CLIMA 2016 - proceedings of the 12th REHVA World Congress

volume 8

Heiselberg, Per Kvols

Publication date:
2016

Document Version
Publisher's PDF, also known as Version of record

A Building Model Framework for a Genetic Algorithm Multi-objective Model Predictive Control

K. Arendt[#1], A. Ionesi[#2], M. Jradi[#3], A. Singh[#4], M.B. Kjærgaard[#5], C.T. Veje[#6], B.N. Jørgensen[#7]

[#]*Center for Energy Informatics, University of Southern Denmark*
Campusvej 55, Odense, Denmark

[1]krza@mmmi.sdu.dk

[2]ai@mmmi.sdu.dk

[3]mjr@mmmi.sdu.dk

[4]asi@mmmi.sdu.dk

[5]mbkj@mmmi.sdu.dk

[6]veje@mmmi.sdu.dk

[7]bnj@mmmi.sdu.dk

Abstract

Model Predictive Control (MPC) of building systems is a promising approach to optimize building energy performance. In contrast to traditional control strategies which are reactive in nature, MPC optimizes the utilization of resources based on the predicted effects. It has been shown that energy savings potential of this technique can reach up to 40% compared to conventional control strategies depending on the particular building type. However, the effort needed to implement MPC in buildings is significant and often considered prohibitive. That is why until now fully-functional MPC has been implemented only in few buildings. The following difficulties hinder the widespread usage of MPC: (1) significant model development time, (2) limited portability of models, (3) model computational demand. In the present study a new model development framework for an MPC system based on a Genetic Algorithm (GA) optimization is proposed. The framework is intended to allow easy model adaptation for new buildings and fast simulations to meet the strict performance requirements of the GA optimization approach. This is achieved by the introduction of the generic zone model concept and the implementation of the Functional Mock-Up Interface, which is used to link the models with the MPC system. The framework was used to develop and run initial thermal and CO_2 models. Their performance and the implementation procedure are discussed in the present paper. The framework is going to be implemented in the MPC system planned to be deployed in chosen public and commercial buildings in Denmark and United States.

Keywords – building energy simulation; model development framework; model predictive control; functional mock-up interface; multi-objective optimization

1. Introduction

Buildings are responsible for about 40% of energy use in the developed countries. While the exact structure of the energy consumption in a building depends on the building's type and function, in most cases the majority of energy is used to maintain the indoor thermal comfort, visual comfort and air quality.

Currently, in most buildings the efforts to decrease the energy consumption are not well coordinated. Building heating, cooling, ventilation and lighting systems are controlled by separate control systems and the influence of building dynamics is usually disregarded. While all these efforts result in the energy reduction, potentially better results could be achieved by a fully integrated approach in which all building systems are managed by a single control system being able to predict the overall effect of their operation.

Such an integrated system is currently being developed within the COORDICY project [1], a strategic DK-US interdisciplinary research project for advancing ICT-driven research and innovation in energy efficiency of public and commercial buildings. The system, called Controleum [2, 3, 4], is responsible for choosing an optimal control strategy for all HVAC and lighting systems in the building based on the predicted future indoor conditions. Controleum analyzes each room separately. The time horizon can vary from several minutes to few days. The predictions are based on numerical simulations, performed for a number of possible control strategies in each of the rooms. The Genetic Algorithm (GA) was chosen as the main optimization technique. By definition, this kind of a system is considered as a Model Predictive Control (MPC) system.

In contrast to traditional control strategies which are reactive in nature, MPC adapts the strategy based on the expected indoor/outdoor conditions and predicted events. As an example a standard PID controller applies a change in system settings after a discrepancy between the setpoint and actual controlled parameter is found. An exemplary limitation of this approach is that it does not enable to take the advantage of building thermal dynamics. An MPC system, on the other hand, can find that an optimal strategy is to take some actions before the expected event, e.g. due the expected rise of the electricity price. An exemplary action could be a prior heat up of the indoor space and the utilization of the thermal mass during a price peak, or the adaptation of the ventilation rate to the expected pricing scheme. It has been shown that energy savings potential of this technique can reach up to 40% compared to conventional control strategies [5].

