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Identification and Model Selection of Building Models

Eva Žáčeková and Zdeněk Váňa

Abstract— **Besides retrofitting, modernization and new ways of construction of the buildings, the cheaper and recently a very popular approach how to optimize energy consumption is to employ better control algorithms for the buildings. Predictive control has proven to be a strategy useful in many industries and became a suitable option for the building sector as well. The main bottleneck of this approach is a need for a fine model.**

There exist a number of building models and identification approaches. This paper provides a brief survey of the building modeling approaches and discusses their properties and applicability for the predictive control. Having a number of potential models at hand, the procedure of the model selection suitable for predictive control is presented. Finally, the performance of the model selection procedure is examined in a two zone building. The results are then presented and the conclusions drawn.

I. INTRODUCTION

Model Predictive Control (MPC) implemented within Building Automation Systems or applied to control of Heating Ventilation Air Conditioning (HVAC) has been widely studied lately [1], [2] and has been employed in real operation as well [3], [4].

The control part has become almost a standard solution, however, the bottleneck for MPC to spread wider is the model which is indispensable for the controller design. Therefore there is still an intensive research in the field of building model identification [5], [6], [7], [8], [9].

There is a plenty of identification or modeling techniques resulting into a variety of different models and it must be decided how to choose one suitable for the control purposes. In case of static models the procedure is well-established, however for dynamic models, especially those Multiple-Input Multiple-Output (MIMO), it is a peculiar task. The problem is thus not only the identification of a model which is in accordance to the physical reality and matches the data measured on the process, but also a choice of its parameters. The final set of parameters used within the model should be as small as possible, yet containing a sufficient level of information extracted from the data.

In case of models with given sets of inputs and outputs and with open set of states (parameters), a natural question arises: what is the minimum possible set of states which contains (statistically) the same information as a set one element larger. Or rephrased, what (statistically significant) information is gained from the addition of a state. There are several tests which solve this issue [10], [11].

Eva Žáčeková and Zdeněk Váňa are with Department of Control Engineering, Faculty of Electrical Engineering of Czech Technical University in Prague, Technická 2, 166 27 Praha 6, Czech Republic

A different problem is to select an appropriate model when the sets of inputs and outputs are not fixed, i.e. these sets are to be chosen during the identification procedure. Such a task of model selection becomes more difficult than in the previous case. The interpretation of the estimation problem shifts as well. The objective is still to select the best model for control, however, apart from the minimum number of states, the number of inputs and outputs is of interest as well. While the inputs are limited and restricted by the HVAC system structure, the system outputs can be expanded by adding supplementary measurement equipment (however, it is not always invited due to additional costs). It is certainly of the best interest to have the lowest number of sensors satisfying the required model quality, therefore one of the objectives of this paper is to show, that even with less complex models (in sense of number of inputs and outputs) it is possible to acquire reasonable model quality.

As the model identification is considered to be very time-demanding, the other objective is to evaluate a variety of methods with respect to their applicability to the building modeling from both the quality and the complexity points of view.

In this study, a model in building simulation software Trnsys[1] will be used to achieve the aforementioned goals. Such a model can be considered as a simulator of the reality because it contains full physical description of a building. Moreover, in contrary to the real building, one can easily take measurements of any quantities without additional costs and verify thus which set of measurements is necessary for obtaining a resulting model for control of a certain quality.

The paper is further structured as follows. Section II describes the building under investigation. Building modeling and identification approaches are discussed in Section III. The case study, in which the performance of the suggested approaches is examined is given in Section IV. Finally, the conclusions are drawn in Section V.

II. BUILDING UNDER INVESTIGATION

The investigated building is schematically outlined in Fig. 1. It is a medium weight office building with two zones separated by a concrete wall. Both zones have the same dimensions ($5 \times 5 \times 3$ m) and the south oriented wall of each zone involves a window ($3.75\,\mathrm{m}^2$). Such a system structure was chosen because it also involves transient properties between zones. The HVAC system used in the building is of active layer type. Technically, the HVAC system consists of a set of metal pipes placed in the ceiling distributing supply

[1] http://www.trnsys.com/

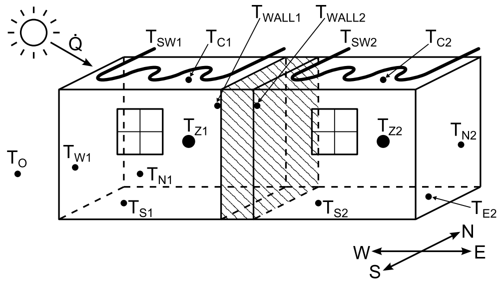

Fig. 1. A scheme of the modeled building

water which then performs thermal exchange with concrete core. Both zones are equipped with unique heating circuit where the mass flow rate of the supply water is held constant and then, the supply water temperature (which is independent for each heating circuit) is the only manipulated variable in particular heating circuit.

