TECHNISCHE UNIVERSITÄT WIEN
Vienna University of Technology

DIPLOMARBEIT

PREDICTIVE THERMAL CONTROL WITH DIFFERENT SENSOR CONFIGURATIONS

ausgeführt zum Zwecke der Erlangung des
akademischen Grades eines Diplom-Ingenieurs

unter der Leitung von

Univ.Prof. Dipl.-Ing. Dr.techn. Ardeshir Mahdavi

E 259-3 Abteilung für Bauphysik und Bauökologie
Institut für Architekturwissenschaften

eingereicht an der
Technischen Universität Wien
Fakultät für Architektur und Raumplanung

von

Norbert Sterl

Matrikelnr. 7625103
Johnstrasse 69/22, 1150 Wien

Wien, November 2015

ABSTRACT

Saving energy in general and heating energy in particular has always been in the focus of research and development. Progress of technology, the potential of modern electronics, and advances in the digital world have led to many new practical opportunities to reduce the heating demand of buildings.

In this context, one field of research concentrates on state-of-the-art control strategies.

Electronics and microprocessors have become very powerful and reasonably priced and applications as embedded control have taken an important role in our life. This technology has also entered the thermal control of buildings, homes and apartments.
'Smart' 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.

Use of advanced control systems is an important direction of research. And there, control algorithms using predictive control algorithms are one of these potential ways and are showing promising results. These prediction algorithms allow for optimized control strategies, taking into account a wide range of input parameters. The basis for the prediction and optimization process is a good knowledge about the systems characteristics, either by an empirically established set of system responses or by a mathematical model representing the thermal dynamics of the controlled zone. Both ways allow forecasting the thermal systems output as a reaction to an applied control input and to disturbance parameters.

For a selected actual room, different predictive types of controllers and their respective energy saving potential is discussed. Switching thermostats with simple predictive methods as well as more complex model predictive control algorithm are compared. Also variations of sensor and input data configurations are compared in view of the achieved simulated energy savings.

Keywords
thermal building/room model, grey-box room model identification, predictive switching thermostat, model predictive thermostat control, smart thermostat

CONTENTS

1 INTRODUCTION

1.1 Overview

Extensive research and development activities are directed to make buildings, offices and homes more efficient with respect to the heating energy use, by using state-of-the-art building and material technology, and by applying the latest technologies in electronics and information technology.

'Smart technologies' are finding their way not only into everyday life but also to building and home control. So are 'smart' thermostats a fast growing market and attract start-ups as well as big players in computer engineering. Readily available electronics, embedded controllers allow to come up with efficient systems, sensor technology can link the computing power with many external parameters and ambient conditions.

Research activities and applied technologies follow different paths to achieve energy savings.

One of the subcategories of research is towards the use of modern control technology for temperature control, either by advanced control algorithms or by increased use of digital technology as microprocessors, embedded control etc. Reasonable production and product cost support continuous progress in this field and will boost the growth of this market segment.

The objective of this thesis is to perform a comparative analysis of selected predictive control algorithms for their energy saving potential. Also different sensor settings and the availability of data and their forecasts is put in relation to achievable heating energy savings.

The results will provide selection assistance for predictive controller systems with respect to reachable reduction of heating energy and the definition of an associated sensor system.

1.2 Motivation

Some research approaches are based on using either data driven models with extensive data volumes and records gathered over a long time and/or using high numbers of input variables and sensor data. This thesis will use 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. Simplified numerical representations and reasonable accurate models can provide good results and are more easily applicable and practicable for a commercial environment and for use in embedded controllers.

The objective is to provide a comparative result of thermal control by different predicting algorithms and to establish the effect of different data sources and sensors and their forecasts on potential heating energy savings.

Some control theory and model approaches are using either data driven models [14] with extensive data volumes and records gathered over a long time [4] and/or using high numbers of input variables and sensor data [4]. Others are using an approach with quite complex physical models [14] 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 [22].
Simplified numerical models [18,14] can provide reasonable accurate model results [24] and are more easily applicable and practicable for a commercial environment and for use in embedded controllers.

2 BACKGROUND

2.1 Overview

Extensive research and development activities are directed to make buildings, offices and homes more efficient with respect to the heating energy use, by making use of state-of-the-art building and material technology, and by applying the latest technologies in electronics and information technology.
One of the subcategories of research is towards the use of modern control technology for temperature control, either by advanced control algorithms or by increased use of digital technology as microprocessors, embedded control etc. Reasonable production and product cost support continuous progress in this field and will boost the growth of this market segment.

The segment of 'smart' systems is present in the building community and customers with mobile computing affinity.
Some products call themselves 'smart thermostats' [38,39,40] which shows that the field of digital thermal control has become reality. These 'smart' devices follow different ideas and strategies and they will play an important role in the field of thermal control of private and commercial buildings.

The main directions these smart thermostats are following, are automated and/or manual remote control, occupancy learning functionality, automated learning of user habits and schedules and others.

Research in the field of temperature control strategy is directed towards the design and application of complex control theories as adaptive and predictive control, self-parametrizing and robust controllers etc. [9,13]. For all theoretical approaches mathematical representations of real buildings, rooms or zones are necessary to be able to simulate various configurations, strategies and algorithms and to evaluate potential energy saving potentials.
Some model approaches are using either data driven models [14] with extensive data volumes and records gathered over a long time [4] and/or using high numbers of input variables and sensor data [4]. Others are using an approach with quite complex physical models [14] 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 [22].

Simplified numerical models [18,14] can provide reasonable accurate model results [24] and are more easily applicable and practicable for a commercial environment and for use in embedded controllers.

Amongst the sought optimal control strategies is the application of controllers making use of forecasted and predicted parameters [3]. With such predicted input- and disturbance parameters the temperature control system can anticipate necessary actions, the controllers change from basically 'reacting' to already occurring deviations from the desired outputs to forward-looking 'acting' in view of expected impacts on the system.

2.2 Predictive control

Predictive control is a modern method for process control. In a very general sense, this method is using anticipated future conditions to optimize its controller strategy.
In the present topic - control of a room temperature - these anticipated conditions comprise:

- **future input or independent variables**
  as the control signal itself e.g. the heating energy supplied to the process.
- **future output or dependent variables**
  of the controlled process as room temperature.
- **future disturbance variables**
  also independent variables, to a system or process like be e.g. weather conditions like ambient temperature, solar irradiation, wind speed, occupation, gains etc.

A possible indication or forecast of such variables allows to derive an optimal input signal sequence in order to bring the dependent variable or output signal to a targeted point.

The principle advantages are obvious, but the question remains of how to establish such forecast for the impacting variables as well as on system behavior itself and its output parameters; and of how to make use of knowledge and physics background of a system to obtain useful input/output predictions.

Disturbance variables are difficult to predict, but statistical methods like time series could give good estimates of expected value ranges. In the underlying case, some of the disturbance parameters could be estimated using e.g. weather forecasts.

For all predictive methods it is not enough to get more information on forecasted impacts on the system, but they also require a quite precise knowledge on the dynamic behaviour of the controlled system itself. The real systems are modelled to represent the dynamics and other input-output relations. These models allow to 'test' control strategies before applying them to the real system. In this way the possible input variations can be optimized resulting in an optimal input sequence .

2.2.1 Simple predictive control

One method to gain necessary system dynamics knowledge would be to measure its inputs and outputs and to establish a dynamic relationship. This can be done by applying test signals to the input as step functions signals or impulse functions. With the measured output the dynamic system response can be derived. In the case of room temperature control this could be e.g. a change in heating power from 0 to full power, and measuring the response of the room temperature.

Knowing the dynamic characteristics a future response of the system can be derived, which in its term allows to adapt the input signal to reach room temperature targets at a required time and before the actual system response takes place. So such an algorithm is 'predicting' the systems response and thus its output.

2.2.2 Model predictive control

'Model predictive control' or MPC is a modern type of control and is used in industry since the 80's [8,17]. The introduction of microprocessors and digital process control allowed this advanced control method to establish its place especially in process industries. Further miniaturization, efficiency and availability of embedded controllers make this technology also available for applications in buildings and homes.

For this control method, a more general method for predicting the output of a system is used. As the name refers to, it is using a dynamic 'model' of the process. Such models are mathematical representations of the physical background of the system by differential equations or other mathematical relations (see subchapter 'mathematical model' below). Models are in general not a 1:1 representation of all sub-processes but need to give a good relation of input signals, disturbance variables and the output of the system. Once such system description is available it is possible to calculate virtual outputs for different input signals.

2.2.3 Mathematical models

A dynamic system can be described in form of a set of equations. Such mathematical model is to represent the dynamics of the actual system as accurately as necessary for the intended use and applied time horizon. Dynamic systems do not have a unique mathematical model description and they can have a quite differing representation or form.

Dynamic system models are described are defined by a set of differential equations. Such mathematical model has to represent the dynamics of the actual system as accurately as necessary for the intended use and applied time horizon. Note that a mathematical model is not unique to a given system. A system may be represented in

many different forms and, therefore, may have many mathematical models, depending on one’s perspective and the intended application and purpose.
Mathematical models may assume many different forms and are often a compromise between necessary accuracy and reasonable simplicity, especially in case of involving numerical calculations.

2.2.4 Model identification

The mathematical models can be derived by describing all physical processes and dependencies. This usually leads to highly complex models. Mathematical model parameters can also be empirically derived from measured data by model identification methods (see subchapter 'model identification' below). Other methods are statistical identification of the model parameters. A model with an optimized parameter set will yield a dynamic behaviour representing the dynamic characteristics of the real system. Various identification methods are discussed in literature [22], as are methods for reducing the overall complexity of the thermal behaviour of buildings [22].
Control oriented approach [22] procedures and grey-box identification allow parameter estimation, parametrization and prediction, the identification [14] of the system dynamics as steady state properties [22] and transfer functions [4].

3 METHODOLOGICAL STRUCTURE

3.1 Overview

Objective of this project is to evaluate potential heating energy savings by implementation of thermostats with advanced control strategies together with sensor setups. The methodology overview is shown in figure 3.1.

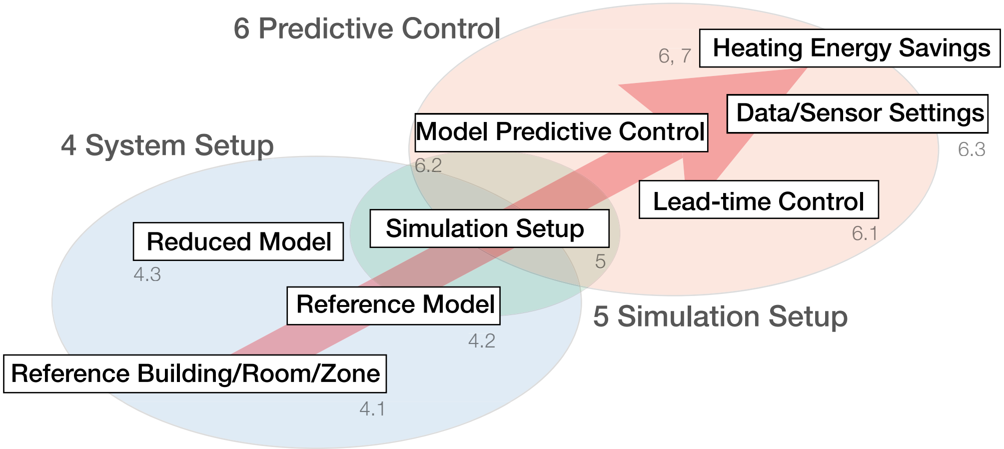

Figure 3.1 - methodology overview

In order to relate the work and the findings to a 'real world scenario' an actual building, or in this case part of a building, is chosen as reference. Its thermal characteristics in form of recorded sensor readings are the basis for a thermal model implemented in the subsequent simulations. A model as best representation for its thermal and geometrical characteristics is used throughout all energy simulation steps as a reference model. All heating energy simulations are run with that model.

For the control algorithms, especially for the model predictive control algorithm, an additional simplified mathematical model representation is developed. A suitable structure, taking into account all important influence factors as external weather conditions, room and adjacent conditions as well as design parameters is established.

In a grey box identification process the parameters are estimated, completing the reduced mathematical representation of the reference room. This model is used in the simulations involving the model predicted control algorithms.

In a co-simulation setup a thermal simulation software and a software running the controller algorithms are combined to run simulations in order to show the heating energy consumption.

To show potential heating energy savings, different predictive control strategies are applied to the reference model. For simple predictive control algorithms, measured model responses are used to predict the systems behavior. For the model predictive control method (MPC), the reduced mathematical model is used for prediction of systems results under impact of independent control variables as heating power and the disturbance factors as weather conditions, etc.

Finally the simulations are run with different virtual sensor settings. These settings refer to the availability of certain measurement data from applied sensors and to the availability of forecasts of these sensor data, like input factors as weather conditions, internal gains and occupancy. These input factors are used in the model predictive control algorithm.
The resulting simulated heating demands and their comparison represent the sought results of this project.

To get an overview of applied methodology towards a comparison of potential reduction of heating demand with advanced control algorithms, the process can be split up in several steps (see figure 3.1 - methodology overview):

The applied methodology and their steps at a glance:

3.1.1 System setup summary

- **Reference Building/Room/Zone**
  To establish potential reductions in heating demand being related to the 'real world' it was decided to link the data and following calculations to an existing building. This building, room or zone with its data and measurements serves as a reference for the next steps - see subchapter 'Reference Building/Room/Zone' below.

- **Reference Model**
  For the subsequent steps a reference model was established for thermal simulation by EnergyPlus software, a widely used simulation package developed by the U.S. Department of Energy Building Technologies Office.

  Why is this EnergyPlus model needed? With this model it is possible to apply controls and change parameters for the room to generate respective thermal responses. These system responses allow to evaluate energy savings (comparability) in different situation and under various controls and to cross check with the reduced mathematical model (see below)
  The parameters for this reference model are optimized to best fit the calculated temperatures to the actually measured data of the reference room (see above). The parameter fitting is performed with GenOpt® [33]. GenOpt® is an optimization program for the minimization of a defined cost function; the input data is provided

by an external simulation program, such as EnergyPlus [32].
See subchapter 4.1.2 'Reference Model' below.

- **Reduced Model**
  In the next step, a reduced mathematical model is developed. This model is a representation of the zone physics, namely the thermal characteristics, by a set of differential equations. The parameters of these differential equations are obtained in a grey-box identification process. A grey-box identification is used when the mathematical structure and representation form can be derived from the underlying physics; the parameters are fitted to the actual input and outputs of the system in question.
  The objective of this model is not to best describe all physical relations in detail, but to obtain a model, best describing the thermal behavior of the zone mathematically, and being as simple as possible. This model is necessary as basis for the Model Predictive Control algorithm. - see subchapter 4.1.3 'Reduced Model' below

3.1.2 Simulation setup

- The thermal simulation is done with EnergyPlus [32], it is widely used and is an open-source, and cross-platform. EnergyPlus itself does not provide reasonable support for adding complex control structures or algorithms. Another software environment is selected for running more complex controllers, in particular the numerically involving model predictive controller algorithms. For its capabilities and tool packages MATLAB® [31] is used.
  Interfaces and protocols are provided to link EnergyPlus to other software, as MATLAB®, via the EnergyPlus 'Building Controls Virtual Test Bed' (BCVTB) [21] or MLE+ [36,19]; this are software environments that allows users to run a communication protocol amongst two software packages for co-simulation. The testbed provides capability to exchange data between the linked software packages during the simulation run. The program setup and the configuration of exchange variables and protocols are completed in this step.

3.1.3 Predictive control summary

- **Lead-time Control**
  This refers to an application of a forward looking control strategy. This method addresses the high energy saving potential for systems with fast dynamic responses, taking into consideration the time needed to warm up a room to the desired temperature at a given time. In contrary to the model predictive control algorithm it does not work on calculated model results, but is based on a simulated or measured thermal response behavior of the system. With these

forecasted outputs such methods can also be considered a 'predictive control'. The results for the heating energy consumption are obtained on a simulation of the reference model in EnergyPlus. - see subchapter 'Lead-time Control' below.

- **Predictive Control**
  In this step a model predictive control algorithm is applied. The algorithm is based on the calculated/estimated model outputs and characteristics of the reduced model, derived before. As described in the 'Reduced Model' section, this method can take into account typical external system inputs as weather parameters like ambient temperature, solar irradiation, wind as well as impact from an adjacent zone and gains within the thermal zone like occupancy gains and gains by appliances. The control is run on the reference model, reflecting the actual reference building. See subchapter 'Predictive Control' below.

- **Sensor Setting**
  As described, the model predictive control takes into account several inputs with an impact to the thermal behavior of the system. Sensors and sensor combinations can provide the necessary data and allow forecasts of these values. The effect on the potential reduction of heating demand will however vary, depending on the thermal and dynamic characteristics of the system. As before, the simulation is run with the reference model on EnergyPlus. See subchapter 'Sensors' below

- **Heating Energy Savings**
  The objective of this project and final result is the comparison of the potential reduction of heating demand with respect to the applied control strategy - lead-time control, model predictive control - and potential sensor/data settings. The results are obtained by EnergyPlus simulations based on the reference model. As the reference model is a good representation of the actual reference building/room/zone, the results are representative for the selected reference building.

In the following chapters these methodology sections and steps are presented in detail together with the respective results.

4 SYSTEM SETUP

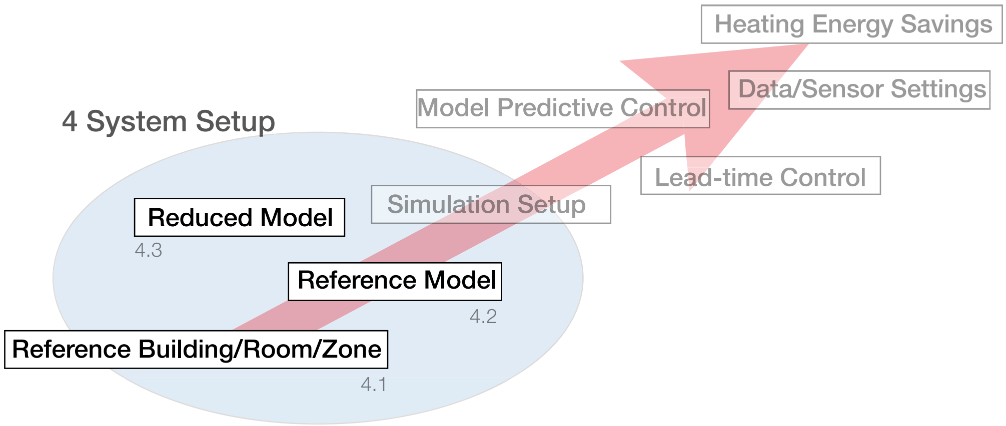

Figure 4.1 - system setup

4.1 Reference building/room/zone

For this project a building part was selected as a representative real-world setup. This building is part of the Vienna University of Technology, the room and the annex weather observation tower is used by the Department of Building Physics and Building Ecology.

The room is only temporarily used by the institute for seminars and research projects and provides access to the weather observation station on the tower.

Photo 4.1 - reference room
(source bpi, TU-Wien)

The reasons for the selection of this room were:

- Some sensors have been installed for previous work, thus various sensor data on the room and the annex hallway are available.
- A weather station on the adjacent tower provides weather data in direct vicinity of the reference room.
- It was possible to obtain sensor data for a prolonged free-running period, that is obtaining thermal characteristics of the room without any perturbations by heating (radiator thermostats off), occupancy gains or gains due to additional appliances.

The room layout and the setup with respect to its direct vicinity are shown in figure 4.2 and figure 4.3.

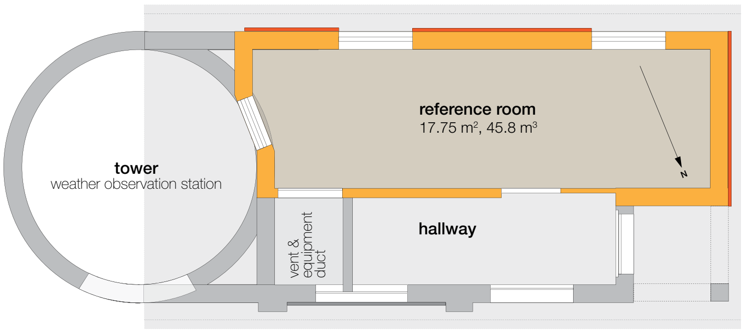

Figure 4.2 - reference room layout

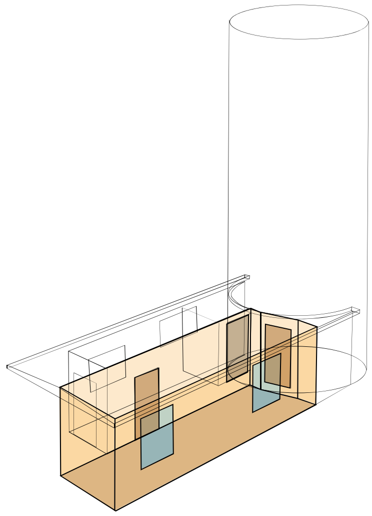

Figure 4.3 - reference room setup

Special characteristics of the reference room:

- Sensible and relatively strong cross ventilation though door to hallway and door to vent & equipment duct (indirect hall area).
- Through the cross ventilation and the connecting wall there is big influence of the conditions in the adjacent hallway. The hallway is the upper part of a complete section staircase, therefore the temperature conditions are relatively stable for the cold season. In warmer period the window across a hallway is kept open for most of the time to provide ventilation. The window is remotely opened but set manually, therefore no information on opening/closing conditions or temperatures is available.
- Some external walls have an extra insulation through a layer of silicon aerogel plaster from a previous research program (see figure 4.4 - aerogel plaster).
- Window blinds are in a constant horizontal setting. This setting was kept throughout this work as all measurements had been done with this setting; this leads to solar irradiation effects that are a nonlinear function of the zenith angle. All fitting process to an optimal model representation and the grey box identification process for the reduced model were done with this setting.
- Sensors and data logging devices (see figure 4.5) are running at full time, the power supplies in use represent an electrical power dissipation of approx. 60W (approx. nominal power of used power supplies). These electrical gains have been used as input for further calculations.

Room sensors

The sensor data for this project has been collected in the period of 3/27 to 5/5 2015. In this period the reference room was in an undisturbed free running mode.

Data logging is event driven, the sensor data is not saved periodically but sensors transmit their reading to a server only when a minimum reading change has been detected.

The event driven data stream was transformed into a periodical form, in an hourly based and in a minute based data list. In both cases the average value for the respective period (1 hour for weather data or 1 minute for internal sensor data) is used.

For the room temperature an average of the sensors room-center, room-door and averaged radiator temperature was used.

For more details on sensors - room and weather sensors - refer to Appendix A.1.

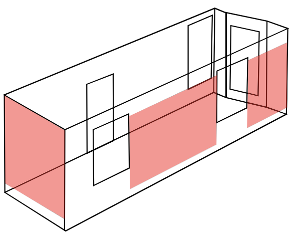

Figure 4.4 - aerogel plaster

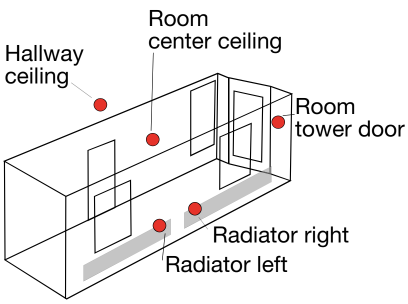

Figure 4.5 - sensor positions

Heating equipment

The room is equipped with 2 radiators of a controlled building central heating. The radiators are 3.0m by 0.5m each and have a total nominal heating power of 3kW (similar model [42]).

