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Development of a Model-based Predictive Controller for a heat distribution network

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Abstract

Research studies concerning heating and cooling systems have increased in recent years, pledging great potential for energy saving, efficient thermal energy distribution and renewable energy source integration. Currently, heating systems are managed on the basis of operator experience or by using adaptive controllers, however these solutions are not suitable when there are remarkable variations in boundary conditions (e.g. weather changes). In this context, Model Predictive Control is a promising strategy as it optimizes the control action based on the prediction of the future behavior of both system dynamics and disturbances by means of simplified models. This paper presents the control of a building heating system through a Model-in-the-Loop Model Predictive Control approach. A detailed model that replicates the behavior of the real system is controlled with a predictive controller based on a novel Dynamic Programming optimization algorithm implemented in Matlab®. The performance of the innovative controller is compared to the results obtained with a PID controller. Overall, the Model Predictive Control strategy is able to fulfill comfort requirements properly while minimizing energy consumption.

Keywords: energy network; building; Model Predictive Control; Dynamic Programming; identification; optimization.

1. Introduction

According to the International Energy Agency, more than 40 % of global energy consumption [1] is due to the air conditioning of residential and commercial buildings (i.e. heating and cooling). Therefore, this sector offers substantial opportunities for improvement in energy efficiency and savings. In particular, District Heating and Cooling Networks

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(DHC), which distribute thermal energy to buildings (e.g. residential and commercial), pledge flexibility, integration of renewable energy sources and more energy efficient buildings [2]. At present, however, the large variety of available energy sources has introduced new challenges such as the efficient allocation of the load and management of these multi-source systems [3]. Moreover, energy distribution optimization is fundamental to minimize primary energy consumption and cost. As conventional approaches to the control and management of energy systems do not allow the exploitation of their full potential, innovative and smart optimization strategies and simulation tools have to be adopted [4]. The application of Smart Technologies is paramount in achieving the key targets (i.e. greenhouse gas emission reduction, energy efficiency improvement and production from renewables) established by the European Commission for 2020 [5]. Recently, the European Union has been financing research projects on smart buildings for flexibility [6] and intelligent DHC. In this direction, other research works foresee promising results by applying innovative control strategies, such as Model Predictive Control (MPC), to these systems [7–9]. Nonetheless, a state-of-the-art methodology that includes both the production and utilization sides of an energy network has not yet been demonstrated and further studies are required.

This paper proposes the development of an MPC controller and a Model-in-the-Loop (MiL) application to a simple energy distribution system consisting of a single building and a boiler. The main purpose of the work is the verification of the procedure for further implementation in more complex systems.

Nomenclature

c	specific heat [kJ/(kg K)]	$\dot{m}$	mass flow rate [kg/s]	P	power [kW]
$\dot{Q}$	heat power [kW]	T	temperature [°C]	t	time [s]

2. Model Predictive Control

MPC is a family of control strategies that uses a dynamic model of the system to predict its behavior over a future time horizon, named prediction horizon. The dynamic behavior of the system and the forecast of external disturbances are exploited to calculate the optimal control law through the solution of a constrained optimization problem that minimizes a cost function. The prediction horizon is discretized in a certain number of time-steps. The output of the MPC is a sequence of open-loop control actions that shall be executed to obtain the optimal behavior of the system. However, only the first element of this control law, corresponding to the first time-step, is actually implemented in the real system. Then, the time horizon is moved one step forward (i.e. *receding time horizon* strategy), the system variables are updated with the current values and the whole calculation is repeated. This state update produces implicit feedback and reduces the influence of the uncertainty of disturbances and modeling approximations.

MPC gained relevant success mainly in process industry as it introduced the possibility to control and simultaneously optimize multi-variable processes subject to constraints, which is typical of the industrial field. Despite the lack of extended applications to the energy sector, recent studies in this area [10] consider MPC as extremely promising due to its many advantages compared to classical controllers (i.e. consideration of predicted disturbance, handling of constraints and concomitant optimization).

MPC requires three main components: (i) a simplified dynamic model of the system, also called the MPC-model, (ii) an optimization algorithm which solves the optimization problem to return the optimal control trajectory, and (iii) a controller. The implementation of these elements in the Matlab® environment is discussed in the following.

2.1. Description of the MPC-model

The system that has been chosen to implement and test the proposed approach consists of a single building and a boiler. Further applications will be possible starting from this test case. The most time-consuming part of the MPC implementation is generally the development of a suitable building model for control and operation, as a standard procedure does not exist and each case should be evaluated separately [10]. Nonetheless, gray-box models, which adopt a simplified description while maintaining a physical meaning of the parameters, seem to be advantageous [11]. As a matter of fact, a reduced-order gray-box model guarantees a lower computational effort, which is necessary for

MPC on-line optimization, compared to a more complex one. Furthermore, a physics-based approach, properly set up on conservation equations, can efficiently simulate real system dynamics.