A. Trnsys simulator

Trnsys is an energy simulation software primarily used by engineers in the field of renewable energy and buildings. For control engineers, a Trnsys model can be used for validation of control algorithms or as a data generator for building modeling. The Trnsys model as such cannot be used directly in the optimization, i.e. in predictive control, because the model is in implicit form and thus general nonlinear solvers would have to be utilized, which is computationally intractable.

Various components were employed in the modeling of the building *i)* Type56 for the building construction, *ii)* Type15 for simulation of the weather profile corresponding to Prague, Czech Republic, *iii)* For purposes of model identification, the link between Trnsys and Matlab was established based on Trnsys Type155. The communication link was used to generate identification data in order to excite the system properly. Pseudo random binary sequence was used as the excitation input signal. Time-step of the simulation was set to $T_s = 0.25\,\mathrm{h}$. This time-step guarantees proper convergency of Trnsys internal algorithms.

B. Detailed First Principles Model

The basics of the heat transfer in buildings is recalled here and is used further on to assemble a full detailed first principles model considered as a baseline later on. For model being in accordance with physical reality, all ways of heat transfers are to be considered

1) Conduction: heat transfer through walls (solid body) and expressed as

$$\dot{T}_2 \approx \frac{T_1 - T_2}{k_{cd}} \approx \frac{\dot{Q}}{k'_{cd}}, \tag{1}$$

where T_1 is a temperature of the source, T_2 is a measured temperature of some entity, $\dot{Q}$ is heat flux and k_{cd}, k'_{cd} stand for conduction time constant of the process (A.K.A. $R \times C$ with R and C being the thermal resistance and capacity of the mass).

2) Convection: heat transfer through the air (liquid) written as

$$\dot{T}_2 \approx \frac{T_1 - T_2}{k_{cv}} \cdot \sqrt[4]{\frac{T_1 - T_2}{T_1 + T_2}}, \tag{2}$$

with time constant k_{cv}. Eq. (2) can be also approximated by $\dot{T}_2 \approx \frac{T_1 - T_2}{K_{cv}}$ as $\sqrt[4]{\frac{T_1 - T_2}{T_1 + T_2}}$ is considered constant for building heating process [12].

3) Radiation: corresponds (similar as a convection) to heat transfer through the air, expressed as

$$\dot{T}_2 \approx \frac{T_1^4 - T_2^4}{k_{ra}} \tag{3}$$

with time constant k_{ra}. Note that the temperatures are in Kelvins. Then, the heat transfer from heating pipes to the ceiling surface and all heat transfers through the walls can be described by conduction whilst heat transfers between walls surfaces and the air inside the zones can be expressed as convection and radiation, respectively. For the sake of simplicity, functions $\mathcal{D}$ for conduction and $\mathcal{R}$ for convection and radiation are defined as

$$\mathcal{D}(T, D) = \sum_{T_d \in D} \frac{T_d - T}{k_i}, \tag{4}$$

$$\mathcal{R}(T, R) = \sum_{T_r \in R} \frac{T_r - T}{k_i} + \frac{T_r^4 - T^4}{k_j}, \tag{5}$$

where D, R are sets of all appropriate sources of heat, T is the influenced temperature and k_i, k_j are unknown time constants, indices i, j only mark that all used constants are different (even for all utilizations of functions $\mathcal{D}$ and $\mathcal{R}$). Then, the building description comprises, in general non-linear, differential equations:

