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Heiselberg, Per Kvols

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Exploring the Energy Saving Potential of Model-Predictive Controls via Dynamic Co-Simulation

Norbert Sterl, Matthias Schuss, Ardeshir Mahdavi

Department of Building Physics and Building Ecology,

Vienna University of Technology, Vienna, Austria

bpi@tuwien.ac.at

Abstract

Recent advances of environmental control technologies have led to new practical opportunities to reduce the heating demand of buildings. The applied technologies follow different paths to achieve energy savings, the use of advanced control systems as predictive control algorithms show promising results with considerable optimization potential.

In the present contribution, we describe the development of an advanced control algorithm that, starting from an actual room's comprehensive thermal characterization, derives a simplified mathematical model. Moreover, the procedure involves a co-simulation setup that incorporates the implementation of a realistic dynamic heater behavior.

Heating demand with different control algorithms from simple 2-point switching control, analogue PI-controller, to predictive control and model predictive control (MPC) strategy are implemented and compared. Together with the control algorithms, the dynamic thermal characteristics of the room heating elements, realized as radiators or floor heating, are modeled with their different time constants for heating up and cooling down and considerably different orders of time constants. The energy saving potential of the proposed approach is documented via comparative simulation studies.

Keywords - co-simulation, predictive control, heater dynamics

1. Introduction

Recent advances of environmental control technologies, the potential of advanced electronics, and innovations in the digital realm have led to many new practical opportunities to reduce the heating demand of buildings. 'Smart' and advanced thermostats are a fast growing market and attract start-ups as well as big players in computer engineering. The applied technologies follow different paths to achieve energy savings, the use of advanced control systems is one important direction of research. In this context, predictive control algorithms show promising results with considerable optimization potential and the capacity to accommodate a wide range of input parameters.

Some control theory and model approaches are using either data driven models [6] with extensive data volumes and records gathered over a long time and/or using high numbers of input variables and sensor data [2]. Others are using an approach with quite complex physical models [6] or are developing models for prediction of input and system variables to reach high precision levels. Most approaches require high hardware and computer complexity and resources [9]. Simplified numerical models [8,6] can provide reasonable accurate model results [10] and are more easily applicable and practicable for a commercial environment and for use in embedded controllers.

This project takes an approach for minimal system complexity and is not striving for extreme data precision but focuses to provide a selection help for such thermal system models with limited hardware resources. The objective is to provide a comparative result of thermal control by different predicting algorithms and their forecasts on potential heating energy savings.

2. Model

2.1 Reference Building

For this project a representative real-world setup was selected. This building is part of the Vienna University of Technology; reasons for the selection of this room were the availability of various sensor data and the weather station on the adjacent tower, providing weather data in direct vicinity of the reference room (Fig. 1). Furthermore it was possible to take measurements for a prolonged free-running period and to obtain the thermal characteristics without any heating or occupancy perturbations.

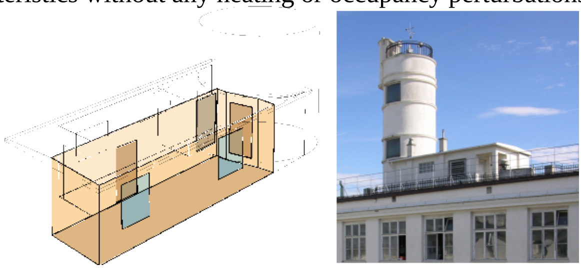


Fig. 1 - Reference building

2.2 Reference Model

For the heat energy simulations a reference model for EnergyPlus was developed. The parameters of the model were fitted to the measured data following the method as presented in [16]. This model representation allows freely exerting inputs as heating power, occupancy schedules, thermostat settings etc. Hence the reference model is more versatile compared to the real zone, which only had been measured for a limited period and in free running mode. This reference model also represents the thermal reference system for the simulation of different control strategies and is used to derive the difference of heating demand for a longer period beyond the measurement period. Moreover the reference model also serves to establish the thermal dynamics as step responses to isolated inputs. In turn, these system responses are used to develop thermal systems lead times; derived lead time tables are the basis for the table look-up function of lead-time control algorithms which allow adjusting the heating process to reach the thermostat settings exactly in time.

2.3 Reduced Model

What is the use for yet another model? For algorithms, as for the 'Model Predictive Control' (MPC), a mathematical representation of the underlying system is required. Such model allows simulating and estimating the depending variables as e.g. the room temperature as direct result to applied input variables as e.g. heating energy input.

