CISBAT 2017 International Conference – Future Buildings & Districts – Energy Efficiency from Nano to Urban Scale, CISBAT 2017 6-8 September 2017, Lausanne, Switzerland

System identification of thermal building models for demand response – A practical approach

Michael D. Knudsen, Rasmus E. Hedegaard, Theis H. Pedersen, Steffen Petersen

Department of Engineering, Aarhus University, Inge Lehmannsgade 10, 8000 Aarhus C, Denmark

Abstract

Model predictive control is a promising control scheme to utilize space heating in buildings for price-based demand response. It is, however, crucial to have an adequate thermal model of the building in order to make this work. It is often very time-consuming to construct these models and common system identification approaches suggest experimental input signals that are difficult to obtain in practice, which often leads to thermal discomfort. This paper proposes an alternative approach where an initial model is identified from historical data and then later re-identified based on control input generated from a model predictive control using the initial model.

Keywords: Model predictive control; Black box models; System identification; Demand response, Space heating;

1. Introduction

   Model predictive control (MPC) is a versatile control scheme applicable in a wide range of fields, which use a plant model to predict and optimize the future behavior of the dynamical system in question. Several studies have suggested that MPC of heating, ventilation and air-conditioning systems in buildings holds significant demand response potentials, see [1-3] to mention a few. A practical challenge when using MPC for building systems control is to

Corresponding author. Email address: mdk@eng.au.dk

construct an adequate model of the building thermodynamics. Such models can be obtained through system identification techniques using measured data. It is often suggested to generate the training data using intrusive experiments, which aims to excite the dynamics, e.g. a pseudo random binary sequence (PRBS) [5-6]. A PRBS is periodic and deterministic with white noise-like properties [4]. Consequently, models can be fitted well at all frequencies, or a band-limited selection of frequencies, and have a low crest factor and high signal to noise ratio (SNR). However, it is often not possible or desirable in practice to generate a perfect PRBS for a space heating system. Baseboard heaters are often equipped with a thermostat with direct feedback (e.g. a P-regulator) that must be circumvented. This might be done by changing the thermostat setpoint according to the PRBS, but it is difficult to obtain an exact PRBS heat power input using a temperature setpoint without a risk of violating user thermal comfort.

To avoid week-long excitation experiments with high risk of user comfort violations before MPC can be applied, we propose that historical data already logged by the energy management system during standard heating system operation can be used to estimate an initial thermal building model. This initial model is likely to be of relatively poor quality since standard operation often uses a feedback controller (e.g. P-regulator) to ensure that the indoor temperature only have small deviations from the set point and therefore a low SNR. However, this drawback may be more than compensated by the fact that intrusive and costly experimentation can be avoided. The initial model generated from standard operation data can be applied directly in an MPC subjected to time-varying tariffs for a certain training period and then re-identified using the operation data obtained in the training period. This new data set will be more informative than the historical data, and it may result in a just-as-good – or even more suitable – model for MPC as a model based on a PRBS experiments since it have frequency content close to what could be expected when the space heating system is operated to minimize energy cost. This paper reports on a simulation-based study that aims to investigate whether the above-described proposal has the postulated benefits.

2. Method

The case building used in this study was a newly retrofitted two-bedroom apartment (75 m^2) equipped with electrical baseboard heaters. The apartment was modelled in EnergyPlus (EP) and the heaters received control signals from MATLAB via the Building Controls Virtual Test Bed (BCVTB) [8] and it was therefore possible to apply MPC controllers (Section 2.2) and online system identification (Section 2.3). For further details regarding the model assumptions, see Pedersen et al [7].

2.1. State-space representation

It was assumed that the thermal dynamics of the EP case building could be approximated with sufficient accuracy by a low-order state-space model:

$$x[k+1] = \boldsymbol{A}x[k] + \boldsymbol{B}u[k] + \boldsymbol{E}d[k] + w[k] \qquad (1a)$$

$$y[k] \quad = \mathbf{C}x[k] + v[k] \qquad (1b)$$

The state matrix $\boldsymbol{A}$ represents the dynamics of the system and describes how the states x evolve from time step k to $k+1$. The input matrix $\boldsymbol{B}$ and the disturbance matrix $\boldsymbol{E}$ describes how control inputs and uncontrollable (but measurable) disturbances are channeled to the states, respectively. The output matrix $\boldsymbol{C}$ describes how the states are channeled to the output y while w and v are process and measurement noise, respectively. In this study, the system was treated as a black box and the states x does therefore not correspond to physical entities. The input u was heating power while the components of the disturbance d were external air temperature and solar irradiation. The time-varying internal heat load from two occupants was included in the EP model, but was assumed unmeasured and unpredictable to add realism to the simulations and was therefore included in the process noise term w. The measured output y was room air temperature and a white noise with standard deviation = 0.067 °C was imposed on the temperature sensor to further increase realism.