However, the effort needed to implement MPC in buildings is often considered prohibitive. Comparing to traditional control systems, which can be easily tuned without any knowledge about the building itself, MPC requires a lot of information and sensors in order to be effective. Models have to reflect the building structure, topology, material thermal properties,

system operation, occupancy, equipment and much more. Simulations require a weather forecast and occupancy predictions. Sensor readings are needed to set initial conditions in simulations.

Thus, until now fully-functional MPC has been implemented only in few buildings [6]. The main implementation difficulties are associated with the significant model development time and the limited portability of models. Additionally, some optimization techniques, like the Genetic Algorithm, require hundreds or thousands of simulations to choose the optimum control strategy, which puts an additional constraint on the model computational demand.

The present paper presents a building model framework for a Genetic Algorithm multi-objective Model Predictive Control system, being developed within the project COORDICY. The framework is intended to allow easy model adaptation for new buildings and fast simulations to meet the strict performance requirements of the GA optimization approach. This is achieved by the introduction of a generic zone model concept and the implementation of the Functional Mock-Up Interface [7].

Controleum is planned to be implemented in the chosen case study buildings in Denmark and United States. Three main candidates for the implementation are the OU44 building at the Odense Campus of the University of Southern Denmark (DK) and the Sudardja Dai Hall building at the University of Berkeley (USA).

2. Model Development Framework

Controleum performs the optimization on both the zone and the building level. Two kinds of building models are expected to be provided for each case study building: zone models, system models (HVAC, lighting). The aim of zone models is to predict the indoor environment parameters for a specified time horizon depending a chosen control strategy. The aim of system models is to calculate the energy consumption of each system and to check if the selected control strategy is viable to be applied.

It was decided to model zones separately rather than using a whole-building modeling approach. The separation of zones gives a capability to iterate over a single zone without the need to re-calculate all zones in a building. The model framework has to be flexible enough to enable a rough strategy selection for a longer time horizon and a subsequent refinement of the strategy in selected rooms for the short-term future. Controleum can operate on different time scales in differnet zones.

Each zone in a building is modeled using the generic zone model (GZM). The concept of GZM is that the number of models in a building should be reduced to minimum and each model should be simple enough to automatically read all input parameters from a Building Information Model

(BIM) or to enable automatized parameter estimation based on historical measurements. In other words, a single model is used to simulate all zones, and all information needed by the model to create an instance of a zone is supplied by the master environment (Controleum). All model parameters needed to instantiate a new zone are treated as model input parameters.

Since each model type needs different parameters, an additional translational layer around the model is needed to convert the available data into the usable inputs. For example a simple lumped model based on an RC thermal network is defined by resistors and capacitors representing building partitions. These parameters are calculated based on the dimensions and material parameters (thermal conductivity, specific heat capacity, density) of each layer. Depending on the structure of the model, each resistance/capacitance can represent one, two or all sourounding partitions. Alternatively these parameters can be estimated based on the historical measurements using one of the available techniques, for example the Unscented Kalman Filter [8]. Both methods, the direct calculation from BIM and the paremeter estimation, can be used interchangebly, depending on the available data. For example the parameter estimation may not provide reliable results if there is insufficient number of sensors in a room. On the other hand, the direct calculation from BIM relies on the BIM quality. A seamless switch between the methods based on the model accuracy should be implemented.

To enable such a level of flexibility, the model itself should be isolated from the code responsible for the preparation of input data, and a uniform interface should be formulated for the communication between the control system and the models. The Functional Mock-Up Interface (FMI) – an open, tool independent standard for exchange of simulation models [7] provides this flexibility. The standard specifies how to export a model to a Functional Mock-Up Unit (FMU) and how to communicate with the model. An FMU is a zip file containing a DLL library (with a model and possibly a solver) and an additional XML file describing the model and its variables.