The objective for the mathematical representation is to provide a best fit of the thermal characteristics of the model with the real system. Thus, if the mathematical representation has similar thermal dynamic characteristics as the reference room, input sequences can be applied to the model and the resulting simulated output will be sufficiently close to the output the real system under identical conditions. This allows to 'predict' the output trajectory in time, based on the known input parameters over time (applied heating power), it is hence possible to vary and optimize potential input sequences without applying them to the actual system. Optimizing the input sequences in the mathematical model - e.g. heating power over future time - and evaluating the output variables with target-/cost functions leads to 'optimal' input trajectories in time. This represents the operating mode of a model predictive control algorithm (MPC).

The mathematical representation needs to be as close to the actual thermal dynamics but, for hardware and numerical resources reason, especially the limited possibilities in embedded controllers, at the same time as simple as possible.

2.4 Model Structure

In the literature [1,3,4,5,6] a variety of different model structures for the description of thermal behavior of rooms are presented and discussed. The physical background and the thermal dynamics are described by a set of differential equations. For easier representation these are 'translated' into electrical circuit equivalents. Such reduced model descriptions and their parameters represent the dynamic characteristics only, any geometry and material details are subsumed in virtual elements as capacities and resistances.

This project follows the systematic approach and categorization of [1]. The basic model structures, terminology and states of the model were adopted. Some modifications were applied to make the models more suitable for this project as:

- the solar irradiation energy applied via a sol-air temperature (Tsolair, see below) instead of feeding solar energy to the envelope element,
- adding the parameter of an adjacent thermal zone (Tadj) to represent temperature and cross ventilation effects. This especially in view of the actual situation with considerable cross ventilation from a hallway.

For the selected model (Fig. 2, Table 1) a direct thermal influence from ambient temperature and adjacent temperature is added. These parameters allow modelling an effect of infiltration and ventilation as well as cross ventilation from an adjacent thermal zone (e.g. hallway). The thermal characteristics of the radiators (and interior) with their thermal capacity add a lag time to the dynamics of the systems (also see 'radiator dynamics' below).

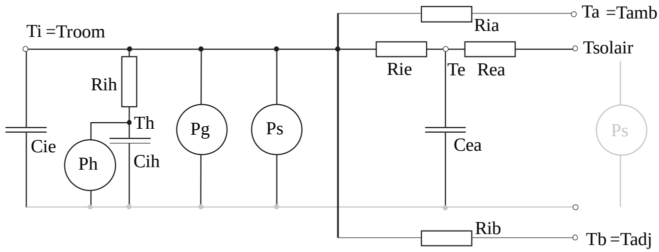


Fig. 2 - Model structure

Table 1: Model Parameters

Parameter	Description	Parameter	Description
Ti	Troom, interior temperature, representation as a state [°C]	Ria	thermal resistance interior-ambient [°C/kW]
Te	state representing virtual envelope temperature [°C]	Rib	thermal resistance interior-adjacent [°C/kW]
Th	state representing virtual radiator temperature [°C]	Rie	thermal resistance interior-envelope [°C/kW]
Ci	thermal capacitance, internal [kWh/°C]	Rea	thermal resistance envelope-ambient [°C/kW]
Ce	thermal capacitance, envelope [kWh/°C]	Rih	thermal resistance interior-heater [°C/kW]
Ch	thermal capacitance, heater [kWh/°C]		

2.5 Mathematical Description

The representation of the system by its equivalent electrical circuit can be directly translated into form of differential equations (1). For the selected model, including all important parameters, the description in form of a set of differential equations leads to:

$$
\begin{aligned}
dT_i &= \frac{1}{R_{ie}C_i}(T_e - T_i) + \frac{1}{R_{ih}C_i}(T_h - T_i) + \frac{1}{R_{ia}C_i}(T_a - T_i) + \frac{A_w}{C_i}P_s + \frac{h_g}{C_i}P_g + \frac{1}{R_{ib}C_i}(T_b - T_i) \\
dT_e &= \frac{1}{R_{ie}C_e}(T_i - T_e) + \frac{1}{\mathrm{R}_{ea}\,C_i}(T_{solair} - T_e) \\
dT_h &= \frac{1}{R_{ih}C_i}(T_i - T_h) + \frac{h_h}{C_h}P_h + \frac{1}{R_{ib}C_i}(T_b - T_i)
\end{aligned}
\qquad (1)
$$

Mathematical models as representation of dynamic systems in control engineering are often transformed to such set of coupled first order differential equations. Every such differential equation is describing a 'state' variable. The states of such state space model do not represent an actually measurable physical parameter, some virtual states can only be mathematically accessed or observed but cannot be directly measured. Also the interpretation of such states in form of accessible physical parameters is not necessarily simple or possible.