Each radiator is controlled by a radiator thermostat; the setting for the measurement period was on completely off position. The two sensors mounted on the radiators allowed to verify that no heating gains were introduced during that measurement period.

Hallway

The hallway towards the indoor wall of the reference room is linked to the upper part of a complete section staircase (TU, Stiege 4) thus forming a big thermal zone. Directly in front of the reference room there is a window. In warmer period the window is kept open for most of the time to provide ventilation to the staircase. The window is remotely opened but the setting is operated manually, therefore no information or data on opening/closing conditions or temperatures is available.

4.2 Reference model

As described before, for the heat energy simulations a reference model is needed. It allows exerting inputs as heating power, occupancy schedules, thermostat settings etc. This makes the reference model more versatile compared to the real zone, which only was measured in free running mode (no thermal inputs or gains apart from weather effects). The reference model will also represent the thermal reference system for different control strategies and is used to derive the difference of heating demand for a longer period than the measurement period.

The reference model also serves to establish the thermal dynamics and to simulate step responses to isolated inputs. These step responses are used to develop the necessary leading time of the thermal system; this in turn allows controlling the heating process to reach the thermostat settings exactly in time. These lead time tables are the basis for the table look-up function of the lead-time control algorithms.

The geometry was modelled in SketchUp [34] with OpenStudio® plug-in [35]. Secondary zone geometries were partially selected for a geometry fit and limited complexity (e.g. weather tower). The outline geometry of these adjacent zones are retained for reasons of shading and influence of thermal mass.

Thermal zones

Thermal zones setup, see figure 4.6 and figure 4.7.

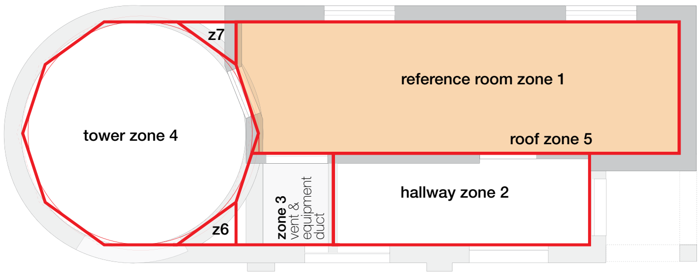

Figure 4.6 - reference room, thermal zones, 1

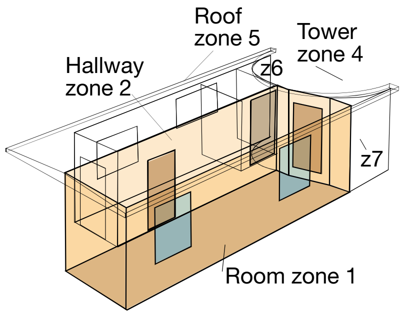

Figure 4.7 - ref.room, thermal zones, 2

- **reference room, zone 1**
  This is the core zone for all evaluations and control simulations.
- **hallway. zone 2**
  The hallway being linked to the central building staircase represents the 'indoor adjacent temperature zone'. The temperature is not varying as much as in the other zones, however there is a big influence of the ambient conditions as the window is mostly opened at higher ambient temperatures.
- **vent and equipment duct, zone 3**
  This is a duct towards the northern outside walls and a split glass block window. It is indirectly thermally connected to the staircase and contains building control equipment.
- **tower, zone 4**
  References the tower shaped access to the weather observation station and is a free running building zone.
- **roof, zone 5**
  Thermal zone representing a relatively flat space between the roof and the ceiling of thermal zone 1 and presumably only contains a construction for the metal covered roof.
- **zones 6 and 7**
  These areas are basically walls and/or hollow space with only minor effect on the reference room.

Materials of the model were changed to materials as used in the reference building or, where the materials were unknown, to assumed material combinations giving U-values as required in the building code for the building period of construction.

Fitting Model to measured data

To establish a model behavior and dynamics for the reference model, as close as possible with respect to the reference room and with its measured data in the period of 3/27 to 5/5, selected model parameters were adjusted for a best fit in an optimization process. The optimization was run in GenOpt®.

For the search for best fit and the optimization process a target function based on statistical parameters was defined. Various statistical parameters can be used for measuring the fit. Previous research [16,25] propose to use 'coefficient of root mean squared deviation variation CV(RMSD)' and the 'coefficient of determination R^2'. They are reliable and practical indicators for fitness analysis:

- **coefficient of variation of root mean squared deviation CV(RMSD)**
  With squared errors to measures the deviation of predictions from actual values. Objective is to minimize the errors in the fitting process, hence a small value of RMSD is sought, with zero representing an ideal fit.
- **coefficient of determination R^2**
  In the present context R^2 is representing a similarity between predicted and simulated values. The indicator is a representative for 'goodness of fit' and determines the likelihood between actual data points and the regression line. R^2 is in the range 0..1 with 1 showing the best fit [16].

In the following relations (equations 4.1 to 4.3) $m=[x_1,x_2,....x_n]$ is representing the measured values whereas $s=[y_1,y_2,...y_n]$ stand for simulated values of the reference room temperature during the measurement period; n refers to the number of measurements and m_{mean} to the mean of the measured values.

$$RMSD = \sqrt{\frac{\sum_{i=1}^{n}(mi - si)^2}{n}} \qquad (4.1)$$

$$CV(RMSD) = \frac{RMSD}{m_{mean}} * 100 \qquad (4.2)$$

$$R^2 = \left(\frac{n\sum m_i s_i - \sum m_i \sum s_i}{\sqrt{\left(n\sum m_i^2 - \left(\sum m_i\right)^2\right).\left(n\sum s_i^2 - \left(\sum s_i\right)^2\right)}} \right) \qquad (4.3)$$

In the fitting process via an optimization in GenOpt® a set of parameters was selected as variables for variation:

- **window material**
  Taken from EnergyPlus material list/database. The effect of this material controls the solar irradiation rate into the room.
- **infiltration**
  In air changes per hour [ach], with identical setting for all thermal zones (zone 1 to zone 7). This selection to account for the felt draw and the exposed position of the building for the wind.
- **ventilation crossfeed rate**
  From the adjacent hallway section into the reference room zone 2 to zone 1.
  As described above, there is a sensible air intake from the hallway and the indirectly connected vent duct. This parameter will link the thermal characteristics of the room to that of the hallway.
- **thermal conductivity of the concrete blocks in the external walls**
  This material has a high impact on the insulation of the outside walls. This stands for all outside wall types, with and without the special Aerogel Fixit system.
- **thermal conductivity of the outside plastering**
  Together with the previous parameter, this parameter will adapt the conductance of the outside wall.

The target function as implemented in GenOpt® is:

$$f = \left(CV\left(RMSD\right)\right) + \left(1 - R^2\right) . \frac{CV(RMSD)_{ini}}{\left(1 - R^2_{ini}\right)} \tag{4.4}$$

The applied calculation equation (4.4) refers to an arbitrary initial term. To evaluate the influence of that term and show the changes in the optimization results, the initial term was replaced by a fixed weighing. The influence in the optimization results remains marginal, for the reference model the main influence are with resulting ventilation and cross feed ventilation rates (see table 4.1).

Table 4.1 - model fitting target function results

target function	RMSD	1*CV(RMSD) +1*R2	1*CV(RMSD) +10*R2	1*CV(RMSD) +50*R2	1*CV(RMSD) +100*R2	1*CV(RMSD) +1000*R2	1*CV(RMSD) +10000*R2	selected parameters
rmsd-term	0.7420	0.7422	0.7422	0.7429	0.7467	0.8011	0.8260	
r2-term	0.9711	0.9711	0.9713	0.9716	0.9719	0.9731	0.9731	
r2term weighing factor	0	1	10	50	100	1000	10000	
glass []	202	202	202	202	202	202	202	202
lambda outside gypsum [W/mK]	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
infiltration [ach]	0.35	0.035	0.35	0.35	0.3375	0.3	0.3	0.3625
lambda wallblock [W/mK]	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45
crossfeedrate [m3/s]	0.0019	0.0019	0.0021	0.0031	0.0035	0.0081	0.0100	0.0025

EnergyPlus model reference model

The resulting simulation model with optimally fitted parameters is a good representation of the chosen reference building/room. Selected and optimized parameters are not directly representing the used materials but lead to comparable thermal behavior. This model is not representing the real world, material and conditions, but is a reasonably good approximation of the thermal characteristics within the measurement period from 3/27 to 5/5 (figure 4.8).

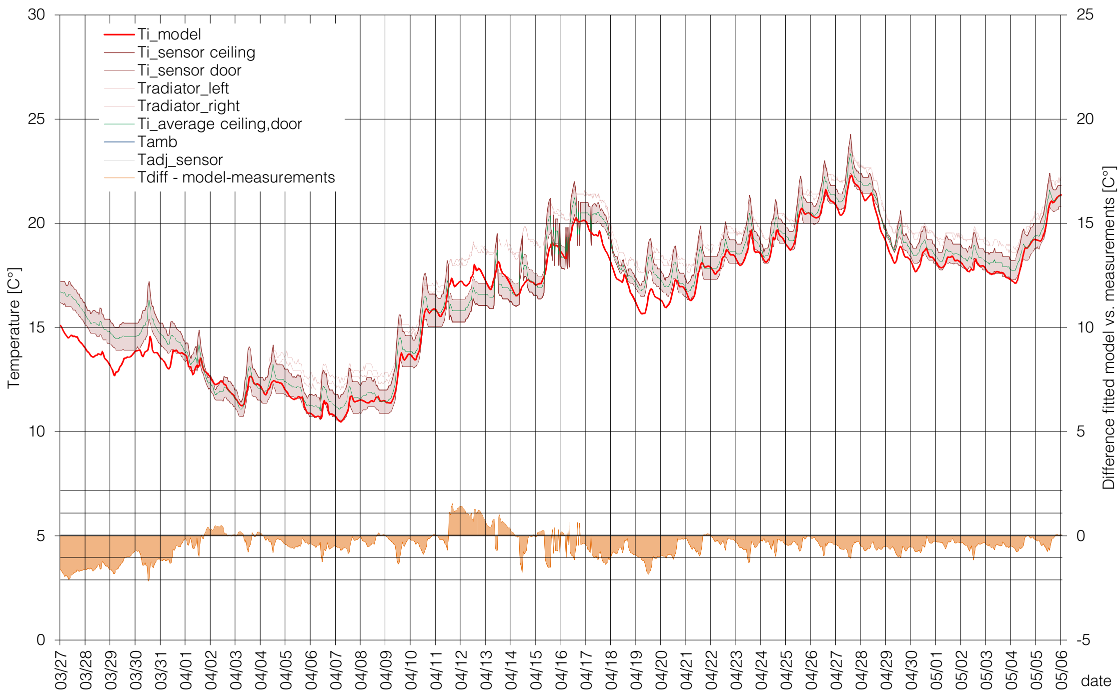

Figure 4.8 - fitting results of reference model

It needs to be noted, that the deviations at the beginning of the simulation period are partially due to the initial adaption period within the EnergyPlus simulation process.

Hallway and staircase

The hallway temperature has a non-negligible effect on the thermal characteristics of the reference room - once through the relatively thin separation wall and secondly through a cross ventilation between the hallway and the reference room.

For the thermal zone of the hallway temperature readings are also is available for the measurement period from 3/27 to 5/5.

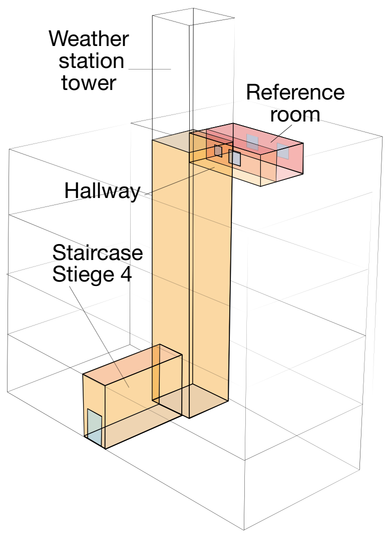

Figure 4.9 - staircase model

The hallway is representing the upper part of an entire building section staircase. The staircase is surrounded mostly by heated areas (offices, institute rooms) and the thick walls in that area represent a big thermal mass, hence the temperature from that zone remains relatively stable in cold periods. On the other hand, in the warmer period the window across the reference room is reported to be kept open for most of the time to provide ventilation to the staircase.

To avoid averaged temperature (e.g. from the measurement period) across the entire year and to be able to select a sensor setting including the hallway temperature sensor, another source for a representative zone temperature was sought. Similar to above described method, a simple staircase model was established and the thermal characteristics fitted to the existing measurements.
This procedure allows calculating an estimated zone temperature (T_{adj}) for the entire simulation period. The temperature from the simulation run serves as input for the hallway thermal zone to above described reference model.

For further details and results on the hallway modelling, please refer to Appendix A.2.

Model step response functions
The thermal dynamics of the EnergyPlus reference model were established by simulation. This is to crosscheck the magnitudes of response times and to establish the heating time lags. These results, especially the effect on the room temperature (T_i) are an indicator for system responses and necessary for the look-up tables for the simple predictive control.

To separate certain parameters, virtual weather files were established and used. In these files certain external disturbance parameters were kept constant or were set to a value not influencing the investigated thermal response.

Several time responses to input step-functions were established:

- Room temperature (T_i) step response to a **step of ambient temperature** T_{amb} (table 4.2) - indicator for the time thermal capacitance of the building envelope

Table 4.2 - step response T_{amb}

Room temperature step response - Tamb step				
Step Tamb [°C]	-20°C-0°C	-10°C-10°C	0°C-20°C	10°C-30°C
delta Troom [°C]	12.8	12.1	11.7	13.29
63% [min]	3200	3000	2950	3130
95% [min]	16500	14800	14100	15550

- Room temperature (T_i) step response to a **step of heating power** (P_h from 0 to 3kW) (table 4.3) - indicator of thermal dynamics within the room and thus primary information for the heating lag-time

Table 4.3 - step response heating power

Room temperature step response - Heating power step (3kW)						
Tamb [°C]	-20	-10	0	10	20	30
delta Troom [°C]	35.8	36	36.1	35.9	35	33.8
63% [min]	899	912	910	880	820	747
95% [min]	10357	10145	10300	10000	9575	9168

- Room temperature (T_i) step response to a **step of the temperature in the adjacent room/hallway** T_{adj} (table 4.4) - indicator for thermal dynamics and reaction on changes in adjacent building parts.

Table 4.4 - step response T_{adj}

Room temp. step response - Tadj step		
Tamb [°C]	0	20
Tadj [°C]	0°C-20°C	0°C-20°C
delta Troom [°C]	7.6	7.2
63% [min]	1823	2018
95% [min]	16800	17745

- Room temperature (T_i) step response to a **step of heating power with different radiator radiant fractions** (table 4.5) - this analysis was performed to fit the heating by the EnergyPlus actuator 'other gains' to the reaction of the standard EnergyPlus heating characteristics. The actuator 'other gains' was selected as it is accessible from external programs and thus can be controlled from programs other than EnergyPlus.

Table 4.5 - step response to radiator f(radiant fraction)

Room temperature step response - Heating power step (3kW) - radiator radiant fraction													
Tamb [°C]	10	10	10	10	10	10	10	10	10	10	10	10	10
radiator radiant fraction	0	0.01	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
delta Troom [°C]	36.5	36.5	36.2	35.9	35.3	34.6	33.9	33.2	32.4	31.6	30.6	29.4	28.2
63% [min]	830	831	853	876	924	976	1033	1094	1161	1235	1338	1455	1613
95% [min]	3295	3296	3318	3342	3390	3440	3495	3555	3623	3700	3795	3940	4047

4.3 Reduced model

General

What is the use for yet another model?

For algorithms, as for the 'Model Predictive Control' control strategy, a mathematical representation of the underlying system is necessary. With such a model it is possible to calculate/estimate/simulate the resulting or depending variables - e.g. the room temperature - as direct result to the applied input variables - 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. Under the assumption of a mathematical representation with similar thermal dynamic as the reference room, input sequences can be applied to the model and the resulting output will be close to the output the real system - our reference room - under the same conditions.

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.

Hence, a mathematical model needs to be derived to represent
a) the thermal dynamics of the reference room and/or
b) the reference model which had been fitted to the real system.

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. In an optimization process under a defined target function, an optimal input sequence can be found.
Optimizing the input sequences in the mathematical model - e.g. heating power starting at current time and over future time - and evaluating the output variables with target- or cost functions will lead to 'optimal' input trajectories in time (model predictive control algorithm)

In this project, the mathematical representation will be fitted to a). In spite of running the simulations for heating demand with the reference model (EnergyPlus model) the reference room and the available measurements were selected for the fitting process of the mathematical model. Reason is that a potential practical application also would be linked to sensor measurements of the respective thermal zone and not to a simulation model.

4.3.1 Model structures

In the literature [2,14,11,12,7] 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.

It needs to be noted that such reduced model descriptions represent the dynamic characteristics only, any detailed geometry and material details are subsumed in virtual elements as capacities, resistances, etc. There is no direct physical interpretation for the values of these virtual elements [2], these parameters combine and represent several underlying physical effects and thermal characteristics.

This project follows the basic model structures and systematic approach and categorization of [2].
Some modifications were applied to make the models more suitable for this project as:

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

In this process the modelling is started at a very simple model with only few differential equations (see figure 4.10, equation 4.5). The variables of the differential equations are corresponding to the states (Ti, Te, Th) in a state space description of the system.
For easier notation the terminology of [2, 11], referencing to the the states of the model, is adopted (see table 4.6 and figures 4.10 to 4.11):

In the underlying case the systems, in the nomenclature as in [2, 11], are:

- **Ti:** represents the simplest system and is a representation in one differential equation respectively one state space variable (Ti) only. This model does not sufficiently fit to the thermal characteristics of the reference model, nor does it allow the variation of any input variables apart from the ambient temperature T_a=T_{amb} (e.g. sensor readings).
- **TiTe:** the thermal mass property of the envelope/wall is added. This property requires an additional first order differential equation. In the state space description a second variable (Te) is added.

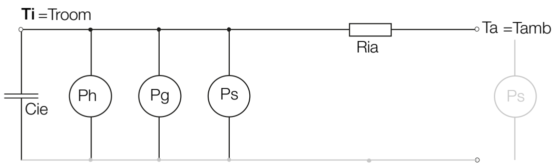

Figure 4.10 - Ti model structure

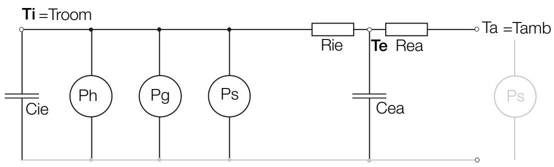

Figure 4.11 - TiTe model structure

- **TiTe_RiaRib:** 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 number of describing differential equations and states remains unchanged.
  This model is representing the reference model and its impacts quite well. It also allows to study and vary different sensor settings.
- **TiThTe_RiaRib:** in this representation an additional physical effect is described in another differential equation or state respectively; it is the thermal characteristics of the radiators (and interior). Their thermal capacity adds lag time to the dynamics of the systems described above also see 'Radiator dynamics' below).

Table 4.6 - model terms

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

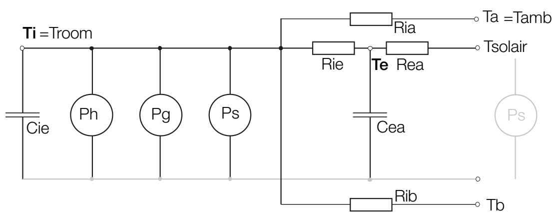

Figure 4.12 - TiTe_RiaRib model structure

For the control calculations in the next chapters the TiThTe_RiaRib structure is selected.
Even using a different way for the simulation of the radiator dynamics (see 'Radiator dynamics' further below), this model was retained as it offers the most versatile structure for adaptions with respect to different sensor settings.
The equivalent circuit diagram of the selected TiThTe_RiaRib structure is shown in figure 4.13.

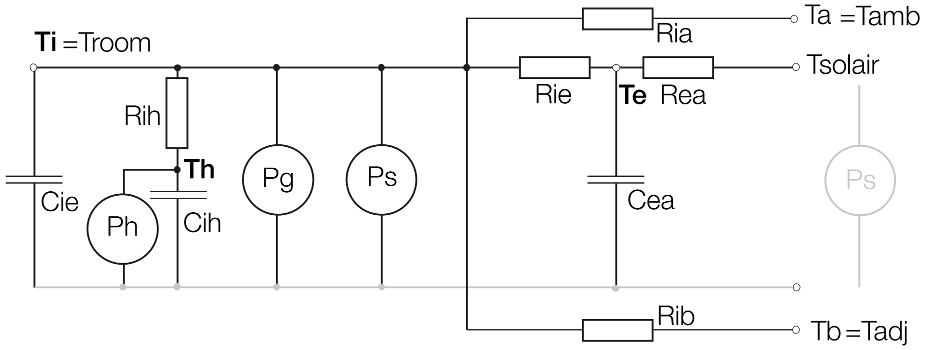

Figure 4.13 - TiThTe_RiaRib model structure

Output-/Input parameters

The output parameter is:

- **T_i [°C]**
  Is representing the interior temperature of the reference room (T_{room}). This is the temperature the thermostat or controller has to keep within the required limits, set forth by the thermostat schedule and thermostat setting values.

The input parameters to this model are:

- **T_a [°C]**
  Representing the ambient temperature in direct vicinity of the reference room.
- **P_s [kW]**
  Factor the solar gains by solar radiation power through the window areas.
- **P_h [kW]**
  Represents the main input/control factor, the heating power applied to the room. The heating power is in the range of zero to the maximum radiator heating power of 3000W.
- **P_g [kW]**
  For other thermal gains as electrical gains from appliances or occupancy gains.
- **T_b [°C]**
  Referring to the temperature of an internal zone adjacent to the reference room, also indicated as adjacent temperatureT_{adj}.
- **T_{solair} [°C]**
  According to the ASHRAE® handbook [37] the sol-air temperature is "the outdoor air temperature that, in the absence of all radiation changes gives the same rate of heat entry into the surface as would the combination of incident solar radiation,..., and convective heat exchange with outdoor air" [37].
  This virtual temperature is selected to include solar radiation gains to the walls, instead of applying the energy into the envelope as proposed by [2].
  The concept of T_{solair} as a function of solar irradiation, wind speed, radiation impact angle and area, also allows the potential implementation of a wind speed sensor and of information concerning building orientation and geometry.

  T_{solair} is calculated to:

$$T_{solair} = T_{amb} + \frac{\alpha . P_{s,total}}{h_o} - \frac{\varepsilon . \Delta R}{h_o} \tag{4.5}$$

with:

α absorptance of surface exposed to solar radiation

$P_{s,total}$ total solar radiation to surface [kW/hm^2]

h_o heat transfer coefficient for convection and long wave radiation [kW/hm^2], approximated with h_c (convective surface film) as
h_c=5.6+3.9v_{wind} for v_{wind} ≤ 5 m/s
h_c=7.2$v_{wind}^{0.78}$ for v_{wind} ≥ 5 m/s

ε emittance of surface

ΔR difference between long wave radiation from sky and surroundings and emitted radiation (black body) at the ambient temperature T_{amb}. According to 2009 ASHRAE® Handbook [37] it is common practice to assume R=0 for vertical surfaces, as the usually higher temperatures of surfaces of terrestrial objects partially compensate the sky's low emittance.