The FMI is implemented in the Controleum system in a module called Model Manager (Fig. 1). The implementation is based on the javaFMI wrapper library [9], but introduces additional functionality needed by the Controleum system. Apart from a higher level of building-specific abstraction, the added functionality enables to query the model about its type (zone/system) and needed inputs, including the information about the source to be used to get the input data from (e.g. from sensor readings, from weather forecast, from control system).

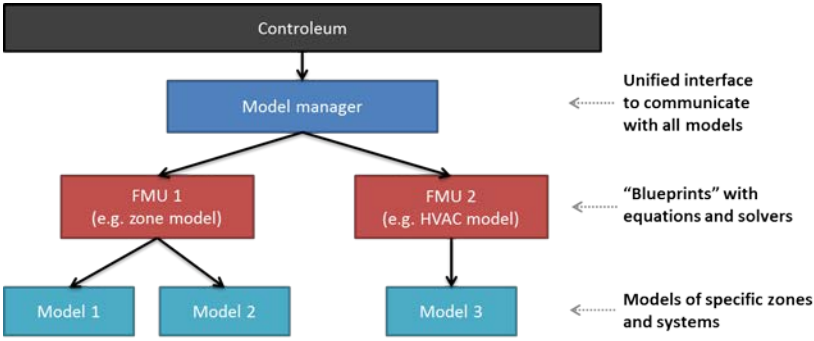

Fig. 1 Schema of the Controleum-model interface

The Model Manager serves as an entry point in the communication with all models. Controleum can use the Model Manager's API to:

1) create an instance of a specific model (specific FMU),
2) set the simulation time and time stepping,
3) get the model ID, name and description,
4) get names of needed sensor readings (inputs),
5) get names of needed weather forecast parameters (inputs),
6) get names of needed zone/system parameters (inputs),
7) get names of needed control parameters (inputs),
8) get names of available outputs,
9) set zone/system parameters (e.g. geometry, materials),
10) simulate the model (with a specific set of input parameters),
11) get lists with results (after simulation completes),
12) terminate the model and free the memory.

Each FMU serves as a "blueprint" for instantiation of specific zones or systems (Fig. 1). New FMUs can be easily added or replaced and the models updated, making the system extremely flexible. Controleum does not have to know anything about the model being plugged in, since all information needed to use the model can be fetched by the Model Manager.

The GZM outputs are temperature, relative humidity, CO_2 concentration and illuminance (Fig. 2). Each output is calculated by a specific submodel. The submodels may be coupled with one another, depending on the complexity of the model. If any of the outputs is not needed (e.g. because a specific parameter cannot be controlled in the building), the respective submodel does not have to be included in the FMU.

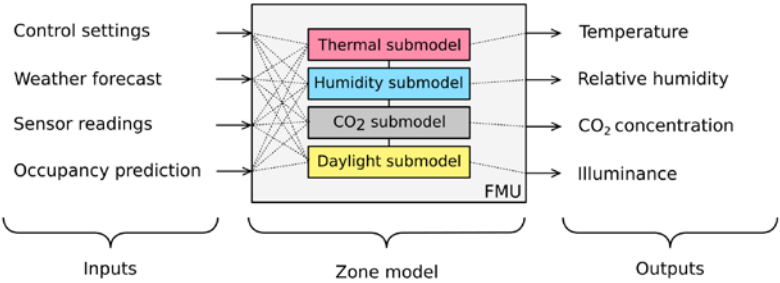

Fig. 2 Inputs, outputs and the modular structure of the model enclosed in the FMU

Models can be implemented in any FMI-compliant tool. The initial models for the system were developed in the Modelica language [10], which is an equation-based, object-oriented modeling language, allowing a rapid model development. Using a Modelica it is easy to isolate the mathematical formulation of the model from the data management and solution approach. Additionally, some of the major Modelica environments, like Dymola, OpenModelica or JModelica provide a strong support for the FMI.