2.2. Model predictive control

In each hour, the MPC solved a mathematical program (Eq. 2a-2f) and determined hereby a sequence of electrical heating power actions that minimized the operational costs for a finite prediction horizon of 48 hours (Eq. 2a). The optimal solution had to respect system dynamics (Eq. 2b-c) as well as limitations on maximum radiator power (Eq. 2d) and acceptable room temperatures (Eq. 2e). Only the first control action $u[0]$ was implemented and the program solved the program again in the preceding hour but for a shifted time-horizon (receding horizon). The initial state x_0 was estimated to $\hat{x}_{ini}$ by a Kalman filter incorporating noisy sensor feedback (Eq. 2f). Time-varying tariffs $c[k]$ were taken into account to allow for price-based demand response by shifting consumption from high- to low price periods.

$$\underset{u}{\text{minimize}} \quad J = \sum_{k=0}^{47} c[k] \cdot u[k] \tag{2a}$$

$$\text{subject to} \quad x[k+1] = \boldsymbol{A}x[k] + \boldsymbol{B}u[k] + \boldsymbol{E}d[k] \tag{2b}$$

$$y[k] = \boldsymbol{C}x[k] \tag{2c}$$

$$0 \le u[k] \le 1000\ W \tag{2d}$$

$$21\ °C \le y[k] \le 24\ °C \tag{2e}$$

$$x[0] = \hat{x}_{ini} \tag{2f}$$

2.3. System identification procedure

The matrices **A**, **B**, **E** and **C** were estimated using the N4SID subspace identification [4]. A number of design choices are available in subspace identification and it is out of the scope to go into any details thereon. The model order (i.e. number of states) was determined based on the logarithm of Hankel singular values [9]. The process does not involve cross validation and the whole dataset was used for training (i.e. no need for validation data). The identification procedure was fully automated and the model could therefore be re-identified continuously (i.e. every month) although this study only re-identifies a model once after 14 days.

The initial model was identified based on EP simulation data from October 1 to December 31, where the apartment was controlled by a P-regulator to track a set point of 21 °C. The initial model was used in the MPC for 14 days from January 1 to 14, generating a new data set used to identify a new model, which were used in the MPC for the remaining heating season of January 14 to April. The simulation results are presented in the following section and compared to results obtained by using the common approach of PRBS.

3. Results and discussion

Figure 1 (top) shows data logged from standard space heating operation with a P-regulator tracking a constant set point of 21 °C in a historic period from oct-jan. Notice that the measured room air temperature has high frequency fluctuations due to the imposed sensor noise. This data set was used to identify an initial state space second order model. This initial model was then used in the MPC for a period of 14 days. The generated heating input from this period and the resulting indoor air temperatures are shown in Figure 2 (top). The indoor air temperatures are within the predefined temperature range (Eq. 2e). This new dataset was used to identify a new second order model, which was used in the MPC for the rest of the heating season (end March). The performance of this approach was compared to a model generated from a PRBS experiment shown in Figure 2 (bottom). The PRBS input led to violations of the predefined temperature range in Eq. 2e.