The continuous system description as above can be converted to discrete systems where parameters are evaluated at discrete points in time only. Similar to the continuous state space description, discrete systems can then be described in difference equations (2) in the form of:

$$
\begin{aligned}
x(t+1) &= A * \mathrm{x(t)} + B * u(t) \\
\mathrm{y(t)} &= C * x(t) + D * u(t)
\end{aligned}
\qquad (2)
$$

The parameters of the differential equation and the state space matrices respectively were obtained through a grey box identification process in MATLAB®, best fitting the system output to the measured values of the reference room and the results of the reference model simulation.

2.6 Radiator Dynamics

The response characteristics of the radiators represent asymmetric dynamic effects and require special adaptions to the mathematical and simulation model. Radiators represent a first order lag element; unfortunately not just a 'simple' PT1 element but with different thermal dynamics and time constants for heating up and cooling down (Fig. 3). For heating up, hot fluid is immediately available from the heating system, only the metal parts need to be warmed up, whereas for cooling down the heat is stored in the metal parts as well as in the contained water. Considerable differences in time constants (Table 2) for heating up and cooling down are in the range of factor of 5 to 6.

To generate such thermal characteristics a PT1 subsystem was programmed in MATLAB®, the dynamically resulting heat energy subsequently is transferred as heating input to the EnergyPlus model. The time constants of the mathematical representation of the radiator system are adapted, depending whether the radiator is heating up or cooling down.

Table 2: Radiator dynamics

Time constants heating system	time heating up [min]	time cooling down [min]
radiator heating	5	30
floor heating, dry structure	27	123
floor heating, wet structure	90	638

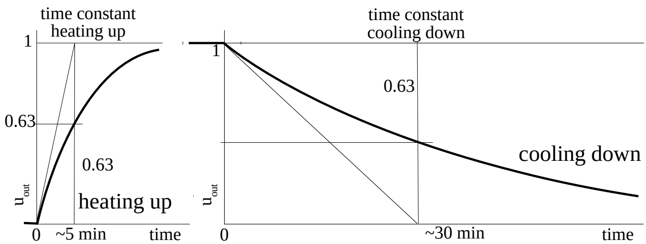


Fig. 3 - Radiator dynamics

3. Simulation and Co-Simulation

The thermal simulation of the reference model was run in EnergyPlus, whereas the control algorithms and calculation of applied heating power was run in the MATLAB® environment. The co-simulation of the algorithms in MATLAB® and the thermal dynamics in EnergyPlus was controlled by the MLE+ toolbox; it is an open-source MATLAB® toolbox for co-simulation with the simulation software EnergyPlus via the BCVTB interface and provides objects and parameters for running the co-simulation.

3.1 Lead time control - simple 'predictive' control - look-up tables

For systems with short response time, as in the example of the reference room, the biggest savings are expected during the warm-up period. In order to reach the required thermostat setting at a given time, standard thermostat-timers have to be set to start heating well before the stipulated time to cover the worst case of heating-time and to get the temperature to the requested level. Thus, in all cases but the 'worst case' (lowest initial room temperature) and a higher temperature, the heater will start too early for the room temperature to reach its target temperature. The room will be heated earlier than requested. The heating energy for this time span is not necessary and could be saved. For the reference model the worst starting temperature is 6.5°C, the time required to heat the room to the set temperature is around 60 minutes.

A setting for the thermostat timer to start heating as late as possible, but sufficiently early to exactly reach the set temperature at the scheduled would be the best strategy to satisfy the combined target of least heating energy use and to get to the requested temperature level at the stipulated time (Fig. 4).

This saving can be realized if the lead time is derived as a function of the initial room temperature and the known response time of the system. The measured/simulated thermal response characteristic of the room allows forecasting the system response. A control, adapting the heating lead time by measurement or by look-up tables of simulation results of a 'reference' model represents in principle a form of 'model predictive control'. However, as such control strategy does not exactly correspond to a 'model predictive control' in terms of control theory, the term look-up control, or simple predictive control is used in the context of this project.