3. Implementation of Initial Models

The presented building model framework was used to develop two test generic zone models. The models were used to calculate the indoor temperature and CO_2 level in a small conference room in the Green Tech House building (Green Tech Center, Denmark). The selected room has an area of 20.38 m^2 and is located at the third (top) floor. The room is equipped with mechanical ventilation and one radiator. The model performance was studied based on offline simulations, i.e. without Controleum. Results for a 24 hour long period (November 27, 2015) are discussed hereafter.

The models share the same CO_2 balance submodel, but differ in the thermal submodel. The CO_2 balance model is based on the following transient balance equation:

$$dV_{CO2} / dt = n \times V_{CO2occ,su} + V_{CO2ve,su} - V_{CO2ve,ex} \,, \qquad (1)$$

where V_{CO2} is the CO_2 volume in the room [m^3], n is the number of occupants, $V_{CO2occ,su}$ is the CO_2 generation rate per person [m^3/h], $V_{CO2ve,su}$ is the CO_2 supplied by ventilation and infiltration (sum) [m^3/h], $V_{CO2ve,ex}$ is the CO_2 extracted by ventilation and infiltration (sum) [m^3/h] and t is time. The CO_2 supplied by ventilation/infiltration is calculated based on the CO_2

concentration in the fresh air, which for the considered location is 420 ppm. The ventilation airflow rate is calculated based on the ventilation valve position (linear dependence, maximum airflow 500 m^3/h). The infiltration airflow rate depends on many factors difficult to be quantified. In addition, the infiltration can be divided to the airflow from the outdoors and from the surrounding indoor spaces (interzonal airflow). For the purpose of the study this phenomenon is significantly simplified and it is assumed that the total infiltration rate is constant, equal to 38.3 m^3/h (0.5 air changes per hour), and that the infiltration air entirely flows in from the adjacent hall space. The infiltration rate is calibrated based on the CO_2 dissipation rate during periods when the ventilation system was turned off and the door and the operable window were closed.

The thermal submodels are based on the thermal RC network approach (Fig. 3a). The R3C3 model consists of three thermal capacitors and three resistors. The capacitors represent the external partitions, internal partitions and indoor air. Each partition (walls, floors, windows) is divided into two equal parts and each resistor represents its inner ($R_{ext,i}$) or outer part ($R_{ext,e}$). Only the inner part of all internal partitions is taken into account ($R_{int,i}$) and an adiabatic boundary condition is assumed at each partition's midplane. Since all external and internal partitions are represented by single nodes with lumped parameters, the respective capacitances and resistances are calculated as follows:

$$C_{wall} = \sum \rho_{lay} c_{lay} V_{lay}\,, \tag{2}$$

$$C_{tot} = \sum C_{wall}\,, \tag{3}$$

$$1/R_{wall} = (\sum d_{lay} / \lambda_{lay}) / A_{wall}\,, \tag{4}$$

$$1/R_{tot} = \sum 1 / R_{wall}\,, \tag{5}$$

where C is the thermal capacitance [J/K], R is the thermal resistance [K/W], d is the width [m], λ is the thermal conductivity [W/m K], A is the surface area [m^2] and the subscripts *lay*, *wall* and *tot* stand for layer, wall and total, respectively.

In addition to the thermal conduction through building partitions, there are heat loads applied directly to the indoor air node resulting from the heating q_h, solar radiation q_{sol}, occupancy q_{occ} and convection q_{con} (ventilation and infiltration).

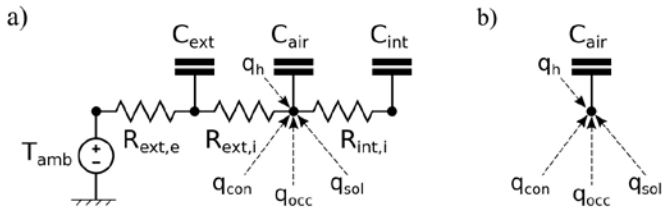

Fig. 3 Thermal submodels: a) R3C3, b) R0C1

The second thermal submodel, R0C1, is equivalent to R3C3 but without the thermal conduction through internal and external walls (Fig. 3b). In other words, only the heating, solar radiation, ventilation, infiltration and occupancy are taken into account.