Besides not violating the temperature range, the MPC-based excitation signal has the benefit of being negatively correlated with the energy tariffs (boosts temperature in low price periods) and as such, it is more cost-effective than the PRBS. In fact, the MPC-based signal reduces costs compared to a normal constant set point tracking P-regulator.
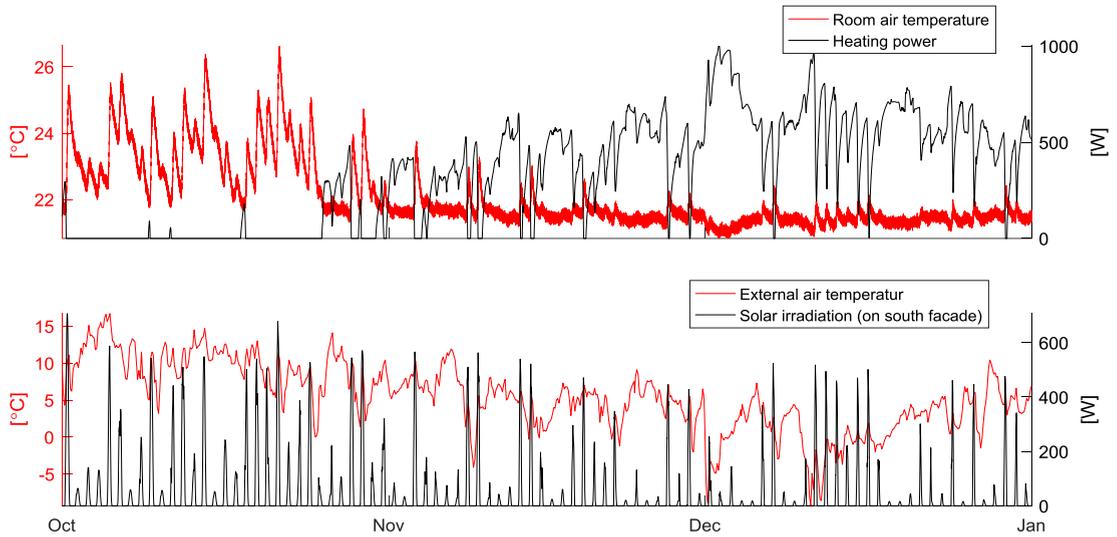
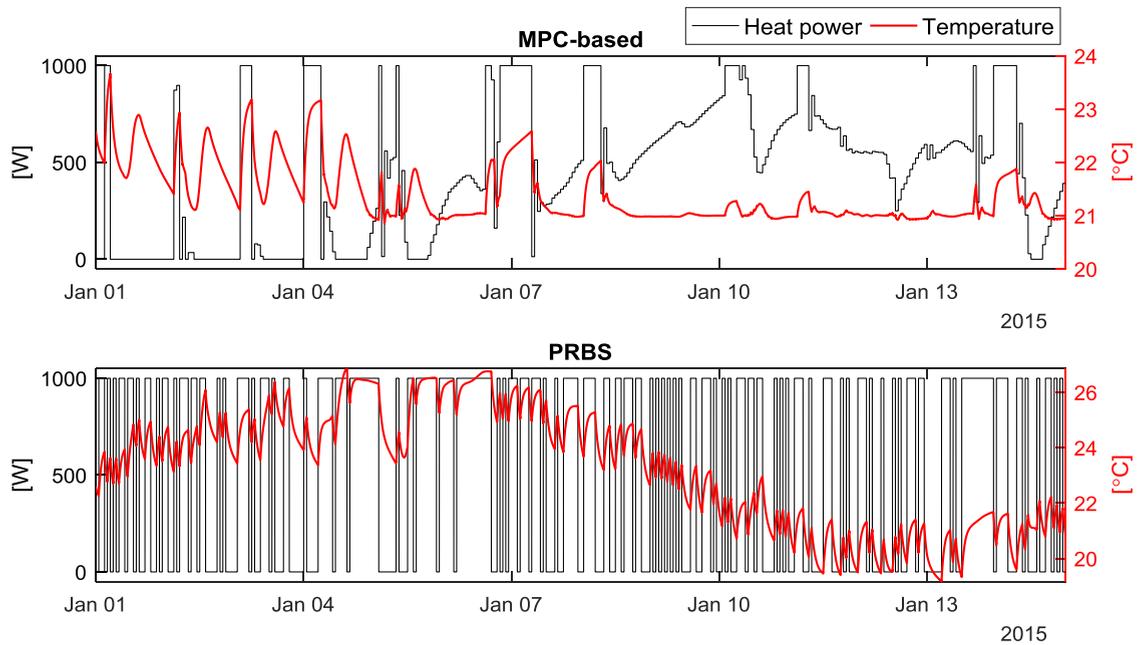Figure 1. Historical data from normal operation.

Figure 2. Heating power (black) in the training period when using PRBS and MPC generated heat input, respectively. The red curves show the resulting room temperatures.