$$\begin{aligned}
\dot{T}_{c_1} &= \mathcal{D}(T_{c_1}, \{T_{sw_1}, T_o\}) + \mathcal{R}(T_{c_1}, \{T_{z_1}\}) + \frac{\dot{Q}_c}{k_i}, \\
\dot{T}_{wall_1} &= \mathcal{D}(T_{wall_1}, \{T_{wall_2}\}) + \mathcal{R}(T_{wall_1}, \{T_{z_1}\}), \\
\dot{T}_{s_1} &= \mathcal{D}(T_{s_1}, \{T_o\}) + \mathcal{R}(T_{s_1}, \{T_{z_1}\}) + \frac{\dot{Q}_s}{k_i}, \\
\dot{T}_{w_1} &= \mathcal{D}(T_{w_1}, \{T_o\}) + \mathcal{R}(T_{w_1}, \{T_{z_1}\}) + \frac{\dot{Q}_w}{k_i}, \\
\dot{T}_{n_1} &= \mathcal{D}(T_{n_1}, \{T_o\}) + \mathcal{R}(T_{n_1}, \{T_{z_1}\}) + \frac{\dot{Q}_n}{k_i}, \\
\dot{T}_{z_1} &= \mathcal{R}(T_{z_1}, \{T_{c_1}, T_{wall_1}, T_{s_1}, T_{w_1}, T_{n_1}, T_o\}) + \frac{\dot{Q}_s}{k_i}, \\
\dot{T}_{c_2} &= \mathcal{D}(T_{c_2}, \{T_{sw_2}, T_o\}) + \mathcal{R}(T_{c_2}, \{T_{z_2}\}) + \frac{\dot{Q}_c}{k_i}, \\
\dot{T}_{wall_2} &= \mathcal{D}(T_{wall_2}, \{T_{wall_1}\}) + \mathcal{R}(T_{wall_2}, \{T_{z_2}\}), \\
\dot{T}_{s_2} &= \mathcal{D}(T_{s_2}, \{T_o\}) + \mathcal{R}(T_{s_2}, \{T_{z_2}\}) + \frac{\dot{Q}_s}{k_i}, \\
\dot{T}_{e_2} &= \mathcal{D}(T_{e_2}, \{T_o\}) + \mathcal{R}(T_{e_2}, \{T_{z_2}\}) + \frac{\dot{Q}_e}{k_i}, \\
\dot{T}_{n_2} &= \mathcal{D}(T_{n_2}, \{T_o\}) + \mathcal{R}(T_{n_2}, \{T_{z_2}\}) + \frac{\dot{Q}_n}{k_i}, \\
\dot{T}_{z_2} &= \mathcal{R}(T_{z_2}, \{T_{c_2}, T_{wall_2}, T_{s_2}, T_{e_2}, T_{n_2}, T_o\}) + \frac{\dot{Q}_s}{k_i}.
\end{aligned} \tag{6}$$

TABLE I

NOTATION OF THE SYSTEM INPUTS AND MEASURED DISTURBANCES

Notation	Description
T_{sw_1}	Supply water temperature, zone 1
T_{sw_2}	Supply water temperature, zone 2
T_o	Ambient temperature
$\dot{Q}_c$	Total solar radiation on a horizontal plane
$\dot{Q}_s$	Total solar radiation on south side
$\dot{Q}_w$	Total solar radiation on west side
$\dot{Q}_n$	Total solar radiation on north side
$\dot{Q}_e$	Total solar radiation on east side

TABLE II

NOTATION OF THE SYSTEM STATES USED IN DESCRIBED MODELS

Notation	Description
T_{c_1}	Ceiling core temperature, zone 1
T_{s_1}	Core temperature measured on south side, zone 1
T_{w_1}	Core temperature measured on west side, zone 1
T_{n_1}	Core temperature measured on north side, zone 1
T_{z_1}	Zone temperature, zone 1
T_{c_2}	Ceiling core temperature, zone 2
T_{s_2}	Core temperature measured on south side, zone 2
T_{e_2}	Core temperature measured on east side, zone 2
T_{n_2}	Core temperature measured on north side, zone 2
T_{z_2}	Zone temperature, zone 2
T_{wall_1}	Core temperature measured on east side, zone 1
T_{wall_2}	Core temperature measured on west side, zone 2

The vectors of inputs and states are defined as $u^T = \left[T_{sw_1},\, T_{sw_2},\, T_o,\, \dot{Q}_c,\, \dot{Q}_s,\, \dot{Q}_w,\, \dot{Q}_n,\, \dot{Q}_e\right]$ and $x^T = [T_{c_1},\, T_{wall_1},\, T_{s_1},\, T_{w_1},\, T_{n_1},\, T_{z_1},\, T_{c_2},\, T_{wall_2},\, T_{s_2},\, T_{e_2},\, T_{n_2},\, T_{z_2}\,]$. The notation is explained in Table I and Table II, respectively. Note, that the temperature of each wall except floors together with zones temperatures are measured and considered as states. Non-linear model represented by Eq. (6) can be simplified to a linear one in a following way. The non-linear part $\mathcal{R}_{nl}(T,R)$ of Eq. (5) can be linearized at operating point *op* naturally chosen as stable state with maximum entropy $op = [T, T_r]$, where $T_r = T$ for all $T_r \in R$. Then $\sum_{T_r\in R} \frac{\partial \mathcal{R}_{nl}(T,R)}{\partial T_r}\Big|_{op} \approx \frac{T_r - T}{\overline{k}_i}$ holds, where $\overline{k}_i$ is obtained constant of proportionality, which finally influences the constant k_i in linear term of Eq. (5). Under this assumption, the linear approximation of Eq. (6) can be written in the same form, but $\mathcal{R}(T,R)$, which must be redefined as

$$\mathcal{R}(T,R) = \sum_{T_r\in R} \frac{T_r - T}{K_i}. \quad (7)$$

Note, that constants K_i in Eq. (7) and k_i in Eq. (5) have different meanings and $\frac{1}{K_i} = \frac{1}{k_i} + \frac{1}{\overline{k}_i}$ holds. Eq. (6) and its linear approximation represent the "complex" models, i.e. will be considered as fully describing the system.

