General description of the Model Predictive Control common exercise

1. Introduction

The aim of this common exercise is assessing the performance of predictive models, which characterize building's thermal behavior. This common exercise is a part of Annex 71 project subtask 2. The aim of this exercise is twofold. First, we are going to show that MPC might outperform conventional controllers such as PID and Rule Based Controller. Secondly, we are going to evaluate the effect of different modeling techniques on the performance of the model predictive control. Model Predictive Control optimizes the performance of the system by taking into account prediction of different disturbances such as weather forecasts, occupancy profiles, etc.[1] MPC is comprised of two major components: the predictive model and the optimizer. The output of the MPC, which is the optimal control inputs, is then applied to the real system or the emulator (fig 1). In this exercise, model predictive controller is going to be designed and then applied to the Twin house O5. There are three main parts in this exercise namely: emulator, predictive model and the optimizer. These major parts are explained below:

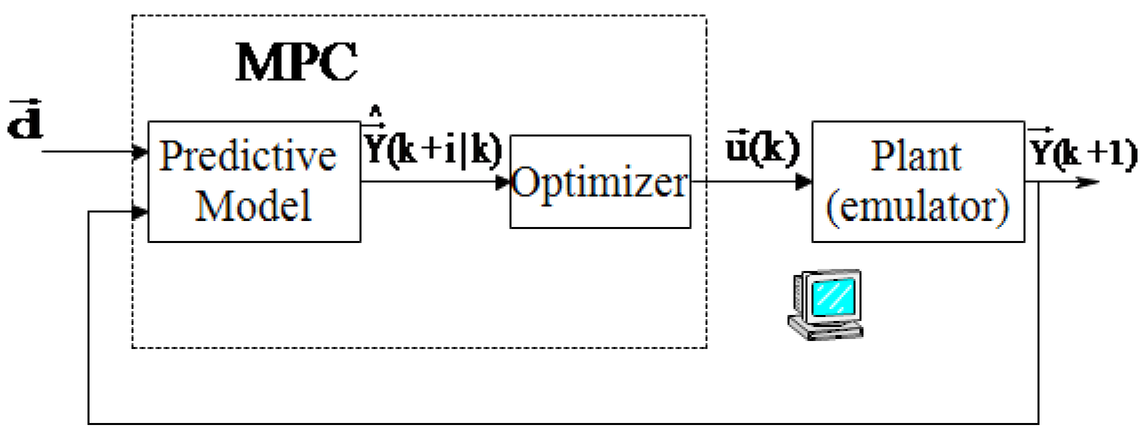

Figure 1- MPC general Scheme

2. emulator

The Emulator in this exercise is a Modelica Model which represents the thermal behavior of the Twinhouse O5 during user 1 phase (19.12.2018 14:00 to 1.2.2019 10:30). The full description of this experiment is in the file "Experimental specification BESmodVAL_annex71_v5.0.pdf" along with a detailed description of the developed Modelica model in "Report_v2.pdf". Heat pump has been modeled for this exercise. The modeled heat pump is an air source heat pump

Which supplies water for the under floor heating system utilized in the O5 house. The two control signals (u_1 and u_2) correspond to heat pump's status (on/off) and its supply water temperature correspondingly which are explained in the section 4.

This emulator is then used to artificially excite the building and the results for this simulation could be used to model the building's thermal dynamics (see "Twin_house_O5_exp1_60min.xlsx"). All the boundary conditions are provided in the files "Twin_house_O5_exp1_10min.xlsx" and "Twin_house_weather_exp1_10min_compensated.xlsx". These files include data for ventilation system, weather condition and internal heat gains during the experiment.

Although the emulator represents the O5 house, the following exceptions and points should be considered regarding the performance of the emulator:

- Christmas problem is excluded from the model so that period (24.12 7:00 to 25.12 11:00) can be also used for identification purposes. Hence, the whole period of user 1 could be used for training your models.
- Make sure to include the heat gains applied to the building due to the unwanted operation of the electrical heaters at the beginning of the user 1 phase.
- For the sake of simplicity, external heaters are not modeled in this emulator. To compensate for this, the heat pump's nominal power has been increased.
- Domestic Hot water demand is not included in this model neither.
- Since they represent the actual heat pump, which differs from the one, used in the emulator.

3. Model

A wide range of modeling techniques have been applied to identify buildings thermal behavior. The models used in this exercise should predict the building's representative temperature in the next hour given all the heat inputs (Heat pump's status and its supply water temperature) and boundary conditions.

An important aspect in this part is that the choice of model which could affect the choice of the optimizer. In other words, a non-linear model most likely results in a nonconvex optimization problem, which narrows down the range of optimizers, which could be used for this exercise [2]. Considering the latter, there are two options provided for the participants, which are described below.

3.1 Option 1

The participants develop a linear model representing the thermal behavior of the O5 building. To this end, data provided in the attachment could be used and the final model should be provided in the form of continuous state space model. The output of their model should be the prediction of the building's representative temperature (volume-average temperature of all zones) for the next hour.

Next step would be to apply this model in a linear MPC context (described in the section). Finally, the results for these linear models will be compared against each other and the non-linear approaches as well.

3.2 Option 2

The participants who choose to develop a non-linear model are to follow the instructions provided here. As mentioned earlier, using a non-linear model in the context of the MPC, most likely results in a non-convex optimization problem and the suitable choice for the optimizer might depend on the selected modeling techniques [2]. Consequently, participants who wish to develop a non-linear model are asked to provide the whole designed MPC not just the model (see fig 2), which is mainly composed of the predictive model and the optimizer.

