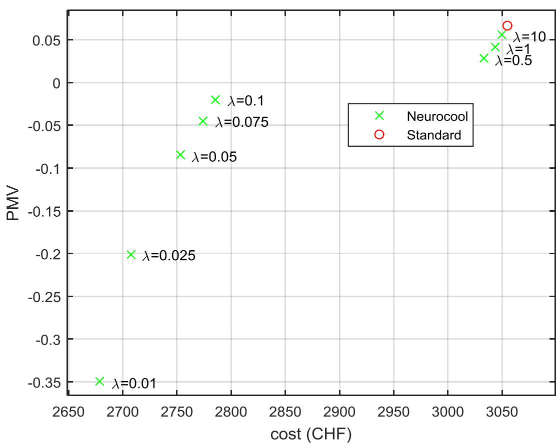

Figure 4: Simulation results (case A), PMV as a function of operational cost (MPC in green and standard controller in red)

b. Simulation case B: AHU with air heating/cooling only

In case B, the AHU is capable of the following air treatment:

- Air flow: 3 states, 0, 500 and 1000 m^3/h
- Pulsed air temperature: 17 to 30 °C
- Pulsed air absolute humidity: not controllable

The zone that is controlled has a volume of 232 m^3.

The comfort and regulation settings are the following:

- Minimum / maximum temperature in the zone: 22.25 – 25.25 °C (average: 23.75 °C)
- Minimum / maximum relative humidity in the zone: not controlled
- Air flow: variable, depending on the simulation case
- Scheduler: no occupancy at night (6PM to 7AM).

The climate corresponds to Geneva in Switzerland (year 2014), the simulation lasts 100 days and starts at day number 130. This corresponds to May 10th to August 18th.

Three simulation cases are considered:

1) Standard controller (zero flow at night, maximal flow during the day)
2) MPC with fixed flow (zero flow during night, maximal flow during the day)
3) MPC with optimized flow (zero, medium or maximal during the night, medium or maximum during the day)

Figure 5 compares case 1) and 2), Figure 6 compares case 1) and 3). It is to be noted, that the comfort is computed only during occupancy hours (i.e. 7AM to 6PM).

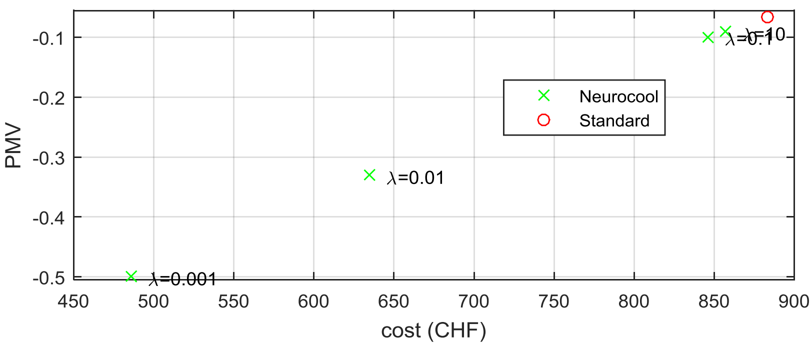

Figure 5: Simulation results (case B), comfort (PMV) as a function of energy for "zero flow at night and maximal flow during the day" (green: MPC with decreasing value of lambda, red: default controller)

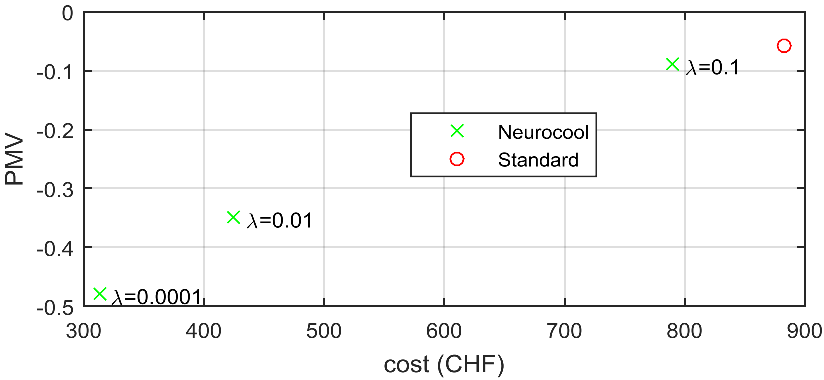

Figure 6: Simulation results (case B), comfort (PMV) as a function of energy for "allow non-zero flow at night and medium or maximal flow during the day" (green: MPC with decreasing value of lambda, red: default controller)

Figure 5 shows that if the same air flow scheduling as for the standard controller is used (i.e. only the pulsed air temperature is optimized), the savings are (for a similar PMV) of 3% only (standard: 883CHF, MPC: 857CHF). For a PMV of -0.5, the cost is almost divided by two.

It can be observed in Figure 6, where air flow and pulsed air temperature are optimized, that for a similar comfort (lambda = 0.1), the MPC provides savings of 11% (standard: 883CHF, MPC: 789CHF). If we allow the PMV to reach the +-0.5 limit, then expenses linked to using the MPC represent only one third (standard: 883CHF, MPC: 312CHF) of the reference controller.

4. Conclusion and outlook

This article presented a novel MPC controller for HVAC systems. Emphasis was put on the simulation environment and simulation result analysis. It was shown, that when compared to a standard controllers, cost savings of 11% can be achieved for similar comfort. If the comfort is degraded, but maintained within the limits imposed by the relevant norms, the exploitation costs can be divided by almost three. It is to be ponited out, that NeuroCool automatically adapts it's working point as a funciton of the provided comfort norms and lambda. In addition it provides all the anticipation features that are intrinsically linked to MPC. Such features are absent in the standard controller, that is thus unable to provide this type of savings.

Currently this MPC is running on test sites. The algorithmic deployment, test site description and preliminary results are presented in [11].

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