Apart from these equations, some simpler models are derived and the possibility of their acceptance as *good* representative of the system is investigated.

III. IDENTIFICATION APPROACHES

A number of building modeling approaches has been developed over the years, from a wide variety of results, some instances can be listed *i)* probabilistic semi-physical modeling [6], *ii)* grey box modeling using the Resistance Capacitance (RC) in an analogue to electric circuit [13], [14], [15], [16], *iii)* subspace identification methods (4SID) [4], [7], *iv)* MPC relevant identification (MRI) [5].

In the following, the methods, which will be used for further investigation, are discussed in detail.

A. Semi-physical modeling

Having a physical description of the system Eq. (6), it is possible to estimate the model parameters directly, i.e. utilizing differential equations in continuous form or by reformulating the problem into the discrete world.

The former approach makes use of Maximum Likelihood (ML) estimates including prior knowledge of the system Eq. (6), and the estimation problem is formulated as follows

$$\begin{aligned} \theta^*_{ML} &= \arg\max_\theta\{\ln(L(\theta, Y_1^N|y_o))\}, \\ L(\theta, Y_1^N|y_o) &= \prod_{k=1}^{N} \frac{\exp(-\frac{1}{2}\varepsilon_k^T R_{k|k-1}^{-1}\varepsilon_k)}{(\sqrt{2\pi})^m\sqrt{\det(R_{k|k-1})}} p(y_o|\theta). \end{aligned}$$

Due to standard notation, L is likelihood function, Y_1^N stands for N measurements, y_o are initial conditions, m is a dimension of the problem (number of outputs), θ is vector of unknown parameters, $p(y_o|\theta)$ is conditional probability of initial conditions on parameters, ε_k are residuals and $R_{k|k-1}$ is residual covariance matrix. It must be noted here, that the problem can be solved only in iterative manner, when ε_k and $R_{k|k-1}$ are computed given estimate $\hat{\theta}$. However, to compute $\hat{\theta}$, the knowledge of the noise properties must be assumed. The procedure is already implemented in CTSM [17].

B. Grey box modeling

The other approach is to reformulate the original continuous-time model Eq. (6) to the discrete world as

$$\begin{aligned} A &= e^{A_c T_s} = I + A_c T_s + \frac{A_c^2 T_s^2}{2} + \ldots \approx I + A_c T_s, \\ B &= \int_0^{T_s} e^{A_c \tau} d\tau \approx \int_0^{T_s} I d\tau B_c = T_s B_c, \end{aligned}$$

where A_c, B_c and A, B are model matrices of continuous- and discrete-time models, respectively. T_s stands for sampling time. This corresponds to the Euler's discretization, thus can be applied for non-linear systems as well. Then the state equation can be written as

$$\begin{aligned} X_1^N &= AX_0^{N-1} + BU_0^{N-1} + E_0^{N-1} = \\ &= \begin{bmatrix} A & B \end{bmatrix} \begin{bmatrix} X_0^{N-1} \\ U_0^{N-1} \end{bmatrix} + E_0^{N-1}, \end{aligned} \quad (8)$$

with $N+1$ being the number of samples and

$$\begin{aligned} X_k^{k+N-1} &= \begin{bmatrix} x(k), & x(k+1), & \ldots, & x(k+N-1) \end{bmatrix}, \\ U_k^{k+N-1} &= \begin{bmatrix} u(k), & u(k+1), & \ldots, & u(k+N-1) \end{bmatrix}, \\ E_k^{k+N-1} &= \begin{bmatrix} e(k), & e(k+1), & \ldots, & e(k+N-1) \end{bmatrix}. \end{aligned}$$

For standard optimization using least-squares technique (LS), Eq. (8) is rewritten as

$$\mathrm{vec}X_1^N = \left(\begin{bmatrix} X_0^{N-1} \\ U_0^{N-1} \end{bmatrix} \otimes I_n\right)^T \mathrm{vec}\begin{bmatrix} A & B \end{bmatrix} + \mathrm{vec}E_0^{N-1},$$

with I_n being $n \times n$ identity matrix, n represents system order, (vec $\bullet$) is vectorization of a matrix and ($\bullet \otimes \bullet$) is a Kronecker product. Extra lines for the structure preservation of A and B as well as other required constraints can be added into the regressor matrix and left-hand side matrix. Then, the unknown parameters are estimated using LS.