Figure 3 depicts the one-step ahead prediction errors for the different models. For the MPC-based model, the errors to the left of the vertical dotted line are the errors for the initial model based on historical data while the errors to the right belong to the re-identified model based on MPC generated input. It clearly shows that the new model contains less prediction errors. For comparison, the bottom plot shows the prediction errors for the model based on PRBS input and they are seen to have errors of the same magnitude.
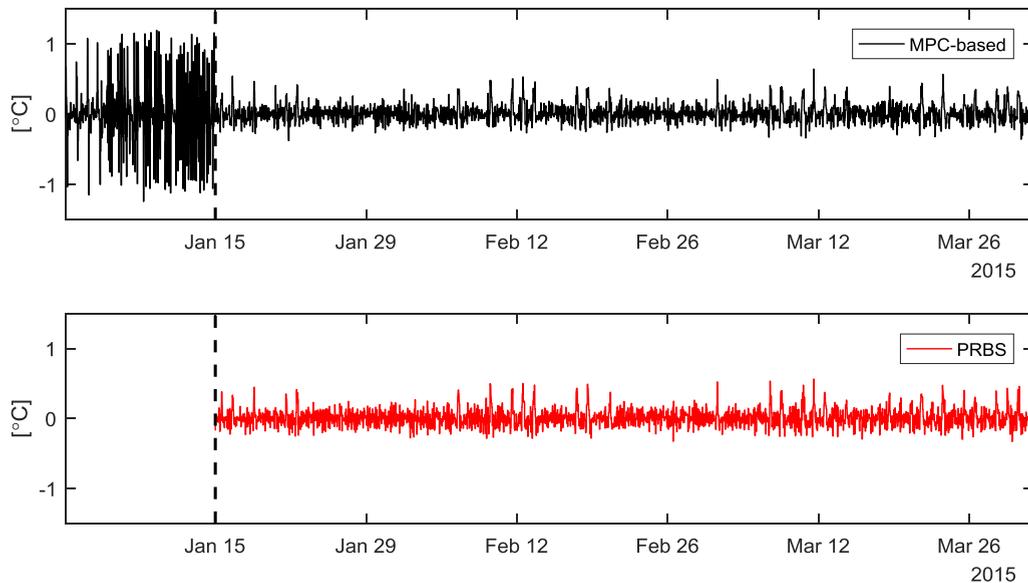
Figure 3. Top plot depicts the one-step ahead prediction errors for the MPC-based model before and after the re-identification (indicated with dotted vertical line). The bottom plot shows the one-step ahead prediction errors for the PRBS based model.

The MPC using a model based on the MPC generated input reduced energy costs by 13.7% compared to the baseline P-controller in the period January 15 to April. For comparison, the MPC using a PRBS based-model reduced costs by 13.5% and thus no significant difference in performance.

Conclusion

This paper proposes a method that avoids the use of dedicated excitation experiments, which often are regarded as mandatory to make sufficiently precise system identification of models for MPC of space heating systems. This paper presents simulation results suggesting that data from standard operation of the heating system can be used to identify an initial model with sufficient quality to be used by an economic MPC for a subsequent training period. Data from this training period can then be used to generate new control input that are informative enough to re-identify a model with qualities comparable to that of a PRBS based model. The benefits of this approach is that it does not require an intrusive experimental period with potential thermal discomfort and excessive energy costs. Furthermore, the perspective of this method is that re-identification of the building model can be done with an appropriate frequency to make it up-to-date with current conditions. Further studies are needed to investigate the benefits of a running re-identification of the model used for MPC of space heating systems.

Acknowledgements

References

[1]   M.D. Knudsen and S. Petersen. Demand response potential of model predictive control of Space heating based on price and carbon dioxide Intensity signals. Energy and Buildings 125 (2016), pp. 196-204.

[2]   R. Halvgaard, N.K. Poulsen, H. Madsen, J.B. Jørgensen. Economic Model predictive Control for Building Climate Control in a Smart Grid. Innovative Smart Grid Techn. (2012), pp. 1-6.

[3]   E. Vrettos, K. Lai, F. Oldewurtel, G. Andersson. Predictive control of buildings for demand response with dynamic day-ahead and real-time   prices. Eur. Control Conf. (2013), pp. 2527-34.

[4]   L. Ljung. System Identification – Theory for the User. 2nd ed. Prentice Hall PTR. 1999.

[5]   P. Bacher, H. Madsen. Identifying suitable models for the heat dynamics of buildings. Energy and Buildings 43 (2011), pp. 1511-22.

[6]   I. Hazyuk, C.Ghiaus, D.Penhouet. Optimal temperature control of intermittently heated buildings using Model Predictive Control: Part I – Building modeling. Building and Environment 51 (2012), pp. 379-87.

[7]   T.H. Pedersen, R.E. Hedegaard, S. Petersen. Space heating demand response potential of retrofitted residential apartment blocks. Energy and Buildings 141 (2017) pp. 158-66.

[8]   M. Wetter. Co-simulation of building energy and control systems with the Building Controls Virtual Test Bed. Journal of Building Performance Simulation (2010), pp. 1-19.

[9]   A.K. Tangirala. Principles of System Identification: Theory and Practice. CRC Press. 2015.