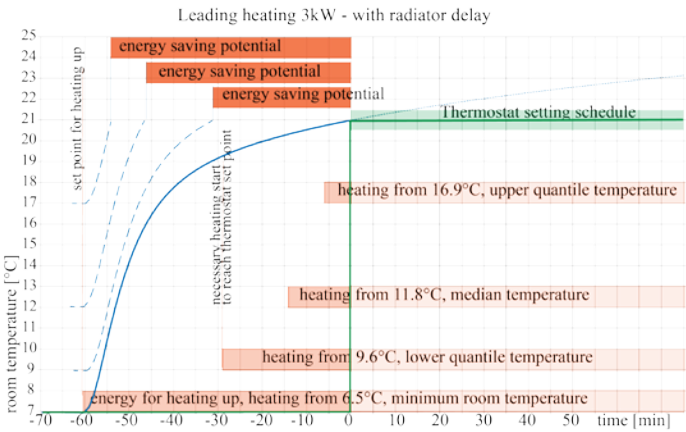


Fig. 4 - Saving potential in heating up period

Thermostat controller algorithms representing simple on/off controller and 2-point switch controller with hysteresis have been programmed in MATLAB®, using the table look-up technique. These control strategies have shown that with relatively little information on measured data and system response characteristics there are potential heating energy savings. In view of the simplicity of the system - e.g. it does not require any other sensors than the room temperature sensor - the saving potential is considerable.

Advantages:

- Does not need any additional sensors apart from the room sensor, which is in any case necessary for the control of a room temperature.
- Relatively simple way to get to the look-up tables by e.g. using defined heating curves and measuring the response (e.g. step response, cooling response during night setback period).

Disadvantages:

- Does not take into consideration any other influence parameters as e.g. appliances that are running also in non-heating periods which however may reduce the heating up period.

Model predictive controller

The model predictive control method consists in optimizing its input variable for desired output by evaluating the response of the mathematical model. As the model is representing the room dynamics, including the radiator inertia, the principle model predictive control strategy is 'designed' to adjust for lagging effects as radiator lag.

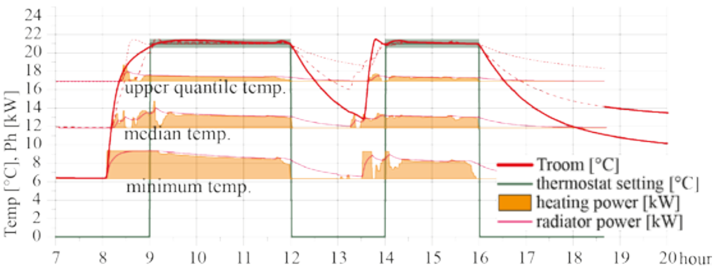


Fig. 5 - Model predictive controller

The results (Fig. 5) show a relatively smooth temperature trend, which however can show some disturbances due to slight dynamical differences between reference model and mathematical model.

Comparison of heating demand simulation

Due to the numerically more involving algorithms of the PI and MPC controller and the consequently longer simulation runs, the simulation concentrated on 4 selected days. These are the days with minimum starting temperature for heating up, and the days representing the lower-, upper- quantile and the median starting temperature respectively.

Table 3 shows the heating energy for the different starting temperatures in the room and with different control strategies as a 2 point switch with fixed lead time and variable lead time (look-up table) controls as 2 point switch and PI-controller. A model predictive controller (MPC) completes the set. The 2 point switch with fixed lead time corresponds best to standard thermostats and serves as reference of heating energy demand. Indicated values for heating power refer to 24 hours timespan of the specified days.

Table 3: Heating power vs. control strategies

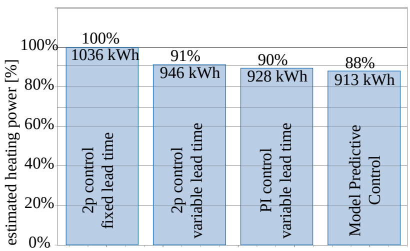
	2p control - fixed lead time				2p control - variable lead time				PI control - variable lead time				Model Predictive Control			
heating power	minimum temperature	lower quantile temperature	median temperature	upper quantile temperature	minimum temperature	lower quantile temperature	median temperature	upper quantile temperature	minimum temperature	lower quantile temperature	median temperature	upper quantile temperature	minimum temperature	lower quantile temperature	median temperature	upper quantile temperature
heating energy [kWh]	18.2	14.1	11.9	5.7	17.1	12.8	10.6	5.0	17.8	12.9	10.2	3.8	17.4	12.8	10.0	3.7
relative heating power [%]	100%	100%	100%	100%	94%	90%	89%	88%	98%	91%	86%	67%	96%	91%	84%	65%