C. MPC relevant identification

For minimization of multi-step ahead prediction error a following criterion is considered

$$J_{MRI} = \sum_{k=0}^{N-P} \sum_{i=1}^{P} \left(y(k+i) - \hat{y}(k+i|k)\right)^2, \qquad (9)$$

where $\hat{y}(k+i|k)$ is the i-step output prediction constructed from data up to time k, N is the number of samples and P is prediction horizon for identification. The multi-step output prediction $\hat{y}(k+i|k)$ is expressed as a multiplication of the regressor Z and the vector of the unknown parameters θ (for e.g. ARX model)

$$\hat{y}(k+i|k) = Z(k+i)\hat{\theta}, \quad i \in 1, 2, \ldots, P, \qquad (10)$$

where $\hat{\theta} = \left[\hat{b}_{n_d}, \; \cdots, \; \hat{b}_{n_b}, \; \hat{a}_1, \; \cdots, \; \hat{a}_{n_a}\right]^T$ and regressor $Z(l) = [u(l-n_d), \cdots, u(l-n_b), y(l-1), \cdots, y(l-n_a)]$ with $l = k+i$. n_a denotes the number of the delayed inputs in the regressor, n_b is the number of the outputs in the regressor and n_d represents the delay of the outputs compared to the inputs ($n_d = 0$ means the direct input-output connection). In case of MIMO system, $y(k) = [y_1(k), \; \cdots, \; y_{n_o}(k)]^T$ is the output vector, where n_0 is the number of the outputs. Every output $y(a)$ in the regressor $Z(k+i)$ with $a > k$ is not available at the actual time k, therefore an output prediction $\hat{y}(a|k)$ must be obtained. To acquire the prediction $\hat{y}(k+i|k)$, the following expression is applied i-times

$$\hat{y}(k+1|k) = Z(k+1)\hat{\theta}. \qquad (11)$$

Obviously, $k \geq \max(n_a, n_b)$. The recursion starts with the current output $y(k)$. Then the optimal values of the coefficients of the deterministic part of the system contained in the unknown vector θ can be acquired by solving the following non-linear optimization task

$$\theta^* = \arg\min_{\theta} \sum_{i=1}^{P} \sum_{k=0}^{N-i} (y(k+i) - Z(k+i, \hat{\theta})\hat{\theta})^2. \qquad (12)$$

If all the state variables are measurable (corresponding to the measured outputs) and $n_a = n_b = 1$, a relation between the regressor θ and the system matrices A and B of the state space description exists as $\theta^* = \left[\begin{smallmatrix} B \\ A \end{smallmatrix}\right]$.

TABLE III
MODELS UNDER INVESTIGATION

Inputs, States	**Model** 1	2	3	4	5	6	7	8
T_{c_1}	✓	✓	✓	✓	×	✓	✓	✓
T_{wall_1}	✓	✓	✓	✓	✓	×	✓	✓
T_{s_1}	✓	×	✓	×	×	×	✓	×
T_{w_1}	✓	×	×	×	×	×	×	×
T_{n_1}	✓	×	✓	×	×	×	×	✓
T_{z_1}	✓	✓	✓	✓	✓	✓	✓	✓
T_{c_2}	✓	✓	✓	✓	×	✓	✓	✓
T_{wall_2}	✓	✓	✓	✓	✓	×	✓	✓
T_{s_2}	✓	×	✓	×	×	×	✓	×
T_{e_2}	✓	×	×	×	×	×	×	×
T_{n_2}	✓	×	✓	×	×	×	×	✓
T_{z_2}	✓	✓	✓	✓	✓	✓	✓	✓
T_{sw_1}	✓	✓	✓	✓	✓	✓	✓	✓
T_{sw_2}	✓	✓	✓	✓	✓	✓	✓	✓
T_o	✓	✓	✓	✓	✓	✓	✓	✓
$\dot{Q}_c$	✓	×	×	✓	×	×	×	×
$\dot{Q}_s$	✓	×	✓	✓	×	×	✓	×
$\dot{Q}_w$	✓	×	×	×	×	×	×	×
$\dot{Q}_n$	✓	×	✓	×	×	×	×	✓
$\dot{Q}_e$	✓	×	×	×	×	×	×	×

IV. Case study

Using the physical description of the building Eq. (6) a set of models with varying complexity has been created. Eight models with different input, output and parameter sets are thoroughly described by Table III. The parameters of these models were estimated using different identification approaches as described in the previous sections. The techniques will be further referred as *i)* Grey box – according to the Section III-B, *ii)* CTSM – likelihood method according to Section III-A, *iii)* MRI – MPC relevant identification, see Section III-C.