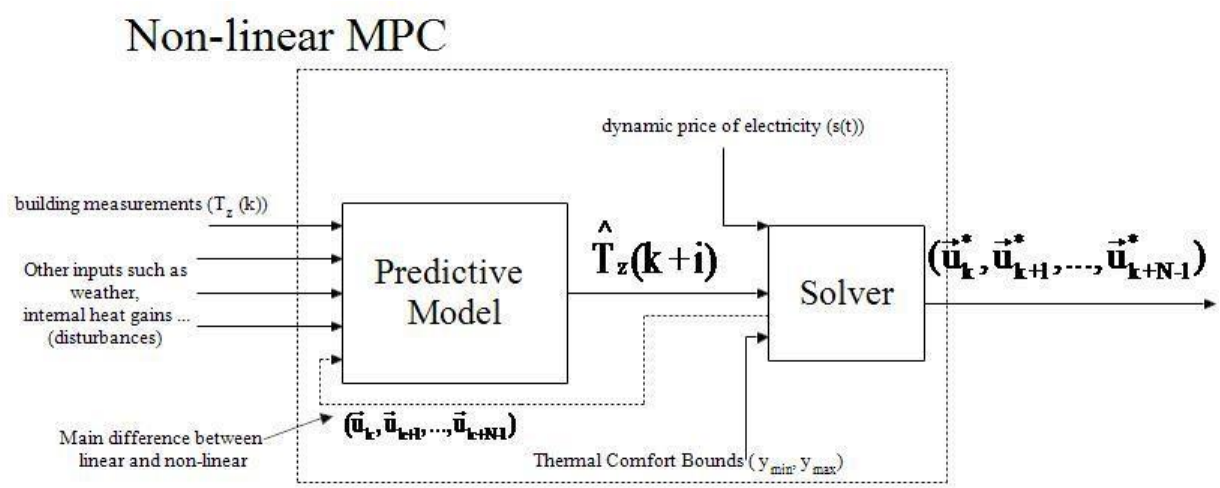

Figure 2- nonlinear MPC general scheme

The boundary conditions data provided in the attachment could be used to develop the controller. The output of the designed MPC would be a vector composed of two arrays. The heat pumps status and heat pump's supply water temperature.

4. Optimizer

Description of the optimizer is presented for people who choose option 2. The full optimization problem could be seen below:

$$\min_{\vec{u}_t,\vec{u}_{t+1},\ldots\vec{u}_{t+N-1}} \sum_{k=0}^{N-1} [Lv_{t+k+1} + C_{el,t+k}\ P_{el,t+k}]$$

$$\text{s.t}:$$

$$y_{k+1} = f(x_k, u_k, d_k)$$

$$Pel_{t+k} = g(\vec{u}_{t+k}, \vec{d}_{t+k})$$

$$y_{t+k+1} + v_{t+k+1} \geq y_{min,t+k+1}$$

$$y_{t+k+1} - v_{t+k+1} \leq y_{max,t+k+1}$$

$$\vec{u}_{min} \leq \vec{u}_{k+t} \leq \vec{u}_{max}$$

$$v_{t+k+1} \geq 0$$

$$u_2 \text{ is boolean}$$

$$k = 0,1,\ldots N-1$$

N: Prediction horizon (in this exercise is set to 24 hours=24 time steps)

L: Weighting coefficient between two terms in the cost function

V_{t+k+1}: slack variable that allows violation of comfort bands and is to be penalized in the cost function

Cel: electricity price at the corresponding time step

Pel: electricity consumption by the heat pump at the corresponding time step

y: prediction of the building's representative temperature

d: vector of various disturbances fed to the model

$y_{min,t}$, $y_{max,t}$: thermal comfort bands defined based on the time of day

g(.) :performance map for the heat pump

u_1: Status of the heat pump (on/off)

u_2: Supply water temperature of the heat pump

u_{min} ,u_{max}: control input limits

To avoid inefficient operation of the heat pump (operation under low modulation rates) a minimum supply temperature of 28 degrees ($u_{2,min}$) is considered and a maximum supply temperature of 45 degrees ($u_{2,max}$) is defined in this exercise as well. Heat pump's status (u_1) a Boolean variable for which the value 1 means heat pump is working and 0 means it's off. Weighting coefficient (L) used for penalizing thermal comfort violation is to be tuned in the optimization process since it has no physical interpretation.

Dynamic electricity profile is also provided in the "electricity price.xlsx". We assume this profile is valid for the whole optimization period. Thermal comfort band, which is assigned to this exercise, is 20-24 during the day (7:00 to 23:00) and 18-22 during the night (23:00 to 7:00). All the data required for designing the MPC is provided in the file "Twin_house_O5_exp1_60min.xlsx.

The criteria used to evaluate the performance of the controllers' are total discomfort level described as time x temperature (kh) and Total cost of electricity during the period in which controller is applied.

Table 1. Zone volumes

Zone	**Volume (m^3)**
Kitchen	19.34
Doorway	15.18
Bedroom	29.1
Corridor	14.2
Bathroom	18
Dining Room	29.1
Living room	87.5
Staircase	21
Children room 1	56.2
Children room 2	59

References:

[1] A. Afram and F. Janabi-Sharifi, “Theory and applications of HVAC control systems - A review of model predictive control (MPC),” *Build. Environ.*, vol. 72, pp. 343–355, 2014.

[2] F. Allgower and A. Zheng, *Nonlinear Model Predictive Control*. springer, 2000.