The simplified building model that is embedded in the MPC controller is developed from the building dynamic energy balance equation that describes the evolution of the internal temperature T [11]

$$\frac{dT}{dt} = -a \cdot \left(T - T_{\text{ext}}\right) + b \cdot \dot{Q} \tag{1}$$

The heat exchange through the walls to the external environment and the thermal power from the heating system influence the internal building temperature evolution through the coefficients a and b, respectively, which take into account the building heat capacity as reported in [11]. Forced ventilation is absent and air infiltrations are neglected. The thermal power given to the building is expressed as the water enthalpy difference through the space heaters:

$$\dot{Q} = \dot{m} \cdot c \cdot \left(T_{\text{boiler}} - T_{\text{R}}\right) \tag{2}$$

The internal building temperature T is the system state and controlled variable. During building occupation, the internal temperature has to be kept reasonably equal to 20 °C. The water mass flow rate and temperature (i.e. boiler outlet temperature T_{boiler}) are the manipulated variables of the system (i.e. inputs). The return water temperature T_{R} is fixed to 60 °C as a design parameter, according to the assumption that it is regulated by the space heater controllers. The external ambient temperature T_{ext} is the disturbance.

2.2. Forecasting of external data

One of the main advantages of MPC is its capability to optimize the operation of the system starting from the forecast of the disturbance throughout the prediction horizon. Therefore, the external ambient temperature is forecasted through a piecewise function that reasonably builds the daily profile using the maximum and minimum temperatures of the current day, the minimum temperature of the following day and the sunrise and sunset hours [12]. This profile is randomly altered in order to account for weather variability. This methodology has been exploited to test the MiL application. Extension to real systems can be conducted by using real-time weather forecast databases.

2.3. Optimization algorithm

Within the MPC framework, an optimization problem has to be solved at each time-step. Therefore, an optimization algorithm that combines low computational time with feasible accuracy had to be chosen.

The Dynamic Programming (DP) algorithm is based on Bellmann's principle of optimality which states that the tail of an optimal trajectory of an optimization problem is still optimal for the tail sub-problem. According to this concept, the time scale and the whole state-space of an optimization problem are discretized and the global problem is divided into smaller sub-problems that are solved recursively by proceeding backward in the time scale. This iterative procedure returns an optimal control map which is then exploited to identify the optimal control sequence through a forward calculation that starts from the initial condition.

In [13], a Matlab® function, which solves generic DP problems with up to five state variables, has been proposed and is widely used in several applications. In this work, a novel and simpler function based on the same concept is developed in Matlab® and is designed to handle the presented application and other problems with the same structure, i.e. one state (e.g. internal building temperature), two inputs (e.g. water mass flow rate and temperature) and one disturbance (e.g. external temperature). Its implementation is arranged into three parts:

- a function for the definition of the data structure where the required problem parameters are defined (i.e. time scale, state and input grids, and disturbance array);
- the model function (MPC-model) that contains the discretized state function and the cost function to be evaluated;
- the algorithm function that calls the data and model, and returns the optimal control trajectory.

This architecture gives the possibility to maintain generality and to treat a wide variety of conditions by modifying the data or model functions. The novel function takes approximately one quarter of the time requested in [13] to solve the same optimization problem and allows a variable-step state/input discretization (e.g. local grid refinement).

For the application to the energy system defined in Section 2.1, the state equation Eq. (1) is discretized. The input grid is created according to the lower and upper constraints of the input variables. The state grid is discretized according to the state boundary values with a step of 0.25 °C suggested by a sensitivity analysis as a balance between accuracy and calculation effort. The cost function for each time-step is assumed as the total energy consumption:

$$\text{cost} = \left[\dot{Q} + \dot{Q}_{\text{loss}}(T_{\text{boiler}}, T_{\text{ext}}) + P_{\text{pump}}(\dot{m}^3) \right] \cdot \Delta t \tag{3}$$

This gathers the contributions of the thermal power sent to the building space heaters $\dot{Q}$ described by Eq. (2), the pump power P_{pump} and the heat loss through the pipes $\dot{Q}_{\text{loss}}$, based on the physical characteristics of the distribution system. Due to the internal temperature requirements, the lower and upper state constraints are reasonably assumed as 19.5 °C and 20.5 °C, respectively, when the building is occupied. A penalty factor is therefore added to the cost function associated with the unacceptable state values in order to force compliance with the constraints.