1) Model selection criteria: Two popular choices for model selection are defined as

$$FIT = 100 \times \left(1 - \frac{||y_j - \hat{y}_j||}{||y_j - mean(y_j)||}\right)\%, \qquad (13)$$

$$R = 1 - \frac{var(y_j - \hat{y}_j)}{var(y_j)}, \qquad (14)$$

where y_j denotes the j^{th} output of the model. The former index is called fit factor (100% represents zero error, i.e. even noise is fully described by the model), while the latter index is a coefficient of determination (1 means a model that fully describes data). Note, that Eq. (13) are Eq. (14) are unreliable in case of purely statistically based methods such as 4SID applied to estimation of the dynamic models intended for control as they usually have the far highest fit, but for the cost of spoiled system structure. Therefore the other measures, such as behavior in frequency domain and step test (important for control) should be taken into account as well.

The results can be then viewed upon from different perspectives as follows.

2) Selection of the best model intended for subsequent control: Apart from the selected control algorithm a complexity of the model must be taken into account alongside with the suitability of the model for the selected control algorithm. For the example presented in this paper (see Fig. 1), MPC algorithm was implemented with control horizon of 24 hours. Therefore a good prediction properties on this horizon are to be expected. The sampling period of the measured data is 15 minutes and the identification utilizes the set of input-output (IO) data with length of 1500 samples. The data of the same length are used for validation.

Fig. 2 and Fig. 3 show fit factors computed for simulation (open loop) and 96-step ahead prediction. Model 5, which is less complex than e.g. Model 1, seems to have a nice quantitative quality indices, see coefficient of determination in Table IV for all three identification methods. Open loop simulation depicted in Fig. 4 shows that Model 5 reliably follows the basic dynamics of the building's temperature, however has problems to precisely follow the faster dynamics, which is a price for its simple structure. Analyzing the step responses (Fig. 5), it can be seen, that the time constant is about 2 days for the direct influence of the supply water on the zone temperature and 4 days for indirect influence of the supply water on the neighboring zone. Both constants are higher than the control horizon in use, therefore a quality of the model at steady state is of no interest. On the other hand, sign of steady state, which determines the direction of the heat transfer, is very important as well as initial behavior during the step responses, which bears the information about zone temperatures' rate of change.

The most complex Model 1 recorded the best step response which is almost the same as the measured one, moreover for grey box modeling shows very good fitting and high coefficients of determination in both simulation and prediction cases. It is able to follow even the faster dynamics. On the other hand, the price is its complexity, which can be a disadvantage for MPC.

3) Selection of the identification method for the model construction: When selecting the best method for the building modeling intended for the subsequent predictive control, a variety of factors must be taken into account, such as quality quantitative indices and good prediction properties of the model on the control horizon, but one should not forget on the time and resource demands of the respective methods. From a number of numerical results (see the fit factors, coefficients of determinations, step responses) it can be seen, that grey box models on average recorded the best and most consistent results for a variety of models on both simulation and prediction cases. The only case when the grey box modeling is overcome, is a case of multi-step ahead error minimization, which recorded better results for the k-step ahead prediction. These numerical results can be afterwards statistically evaluated.

It must be noted here, that the time demanded by the respective identification methods varies significantly. While the grey box modeling requires only couple seconds even for thousands of data samples and relatively complex models