The computational time of both models (R3C3+CO_2 and R0C1+CO_2) is below 10 ms per 24 h simulation time (counted on a modern desktop computer, single core computations). The exact time, however, depends not only on the computer performance and the model type, but also on the "smoothness" of input functions and the precision restrictions, since an adaptive time step technique is employed.

4. Performance of Initial Models

The results are presented for two occupancy schedules (Fig. 4). The schedules are based on the PIR sensor measurements in the chosen room.

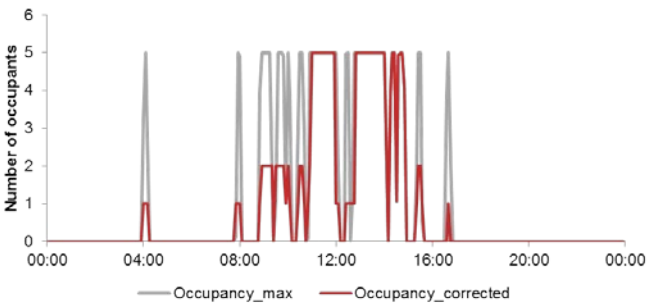

Fig. 4 Two occupancy schedules taken into account in simulations

The PIR sensor can only indicate the presence in the room, and not the actual number of occupants. Therefore, the first schedule (maximum occupancy) assumes that there is maximum number of occupants every time

the PIR sensor indicates presence. The second schedule (corrected occupancy) is arbitrarily corrected based on the typical usage of conference rooms. In example, it is unlikely that 5 people occupied the conference room for 5 minutes at 4:00 a.m. Likewise, small meetings are usually shorter than long ones. Although the accuracy of both schedules is unsure, the aim of both cases is rather to analyze the influence of the uncertainty in the occupancy data than to calibrate the number of occupants to fit the simulation results with actual data.

The results show that the occupancy prediction highly affects both the indoor temperature and CO_2 concentration (Fig. 5-6). The knowledge about the presence in the room is not sufficient to accurately predict both indoor environment parameters. The indoor temperature in the case of maximum occupancy (Fig. 5a) is generally overestimated (up to 1.5 °C) throughout the majority of the analyzed period.

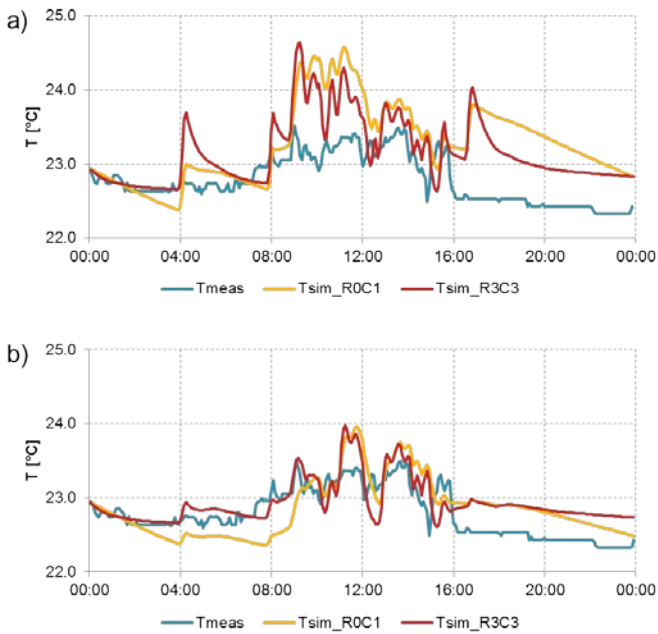

Fig. 5 Simulation temperature results vs. measured temperature: a) maximum occupancy, b) corrected occupancy