4.3.2 Mathematical description

The representation of the system by its equivalent electrical circuit can be directly translated to the respective description in form of differential equations. For the simplest model - the Ti model - that leads to (4.6):

$$dT_i = \frac{1}{R_{ia}C_i}(T_a - T_i) + \frac{h_h}{C_i}P_h + \frac{A_w}{C_i}P_s + \frac{h_g}{C_i}P_g \tag{4.6}$$

While the simplest representations do not follow well to the measured dynamics of reference room, the more complex systems show a good fit to the measured data.
For the most comprehensive model - the TiThTe_RiaRib model - still simple, but including all important parameters, the description in form of differential equations leads to (4.7):

$$\begin{aligned} dT_i &= \frac{1}{R_{ie}C_i}(T_e - T_i) + \frac{1}{R_{ih}C_i}(T_h - T_i) + \frac{1}{R_{ia}C_i}(T_a - T_i) + \frac{A_w}{C_i}P_s + \frac{h_g}{C_i}P_g + \frac{1}{R_{ib}C_i}(T_b - T_i) \\ dT_e &= \frac{1}{R_{ie}C_e}(T_i - T_e) + \frac{1}{\mathrm{R}_{ea}\,C_i}(T_{solair} - T_e) \\ dT_h &= \frac{1}{R_{ih}C_i}(T_i - T_h) + \frac{h_h}{C_h}P_h + \frac{1}{R_{ib}C_i}(T_b - T_i) \end{aligned} \tag{4.7}$$

To answer the underlying question of this work - the effect of different sensor/input settings, an important selection criteria for the model structure is that the representation has to incorporate significant influence factors of the room model (e.g. T_b, ...). The model has therefore to provide input parameters linked to different sensor readings.

Such indirect variables are (equation 4.6):

- $T_{ambient}$ - outside temperature
- T_b - temperature of adjacent room
- T_{solair} - is a calculated virtual outside temperature. Apart from the outside temperature T_{amb}, this value takes also into account other impacts as solar irradiation to the wall, wind speed, absorptance of the wall as well as other factors as orientation of building and walls and their size ratio
- P_h - heating power
- P_g - occupancy related gains (e.g. people, appliances)
- P_s - solar irradiation through transparent building elements

If e.g. the dependency of solar irradiation and the presence of such sensor, respectively the availability of such sensor data, should be derived, the model needs the solar irradiation as input parameter. The same is valid for ambient Temperature (T_{amb}), temperature of an adjacent thermal zone (T_{adj}), wind speed, electrical gains, occupancy, and heating energy.

State space description

Mathematical models as representation of dynamic systems in control engineering are often transformed to a set of coupled first order differential equations.

Every such differential equation is describing a 'state' variable, the 'state space' is a mathematical space, with these states as describing the axes. The states, inputs and outputs are defined as vectors within that space. The state variables are system variables, representing a state of the system as function of time. The number of state variables needed to model a given system, is representing the order of the differential equation defining the systems dynamics.

Such state-space descriptions represent a compact method to model and analyse systems with multiple inputs and outputs (scheme figure 4.14).

It needs to be noted, that the states of a given state space model do not represent an actually measurable physical parameter but rather reflect a virtual result of a first order differential equation, necessary for this type of mathematical description. Values of such virtual states can be mathematically accessed or observed but cannot be measured. Also the interpretation of such states in form of accessible' physical parameters is not necessarily simple or possible.

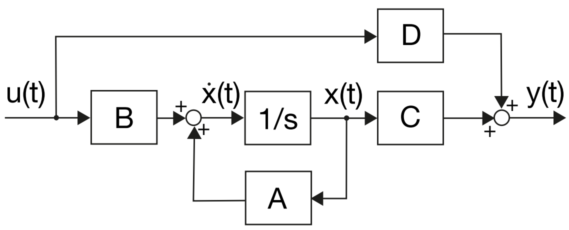

Figure 4.14 - state space system

The general matrix form of a state space description of a system is (equation 4.8):

$$\dot{x}(t) = A * \mathrm{x(t)} + B * u(t)$$
$$\mathrm{y(t)} = C * x(t) + D * u(t) \tag{4.8}$$

with

- *x(t)* being the state vector
- *y(t)* the output vector
- *u(t)* the input (or control) vector,
- *A* the state (or system) matrix,
- *B* the input matrix
- *C* the output matrix and
- *D* the feedthrough (or feedforward) matrix.

By rewriting the differential equations from above (4.7) the matrices state space description for the TiThTe_RiaRib model can be derived as (4.9), with the state and output vectors (4.9):

$$\frac{d}{dt}\begin{bmatrix} T_i \\ T_e \\ T_h \end{bmatrix} = [A] * \begin{bmatrix} T_i \\ T_e \\ T_h \end{bmatrix} + [B] * \begin{bmatrix} T_a \\ P_s \\ P_h \\ P_g \\ T_b \\ T_{solair} \end{bmatrix} \qquad [y] = [C] * \begin{bmatrix} T_i \\ T_e \\ T_h \end{bmatrix} + [D] * \begin{bmatrix} T_a \\ P_s \\ P_h \\ P_g \\ T_b \\ T_{solair} \end{bmatrix} \tag{4.9}$$

with the system matrices (4.10):

$$A = \begin{bmatrix} -\frac{1}{R_{ie}C_i} - \frac{1}{R_{ih}C_i} - \frac{1}{R_{ia}C_i} - \frac{1}{R_{ib}C_i} & \frac{1}{R_{ie}C_i} & \frac{1}{R_{ih}C_i} \\ \frac{1}{R_{ie}Ce} & -\frac{1}{R_{ie}C_e} - \frac{1}{\mathrm{R}_{ea}\,C_e} & 0 \\ \frac{1}{R_{ih}C_h} & 0 & -\frac{1}{R_{ih}C_h} \end{bmatrix}$$

$$B = \begin{bmatrix} 0 & \frac{A_w}{C_i} & 0 & \frac{h_g}{C_i} & \frac{1}{R_{ib}C_i} & \frac{1}{R_{ia}C_i} \\ \frac{1}{\mathrm{R}_{ea}\,C_e} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{h_h}{C_h} & 0 & 0 & 0 \end{bmatrix} \tag{4.10}$$

$$C = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \qquad D = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Model-/Parameter identification

Model identification is the process to determine the values of parameters of the mathematical model and/or the structure of the model representation (e.g. order of the model). The process involves optimization of the parameters and/or structure to best match the mathematical model to measured data.

Depending on the elements to be identified the model identification can be differentiated as:

- **white box identification**: estimate the parameter values of a fully defined physical model (theoretical case)
- **black box identification**: the structure as well as the parameter values are to be established
- **grey box identification**: combines an established theoretical structure of a model with measured data and optimizes the parameter values to best fit the real dynamics in form of available data with the dynamics of the mathematical model.

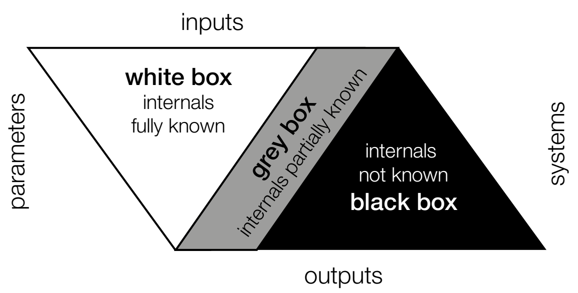

Figure 4.15 - model identification
(source [1])

As the underlying model structure with order of the system and differential equations are established (see above) a grey box identification process is applied. It combines an established theoretical structure of a model with measured data and optimizes the parameter values to best fit the real dynamics in form of available data with the dynamics of the mathematical model.

As emphasized above, the state space description and its parameters describe the system but do not necessarily have a direct equivalent parameter definition in the real world. The parameters that need to be identified are the variables in the system matrix

For the parameter identification process an input time series (T_a, P_s, P_h, P_g, T_b, T_{solair}) with the actual sensor data is applied to the mathematical model. In an optimization process the variables - the mentioned matrix elements - are varied to generate a best fit of the output of the mathematical model with the actual sensor data for these parameters - in this case for the temperature of the reference room (T_{room}, T_i). For this identification process the MATLAB® model identification toolbox is applied.

The identified parameters for the TiThTe_RiaRib model result to (table 4.7):

Table 4.7 - model identification results

Model identification - results

heat capacities	[kWh/°C]	thermal resistance	[°C/kW]	factors	[m2]
Ci	8.00E+00	Rie	1.50E+00	Aw	6.76E-01
Ce	1.00E+03	Rea	3.70E+00		
Ch	6.67E-01	Rih	3.00E+00	factors	[1]
		Ria	4.38E+01	Hfactg	4.36E+00
		Rib	6.25E+00	Hfacth	4.00E+00

With the resulting parameters the system- and input matrix for continuous system result to (4.11):

$$A=\begin{bmatrix}-1.48E-01 & 8.33E-02 & 4.17E-02\\ 6.67E-04 & -9.37E-04 & 0\\ 5.00E-01 & 0 & -5.00E-01\end{bmatrix}\qquad B=\begin{bmatrix}2.86E-03 & 8.44E-02 & 0 & 5.45E-01 & 2.00E-02 & 0\\ 0 & 0 & 0 & 0 & 0 & 2.70E-04\\ 0 & 0 & 6.00E+00 & 0 & 0 & 0\end{bmatrix}\tag{4.11}$$

with a fitting factor of >80%

The fitting factor indicates how well the system with the identified parameters fits the measured data. It is indicated as normalized root mean squared error (NRMSE), expressed as percentage. To facilitate comparison of results the mean squared error (RMSE) is normalized, that is divided by the span of the values (max-min).

State space description - continuous and discrete time system

So far the system description was done for a continuous system. In this case the system is described as a system of coupled differential equations. The differential calculus builds on the assumption of infinitely short time segments, their tangents converging to differentials of the functions (e.g. dx/dt). With this infinite number of time points along the time axis, time is considered as a continuous variable. The state space description is in the form:

$$\begin{aligned}\dot{x}(t) &= A * \mathrm{x(t)} + B * u(t)\\ \mathrm{y(t)} &= C * x(t) + D * u(t)\end{aligned}\tag{4.12}$$

Discrete systems work on a time concept with values at specific points along the time axis only (sample time); in between these points the values remain constant (first order hold). At the discrete time points the values change their value (e.g. measurement value). Thus the number of value changes or measurements between two points in time is finite. This fact does not allow a description in form of differential equations.

Discrete systems are described in form of difference equations in the form of:

$$x(t+1) = A * \mathrm{x(t)} + B * u(t)$$
$$\mathrm{y(t)} = C * x(t) + D * u(t) \quad (4.13)$$

Continuous system descriptions can be converted to discrete system descriptions and the respective difference equations; necessary for such conversions is a definition of a sample time.

Description in discrete form as a set of coupled difference equations (recurrence relations) is not only necessary for digital systems but also much easier to process digitally. All controller algorithms are based on a discrete state space description of the mathematical model.

Radiator dynamics

The response characteristics of the radiators represent very specific dynamic effects and require special adaptions to the mathematical model.
The radiators represent a first order lag element (PT1 element). A PT1 element response to a step input signal is an output asymptotically approaching its final value; in an exponential response function with a time constant t (see figure 4.17 and 4.18). An electrical equivalent would be a RC lag circuit (see figure 4.16)

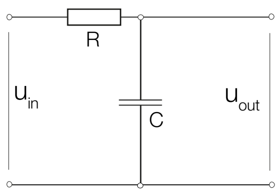

Figure 4.16 - PT1 system

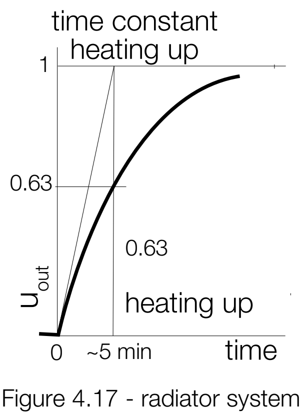

Figure 4.17 - radiator system response - heating up

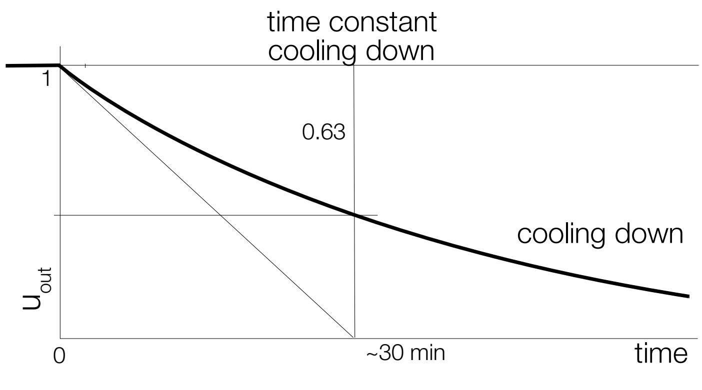

Figure 4.18 - radiator system response - cooling down

'Unfortunately' the radiator is not just a 'simple' PT1 element but shows very different thermal dynamics and time constants for heating up and cooling down.

When heating up, the heating energy is first used to heat up the radiator mass (metal case) itself, the heating energy to the room is a function of its resulting surface temperature. The heating water, provided with high flow/supply temperature does not need any time to be at its maximum temperature, the time constant for warming up is influenced by the thermal mass of the radiator itself (metal case). Time constants for heating up are in the range of 5 minutes.

For cooling down however, the respective time constant is much longer. The radiator cooling not only refers to the metal parts of the radiator but also to the water contained in the radiator. This leads to a time constant for cooling down of approximately 30 minutes as indicated in [41]. These thermal characteristics can be verified by using the technical data of the radiators [42] - weight and water content - and the respective thermal capacity of steel and water.

For the simulations with different controller strategies the radiators are modelled in separate mathematical PT1 elements.

5 SIMULATION SETUP

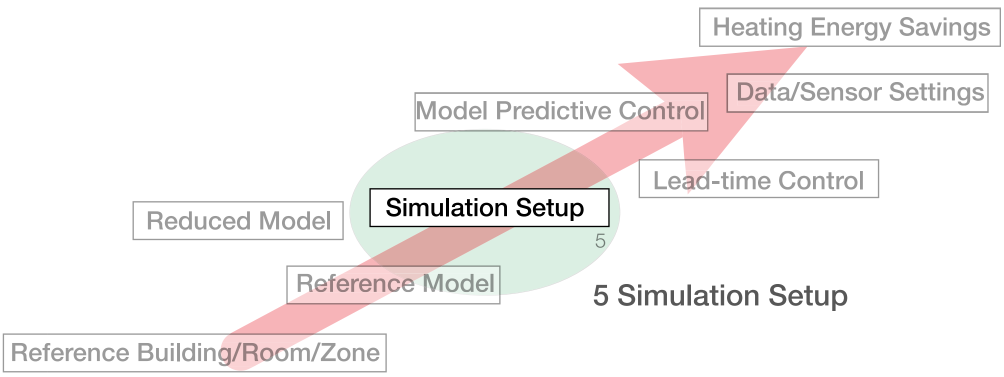

Figure 5.1 - model simulation

5.1 Simulation and co-simulation

Simulations are a common way to forecast characteristics of systems; a building can be such a system, the thermal characteristics as heating energy demand, internal temperatures can be the parameters the simulation is run for.

One of the typical software package for thermal building simulation is EnergyPlus, an open-source, and cross-platform software, developed by the U.S. Department of Energy Building Technologies Office [32].

EnergyPlus provides some capabilities for internal calculations, however for this project this functional support is by far not enough to program more complex controller structures and algorithms or to use forecasted input variables.

For more complex programming MATLAB® is a very capable and widely used program in the engineering community. MATLAB® [30] is a programming environment with its own programming language, with its functionality based on matrix calculations and available software tool packages for various engineering applications it is a perfect choice for running the control algorithms as model predictive control.

In order to combine these capabilities - the thermal building simulation and the capability to run complex algorithms - a cooperation of these software packages is necessary.

The 'Building Controls Virtual Test Bed' (short BCVTB), developed at the University of California, is such a tool [43]. It was especially created for co-simulation of two or more software packages; it is controlled by an own programming language [10].

EnergyPlus

As described before, this building simulation package is primarily designed to evaluate the energy demand for heating and cooling. It also provides the option to incorporate modern systems linking up with the energy demand calculation as e.g. complex HVAC-systems, photovoltaic and solar heating panels, etc.

A model for EnergyPlus requires detailed specification of the geometry of the building, the thermal boundary conditions of building elements, material information together with their thermal characteristics and weather data.

For this work, the model - our reference model - was established in chapter 'Reference Building' (see above).

The co-simulation feature and interface in EnergyPlus has an open communication protocol which can be used with the Building Controls Virtual Test Bed BCVTB and other programs controlling co-simulations as MLE+.

MATLAB®

The MATLAB® environment has been chosen for its functionality to be the program for the implementation of the control algorithms. It offers a wide range of functions for the areas of linear algebra, for matrix operations and the handling of systems described by a set of coupled differential equations.

The description on the MATLAB® underlines the advantages and suitability of this software environment for this project: "MATLAB® is a high-level language and interactive environment for numerical computation, visualization, and programming. Using MATLAB®, you can analyze data, develop algorithms, and create models and applications. The language, tools, and built-in math functions enable you to explore multiple approaches...You can use MATLAB® for a range of applications, including control systems, test and measurement,..."[31]

Virtual Testbed

The 'Building Controls Virtual Test Bed' (BCVTB) allows to link the building simulation software EnergyPlus to another software environment, as MATLAB®. BCVTB is an open-source software platform from the Lawrence Berkeley National Laboratory, allowing engineers to simulate building energy systems and to develop complex control systems [27].

The EnergyPlus interface was originally developed for BCVTB, however the communication protocol is open and can be used by any program to perform co-simulation with EnergyPlus. MLE+ is an example of such programs.

The BCVTB is a software environment based on Ptolemy-II language and has been developed for co-simulation of two or more software environments. Co-simulation refers to at least two simulators, each of them simulating, calculating or solving a set of differential or difference equation, are coupled, providing an exchange of data amongst the two programs while running [27].

MLE+

MLE+ is another open-source MATLAB®/Simulink® toolbox for co-simulation with the building simulation software EnergyPlus. It is designed for engineers and researchers who want to use MATLAB® functionality for thermal building simulation. MLE+ is developed at the Embedded Systems Laboratory at the University of Pennsylvania.

MLE+ tool package provides objects and parameters for the linking process and for running the co-simulation. It can be used for complex control strategies and algorithms and for parameter optimization for simulation run in EnergyPlus. Via MATLAB® it provides full access to the full functionality of its environment, and to the toolboxes [36].

The software tool MLE+ offers a GUI interface, but also comes in a legacy version [19]. This version is used in further co-simulations, running the building simulation in EnergyPlus and the controller algorithms in the MATLAB® environment.

BCVTB is offering a wider linking functionality than MLE+ and is able to couple other programs apart from EnergyPlus and MATLAB®. Other than BCVTB, which is running in its own environment, MLE+ is running within the MATLAB® session. Therefore it integrates better with MATLAB® and the complete functionality of MATLAB®b can be used with MLE+.

5.2 Process and configuration

There are several connection program points, especially in EnergyPlus, to exchange data between the two programs. The difference refers e.g. to as to when the data is provided and read in, whether this is before or after the simulation run, etc. The described process corresponds to the linking process as used in further co-simulations in this project.

The process steps as used in the co-simulation of MATLAB® and EnergyPlus are (see figure 5.2):

- In the MATLAB® environment an MLE+ object is created and a session and interface are established. The MLE+ object and its integrated program routines provide the connection to EnergyPlus
- EnergyPlus is initialized and
- provides the data as defined in a configuration file.
- In the MATLAB® program the data from EnergyPlus is decoded and assigned to variables.
- The MATLAB® program code and function loops are performed - e.g. for the controller algorithms,
- resulting in parameters to be used for the EnergyPlus.
- Valid parameters for the external interface of EnergyPlus are schedule, variable and actuator parameters.
- In the case of this work actuator data is sent to EnergyPlus.
- EnergyPlus then starts a simulation run, using its own parameters and the actuator data sent from the MLE+ session within MATLAB®. After completion of the single simulation calculation run, EnergyPlus provides the new data set to MATLAB® for the next calculation loop.
- At the end of the required calculations in MATLAB®, the EnergyPlus as well as the MLE+ sessions are terminated.

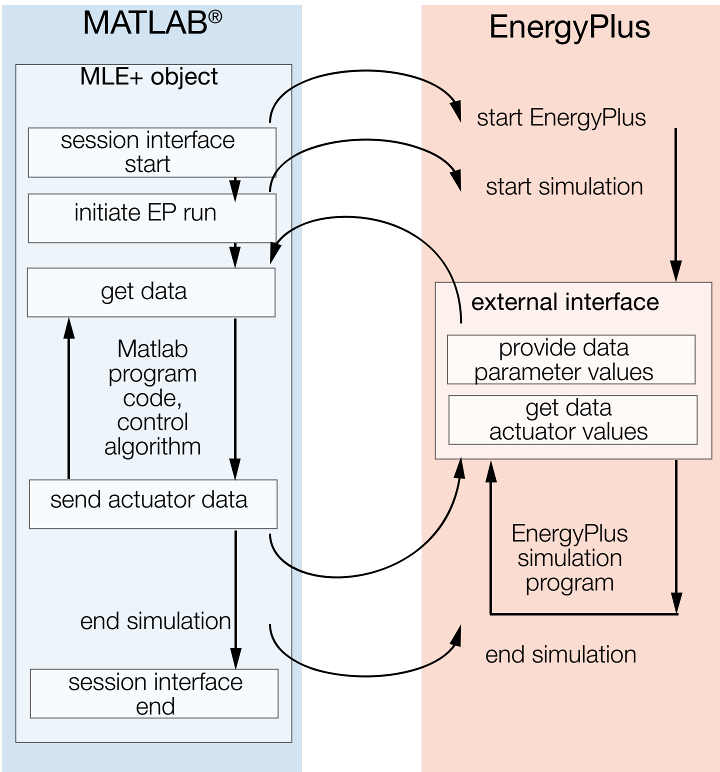

Figure 5.2 - co-simulation process

For the definition of the communication protocol and as to which data will be transferred,

- a configuration file is provided for the MLE+ object in MATLAB®
- the external interface is defined in the 'External Interface' section of the idf file of the EnergyPlus model
- the actuator or schedule parameters of EnergyPlus' external interface are also defined in the 'External Interface' section
- the variables for transmission from EnergyPlus to MATLAB® are defined in the 'Output' section of the idf file
- a socket configuration file defines the communication for the MLE+ object in MATLAB®.