3. Model-in-the-loop

The MiL approach allows methodologies to be tested and sensitivity analysis to be performed without involving the real system which could be unavailable due to the non-heating season or the need to respect building comfort conditions. In order to simulate real building behavior, a detailed continuous-time dynamic model of the system (including the contributions of solar irradiance and thermal power from building occupation), named the MiL-model, is used. It is based on Eq. (1) and solved through a Matlab® Ordinary Differential Equation solver. The MiL-model runs continuously for the desired time span and is controlled by a model of the controller. Two different controllers are implemented and compared: (i) a state-of-the-art PID controller [11], the set-point of which comes into effect at an arbitrary point in time prior to occupation of the building (three hours) and (ii) the MPC controller described above.

3.1. Identification procedure

As the MPC-model parameters *a* and *b* are unknown, an identification procedure has to be carried out from real building data. Identification is a methodology that builds the mathematical models of a system starting from sets of input and output data. In this application, these data are obtained by running the MiL-model controlled by the PID for a simulation time of several days.

The simulations make it possible to obtain sequences of (i) building internal temperature data, (ii) inputs defined by the PID and (iii) the imposed external temperature. Random components are added to both the internal and external temperatures to simulate measurement uncertainty. These data are divided into a training set for identification of the MPC-model parameters and a test set for validation. The training set and the specified model structure are inputs of the identification problem. This consists of estimating the parameters of the model by solving a nonlinear least-squares minimization. The comparison of the newly-identified gray-box model with the test set values allows the evaluation of the reliability of the procedure. Once the MPC-model has been identified, it is possible to apply the MiL-MPC control strategy described above.

4. Results

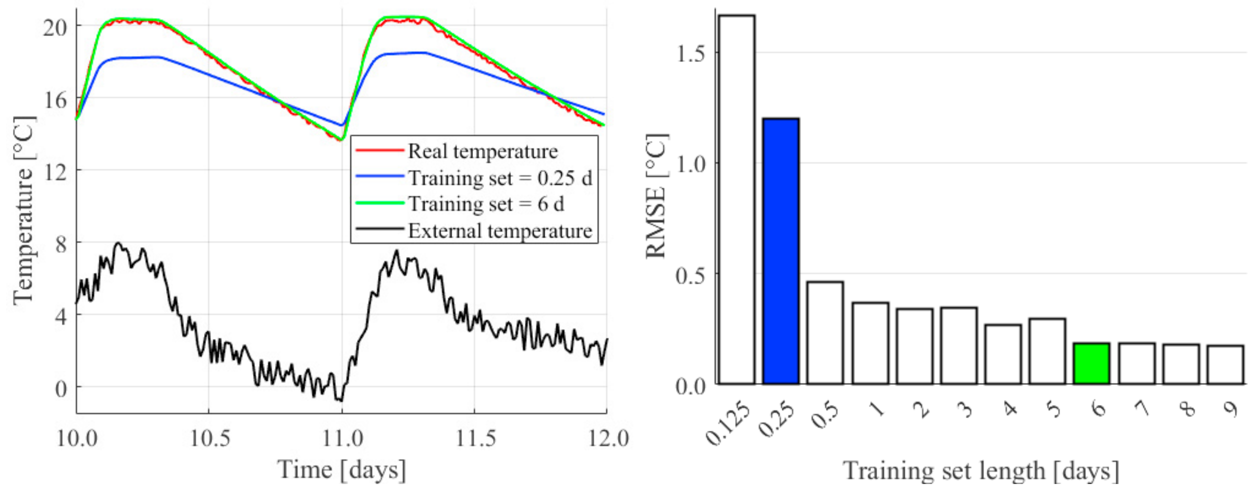
The results of the identification and the control of the test case are discussed. The selected building is a school gym occupied Monday to Friday from 8:00 am to 3:30 pm. The system parameters are summarized in Table 1.

4.1. Identification procedure

The set of real building input and output data is obtained by the simulation of 12 days during the winter season. The test set is chosen as the last two days. Fig. 1a shows that the identification performed on a relatively short training set (e.g. 0.25 days) provides a model which does not adequately fit the measurements. This happens because the heating up and cooling down building dynamics are not sufficiently represented by the training set and cannot be highlighted. Fig. 1b shows the Root Mean Squared Error (RMSE) between the predicted data and measurements with

Table 1. System parameters used for implementation.