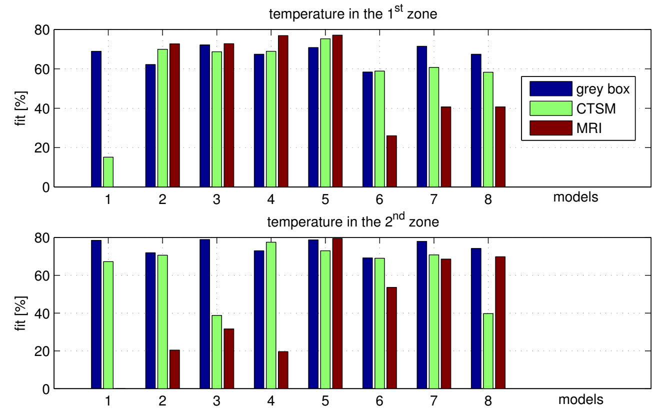

Fig. 2. Open loop simulation

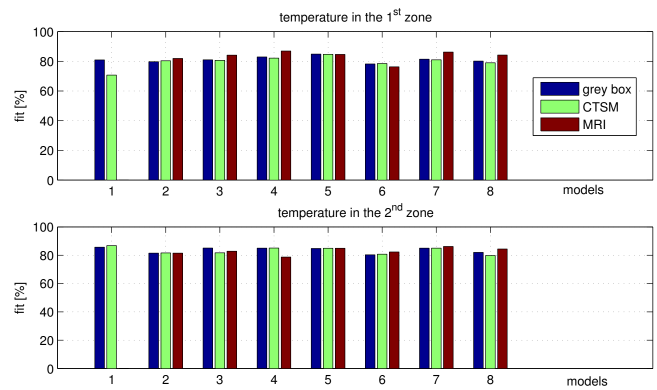

Fig. 3. k-step ahead prediction, $k = 96$

TABLE IV

COEFFICIENTS OF DETERMINATION FOR OPEN LOOP SIMULATION

Model	Zone 1			Zone 2		
	grey box	CTSM	MRI	grey box	CTSM	MRI
1	0.934	0.873	-	0.957	0.928	-
2	0.862	0.910	0.933	0.921	0.934	0.819
3	0.930	0.905	0.934	0.956	0.820	0.876
4	0.905	0.927	0.947	0.935	0.952	0.882
5	0.931	0.946	0.949	0.957	0.944	0.958
6	0.833	0.848	0.784	0.906	0.909	0.870
7	0.923	0.875	0.885	0.952	0.946	0.948
8	0.894	0.839	0.898	0.935	0.788	0.940

(OLS), the MRI slows down significantly for the large data sets and models of higher complexity. CTSM proved to be highly time demanding, usable only for a very small (up to couple hundreds) data samples and relatively simple models.

V. CONCLUSION

A system, two-zone building, was represented by a model created within Trnsys environment. Next, a set of differential equations describing the physics of the building was developed. Using these equations as a prior information, several models have been constructed, each having a different inner and outer structure. Finally, the parameters of these models were identified by several identification approaches aiming two main purposes: *i)* to select the best model suitable for

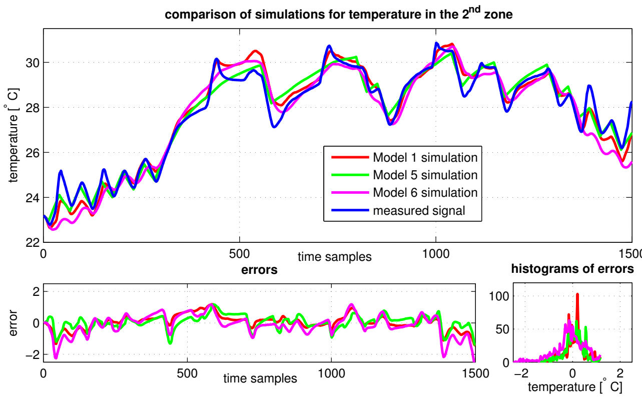

Fig. 4. Open loop simulation using Models 1, 3, 5

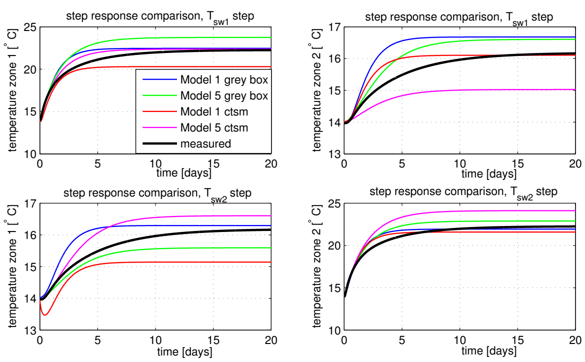

Fig. 5. Step responses: step of the supply water from 20 °C, up to 35 °C.

predictive control and *ii)* to check the applicability of the various identification algorithms.

It was shown, that the relatively simplest model (Model 5, Table III) has good results in all performed tests: computed fit factor and coefficient of determination, comparison of step response and simulation with measured data were surprisingly good as well as fine behavior while using this model for prediction. On the other hand, its simple structure caused that this model fails to describe the zone temperatures in details and only basic trends of temperature evolution are caught. In contrary, the most complex model (Model 1) provides good results in all quantitative and qualitative test. Its structure, however, implies larger time demands for model identification and subsequent optimal.