6 PREDICTIVE CONTROL

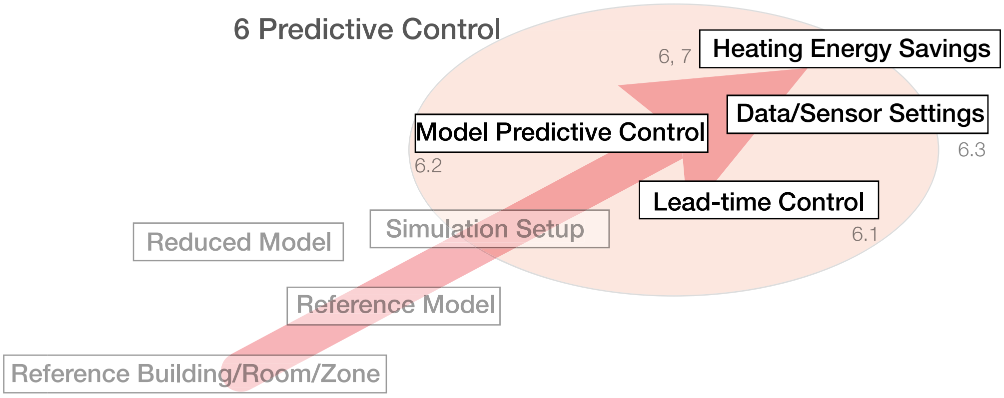

Figure 6.1 - predictive control

General simulation conditions

Unless otherwise stated in the respective subchapter, the boundary conditions for the simulations in subchapter 'Simple Predictive Control' are

- simulation period 1/1-6/30
- no electrical gains
- no occupancy gains
- thermostat schedule: workdays 9:00-12:00 21°C, 14:00-16:00 21°, all other times free running (no thermostat setting)
- ambient $T_{amb}=T_a$ temperature per weather-file
- adjacent Temperature $T_{adj}=T_b$ from simulation results of staircase/hallway model (see chapter 4.1.2)
- simulation time step 1 minute.

Distribution of heating difference and starting temperature

The free running conditions (night and day setback conditions) in between the periods with thermostat setting (21°C) lead to reduced room temperatures. The difference between the thermostat setting of 21°C and the temperature before the beginning of the morning and afternoon heating periods is shown in the histogram in figure 6.2.

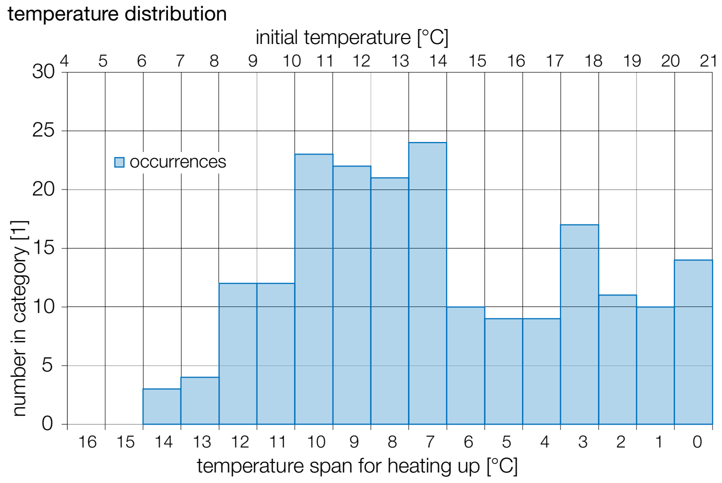

Figure 6.2 - distribution initial temperature span

As the simulation runs, especially with more involving algorithms as model predictive control (MPC), become numerically intensive, the number of simulations needed to be reduced.

For more detailed investigation of temperatures and heating demand, 3 (4) representative days within the simulation period from 1/1 to 6/30 were selected, representing the starting temperature for the heating period in the morning as:

- **minimum temperature:**
  lowest initial temperature 6.5°C on 2/6
- **the median temperature**
  11.8°C on 2/22
- **the upper quantile temperature**
  16.9°C on 4/14.

For most further comparisons and figures the

- **the lower quantile temperature**
  9.6°C on 1/20

was not taken into consideration; the reason is that the potential energy savings are savings are higher for higher starting temperatures (heating system running at partial load in the transition period), resulting in only smaller differences for the lower quantile temperature versus the minimum temperature and the median temperature.

Step response and look-up table

The room temperature step response on input changes in heating power (step function) is the basis for a simple predictive control strategy. Two versions of such step responses have been studied more in detail:

- **step response without thermal radiator dynamics**
  That is an ideal radiator transferring the full input heating power to the room without any lag time.
- **step response with a radiator lag time**
  Due to the radiator dynamics with a power dissipation lag time when heating up the radiator itself. This leads to longer heating times for the room (see figure 6.3).

All step response simulations simulation runs where performed

- without any other direct gains as appliances or occupancy,
- without any other weather inputs like solar irradiation and with a constant ambient temperature (T_{amb}) and
- constant temperature of the adjacent hallway (T_{adj}).

Figure 6.3 shows the responses without (upper curves) and with radiator gain (lower curves). Table 6.1 represents a look-up table as used for the simple predictive control - see subchapter 4.3.1)

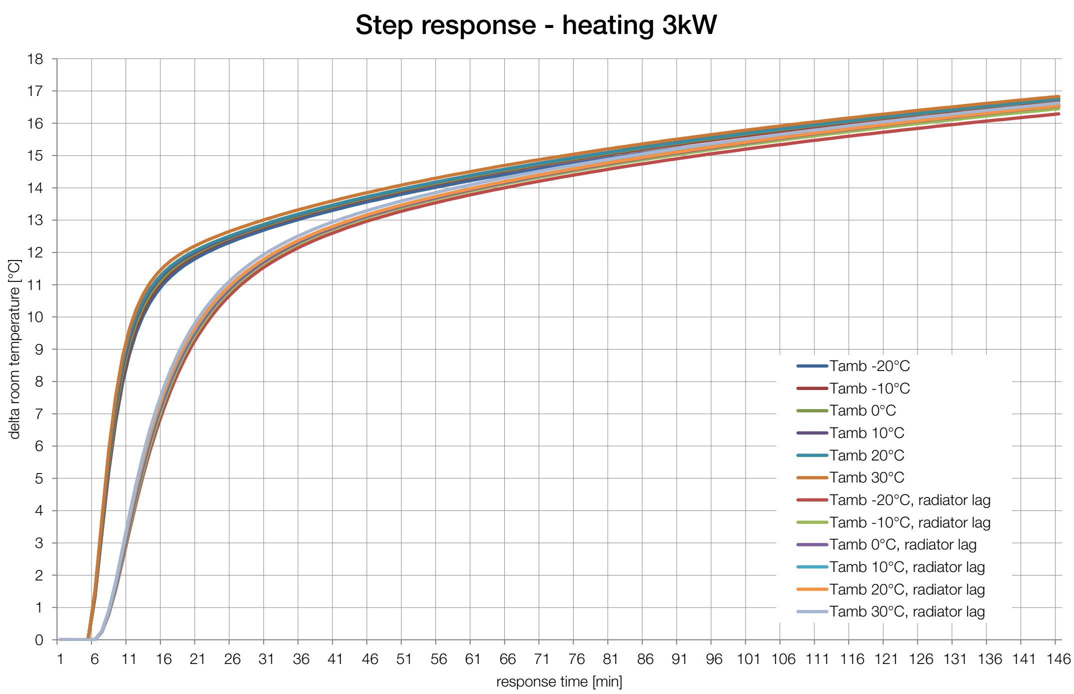

Figure 6.3 - step response wo/w radiator lag

Table 6.1 - lead time look-up table

Look up table	without radiator lag time						with radiator lag time					
ambient temp Tamb [°C]	-20	-10	0	10	20	30	-20	-10	0	10	20	30
tot. temperature rise [°C]	37,4	38,8	39,6	39,4	38,4	37,6	37,2	38,7	39,6	39,4	38,4	37,6
temperature rise [°C]	**minutes to establish temperature rise**						**minutes to establish temperature rise**					
1	0	0	0	0	0	0	3	3	3	3	3	3
2	1	1	1	1	1	1	4	4	4	4	4	4
3	1	1	1	1	1	1	5	5	5	5	5	5
4	2	2	2	2	2	2	6	6	6	6	6	6
5	2	2	2	2	2	2	7	7	7	7	7	7
6	3	3	3	3	3	3	9	8	8	8	8	8
7	4	4	3	3	3	3	10	10	10	10	9	9
8	5	4	4	4	4	4	12	12	11	11	11	11
9	6	5	5	5	5	5	14	14	14	13	13	13
10	7	7	7	7	6	6	17	17	17	16	16	16
11	10	10	10	9	9	8	22	21	21	20	20	20
12	17	16	15	15	15	13	29	28	27	27	27	26
13	30	28	28	27	27	25	41	39	38	38	38	36
14	50	47	47	46	46	43	60	57	56	56	56	53
15	77	74	73	72	72	69	88	84	82	81	82	78
16	115	110	108	106	107	103	127	120	117	116	117	113
17	166	157	153	151	153	149	179	168	163	161	163	159
18	232	218	211	207	211	208	246	229	221	217	221	218
19	314	293	282	276	283	281	330	305	292	287	293	291
20	413	383	365	358	368	368	432	396	376	369	379	379

At a first view, it would be expected that the responses are exponential functions. As can be seen from the results at 63% and 95% the response functions resulting from EnergyPlus simulations are not exponential functions, but functions that seem more close to exponential responses of parallel thermal subsystems. This system behaviour, and especially the effect of the relatively low temperature increase gradient beyond approximatively 12°C temperature rise has an effect on the applied control algorithms see subchapter 4.3.2.

How to get the look up table of a real room

In the described case, the look-up table was established based on simulation, taking the output (room temperature) as thermal response to a step change of an input parameter (heating energy).

Such thermal response characteristic can also be derived from measurements on a real room. If a known input signal sequence is applied, the measured output can be analyzed and a system step response can be derived.

As an example, this could be done for the period of night temperature setback. In that situation, right after the energy supply is cut off, the thermal system is in a free running mode. The room cooling curve represents a thermal step response to the change in input energy. The ambient temperature remains as disturbance parameters, other influence parameters, as e.g. solar irradiation energy, or occupancy would not be a factor during the night. For other measurement situations, disturbance parameters however could negatively influence the accuracy. To avoid that, the major influence factors would also need to be measured.

Multi-dimensional look-up tables

The presented control algorithms refer to one dimensional look-up tables. The necessary heating lead time is the output variable with the heating-up temperature the only input variable.

Of course other input variables could be added, thus forming a multi-dimensional look-up table or -matrix. The output variable (heating lead time) would then be a function of several input parameters. Such input parameters could be heating water flow temperature, parametrized weather data, gain factors, etc.

Look-up table lead control with flow temperature control

Some heating control systems include a control of the heating water flow temperature. This method is applied to reduce heat losses for conditions when heating power demand remains below the nominal system heating power. This is the case for higher ambient temperatures. The flow temperature is usually controlled by characteristic curves, giving the flow temperature set point as function of the ambient temperature conditions.

Such case would be an example for a two dimensional look-up table for the necessary heating lead time. One input parameter being the heating temperature difference as before, the second input parameter then would be the set flow temperature. Lower settings for the flow temperature would yield longer lead times for heating.

The principle results as described below however would not change. The difference is that for lower flow temperatures the heating has to start earlier (longer lead times) as the energy supplied to the room via the radiators is lower than the nominal power. The overall resulting supplied energy - for a longer time, but at lower energy output - remains the same.

6.1 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 warming-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 time the temperature needs to be at the requested level. For this case, the thermostat timer has to be set in a way to cover the worst case of heating-time. That is when the room temperature before heating is at its lowest level.

For the underlying reference model the repartition of room temperatures before the schedule set point (time when a requested temperature should be reached) is shown in figure 6.2. The worst case in the first half year 2015 for heating-up is at a room temperature of 6.5°C (2/6), requiring the heating to cover a temperature difference of 14.6°C. The system responses to input steps of heating energy are simulated and evaluated; results as shown in figure 6.3 and table 6.1, indicate the necessary time to heat the room for given degrees. For the worst starting temperature, the time required to heat the room by 14.5°C is between 50 and 70 minutes.

A setting for the thermostat timer to start heating exactly the required time before the schedule point would be the best setting to satisfy the target of least heating energy use and to get to the requested temperature level at the stipulated time (figure 6.4).

With that start time set to the thermostat, the heater will start with this lead time. Thus, in all cases but the 'worst case' (lowest room temperature), the heater will start too early for the prevailing temperature, resulting in the room temperature reaching its target temperature earlier than requested. The heating energy for this time span is not necessary and could be saved. This saving could be realized if the lead time is derived as a function of the room temperature and the known response time of the system. The known/measured (in this case simulated) thermal response characteristic of the room allows forecasting the system response. Thus a control, adapting the heating lead time as function of the model result is in principle a 'model predictive control'.

As such control strategy does not exactly represent what in control theory is understood under 'model predictive control', however in the context of this project the term look-up control, or simple predictive control is used.

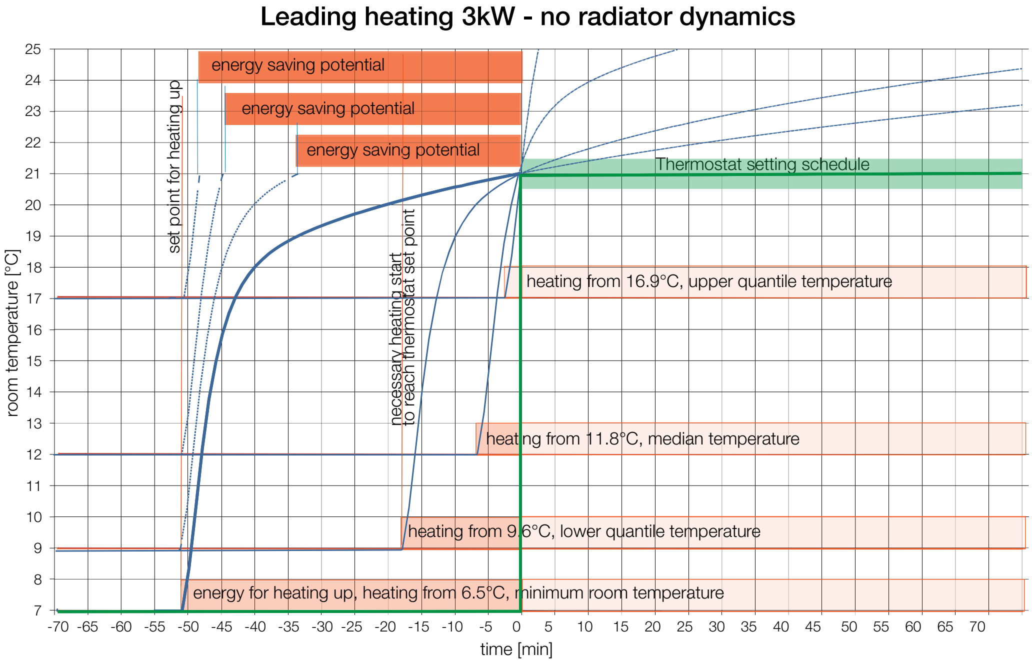

Figure 6.4 - step response without radiator lag

Thermostat controller algorithms representing simple on/off controller and on/off controller with hysteresis (2-point switch) have been programmed in MATLAB®. A co-simulation of the reference model with MATLAB® and EnergyPlus was performed. The results of the three days selected for their initial temperature - worst case day, the median day and the upper quantile day are shown in figures 6.4 and 6.5

Radiator dynamics

When applying the radiator dynamics, with its lagging heating and cooling-down effect, the same as above applies. The results differ in the necessary heating lead time and the heating energy demand. For systems with the radiator lag, a dampening effect keeps the room temperature closer and/or in a more narrow tolerance band around the target temperature. On the other hand, temperature overshoot may occur as the radiator and its stored heat keep heating up the room after the energy supply to the radiator has been switched off. These effects drain some energy.

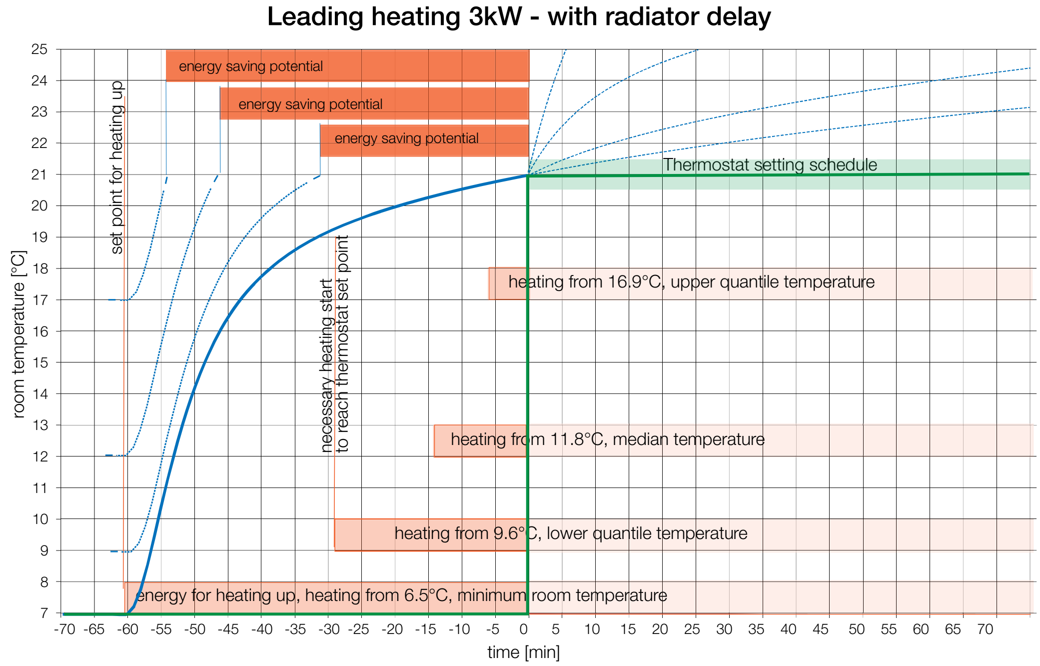

Figure 6.5 - step response with radiator lag

Switching thermostats

For the simulations with switching thermostats, the characteristics of these simple switching devices were programmed in MATLAB®.

Two different versions of switching thermostats were used for the simulations:

- **simple switching thermostat, without hysteresis**
  This thermostat simply switches on, when the room temperature is below the thermostat setpoint, and inversely, switches off when above the set point. This represents a technically (over)simplified case, high switching rates could be the result, especially with fast system dynamics.
- **two point switching thermostat**
  A two point switching device represents a realistic model of a thermostat. The switch/heating is on when the temperature going up and is below the target plus hysteresis temperature; above that level it is off. When the temperature is thus falling, the switch remains off until reaching the target minus hysteresis temperature. Mechanical systems do show such hysteresis behavior and such switching characteristic is reducing the switching rate (see figure 6.6).

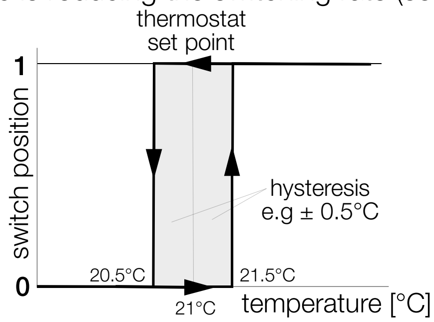

Figure 6.6 - 2-point switch

6.1.1 Results - simple predictive control

Simulation runs with different thermostat setups and with reference models - system without as well as with radiator delay - show the effect of look-up table predictive control versus fixed lead time thermostat settings.

Results without radiator lag

On/off switching thermostat - no lead time:

In this case the thermostat is starting the heating only when triggered by the thermostat schedule, thus the room is heated up to the desired temperature only after a long delay. In the worst case, that is starting from the lowest temperature in the simulation period (6.5°C) this gives a maximum delay to reach the desired temperature of 42 minutes.

This case does not fulfill the requirement - reaching the room temperature at the right time - and is only retained for comparison reasons.

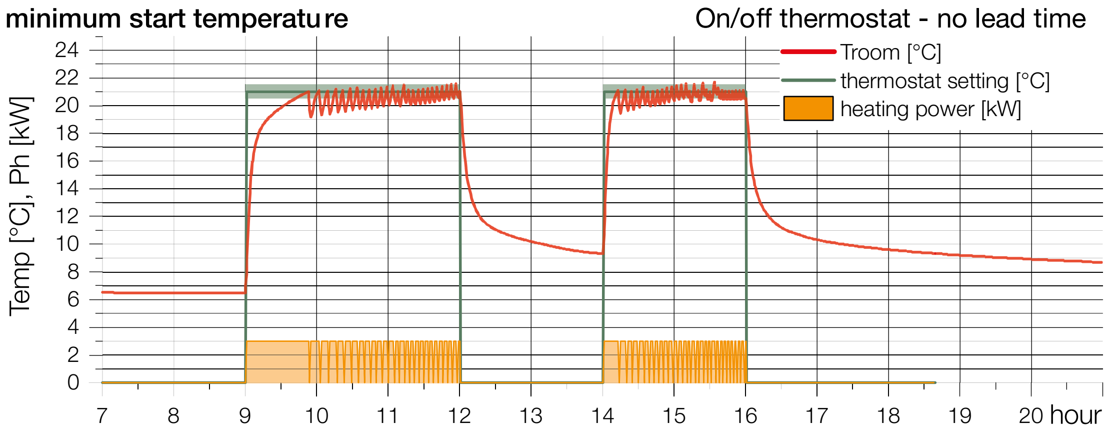

Figure 6.7 - on/off switching thermostat, no lead time

2 point thermostat with hysteresis - with fixed lead time:

In this simulation, a 2 point switching thermostat with a hysteresis of 0.5°C is modelled. In order to counteract the heating up delay, a 42 minutes heating lead time is applied. Figure 6.7 shows the 3 simulation results:

- the lower curve representing the heating from the lowest room temperature (minimum temperature) occurring in the simulation period (1/1 to 6/30),
- the result starting from the median morning starting temperature, and
- the result starting at the upper quantile morning temperature.

The room temperature is at the desired level for all starting temperatures, however for all but the lowest temperature the temperature gets to the desired level well before the required time. This leads to higher heating energy demand than necessary.

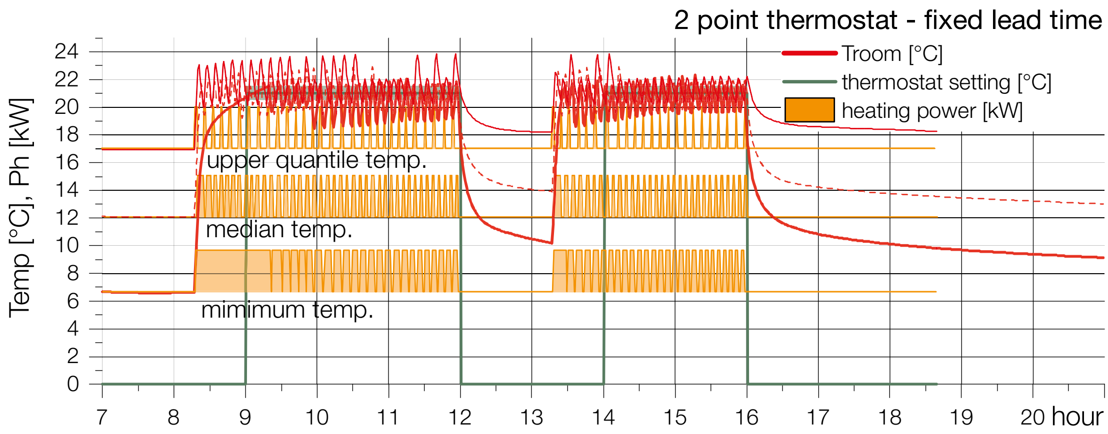

Figure 6.8 - 2 point switching thermostat, fixed lead time

2 point controller - variable lead time:

In this case, the controller is adapting the lead time using the look-up table which was established from the system step responses (see 'Step response and Look-up table' above). Depending on the actual room temperature, the controller establishes the necessary lead time for heating up and starts the heating process at the stipulated time minus the calculated lead time. This results in reaching the desired temperature always on time, but not before. This reduces the heating energy demand vs. previous results - see figure 6.9.