As expected, heating energy savings can be shown, especially for higher initial room temperatures. Under the assumption that all parameters are set for an optimal heating starting point, correct look-up tables are available and the mathematical model has a good fit to the reference model (EnergyPlus model), it would be expected that there are no savings for the case of the lowest initial room temperature. From the results (Table 3) it therefore could be deducted that the expected inaccuracy for the shown heating demand would be in the range of ±2% to±4%.

Summary - model predictive control

Above results for predictive control strategies indicate significant energy saving potentials. The results of simple predictive control (look-up tables) and model predictive control show that optimal heat up start time is accounting for the biggest savings. Especially for the transition period considerable savings - for systems with radiator lag up to 35% - could be achieved. Based on a controller simulation, which was run for the selected days as well as for an entire half year period, the heating energy demand for the half year period was estimated - see Table 4. For the realistic case of a system with radiator lag savings of 12% for a half years period can be shown.

Table 4: Estimated 6 months relative heating power vs. control strategies



estimated 6 months heating power	2p control - fixed lead time	2p control - variable lead time	PI control - variable lead time	Model Predictive Control
results without radiator lag				
heating energy [kWh]	842.4	746.8	780.4	797.9
relative heating power [%]	100%	89%	93%	95%
results with radiator lag				
heating energy [kWh]	1036.8	946.3	928.3	912.9
relative heating power [%]	100%	91%	90%	88%

Systems with slow thermal response

Beyond the actual reference room setup, a hypothetical floor heating with longer time constants and therefore much slower dynamic characteristic was added to the simulations. Simple control strategies, as e.g. 2-point switching, are not suitable for such slow systems, therefore only the model predictive algorithm (PMC) was simulated (Fig. 6). The extended thermal lag times due to the big thermal mass of the floor construction lead to in average considerably higher temperatures in the room and hence cause a generally much higher energy demand.

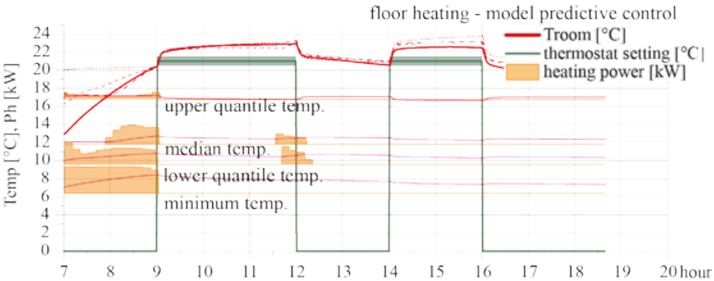


Fig. 6 - Floor heating with model predictive controller (with occupancy)

4. Conclusion

This work has identified potential heating energy savings for conditions of a selected building. Several thermostat strategies - from simple switching to model predictive control algorithms - were simulated.

The simulation results have shown significant saving potential in the heating-up process from setback periods. With tight lead time control energy savings up to 11-15% for systems without radiator lag and 9-10% for systems with radiator lag and for warmer ambient conditions could be shown (Table 4). The lead time control is working with predictions of the system behavior/outputs; either based on look-up tables derived from measured thermal system responses, or on the principles of model predictive control. Objective for all methods is to start the heating process as late as possible, but in time to reach the thermostat set point exactly at the requested time.

This can be done by relatively simple switching thermostats. The look-up table principle is not limited to single input parameters, but can be extended to impact factors as controlled flow temperature systems. The look-up values can also be derived by an intelligent thermostat from measurements of the output and the known switching states, e.g. during phases of heating up or cooling down.

In systems with radiator lag, thermostats with more complex control algorithms, as model predictive control, do show better results, with savings of 4-35% (Table 3) on the specified days; especially for the heating system running in the partial-load operational range (warmer ambient conditions). For setting the beginning of the heating-up process they do work on basically the same principle, therefore the results do not differ. Difference is the 'online' calculation of the right point in time, based on a prediction and optimization process with mathematical model representation of the thermal system.

The advantage of these systems comes for systems with higher thermal lag and for the higher control precision; they work in a narrower band around the thermostat setting and better reduce overshooting of the target temperature through anticipated power reduction.

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