Parameter	Value	Parameter	Value	Parameter	Value
Water mass flow rate	(0 ÷ 8) kg/s	Insulation thickness	0.1 m	Number of occupants	100
Boiler temperature	(70 ÷ 80) °C	Insulation conductivity	0.05 W/(m K)	Individual thermal power	80 W
Pipe length	100 m	Friction factor	0.0145	MPC prediction horizon	3 days
Pipe diameter	0.125 m	Pump efficiency	0.8	MPC time-step width	15 min



(a) (b)

Figure 1. (a) Comparison between results with two different training sets. (b) Root Mean Squared Error for different training set lengths.

varying training set lengths. Acceptable results are obtained with at least one-day-long datasets, provided that they cover typical weekday operation (i.e. with building heating and cooling transients). The values of the MPC-model building coefficients *a* and *b* used for the control are obtained with a 6-day-training set and are $7.2655 \cdot 10^{-6}$ s^{-1} and $7.7944 \cdot 10^{-7}$ °C/kJ, respectively.

4.2. Model-in-the-loop system control

The MiL is run in order to simulate 10 days starting from a Monday. Hence, the system behavior across a weekend can be captured. The comparison between the control performance of the PID and the MPC is shown in Fig. 2. It is possible to notice that the PID is not able to guarantee the required internal temperature defined by the constraints. Moreover, after the weekend the required temperature is not reached. Hence, this approach guarantees neither fulfillment of the desired comfort conditions nor energy minimization. On the other hand, MPC assures compliance with the constraints while optimizing energy consumption. Furthermore, MPC proves to be particularly effective with considerable variations in weather conditions that seem likely to happen due to climate change.

5. Conclusions

The current global energy scenario enables a significant reduction in energy consumption if efficiency in buildings and DHC networks is addressed. In this work, an MiL application of a novel DP-based MPC controller to a building heating system was proposed. Firstly, a gray-box model embedded in the MPC controller was identified by means of an input-output dataset obtained by emulating the real system during the winter season. A sensitivity analysis on the

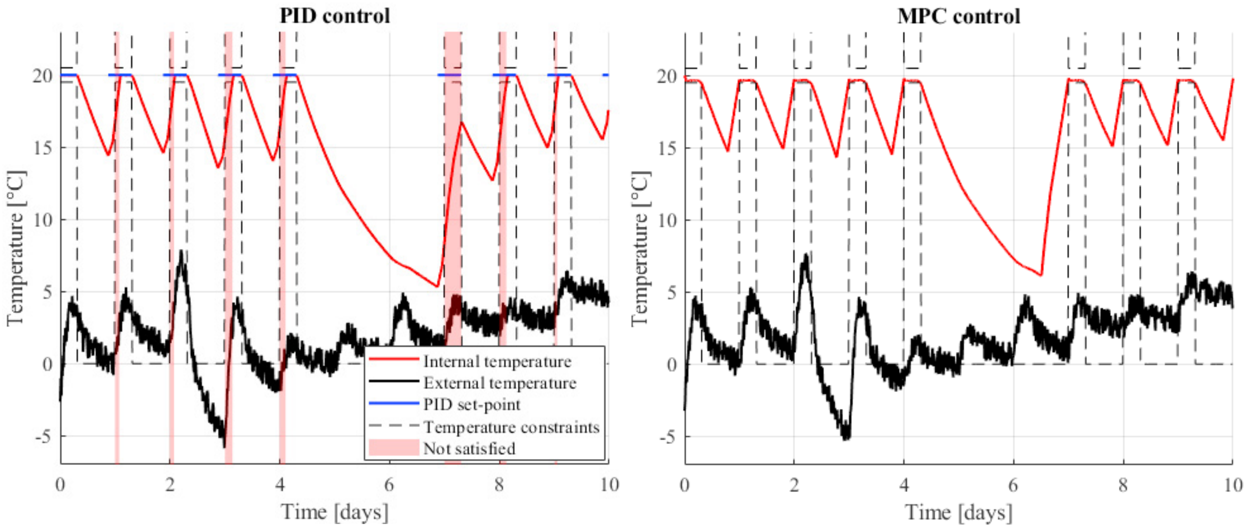


Figure 2. Model-in-the-Loop system operation with PID control (a) and MPC (b).

training set made it possible to state that one-day-long datasets give acceptable fitting results. Then, the MPC control system was simulated in an MiL and its results were compared to those obtained with a classical PID controller. As expected, MPC outperforms the PID regarding both building comfort requirements and primary energy saving.

Further studies and applications of the proposed approach will focus on multi-source complex thermal networks by using a multi-agent strategy with the MPC controller replicated in each branch of the network to control each site. Eventually, future developments commit to the demonstration and exportation of this innovative control approach from MiL to real distribution networks.

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