Starting temperatures in figure 6.9 as described above.

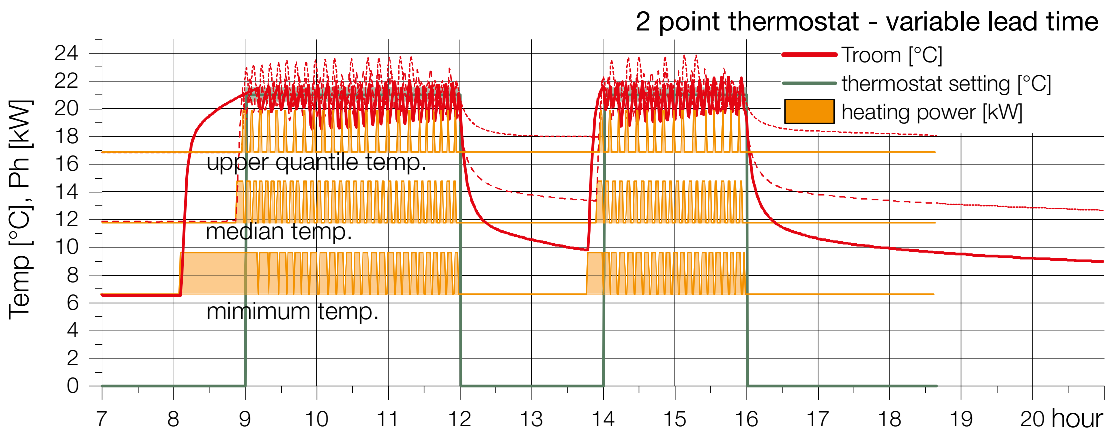

Figure 6.9 - 2 point switching thermostat, variable lead time

Results with radiator lag

The next paragraphs describe the simulations with implemented effect of a radiator lag:

- **when heating up**
  The heating energy is first used to heat up the radiator, which in its turn is providing heating energy to the room as a function of its surface temperature vs. room temperature.
- **when cooling down**
  The heat storage capacity of the radiator and the heating water content leads to lagging heat dissipation from the radiator. The heat dissipation again is a function of the surface temperature vs. the room temperature.
- **time constants** as the heating water does not need any time to be at its max temperature when the controller opens the valve, but reflects a thermal capacity when cooling down, the time constants for heating up and cooling down differ considerably. For heating up described time constants are in the range of 5 minutes, for cooling down of 30 minutes [41]. These mentioned time constants are used in the simulations with radiator lag effect.

Heating energy with thermal radiator inertia

The above mentioned timing effects are even stronger when the heating or response time of the system is longer. This is the case if the radiators are modelled in a way that their response time to input of heating energy is more like in reality. It is not only delaying the heating power of the radiator, but radiators also show different time constants for heating up and cooling down.

For heating up, hot water is immediately available from the heating system, so 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 water inside the radiator. [41] indicates considerable differences in time constants for heating and cooling down in the range of factor of 5 to 6.

To generate such thermal characteristics a PT1 subsystem was programmed in MATLAB®, giving the dynamically resulting heat energy to the EnergyPlus model. The mathematical representation of the radiator system description also changes the time constants, depending whether the radiator is heating up or cooling down.

On/off controller - no lead time - radiator lag

This case is similar as described under 'On/off switching thermostat - no lead time' above, but with the effect of the radiator lag. This additional system lag leads to prolonged periods for heating-up, in this case up to 53 minutes.

This case does not fulfill the requirement - reaching the room temperature at the right time - and is only retained for comparison reasons.

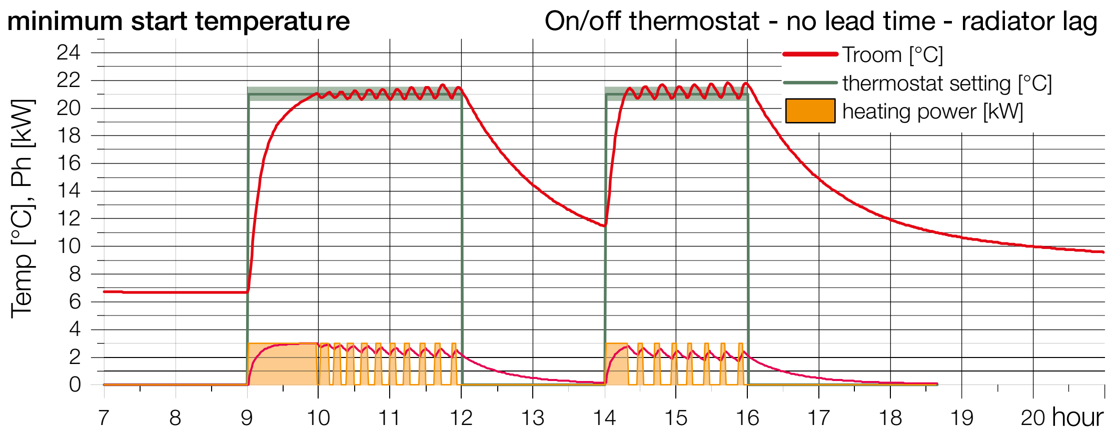

Figure 6.10 - on/off switching thermostat, no lead time, with radiator lag

2 point controller - with fixed lead time and with radiator lag

The set lead time of 53 minutes guarantees that for all conditions in the simulation period the room temperature will meet the desired levels at the given times. However, as described above, the desired room temperature will be reached too early for all initial room temperatures above the worst case temperature - see figure 6.11.

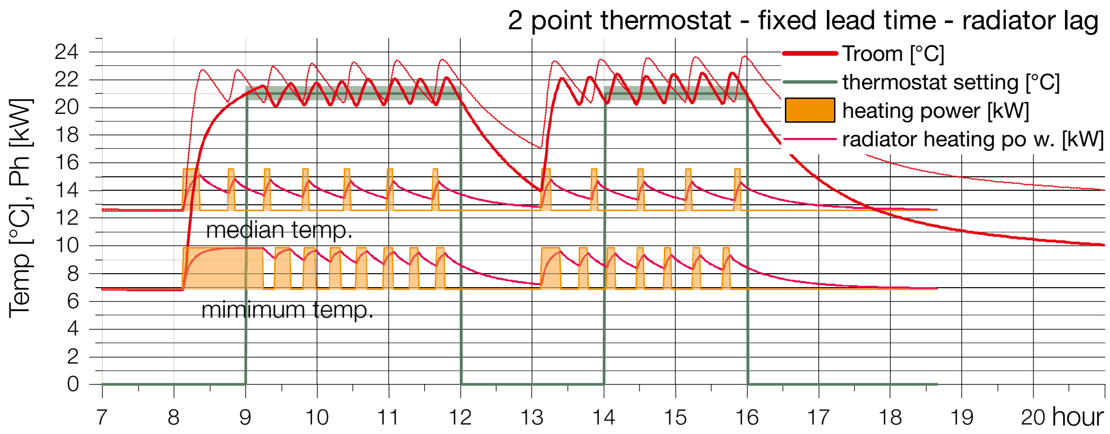

Figure 6.11 - 2 point switching thermostat, fixed lead time, with radiator lag

The dynamic responses get smoother due to the thermal capacity effect of the radiators. On the other hand, the over- and undercutting of the room target temperature (21°C ± 0.5°C) increases. This is due to the characteristics of the switching controller, which only acts when the measured temperature is getting outside of the hysteresis band. For measured temperatures slightly within the hysteresis band, no switching is initiated, leading to relatively strong over- and undershooting of the target within the following control time step of 1 minute (simulation step).

Moreover, slower dynamic system response leads to over- and under-temperature. This overshooting effect is stronger for higher initial room temperatures, which are caused by warmer ambient conditions. For these conditions, less energy is dissipated from the entire system, thus the effect of excess heating capacity effect once the energy supply is cut off, is stronger - also see figure 33 below.

2 point controller - with variable lead time and radiator lag

As described above, in this case a table look-up algorithm is used to derive a heating starting point as function of the actual room temperature in order to reach the desired temperature at the necessary set time. This method prevents the use of heating energy for non-scheduled thermostat periods.

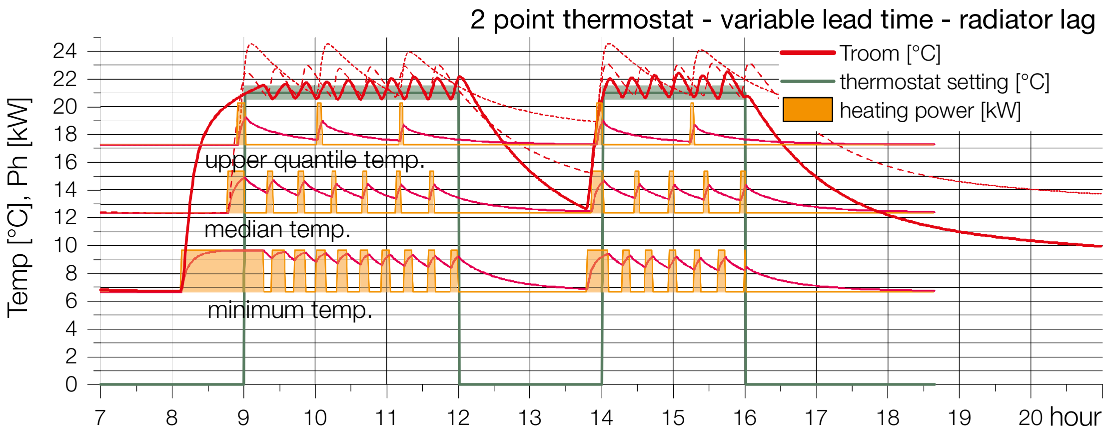

Figure 6.12 - 2 point switching thermostat, variable lead time, with radiator lag

Results and summary

Value comparison

Table 6.2 and table 6.3 show the heating energy demand for different starting temperatures in the room:

- the second part uses a fixed lead time to fulfil the requirements of thermostat setting and timing.
- the third part is showing the results of a table look-up strategy and the energy savings with respect to the fixed lead time algorithm.

The last columns in the respective tables show the heating energy demand within the entire simulation period from 1/1 to 6/30.

Results without radiator lag:

Table 6.2 - simple prediction, results without radiator lag

Results without radiator lag	2p controler - fixed lead time 42min					2 p controller - variable lead time				
	minimum temperature	lower quantile temperature	median temperature	upper quantile temperature	full period	minimum temperature	lower quantile temperature	median temperature	upper quantile temperature	full period
initial room temperature [°C]	6.5	9.6	11.8	16.9	na	6.5	9.6	11.8	16.9	na
heating-up difference [°C]	14.5	11.4	9.2	4.1	na	14.5	11.4	9.2	4.1	na
heating energy [kWh]	14.4	11.4	8.9	3.9	797	14.2	10.2	7.8	3.3	704
max lag to thermostat setting [min]	4	3	2	1	4	4	4	2	1	4
energy savings					6	98%	89%	88%	86%	88%

Especially for higher starting temperatures, the reduction of heating demand is obvious, reaching more than 14% for the specific days and showing savings of 11.6% for the entire period.

Results with radiator lag:

Table 6.3 - simple prediction, results with radiator lag

Results with radiator lag	radiator lag - fixed lead time 53min					radiator lag - variable lead time				
	minimum temperature	lower quantile temperature	median temperature	upper quantile temperature	full period	minimum temperature	lower quantile temperature	median temperature	upper quantile temperature	full period
initial room temperature [°C]	6.5	9.6	11.8	16.9	na	6.5	9.6	11.8	16.9	na
heating-up difference [°C]	14.5	11.4	9.2	4.1	na	14.5	11.4	9.2	4.1	na
heating energy [kWh]	17.3	13.9	11.5	4.8	1015	17	12.6	10.3	4.5	929
max lag to thermostat setting [min]	6	3	3	2	6	0	0	0	0	0
energy savings					6	98%	91%	90%	92%	91%

The heating demand for the case of radiator lag is higher than for the simple system before. This is due to the longer heating effect when cooling down. Nevertheless, the table look-up strategy with variable lead time leads to a potential heating demand saving of up to 10.4% for the median temperature and 9% for the full period.

Summary - simple predictive control

Above control strategies have shown that with relatively little information of the system response characteristics there are potential heating energy savings. In view of the simplicity of the system - e.g. 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 but may reduce the heating up period.

6.2 Model predictive control

6.2.1 Principle

The background of this method has been touched in the introduction section, this section presents a more detailed background, specifically related to the applied algorithm.

To 'predict' the responses of the thermal system a mathematical representation of this system - the model - is used. For this project, this is the reduced model, developed in chapter 4.1.3. This model is not a 1:1 representation of all sub-processes but gives a good relation of input signals, disturbance variables and the output of the thermal system of the reference room.

The MPC algorithm is based on a finite-horizon optimization. In this very case, to get an optimal input signal sequence (heating energy input) to get or maintain the output signal or predicted output signal (room temperature) within a targeted range (thermostat setting).

Output prediction

Virtually applying a known input signal, the system output over a finite period is calculated respectively predicted. This is done by taking the input signal and simulating the output variable in the reduced mathematical model, leading to a forecast of the output variable. In this case this is giving a prediction for the room temperature, taking into account the applied input signal (heating energy) and other disturbance variables (weather, gains, occupancy).

Optimal input signal - optimization

With a numerical minimization algorithm and by minimizing a cost function (e.g. heating energy, temperature deviation) an optimal input signal can be generated. The optimization process can be done by various methods and algorithms as e.g. quadratic programming. For the nature of the limits and boundary conditions of this project, a pattern search method was selected for the minimization process to calculate an optimal heating energy supply.

Apart from selecting the optimization method a target function has to be defined. The target function returns a value which is a function of

- the deviation of the predicted output from the target value - difference of room temperature to thermostat setting
- the amount of input - the amount of heating energy supplied
- the prediction horizon - the time of following the output prediction into the future

In the optimization process, the input signal - the heating energy supply - is varied to obtain the lowest result value of the target function. This optimal result represents an input sequence (heating power over future time) which, applied to the model will result in an optimal fulfilment of the target criteria as specified in the target function.

Forward control of real system

As the mathematical model used in the optimization represents the thermal dynamics of the real system (reference room) it can be deducted that the application of such input sequence to the real system would also lead to optimal results for the given criteria of the target function. That is, for the reference room, the optimal heating input sequence would optimally lead to the desired result of

- maintaining the room temperature within the thermostat setting (target temperature and timing), and
- using a minimum of heating energy to do so

This derived optimal input signal is applied to the system in a form of an open loop control.

Feedback control of the system

The process described so far is a forward control only, without taking into account any disturbance factors or other system deviations from the target state (e.g. opening of windows).

The described process of prediction and optimization is repeated every process time step. With updated and actual output and disturbance parameters, the actual situation is taken into account. The newly optimized input sequence is applied at the next time step. So, in every step usually only the initial element of the input sequence is applied before the entire sequence will be re-evaluated/optimized, and the initial step of the new input sequence is applied to the system. This process of re-evaluation under consideration of the actual parameters is in fact establishing the characteristics of a feedback system.

The described model predictive algorithm hence is a combination of a forward control with a feedback control by its iterative nature.

Prediction and control horizon

For the model predictive control process the predictive horizon defines how far into the future the model output is forecasted. The control horizon defines as to how far the input control sequence is optimized. The control horizon can be shorter than the prediction horizon. A long control horizon requires longer optimization calculations as the number of possible outputs per time step need to be optimized.

As described before, the optimization process is iterated, with every new iteration the actual parameters of states, disturbance variables if available and output measurements are updated and used for the new optimization process. The newly derived input sequence replaces the previous one.

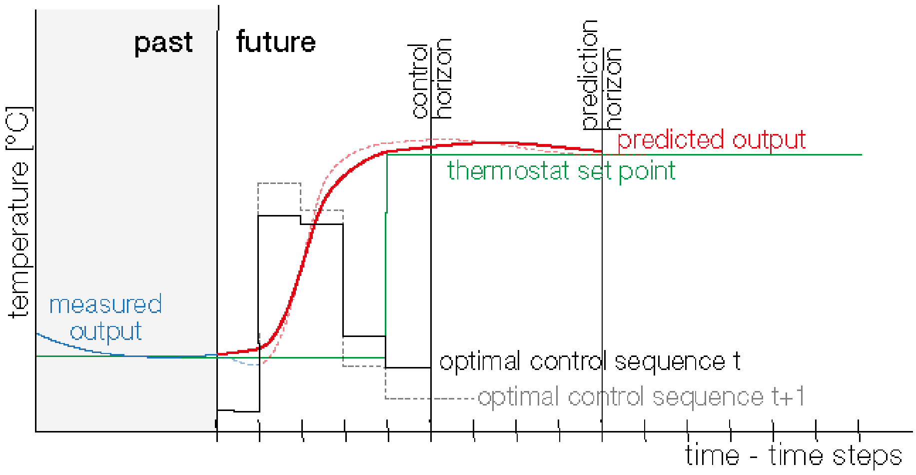

Figure 6.13 - model predictive control

Implementation details

This sub-chapter will give some project specific details on the implementation of the model predictive control algorithm.

The controller is implemented in MATLAB®; the input variables are

- the simulation results provided by EnergyPlus
- 'future' input parameters as ambient temperature, solar- and occupancy gains, adjacent temperature (T_{adj}) and sol-air temperature (T_{solair}) are available to the MATLAB® algorithm (data file)
- actual and future thermostat settings and thermostat status indicating the active thermostat and the thermostat during the night setback period (data file)
- the values of the states of the mathematical model from a state space observer (see below), necessary to define the initial conditions for the prediction process.

Prediction and control horizon

The specified horizons are in multiples of the simulation time steps, that is in units of minutes. The control input consists of 1-10 different variables (function of time) for optimization. For the co-simulation, the optimization is done for 3 variables (u(t1), u(t2), u(t3)) for calculation time reasons. The three control variables refer to periods of 10, 20 and 30 minutes, thus covering a control horizon of 60 minutes (see figure 6.14). The prediction horizon is set to 60 minutes as well. In view of the dynamics of the system these horizons seem sufficient. The first element of the input vector trajectory is then applied to the system.

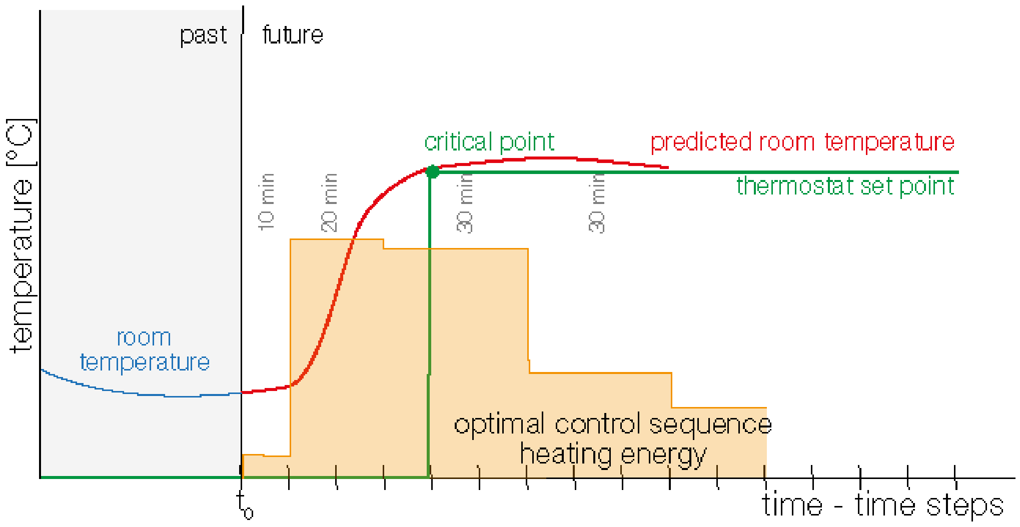

Figure 6.14 - model predictive control - application

The optimization process for input vector u is repeated every 3 minutes. For this next step the actual measurement parameters as well as sensor parameters are used, thus updating the prior conditions. The input vector u is again calculated by pattern search optimization with respect to the target function (4.14). The iteration gives a new input vector, again the first element is applied to the system (see figure 6.15)

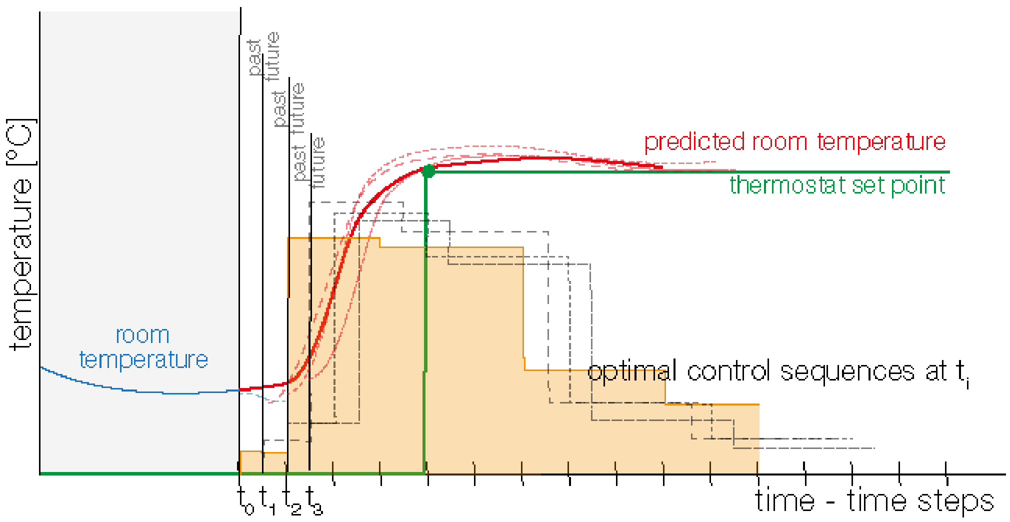

Figure 6.15 - model predictive control - iterations

Target function

The optimization process is varying the input variables to reach a minimum of the target function (6.1).

$$f_{target} = f_{wu} * \sum_{i=1}^{contrh} P_{h,i} + f_{wdev} * \sum_{j=1}^{predh} f_{penalty} * \left\| (T_{target} - T_{room})_j \right\| \qquad (6.1)$$

f_{wu} weighing factor for heating input

P_h heating power

f_{wdev} weighing factor for temperature deviation parameter

$f_{penalty}$ penalty function for temperature deviation magnitude

$contrh$ control horizon

$predh$ prediction horizon

The target function (function 6.1) takes into consideration

- the **heating energy input**, summarized over the control horizon, and
- the **deviation of the room temperature** from the target temperature (thermostat setting). The deviation norm is calculated as squared temperature deviation, multiplied with a penalty term. The penalty term is lower when the room temperature stays within the target temperature ± the specified tolerance, and selected higher for room temperatures beyond the tolerance limits. This was chosen to force the temperature within the tolerance limits, but allow 'floating' within the tolerance band.
  The tolerance limits are set differently, depending whether the thermostat is active (stringer penalty terms) or whether the thermostat is in a setback period (low penalty terms). The reason for this setting is that the system should be left in a free running mode while the thermostat is not active (21°C), but get the temperature within the inactive period to reach the targeted temperature at the beginning of the active thermostat period.