Concerning the most suitable identification algorithm, the best results recorded the grey box approach with high fit factors and coefficients of determination across the whole set of available models for both simulation and prediction. Moreover, having at least the basic knowledge of the system to identify, the grey box approach is far least time-demanding from the construction of the model point of view as well as the identification procedure itself. The only successful competitor in the field of quality of predictions on the control horizon is MRI, however, the parameter estimation is more time-demanding and for larger models and sets of data samples becomes infeasible. CTSM recorded satisfactory results only for cases, when the prior knowledge of the estimated parameters were close enough to the actual values, moreover fails for larger sets of data samples. Even though the aforementioned models demonstrated satisfying results, there is still a model-plant mismatch. This means, that all simulations appear to have relatively large error compared to the measurements and all the simulation errors are correlated (see Fig. 4). It is due to the fact, that the building model in Trnsys has been created in a realistic fashion, with heat transfers occurring between the zones themselves and the zones and ambient environment, and a real weather profile.

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References

[1] Y. Ma, F. Borrelli, B. Hencey, B. Coffey, S. Bengea, and P. Haves, "Model predictive control for the operation of building cooling systems," in *American Control Conference (ACC), 2010*, jun. 2010, pp. 5106–5111.

[2] F. Oldewurtel, A. Parisio, C. Jones, M. Morari, D. Gyalistras, M. Gwerder, V. Stauch, B. Lehmann, and K. Wirth, "Energy Efficient Building Climate Control using Stochastic Model Predictive Control and Weather Predictions," in *American Control Conference*, 2010.

[3] J. Široký, F. Oldewurtel, J. Cigler, and S. Prívara, "Experimental analysis of model predictive control for an energy efficient building heating system," *Applied Energy*, vol. 88, no. 9, pp. 3079 – 3087, 2011.

[4] S. Prívara, J. Široký, L. Ferkl, and J. Cigler, "Model predictive control of a building heating system: The first experience," *Energy and Buildings*, vol. 43, no. 2, pp. 564–572, 2011.

[5] E. Žáčeková, S. Prívara, and Z. Váňa, "Model predictive control relevant identification using partial least squares for building modeling," in *Australian Control Conference (AUCC), 2011*. IEEE, 2011, pp. 422–427.

[6] P. Bacher and H. Madsen, "Identifying suitable models for the heat dynamics of buildings," *Energy and Buildings*, vol. 43, no. 7, pp. 1511 – 1522, 2011.

[7] S. Prívara, Z. Váňa, D. Gyalistras, J. Cigler, C. Sagerschnig, M. Morari, and L. Ferkl, "Modeling and identification of a large multi-zone office building," in *Control Applications (CCA), 2011 IEEE International Conference on*, sept. 2011, pp. 55 –60.

[8] D. Gyalistras, M. Gwerder, F. Oldewurtel, C. Jones, M. Morari, B. Lehmann, K. Wirth, and V. Stauch, "Analysis of Energy Savings Potentials for Integrated Room Automation," in *Clima - RHEVA World Congress*, Antalya, Turkey, May 2010.

[9] K. Deng, P. Barooah, P. Mehta, and S. Meyn, "Building thermal model reduction via aggregation of states," in *American Control Conference (ACC), 2010*. IEEE, 2010, pp. 5118–5123.

[10] C. Gourieroux, A. Holly, and A. Monfort, "Likelihood ratio test, wald test, and kuhn-tucker test in linear models with inequality constraints on the regression parameters," *Econometrica: Journal of the Econometric Society*, pp. 63–80, 1982.

[11] D. Dickey and W. Fuller, "Likelihood ratio statistics for autoregressive time series with a unit root," *Econometrica: Journal of the Econometric Society*, pp. 1057–1072, 1981.

[12] M. Barták, *Úvod do přenosových jevu pro inteligentní budovy*. Prague, Czech Republic: CTU Prague, 2010.

[13] G. Hudson and C. Underwood, "A simple building modelling procedure for MATLAB/SIMULINK," vol. 99, no. 2, pp. 777–83, 1999.

[14] G. Levermore, *Building energy management systems: an application to heating and control*. E & FN Spon, 1992.

[15] M. Jimenez, H. Madsen, and K. Andersen, "Identification of the main thermal characteristics of building components using MATLAB," *Building and Environment*, vol. 43, no. 2, pp. 170–180, 2008.

[16] S. Wang and X. Xu, "Simplified building model for transient thermal performance estimation using GA-based parameter identification," *International Journal of Thermal Sciences*, vol. 45, no. 4, pp. 419–432, 2006.

[17] N. Kristensen, H. Madsen, and S. Jørgensen, "Parameter estimation in stochastic grey-box models," *Automatica*, vol. 40, no. 2, pp. 225–237, 2004.