The type of the thermal submodel (R3C3 or R0C1) does not have such high influence on the temperature result as the occupancy prediction. It is so

even though the thermal conduction through all surrounding partitions in the model R0C1 is entirely neglected. The mean relative error of the model R3C3 for the maximum occupancy is 1.83%, while for the model R0C1 it is 2.36%. In the case of the corrected occupancy both thermal submodels performed much better, with the mean relative errors being equal to 1.05% and 1.20% for R3C3 and R0C1, respectively. The maximum absolute temperature error is around 0.6 °C.

The CO_2 results are also highly dependent on the occupancy prediction (Fig. 6). The accuracy of the simple CO_2 balace equation (1) is sufficient if the occupancy prediction is realistic. In the case of maximum occupancy the CO_2 level is overestimated. The highest difference is found in the morning hours (8:00-11:00) and reaches 280 ppm, indicating that the actual number of occupants in the room had to be lower. The mean relative error in the case of maximum occupancy is equal to 12.34%. The corrected occupancy schedule significantly increases the accuracy of the CO_2 model, with the mean relative error of 4.46%.

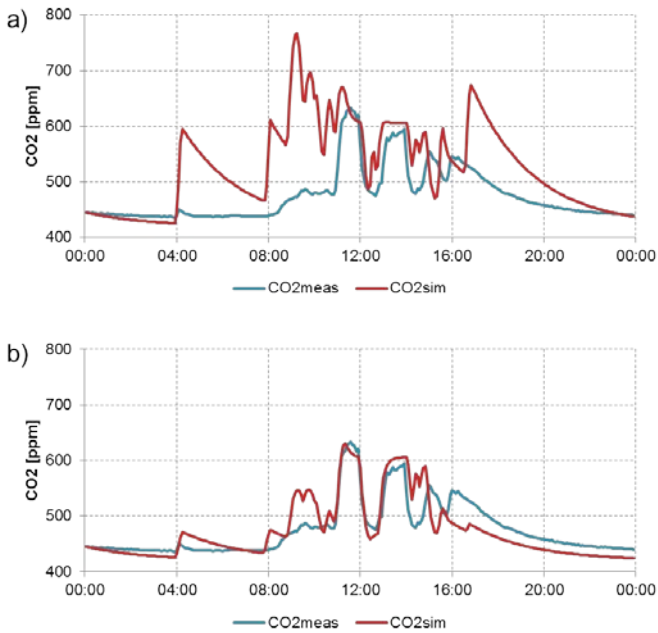

Fig. 6 Simulation CO2 results vs. measured CO2 concentration: a) maximum occupancy, b) corrected occupancy

Based on the results it can be concluded that the accurate occupancy prediction is crucial to obtain high quality predictions of indoor environment parameters. A separate task is already designated in the COORDICY project to advance the occupancy prediction algorithms [11].

In addition, the presented models characterize with a high uncertainty in the infiltration data. The simplified approach adopted in the study is based on the infiltration rate calibrated for the door and window being closed. In this configuration the CO_2 dissipation rate is the lowest possible. Based on the theoretical analysis of the interzonal airflow (empirical correlations from Said et al. [12]) between the room and the hall it is estimated that the open door can cause additional airflow with the rate of 500 m^3/h (for 2 °C temperature difference between the zones), i.e. over 13 times more than the infiltration rate assumed in the study. In general, however, the actual openness of doors is not known. The related uncertainty can have a predominant effect on the final model accuracy. This issue, however, is unlikely to be solved using a fully deterministic approach. Therefore, one of the next aims of the project is to develop a model being able to accurately account for the interzonal airflow. This task may be integrated with the occupancy prediction, since they are strictly related.

5. Conclusions

The results show that even simple generic zone models can provide accurate indoor environment predictions. However, the occupancy prediction and the infiltration rate can have a prevailing effect on the model accuracy.