State observer

The prediction procedure in the MPC optimization process requires initial values for the states. For the used mathematical model these states are the room temperature Ti and the state temperatures linked to virtual heating end envelope temperatures. The virtual temperatures are not available, so the concept of a state observer was implemented (Luenberger observer, figure 6.16).

This concept uses the differences of the actual measured state(s) - in the underlying case this is the room temperature only - and the calculated outputs of the mathematical representation. In this representation all states are available, their values can be used. The difference of these output vectors is fed back into the Luenberger observer. With the input from this feedback loop the states of the mathematical system representation are controlled towards a fit of the two output signals. This allows to read state variables values. As described before, the states do not represent actual physical parameters, so the observed states do not represent and measurable quantities either, but can be used to estimate the initial values for the prediction process.

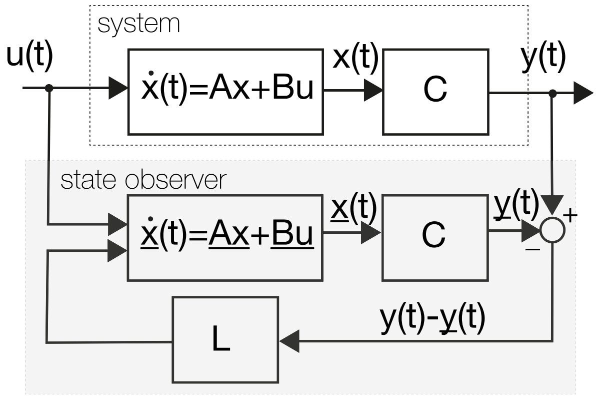

Figure 6.16 - state-space observer

General simulation conditions

Unless otherwise stated in the respective subchapter, the boundary conditions for the simulations for the subchapter 'Model Predictive Control' are

- simulation period 1/1-6/30, for this section the actual control is limited to 4 representative days representing
  - minimum temperature, lowest initial temperature: 6.5°C on 2/6
  - the median temperature: 11.8°C on 2/22
  - the upper quantile temperature: 16.9°C on 4/14.
- model predictive control (MPC)
- no electrical gains, no occupancy gains
- thermostat schedule: workdays 9:00-12:00 21°C, 14:00-16:00 21°, all other times free running (no thermostat setting)
- available sensor/forecast data
  - ambient $T_{amb}=T_a$ temperature per weather file
  - adjacent Temperature $T_{adj}=T_b$ from simulation results of staircase/hallway model (see chapter 4.2)
  - T_{solair} sol-air temperature (no solar gains through transparent envelope)
- simulation time step 1 minute

- simulation for entire period free running mode
- 5 days before selected days for controller analysis, simulation reheating by switching controller
- 24h on the selected day, simulation with specified controller.

6.2.2 Results - model predictive control

Results without radiator lag

On/off switching thermostat - fixed lead time

This simple controller simulation, representing a commonly used controller type, describes the reference case, the results for the other controller types will be compared against this configuration.

Different from before, the switching hysteresis is 0.2°C. This value will be kept for the simulation of switching thermostats throughout this subchapter; this temperature band has been selected to reduce the over- and undershoots as shown in figure 6.17.

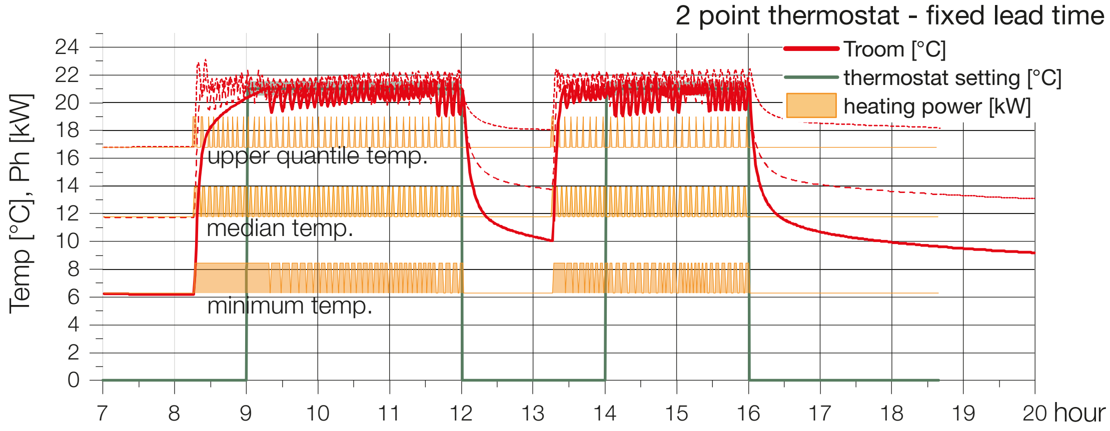

Figure 6.17 - 2 point switching thermostat, fixed lead time

The resulting heating energy demand of course is not optimal, the fixed lead time for all initial temperatures leaves room for improvement.

2 point thermostat - variable lead time

As discussed in the previous chapter. one step to reduce the heating energy demand is to adapt the lead time for heating-up. The controller is adapting the lead time using the look-up table which was established from the system step responses (see ' Step response and Look-up table ' above). Depending on the measured room temperature, the controller establishes the necessary lead time for heating up and starts the heating process at the stipulated time minus the calculated lead time. This results in reaching the desired temperature always on time, but not before.

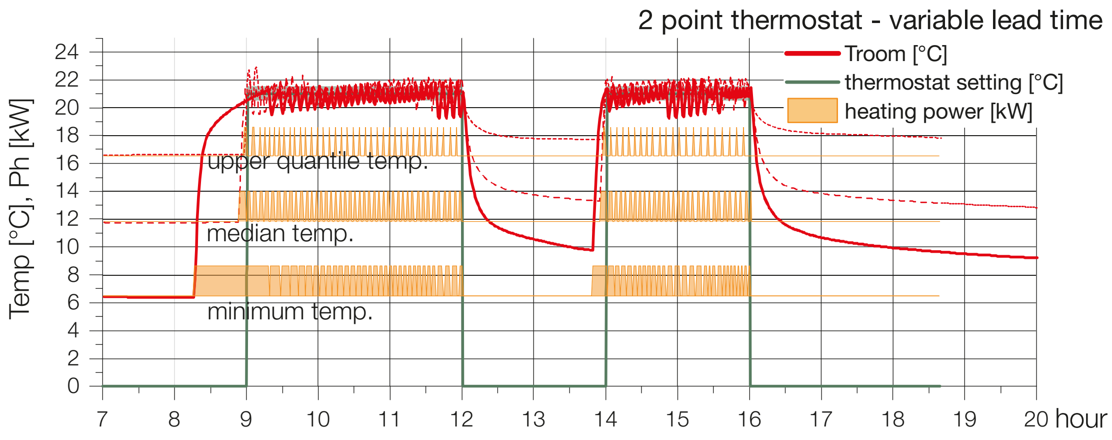

Figure 6.18 - 2 point switching thermostat, variable lead time

PI-controller - variable lead time

The PI controller - with a proportional and integral control parameter - represents a more complex control algorithm than the switching control (see above). This simulation setup also uses look-up tables for adapting the staring time for the heating-up process to reach the requested thermostat setting at the stipulated time.

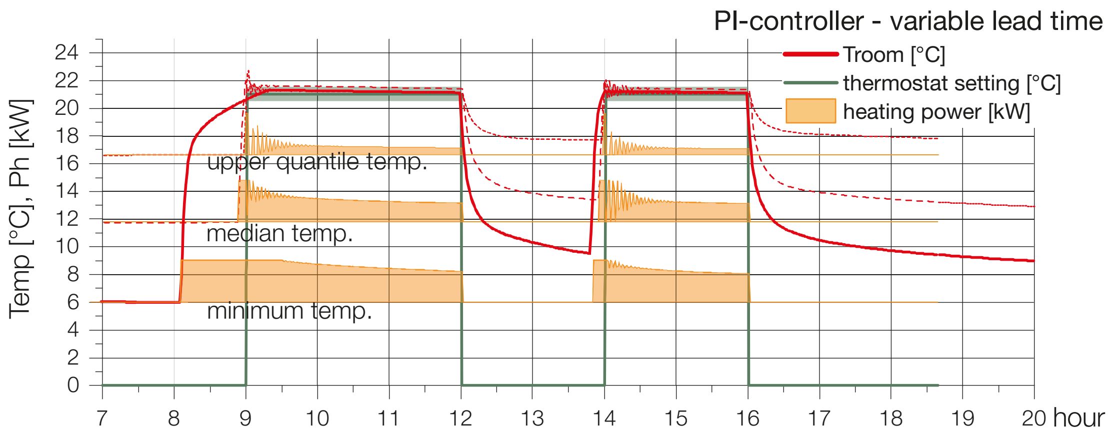

Figure 6.19 - PI-controller, variable lead time

The PI-controller is not switching between two output states - full power on, or no power applied - but has an analogue output in the range of 0...3000W.

This feedback control algorithm results in a smoother temperature trend, the resulting temperature stays closer to the thermostat setting.

Model predictive controller

The model predictive controller, as described above, is a more complex algorithm. It combines a

- forward control with an optimized system input sequence
- feedback control through the iterative nature of the algorithm and the updating of the optimal solution based on the actual target value

The model predictive algorithm does not require any look-up table to optimize the starting point for heating-up. This functionality is implemented in the controller algorithm by evaluating the mathematical model representation.

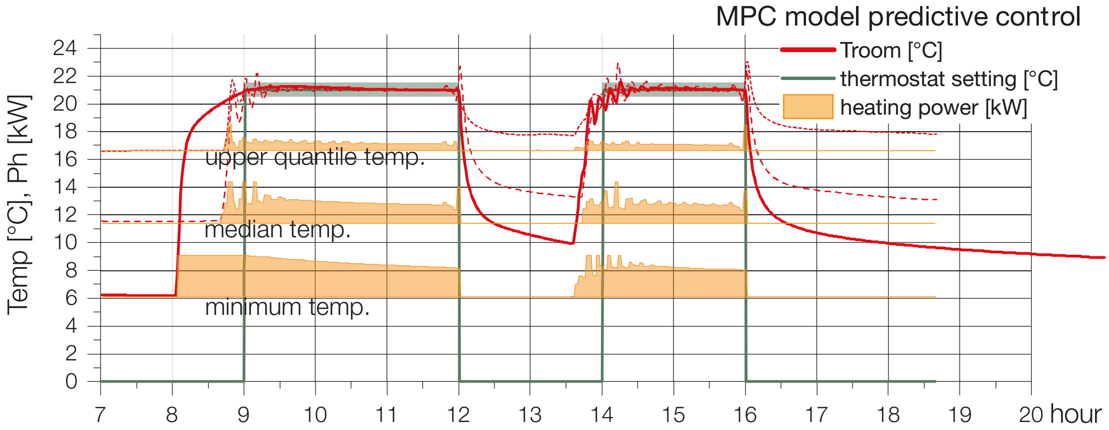

Figure 6.20 - model predictive control

The disturbances at the beginning of the heating periods originates in differences between the initial part of the system response of the real system and the mathematical representation. This difference is indicating a slightly slower temperature increase of the reduced model, thus requesting heat energy to start. The real system (EnergyPlus simulation model) is reacting slightly faster, which in turn results in a 'throttling back' of the heating power.

Results with thermal radiator inertia

On/off switching thermostat - fixed lead time

As described before, this model is used as reference model for the comparison of results.

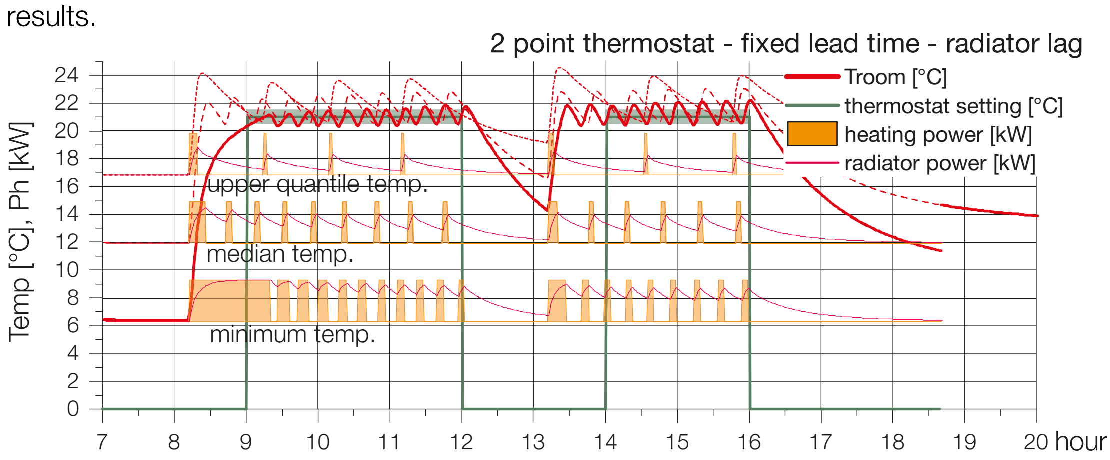

Figure 6.21 - 2 point switching thermostat, fixed lead time, with radiator lag

The thermal inertia of the radiators leads to smoother dynamic responses. However, the overshooting of the room target temperature increases. When the switching controller switches the heating energy supply off, the hot radiator continues to release heating energy, thus the room temperature keeps increasing beyond the thermostat setting. There is no undercutting as the radiator provides the effective heating energy to the room much faster (see chapter 'Radiator dynamics').

The temperature overshooting is stronger for higher initial room temperatures, which are going hand in hand with warmer ambient conditions. For these conditions, less energy is dissipated from the entire system, thus the effect of excess heating capacity effect of the radiator inertia is stronger.

2 point thermostat - variable lead time

switching hysteresis 0.2°C

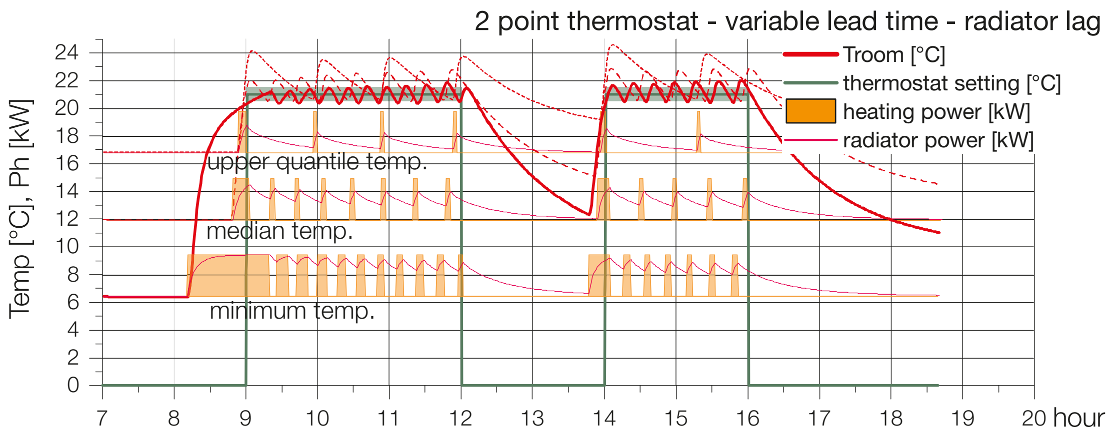

Figure 6.22 - 2 point switching thermostat, variable lead time, with radiator lag

PI-controller - variable lead time

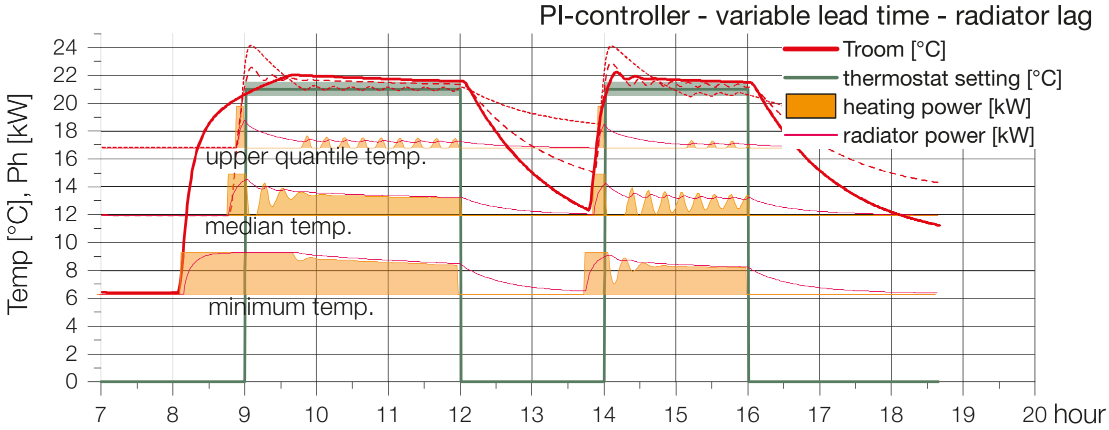

Figure 6.23 - PI-controller, variable lead time, with radiator lag

The higher room temperature over a longer period is due to the integral control parameter. It is overcompensating the proportional error.

The overshooting at the beginning of the thermostat setting period is due to the radiator lag effect.

Model predictive controller

By evaluation of the mathematical model, representing the room dynamics as well as the radiator inertia, the principle model predictive control strategy is 'designed' to adjust for effects as the added radiator lag.

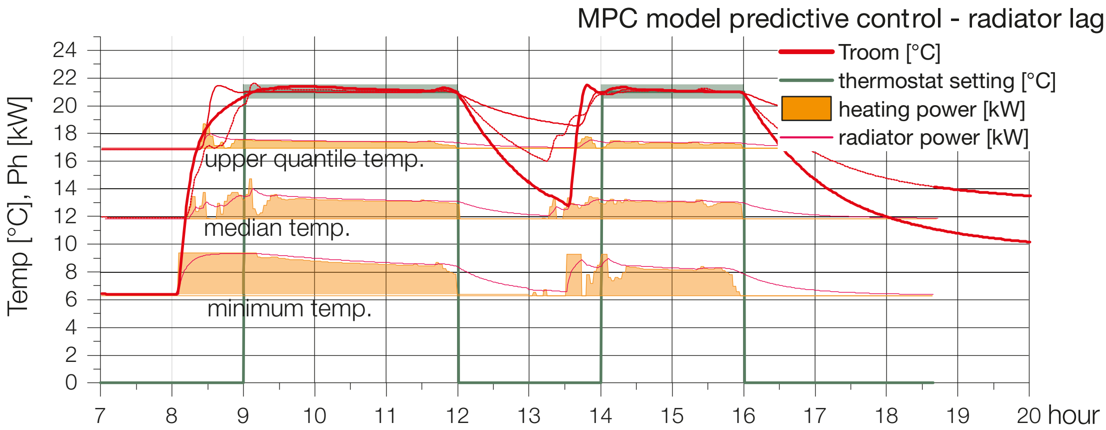

Figure 6.24 - model predictive control, with radiator lag

The results show a relatively smooth temperature trend, which however can show some more disturbances due to numerical reasons and discontinuous optimization results.

Results and summary

Value comparison

Table 6.4 and table 6.5 show the heating energy for the different starting temperatures in the room, the first table 6.4 without radiator lag, the second table 6.5 with the effect of radiator lag:

- The first part of the table refers to a 2point switch with fixed lead time and serves as reference of heating energy demand for the 24 hours of the specific day.
- The second part shows the 2 point switch, but with variable lead time by a look-up table.
- The third part is showing the results of the simulation with an analogue PI-controller with variable heating start.
- The last sub-table refers to a model predictive control.

Results without radiator lag

Table 6.4 - results without radiator lag

Results without radiator lag	2p cont. - fixed lead t.				2p cont - variable lead t.				PI cont. - variable lead t.				Model Predictive Cont.			
	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
initial room temperature [°C]	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9
heating-up difference [°C]	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1
heating energy [kWh]	15.2	12.0	9.5	3.9	14.3	10.4	8.1	3.2	15.1	10.9	8.5	3.1	15.4	11.3	8.6	3.1
max lag to thermostat setting [min]	5	3	2	1	5	3	3	1	0	0	0	0	3	5	4	2
relative heating power [%]					94%	87%	85%	81%	100%	91%	89%	79%	101%	94%	91%	80%

The results are given for 2point switching controller with fixed lead time (first block), 2 point switching controller with variable lead time (2nd block), PI controller (3rd block) and the model predictive controller (4th block). The lines indicate:

- initial room temperature: the temperature before the heating process towards the target temperature of 21°C starts
- heating up difference: difference between starting temperature and target temperature of 21°C
- heating energy: necessary heating energy for the time span of a full day
- maximum lag time to thermostat setting: measures a time delay the room temperature is getting to the desired target temperature
- relative heating power: shows the heating power demand with respect to the first data block

Especially for higher starting temperatures, the reduction of heating demand is obvious, reaching more than 20% in case of higher initial room temperatures.

Results with radiator lag

Table 6.5 - results with radiator lag

Results with radiator lag	2p cont. - fixed lead t.				2p cont - variable lead t.				PI cont. - variable lead t.				Model Predictive Cont.			
	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
initial room temperature [°C]	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9
heating-up difference [°C]	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1
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
max lag to thermostat setting [min]	3	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0
relative heating power [%]					94%	90%	89%	88%	98%	91%	86%	67%	96%	91%	84%	65%

The heating demand for the case of radiator lag is higher than for the simple system before.

As expected, especially for higher initial temperatures, savings in the supplied heating energy can be shown. Under the assumption that

- all parameters are set for an optimal heating starting point,
- optimal look-up table,
- mathematical model with very good fit to the EnergyPlus model,

it would be expected that there are no savings for the case of the lowest initial room temperature. From the results (tables 6.4 and 6.5) 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 the predictive control strategies show that there are potential energy saving potentials. The results also show that the dominant savings can be realized in the heating-up phase. 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.

6.3 Data/Sensor settings

In this section, the impact of available sensor data and future data (forecasts, extrapolations, etc.) on potential heating energy savings are evaluated.
The data/sensors in question are:

- T_{amb} ambient temperature sensor/data
- T_{adj} adjacent temperature (hallway) sensor/data
- T_{solair} data from effects of ambient temperature, wind speed, solar irradiation, absorptance of surface
- P_s gains from solar irradiation through transparent areas
- P_g gains from use of electrical equipment (power supplies, PC's) and occupancy gains

The sensor values in the co-simulation have an impact on the prediction process in the model predictive control algorithm only. For that process estimated or forecasted disturbance parameters are used in the prediction of the system behaviour.

For this simulation it is assumed, that the future values are not only known, but also fit 100% to the available data. In reality, sensor values and measurements would not be 100% accurate, they would allow to extrapolate statistical estimates of future impact values. In this case an estimation error would be expected. For simulations this could be approximated by superposing a statistical error disturbance, however, the underlying simulations were done without statistical disturbances.

For the EnergyPlus simulation itself all current data - that is data measured at the respective simulation time step - is available. But no future aspects can be used in the thermal simulation process.

The availability of data or sensor readings respectively is controlled by the input vector u(t) to the mathematical model (equation 6.2).

$$\begin{aligned} x(t+1) &= A * \mathrm{x(t)} + B * u(t) \\ \mathrm{y(t)} &= C * x(t) + D * u(t) \end{aligned} \tag{6.2}$$

Parameters values which are considered 'available' are set to the data (past & future). If they are simulated as 'not available', the values are replaced either by zero value or by the average (in the total period from 1/1 to 6/30) of that value.
With this method, forecasted sensor data can be 'switched on or off'.

Simulation settings

The following data settings were simulated for their impact on heating energy savings (see table 6.6). The selection groups are done by

- temperature sensors: ambient temperature T_{amb}, adjacent temperature T_{adj} and sol-air temperature T_{solair},
- gains: electrical and occupational gains, and
- solar gains: through transparent areas and via T_{solair}.

Table 6.6 - data/sensor settings

Setting No.	data/sensor settings — sensor settings / sensors	T ambient [°C]	Tsol-air [°C]	T adjacent [°C]	solar gains [W]	electrical gains [W]	electrical gains2 [W]	occupancy gains [W]
0	no data	0	0	0	0	0	0	0
1	sensor setting, previous simulations	1	1	1	1	0	0	0
2	ambient temperature	1	Tamb	0	0	0	0	0
3	ambient, sol-air, adjacent temperature	1	1	1	0	0	0	0
4	avg ambient, sol-air, adjacent temp.	avg	avg	avg	0	0	0	0
5	electrical gains (power supplies)	0	0	0	0	1	0	0
6	electrical gains	0	0	0	0	1	1	0
7	electrical & occupancy gains	0	0	0	0	1	1	1
8	all data	1	1	1	1	1	1	1
9	all avg data	avg	avg	avg	avg	avg	avg	avg

General simulation conditions

The boundary conditions for the simulations for the subchapter 'Data/Sensor Settings' are

- simulation period 1/1-6/30, for this section the actual control is limited to 4 representative days representing
  - lowest initial temperature: 6.5°C on 2/6
  - the median temperature: 11.8°C on 2/22
  - the upper quantile temperature: 16.9°C on 4/14.
- MPC control
- thermostat schedule: all days 9:00-12:00 21°C, 14:00-16:00 21°, all other times free running (no thermostat setting)
- electrical gains - power supplies: 60W, always on
- electrical gains . PC's, 2x250W see occupancy schedule
- occupancy: all days 9:00-12:00 2 persons, 14:00-16:00 4 persons, activity level 100W
- simulation time step 1 minute

- simulation for entire period free running mode
- 5 days before selected days for controller analysis, simulation reheating by switching controller
- 24h on the selected day, simulation with model predictive controller.

6.3.1 Results and summary

Comparison results of sensor settings

For comparison of the results, the relative power saving best shows the effect.

Table 6.7 - results simulations data/sensor settings - general settings

general settings	no sensor data (0)				sensor, previous sims. (1)				all data/sensors (8)				all avg data/sensors(9)			
	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
initial room temperature [°C]	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9
heating-up difference [°C]	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1
heating energy [kWh]	12.2	8.6	5.5	1.4	12.1	8.6	5.6	1.4	12.1	8.2	5.4	0.7	12.0	8.6	5.5	1.3
max lag to thermostat setting [min]	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0
relative heating power [%]					99%	100%	101%	97%	99%	96%	97%	52%	99%	100%	100%	94%

Table 6.8 - results simulations data/sensor settings - temperature data

temperature data	no sensor data (0)				ambient temperature (2)				amb, adj, sol-air temp (3)				average temps (4)			
	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
initial room temperature [°C]	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9
heating-up difference [°C]	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1
heating energy [kWh]	12.2	8.6	5.5	1.4	12.2	8.6	5.7	1.3	12.2	8.6	5.6	1.3	12.2	8.5	5.7	1.4
max lag to thermostat setting [min]	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
relative heating power [%]					100%	100%	102%	95%	100%	100%	101%	95%	100%	99%	103%	98%

Table 6.9 - results simulations data/sensor settings - gains data

gains data	no sensor data (0)				electrical gains (6)				electr. & occup. gains (7)			
	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
initial room temperature [°C]	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9
heating-up difference [°C]	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1
heating energy [kWh]	12.2	8.6	5.5	1.4	12.2	8.4	5.6	1.2	12.1	8.3	5.3	0.8
max lag to thermostat setting [min]	0	0	0	0	1	1	0	0	1	1	0	0
relative heating power [%]					101%	97%	102%	88%	100%	96%	96%	56%

Note that, as discussed in context of previous results (see explanation to tables 6.4 and 6.5 above), the conclusion can be reached that the expected inaccuracy for the shown heating demand would be in the range of ±2% to ±4%.

As all relative energy savings - with one exception - in tables 6.7 to 6.9 are within this inaccuracy band, no tendency or significant change can be detected.

Especially for the days with higher heating differences - the higher heating temperature difference being a result of lower ambient temperatures, higher dissipated energy, and higher energy input - the difference of required heating power with respect to available sensor data is negligible and/or within the inaccuracy bandwidth. This stands true for the results in all tables (6.7, 6.8 and 6.9).

For days with relative high ambient temperature, the heat dissipation is lower, temperature overshoots due to radiator lag are more pronounced. In these cases, additional heating through gains - electrical and occupancy - add to that effect. After all, these gains at full occupancy account for 4*100W occupancy, 2*250W PC's 60W power supplies, which in turn corresponds to 32% of the nominal heating power of the radiators. The model predictive control can anticipate such future heating effect and therefore reduce the heating power supplied to the radiators. Hence the reduction in heating power by significant a percentage (see table 6.9).

Temperature sensors as for ambient temperature, adjacent temperature and virtual sol-air temperature as well as solar irradiation have no significant impact on the savings of heating energy.
The reason for that lies in the slow dynamics compared to the relatively fast dynamics of the heating itself. Whereas the heating and similar impact types as occupancy gains are working in response times in the range of minutes to 1 hour (see figure 6.3 and table 6.1), the time constants and response to changes in ambient and adjacent temperature and solar irradiation on walls, are in a magnitude of several hours to more than a day (see table 6.10).
Thus, with the fast responses of the heating system, the controller easily compensates the effect of these disturbance parameters without excess heating power. No advantages can be drawn from the prediction process. The disturbances are so to speak, corrected away before their long term effect influences the faster system.

A different situation would be expected with heating systems with slower response times. This would be in the case of heating with big thermal capacities involved as e.g. tiled stoves or floor heating systems. For floor heating systems time constants can be much higher. With such system as actuator, the controller needs to anticipate more. For such systems, data or sensors measuring 'slower' disturbance, are expected to show higher impact on potential energy savings.

Table 6.10 - heating systems time constants
source [41]

Time constants - heating systems

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

Another reason to the low impact of sensor forecast data is the selection of the 'critical' point the results are compared against. That is the criterion that the room temperature has to be within the thermostat setting at the beginning of the heating time (thermostat schedule). This makes the model predictive control less flexible in reducing power supply, e.g. in expectation of the coming electrical and occupancy gains. If this criterion is not applied, the results of the different are not directly comparable. It also would be necessary to define penalty parameters, e.g. on user satisfaction, for lower temperatures than set at the thermostat.

6.3.2 Systems with slow thermal response

To underline above statements on fast vs. slow thermal system responses, and to show potential influence of data availability, it is necessary to leave the frame of the reference room.

For thermal simulation of the slower actuator/heating system, the 'test room', identical to the reference room, is 'equipped' with a virtual floor heating system. The floor heating is built in a wet structure, the big thermal mass lead to response time constants of 90 min for heating up, and 640 minutes for cooling down (see table 6.10, [38].
Other changes were made to the parameters governing the model predictive process, to account for the slower system dynamics:

- preheating in model predictive control for 5 days, preheating before with switching controller
- model predictive process till one day after the reference days
- iterative optimization for input sequence every 10 minutes
- control step width of 30, 60, 60, 120, 120 and 240 minutes
- time constants of heating system 90/640 minutes for heating up/cooling down.

Comparison results of sensor settings - floor heating

For comparison of the results, the relative power saving best shows the effect.

Table 6.11 - results simulations data/sensor settings - general settings

floor heating general settings	no sensor data (0)				sensor, previous sims. (1)				all data/sensors (8)				all avg data/sensors(9)			
	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
initial room temperature [°C]	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9
heating-up difference [°C]	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1
heating energy [kWh]	23.3	17.4	13.2	3.7	22.9	17.5	12.5	3.2	21.4	17.0	12.1	2.5	22.5	17.4	12.3	3.1
max lag to thermostat setting [min]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
relative heating power [%]					98%	100%	94%	86%	92%	98%	92%	69%	96%	100%	93%	85%

Table 6.12 - results simulations data/sensor settings - temperature data

floor heating temperature data	no sensor data (0)				ambient temperature (2)				amb, adj, sol-air temp (3)				average temps (4)			
	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
initial room temperature [°C]	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9
heating-up difference [°C]	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1
heating energy [kWh]	23.3	17.4	13.2	3.7	22.6	17.8	12.2	3.6	23.0	17.9	12.7	3.2	22.0	16.8	12.3	3.2
max lag to thermostat setting [min]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
relative heating power [%]					97%	102%	92%	97%	99%	103%	96%	85%	94%	96%	93%	86%

Table 6.13 - results simulations data/sensor settings - gains data

floor heating gains data	no sensor data (0)				electrical gains (6)				electr. & occup. gains (7)			
	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
initial room temperature [°C]	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9	6.5	9.6	11.8	16.9
heating-up difference [°C]	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1	14.5	11.4	9.2	4.1
heating energy [kWh]	23.3	17.4	13.2	3.7	21.2	16.8	11.8	3.3	21.9	16.4	12.8	3.5
max lag to thermostat setting [min]	0	0	0	0	0	0	0	0	0	0	0	0
relative heating power [%]					91%	96%	89%	90%	94%	94%	96%	94%

Due to the much longer prediction horizon and the optimization involving more input parameter steps (6), the expected inaccuracy for the shown heating demand is higher than for previous simulations and probably is in the range of ±4% to ±6%.

For the slower floor heating system the advantageous data availability is for the slower changing impact factors as ambient temperatures, sol-air temperature and adjacent temperature (table 6.12).
For the interior gains, the forecasted data on electrical gains shows positive results for potential heating energy savings.

As above, the effects are visible for the heating systems running in their part load operational range. This is the case for higher ambient temperatures. Under these conditions the gains, as electrical and occupational gains and solar irradiation, have a higher relative impact. With model predictive control these algorithms can achieve some energy savings by anticipating these disturbance effects.

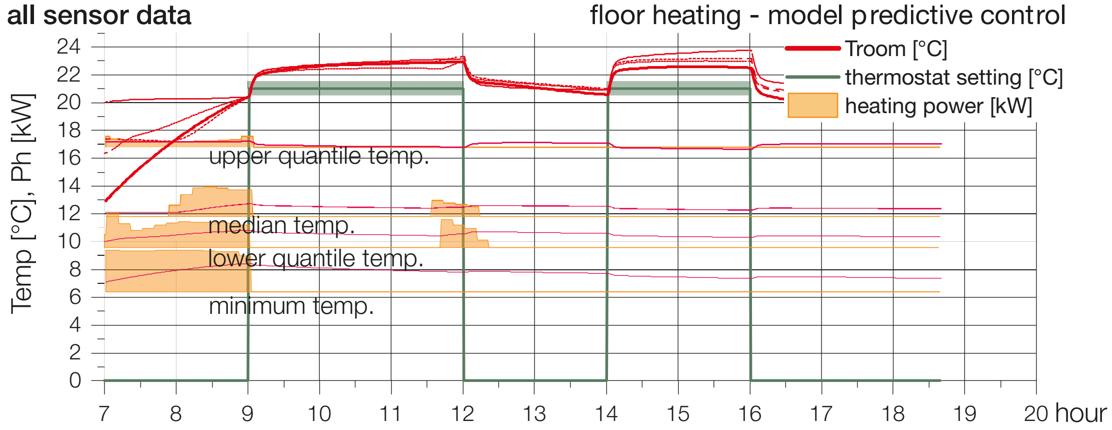

Figure 6.25 - model predictive control - floor heating - all sensor data

Figure 46 and 47 show the supply of heating energy for set up with all sensor data forecasts available (figure 6.25) , and without any no sensor data forecasts (figure 6.26).

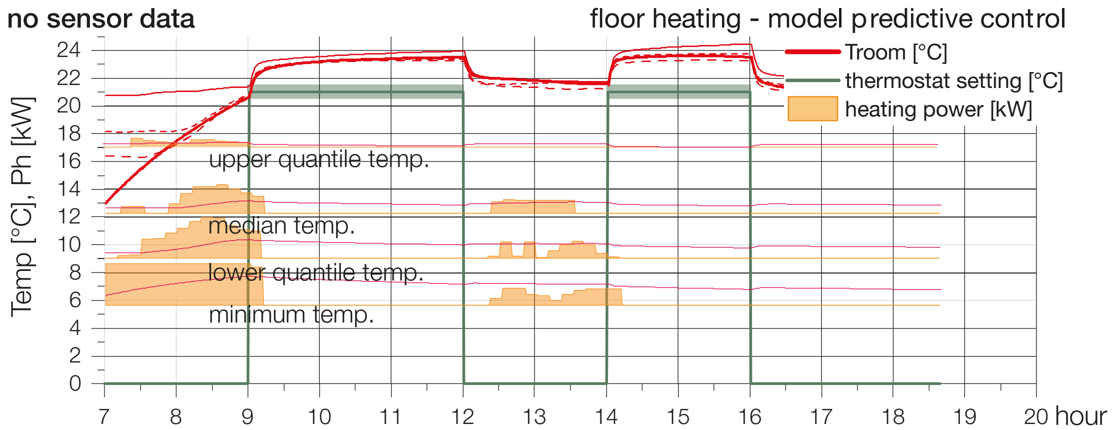

Figure 6.26 - model predictive control - floor heating - no sensor data

The anticipating behaviour can be seen for the supply of the afternoon's period; the available forecasts allow a much more sensitive and anticipating energy control.

It can be seen for all cases however, that the additional heating effect due to electrical and occupancy gains cannot be eliminated. The reason is that the system is forced to pass the critical point at the specified time, that is the room temperature at the beginning of the thermostat setting period has to be at the setting temperature. Therefore the electrical and occupancy gains cannot be eliminated by anticipation as they cut in right after that critical time. The heating of the room cannot be slowed down quickly enough, the thermal mass of the floor heating system keeps on heating at previous level.

As discussed before, when this target function criterion would be changed including an 'allowance term', the gains could be anticipated. Additional energy savings would be the result. However the results of a predictive system with such target function term are not directly comparable to other solutions as e.g. the switching controllers.

The expected energy savings would be expected to be a function of the 'softness' of such allowance terms, that is, if more deviations are allowed, more energy can be saved. But at the same time, the time of complying with the thermostat settings would be reduced.

This effect would also appear with systems with faster heating dynamics, however the faster response time allows to act on disturbances as electrical and occupancy gains quicker, leading to the room temperatures to come down to targeted values very fast.

7 SUMMARY OF RESULTS

7.1 Lead time control - simple 'predictive' control

In the first controller simulation set switching controllers without/with lead time control were investigated. For the controllers simple 2 point switching characteristics with temperature tolerance of ±0.5°C were applied, and the simulation was run for a half year period of 1/1 to 6/30 2015.

Considerable heating power savings could be shown using a heating schedule algorithm with variable lead time versus a fixed lead time (see table 7.1).

A control with fixed lead time was used as the reference for the comparative evaluation of the heating demand; this 2point switching with fixed lead time was also used as reference in the simulations for model predictive control in chapter 7.2 (detailed in chapter 6.1).

Table 7.1 - heating energy - simple predictive control

Results 1st simulation setup	2p controler - fixed lead time 42min					2 p controller - variable lead time				
	minimum temperature	lower quantile temperature	median temperature	upper quantile temperature	full half year period	minimum temperature	lower quantile temperature	median temperature	upper quantile temperature	full half year period
results without radiator lag										
heating energy [kWh]	14.4	11.4	8.9	3.9	797.5	14.2	10.2	7.8	3.3	703.6
relative heating power [%]	100%	100%	100%	100%	100%	98%	89%	88%	86%	88%
results with radiator lag										
heating energy [kWh]	17.3	13.9	11.5	4.8	1015.3	17.0	12.6	10.3	4.5	928.7
relative heating power [%]	100%	100%	100%	100%	100%	98%	91%	90%	92%	91%

7.2 Model predictive control

For this 2nd controller simulation set, a PI-controller and model predictive controller (MPC) with analog controller outputs was simulated.

For comparison two 2 point switching control was added, however with a temperature tolerance of ±0.2°C (chapter 7.1).

A side result shows that for the given simulation setup, the reduction of the tolerance band from ±0.5°C (first controller simulation set, 6.1, 7.1) to ±0.2°C leads to an increase of the heating demand by approximately 4%.

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 - the days with

- **minimum** starting **temperature** for heating up,
- **lower quantile temperature**,
- **median temperature** and
- **upper quantile temperature**.

The results are shown in the following tables, table 7.2 for a system without radiator dynamics and table 7.3 for the simulation with radiator lag effect. Especially for the transition period considerable savings - for systems with radiator lag up to 35% - could be achieved.

Table 7.2 - model predictive control, without radiator lag

	2p control - fixed lead time				2p control - variable lead t.				PI control - variable lead time				Model Predictive Control			
estimated 6 months heating power results without radiator lag	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]	15.2	12.0	9.5	3.9	14.3	10.4	8.1	3.2	15.1	10.9	8.5	3.1	15.4	11.3	8.6	3.1
relative heating power [%]	100%	100%	100%	100%	94%	87%	85%	81%	100%	91%	89%	79%	101%	94%	91%	80%

Table 7.3 - model predictive control, with radiator lag

	2p control - fixed lead time				2p control - variable lead t.				PI control - variable lead time				Model Predictive Control			
estimated 6 months heating power results with radiator lag	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%

Based on the first controller simulation set (table 7.1), which was run for the selected days as well as for the entire half year period, the heating energy demand for the half year period was estimated - see table 7.4 and figure 7.1. The half year period results reflect the potential savings impact of the selected days and hence show reduced heating energy savings. Nevertheless, for the realistic case of a system with radiator lag savings of 12% are shown.

Table 7.4 - heating energy for model predictive control - half year estimate

	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%

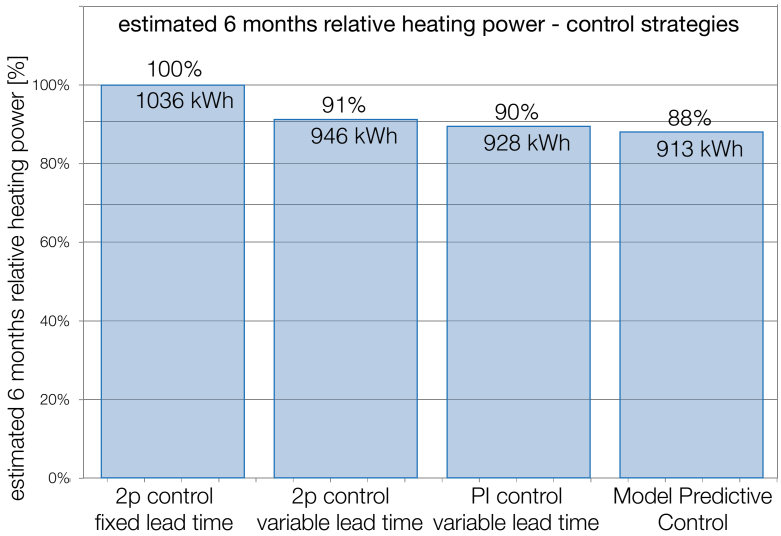

Figure 7.1 - heating energy for model predictive control, with radiator lag

7.3 Data/sensor settings

Systems with radiator heating

In the 3rd controller simulation set a model predictive control algorithm was simulated with different sensor/data settings. As described in detail in chapter 6.3, different sensor/data setups were compared for the selected days - the days with minimum starting temperature for heating up, lower quantile temperature, median temperature and upper quantile temperature. All simulations run taking the radiator dynamics (radiator lag) into consideration. For the detailed results see tables 6.7 to 6.9.

Link of model predictive control and the sensor/data settings simulation results

The results of the model predictive control algorithms (2nd setup, chapter 7.2) represent one base case - sensor/data of previous simulation (1) - for a link to the simulations with different sensor/data settings.
However, there is no direct comparison of the results, as the simulations with different sensor/data settings were done with occupancy related gains (occupancy and electrical gains), whereas the base simulations for different control strategies (e.g. model predictive control) was performed without these gains.

This specific context, together with the simulation results of the selected days is shown in graph 7.2.

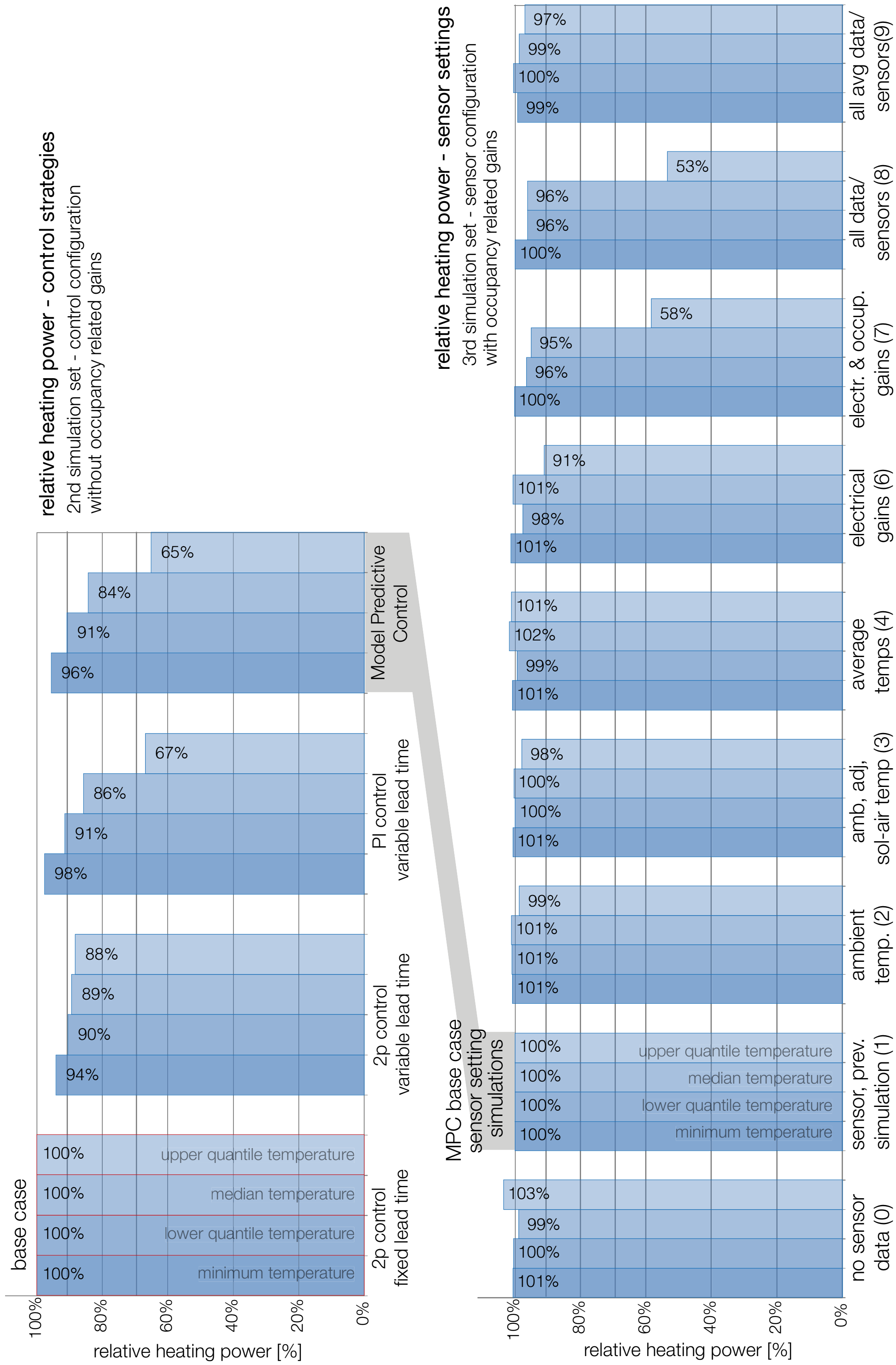

Figure 7.2 - model predictive control & sensor/data settings

For the following comparisons of the various sensor/data settings results (see tables 7.5 and 7.6 and graphs 7.3 and 7.4), the relative heating power is shown with reference to a 'no sensor data'-setting; this setting represents the absence of any sensor/data as opposed by the 'all data/sensors' configuration where the complete data set (see table 6.6) is available.