The presented approach to model development and usage in MPC significantly reduces the model implementation time. However, the entire MPC system has to be more integrated to provide all input data needed to instantiate models and perform simulations. Tasks aimed at the development of such an integrated tool are assigned within the COORDICY project. Modules responsible for the extraction of data from BIM, sensor reading queries and occupancy prediction are under development.

The implementation of the fully integrated system is planned at the end of 2016 in the OU44 building at the Odense Campus of the University of Southern Denmark.

The implementation of the Modelica and FMI standards is partially aligned with the aims of the project IEA EBC Annex 60 [13].

Acknowledgment

The presented work is supported by the Innovation Fund Denmark for the project COORDICY (4106-00003B) and by the EUDP project Demand-Response Capacity Management in Commercial Buildings (64014-0512).

References

[1] B.N. Jørgensen, M.B. Kjærgaard, S. Lazarova-Molnar, H.R. Shaker, C. Veje, Challenge: Advancing Energy Informatics to Enable Assessable Improvements of Energy Performance in Buildings, Proceedings of the Sixth ACM International Conference on Future Energy Systems (ACM e-Energy), 2015, 77–81.

[2] J.C., Sørensen, B.N. Nørregaard, M. Klein, Y. Demazeau, "An agent-based extensible climate control system for sustainable greenhouse production", Agents in Principle, Agents in Practice, Springer Berlin Heidelberg, 2011, 218–233.

[3] M. Rytter, J.C. Sørensen, B.N. Jørgensen, O. Körner, "Advanced model-based greenhouse climate control using multi-objective optimization." IV International Symposium on Models for Plant Growth, Environmental Control and Farm Management in Protected Cultivation, vol. 957, 2012, 29–35.

[4] A. Clausen, Y. Demazeau, B.N. Jørgensen, "Load management through agent based coordination of flexible electricity consumers", Advances in Practical Applications of Agents, Multi-Agent Systems, and Sustainability: The PAAMS Collection, Springer International Publishing, 2015, 27–39.

[5] D. Gyalistras, M. Gwerder, and (Eds.), Use of weather and occupancy forecasts for optimal building climate control (OptiControl): Two years progress report, Automatic Control Laboratory, ETH Zurich, Switzerland, 2009.

[6] J. Cigler, D. Gyalistras, J. Široký, V.N. Tiet, L. Ferkl, Beyond Theory: the Challenge of Implementing Model Predictive Control in Buildings, Clima 2013 – 11th REHVA World Congress & 8th International Conference on IAQVEC – "Energy Efficient, Smart and Healthy Buildings", 2013, 1008–1018.

[7] T. Blochwitz, M. Otter, M. Arnold, C. Bausch, C. Clauß, H. Elmqvist, A. Junghanns, J. Mauss, M. Monteiro, T. Neidhold, D. Neumerkel, H. Olsson, J.-V. Peetz, S. Wolf, The Functional Mockup Interface for Tool independent Exchange of Simulation Models, 8th International Modelica Conference, 2011.

[8] P. Radecki, B. Hencey, Online Building Thermal Parameter Estimation via Unscented Kalman Filtering, 2012 American Control Conference, June 27-June29, 2012.

[9] javaFMI Library, https://bitbucket.org/siani/javafmi, retrieval date: 14.01.2016.

[10] Modelica Association, http://www.modelica.org, retrieval date: 14.01.2016.

[11] K. Imamovic, F.C. Sangogboye, M.B. Kjærgaard, Poster Abstract: Improving Occupancy Presence Prediction via Multi-Label Classification, BuildSys '15 Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built Environments (2015), 113–114.

[12] M.N.A. Said, S.A. Bakarat, E.A. Whidden, Interzonal Natural Convective Heat and Mass Flow Through Doorway-Like Apertures in Buildings: Experimental Results, Journal of Solar Energy Engineering 115 (1993), 69–76.

[13] IEA EBC Annex 60, http://www.iea-annex60.org/, retrieval date: 14.01.2016.