The heating demand for the 6 months period was estimated from the results of the specified days as described for the 2nd simulation setup. The resulting estimates are shown in table 7.5 and figure 7.3.

The resulting lower heating demand stems from the occupancy related gains - occupancy and electrical appliances (PC's) - which were introduced for this 3rd simulation configuration.

The saving effects of the different sensor/data settings is lower due to the faster dynamic characteristics of the room temperature control than of the slower disturbance factors as weather etc. (see chapter 6.3.1).

Table 7.5 - heating energy for different sensor/data settings

estimated 6 months heating power sensor settings with electrical and occupancy gains	no sensor data (0)	sensor, prev. sim. (1)	ambient temperature (2)	amb, adj, sol-air temp (3)	average temps (4)	electrical gains (6)	electr. & occup. gains (7)	all data/sensors (8)	all avg data/sensors(9)
heating energy [kWh]	576	574	578	575	577	571	551	549	570
relative heating power [%]	100%	100%	100%	100%	100%	99%	96%	95%	99%

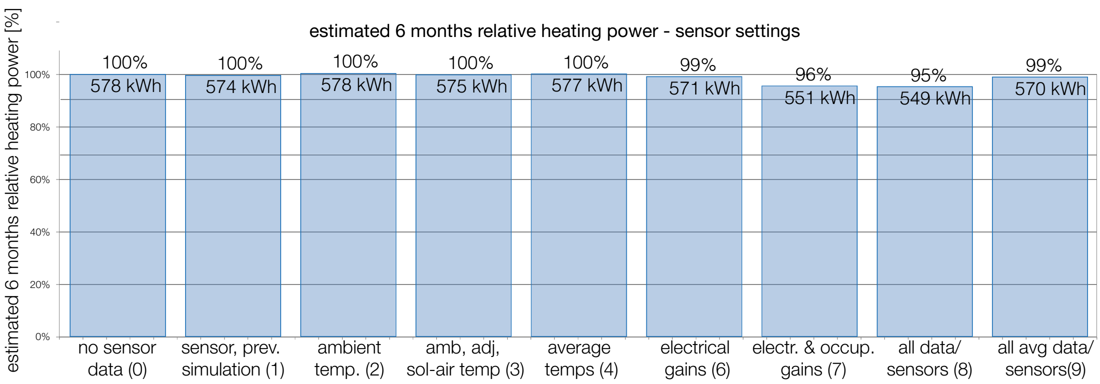

Figure 7.3 - heating energy for different sensor/data settings

Systems with slow thermal response

Beyond the actual reference room system, a hypothetical floor heating with longer time constants and therefore much slower dynamic characteristic was added to the simulations (see chapter 6.3.2). For detailed results see tables 6.11 to 6.13.

The estimated results for the half year period were derived as described above. As expected for such slower thermal systems, potential energy savings could be identified for availability of more environmental data (weather, occupancy). For other definitions of target temperature/time requirements (see description chapter 6.3.2) these potential saving effects, especially for occupancy related gains, could be higher.

The in average much higher temperatures in the room cause a generally much higher energy demand; this higher temperature is a result of the slow cooling down dynamics and the heating effect of the big thermal mass represented by the floor construction.

Table 7.6 - heating energy for different sensor/data settings - floor heating

estimated 6 months heating power sensor settings - floor heating with electrical and occupancy gains	no sensor data (0)	sensor, prev. sim. (1)	ambient temperature (2)	amb, adj, sol-air temp (3)	average temps (4)	electrical gains (6)	electr. & occup. gains (7)	all data/sensors (8)	all avg data/sensors(9)
heating energy [kWh]	1198	1166	1169	1180	1129	1102	1134	1102	1150
relative heating power [%]	100%	97%	98%	99%	94%	92%	95%	92%	96%

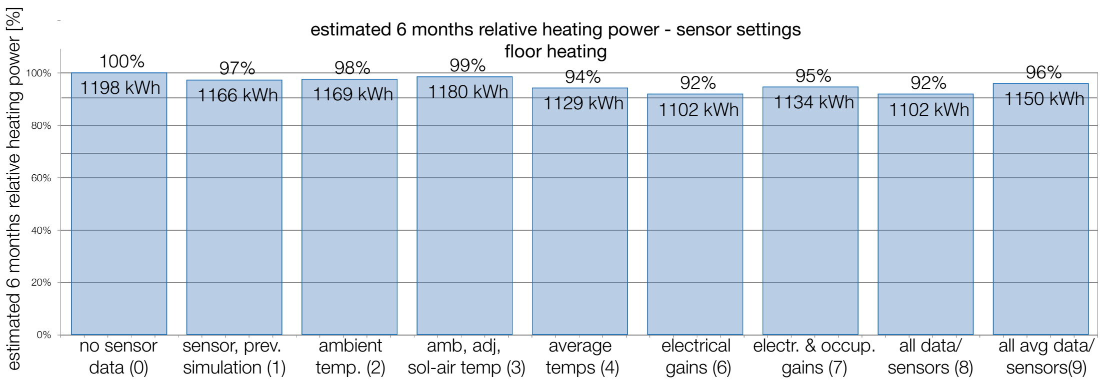

Figure 7.4 - heating energy for different sensor/data settings - floor heating

8 CONCLUSION

This work has identified potential heating energy savings for the conditions in a selected building. Several thermostat strategies - from simple switching to model predictive control algorithms - were simulated. Different setups of the heating dynamics, without and with the effect of thermal inertia of the radiators, were put to test.

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 11-14% for systems without radiator lag, 9-10% for systems with radiator lag and for warmer ambient conditions, could be shown. The lead time control is working with predictions of the system behaviour/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%, also 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.

The simulation of different data/sensor setups - that is availability of forecasts for certain disturbance parameters - has shown the dependency of saving potentials on the thermal characteristic of the system.
Systems with fast dynamic actuator characteristics show no improvement with available forecast data of parameters with a slow dynamic effect. Slow disturbance impacts are compensated by the temperature controller, available forecast data of such impact parameters do not yield an energy saving potential.

For heating systems with slower response time, as e.g. floor heating, a positive effect of available data to anticipate slower external impacts could be shown. Available forecast data on ambient and adjacent temperature indicate heating energy saving potential.

8.1 Outlook

The expected increase in energy cost on one side and technology developments on the other will offer a wide field for research and will continue to drive the development to achieve further energy savings.

In context of this work several interesting topics arose, amongst those were:

- study 'allowance terms' of target function to fulfill comfort requirements and the countertrade of further potential energy saving
- extend to cooling and specifically to natural cooling
- real time system identification (disruptive parameter development, open windows,...) and control algorithms to react to such disturbances
- study the influence of parameters for the model predictive control algorithm as prediction and control horizon, with the background of the heating system dynamics and in view of applications in embedded control with its limitations.
- study the effect of effect of statistical occupancy on the results of model predictive control
- interconnected systems and zones, e.g. in an office building, control in a network, and potential energy savings beyond the single thermal zone

INDEX

List of figures

List of equations

List of tables

LITERATURE

[1] Amara F., Agbossou K., Cardenas A., Dubé Y., Kelouwani S. 2015. Comparison and Simulation of Building Thermal Models for Effective Energy Management. Smart Grid and Renewable Energy, 2015, 6, 95-112, Published Online April 2015 in SciRes..

[2] Bacher P., Madsen H. 2011. Identifying suitable models for the heat dynamics of buildings. Energy and Buildings 43 (2011) 1511–1522.

[3] Barcelli D., Bemporad A. 2009. Decentralized Model Predictive Control of Dynamically-Coupled Linear Systems: Tracking under Packet Loss . Proceedings of the 1st IFAC Workshop on Estimation and Control of Networked Systems, Venice, Italy, September 24-26, 2009.

[4] Batista A.P., Freitas M.E.A., Jota F.G. 2014. Evaluation and improvement of the energy performance of abuilding's equipment and subsystems through continuous monitoring. Energy and Buildings 75 (2014) 368–381.

[5] Bengea S., Adetola V., Kang K., Liba M. J., Vrabie D., Bitmead R. , Narayanan S. 2011. Parameter Estimation of a Building System Model and Impact of Estimation Error on Closed-Loop Performance. 2011 50th IEEE Conference on Decision and Control and European Control Conference (CDC-ECC) Orlando, FL, USA, December 12-15, 2011.

[6] Bernal W., Behl M., Nghiem T.X., Mangharam R. 2012. MLE+: a tool for integrated design and deployment of energy efficient building controls. Proceedings of the Fourth ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings, pp. 123-130. ACM, 2012..

[7] de Wit M. . Hambase, Heat Air Moisture model for Building and System Evaluation. http://sts.bwk.tue.nl/hamlab/readers/bouwsteen100.pdf, Accessed 6/5 2015.

[8] Froisy J.B. 2006. Model predictive control—Building a bridge between theory and practice. Computers and Chemical Engineering 30 (2006) 1426–1435.

[9] Gondhalekar R., Oldewurtel F., Jones C.N. 2013. Least-restrictive robust periodic model predictive control applied to room temperature regulation. Automatica 49 (2013) 2760–2766.

[10] Hafner I. . Möglichkeiten der Co-Simulation mit dem Building Controls Virtual Test Bed für den Bereich der objektorientierten Modellbildung physikalischer Systeme. Diplomarbeit Tu Wien.

[11] Jimenez M.J. , Madsen H. 2008. Models for describing the thermal characteristics of building components. Building and Environment 43 (2008) 152–162.

[12] Jimenez M.J., Madsen H., Andersen K.K. 2008. Identification of the main thermal characteristics of building components using MATLAB. Building and Environment 43 (2008) 170–180.

[13] Kleimingera W., Mattern F., Santini S. 2014. Predicting household occupancy for smart heating control: A comparative performance analysis of state-of-the-art approaches. Energy and Buildings 85 (2014) 493–505.

[14] Kristensen N.R., Madsen H., Jørgensen S.B. 2004. Parameter estimation in stochastic grey-box models. Automatica 40 (2004) 225 – 237.

[15] Liu S., Henze G.P. 2005. Calibration of Building Models for Supervisory Control of Commercial Buildings. Ninth International IBPSA Conference, Montréal, Canada.

[16] Mahdavi A., Tahmasebi F. 2012. An Optimization-based approach to recurrent calibration of building performance simulation models. Reykjavik, Iceland, ECPPM2012 eWork and eBusiness in Architecture, Engineering and Construction..

[17] Morari M., Lee J.H. 1999. Model predictive control: past, present and future. Computers and Chemical Engineering 23 (1999) 667–682.

[18] Nannei E., Schenone C. 1999. Thermal transients in buildings: development and validation of a numerical model. Energy and Buildings 29 1999. 209–215.

[19] Nghiem T.X. . MLE+: a Matlab-EnergyPlus Co-simulation Interface. http://txn.name/mleplus.html, Accessed 30.8.2015.

[20] Niels R.J., Kristensen R., Bacher P.,Kloppenborg J., Madsen H. 2013. Grey-box modeling of the heat dynamics of a building with CTSM-R. http://ctsm.info/pdfs/examples/building2.pdf, Accessed 5.8.2015.

[21] Pang X. Bhattacharya P., O'Neill Z., Haves P., Wetter M., Bailey T. 2011. Real-time Building Energy Simulatuion Using REnergyPlus and the Building Controls Virtual Testbed. Proceedings of Building Simulation 2011: 12th Conference of International Building Performance Simulation Association, Sydney, 14-16 November.

[22] Prívara S., Cigler J., Vána Z., Oldewurtel F., Sagerschnig C., Záceková E. 2013. Building modeling as a crucial part for building predictive control. Energy and Buildings 56 (2013) 8–22.

[23] Renders G., Nuytten T., Saelens D. 2013. Robustness of Reduced-order Models for Prediction and Simulation of the Thermal Behavior of Dwellings. Proceedings of BS2013: 13th Conference of International Building Performance Simulation Association, Chambéry, France, August 26-28.

[24] Siyu Wu, Jian-Qiao Sun 2012. A physics-based linear parametric model of room temperature in office buildings. Building and Environment 50 (2012) 1-9.

[25] Taheri M. 2013. Optimization based calibration of a building thermal performance model. Masterarbeit TU.

[26] Wallace M., McBride R., Aumi S., Mhaskar P. , House J., Salsbury T. 2012. Energy efficient model predictive building temperature control. Chemical EngineeringScience69(2012)45–58.

[27] Wetter M. 2010. Co-simulation of building energy and control systems with the Building Controls Virtual Test Bed. Journal of Building Performance Simulation, 2010, 1–19, iFirst article.

[28] Yudong M. 2012. Model Predictive Control for Energy Efficient Buildings. Electronic Thesis and Dissertations UC Berkeley.

[29] Zakula T., Armstrong P.R., Norford L. 2014. Modeling environment for model predictive control of buildings. Energy and Buildings 85 (2014) 549–559.

[30] MATLAB®. mathworks.com/products/matlab/. Accessed 10.3.-15.9.2015

[31] MATLAB®. http://de.mathworks.com/help/matlab/learn_matlab/product-description.html. Accessed 10.3.-15.9.2015

[32] EnergyPlus Energy Simulation Software. http://apps1.eere.energy.gov/buildings/energyplus/. Accessed 10.3.-15.9.2015

[33] Genopt®. http://simulationresearch.lbl.gov/GO/. Accessed 10.3.-15.9.2015

[34] SketchUp, © 2015 Trimble Navigation Limited. http://www.sketchup.com/. Accessed 10.3.-15.9.2015

[35] OpenStudio®. https://www.openstudio.net/. Accessed 10.3.-15.9.2015

[36] MLE+ Toolbox. http://mlab.seas.upenn.edu/mlep/, Accessed 20.8.2015.

[37] 2009 ASHRAE® Handbook, fundamentals. American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc..

[38] Tado - product information. https://www.tado.com/at/heizungssteuerung-ersparnis, Accessed 5.10.2015.

[39] Ecubee - product information. https://www.ecobee.com/. Accessed 10.3.2015.

[40] Nest - product information. https://nest.com/. Accessed 10.3.2015.

[41] Wissensertes über Niedrigtemperatur-heizkörper. http://www.hydraulischer-abgleich.de/file/Niedrigtemperaturheizkoerper_DE_100907_web_Purmo.pdf, Accessed 15.9.2015.

[42] Korado - product information. www.korado.at, Accessed 5.8.2015.

[43] Building Controls Virtual Test Bed. https://simulationresearch.lbl.gov/bcvtb. Accessed 10.3.-15.9.2015

APPENDIX

A.1 Reference building/room/zone

A.1.1 Data

Position & Geometry:

The reference room is located on the roof of the main building of Vienna University of Technology (48.199°N, 16.369°E), staircase No 4, with a graphically derived orientation of 22.45°W vs. south (source Google Maps)

Room sensors:

Table A.1 - reference room - sensors

Adress	Type	Position
SR04CO2rH_01009222	Temp & rel humidity	ceiling center
SR04rH 0005726f	Temperature	next to door to tower
SR65TF 0006d5ea	Temperature	radiator left
SR65TF 0006d0fd	Temperature	radiator right
SR04rH 00057270	Temperature	hallway
SR04rH 00057258	Temperature	tower

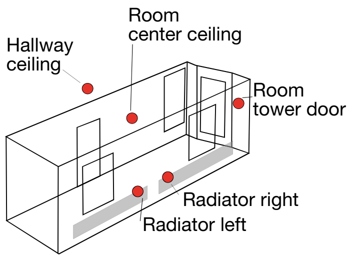

Figure A.1 - reference room - sensor positions

Weather sensors:

The weather data is obtained from logged data from the weather station, run by the Department of Building Physics and Building Ecology at the Vienna University of Technology .

Table A.2 - sensors weather station

Adress	Type	Position
WsThiesTemp1	ambient temperature	weather observation station on tower
WsTem1	ambient temperature	
WsRad1	solar irradiation	
WsSPN1GlobRad1	solar irradiation	
WsThiesWindSpeed1	wind speed	

Weather file

Average values for 2 ambient temperature readings and 2 solar readings, the relative humidity values, wind speed and direction were used to generate a weather file for further use as input to the EnergyPlus simulations.

The weather file in an .epw-format was generated from the above data set using the software Meteonorm

A.1.2 Reference model

Materials

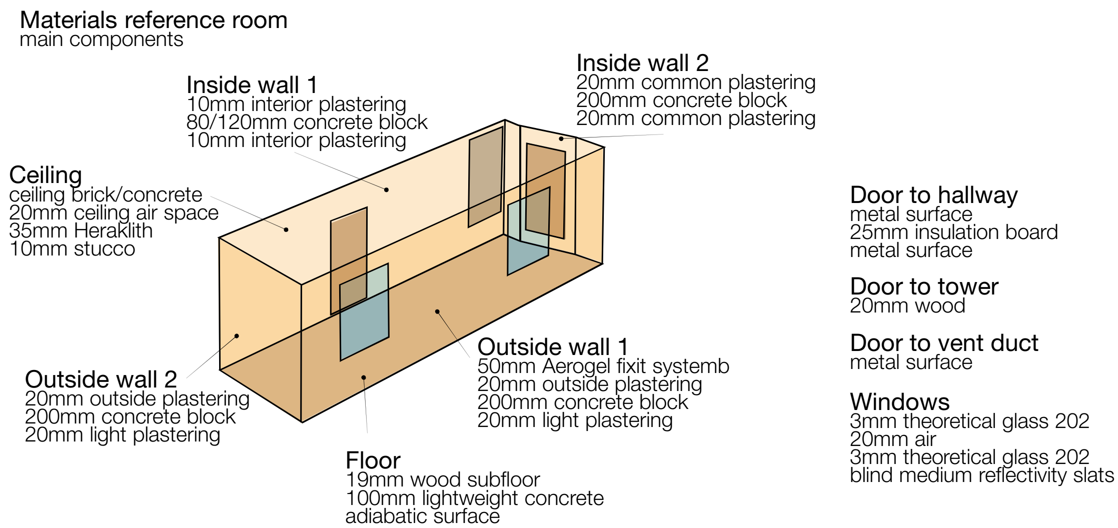

Figure A.2 - reference room - materials

Hallway and staircase

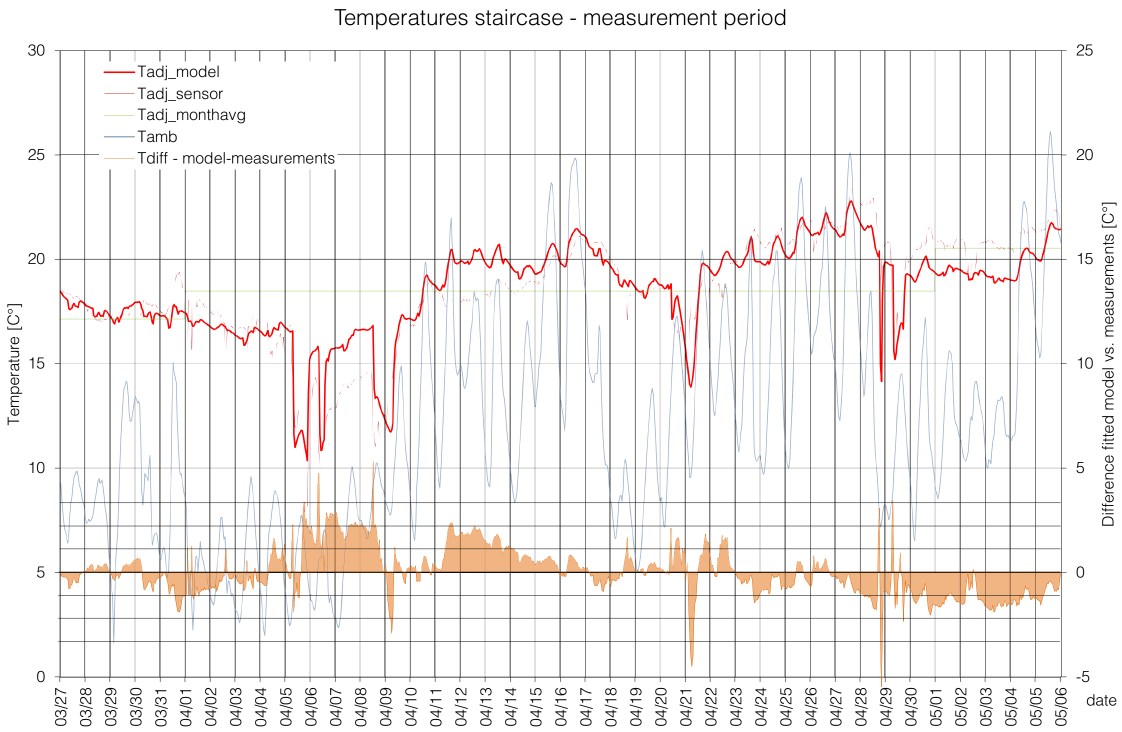

Figure A.3 - staircase model - fitting results

A.2 Reduced model

full state space description (equation A.1)

$$\frac{d}{dt}\begin{bmatrix} T_i \\ T_e \\ T_h \end{bmatrix} = \begin{bmatrix} -\frac{1}{R_{ie}C_i}-\frac{1}{R_{ih}C_i}-\frac{1}{R_{ia}C_i}-\frac{1}{R_{ib}C_i} & \frac{1}{R_{ie}C_i} & \frac{1}{R_{ih}C_i} \\ \frac{1}{R_{ie}Ce} & -\frac{1}{R_{ie}C_e}-\frac{1}{\mathrm{R}_{ea}C_e} & 0 \\ \frac{1}{R_{ih}C_h} & 0 & -\frac{1}{R_{ih}C_h} \end{bmatrix} * \begin{bmatrix} T_i \\ T_e \\ T_h \end{bmatrix} + \begin{bmatrix} 0 & \frac{A_w}{C_i} & 0 & \frac{h_g}{C_i} & \frac{1}{R_{ib}C_i} & \frac{1}{R_{ia}C_i} \\ \frac{1}{\mathrm{R}_{ea}C_e} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{h_h}{C_h} & 0 & 0 & 0 \end{bmatrix} * \begin{bmatrix} T_a \\ P_s \\ P_h \\ P_g \\ T_b \\ T_{solair} \end{bmatrix}$$

$$[y] = [1 \quad 0 \quad 0] * \begin{bmatrix} T_i \\ T_e \\ T_h \end{bmatrix} + [0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0] * \begin{bmatrix} T_a \\ P_s \\ P_h \\ P_g \\ T_b \\ T_{solair} \end{bmatrix}$$

(A.1)