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Building modeling and control using multi-step ahead error minimization

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Abstract— **As the buildings account for about 40% of global final energy use, the efficient building climate control can significantly contribute to the saving effort. *Predictive control* can be used to operate buildings in energy and cost effective manner instead of conventional room automation such as PID, weather-compensated controllers or Rule-Based Controllers (RBC). However, the predictive controller has (besides many advantages as the possibility to incorporate the restriction directly into the controller design or handling of MIMO systems in a simple natural way) a drawback - it is the necessity of a proper mathematical model of the controlled system. Therefore, adequate attention should be paid to the procedure leading to its acquirement. In this paper a multi-step ahead error minimization approach to a building modeling is presented and influence of the solar radiation on the quality of the constructed model is examined. Moreover, the results are demonstrated on a real control of six-floor building of the Czech Technical University in Prague.**

I. INTRODUCTION

In recent years, the Model Predictive Control (MPC) concept has attracted a lot of attention in new areas of applications, e.g. building climate control. There is quite a large number of papers treating this problem, e.g. [1], [2], [3], [4], [5], [6]. For MPC, the knowledge of the mathematical model (suitable for *control*) of the controlled system is crucial. The cost function used within the model parameters identification should be chosen carefully considering the type of the controller, which will make use of the model. The predictive controller minimizes the control error during the whole prediction horizon depending on the predictions of the outputs. Within the MPC design, the quadratic function is one of the frequently used ones. This in fact leads to the controller minimizing the square of the control errors. Hence the model used for the predictive control should be primarily a good multi-step predictor. Such methods, minimizing the multi-step prediction error, are collectively called Model relevant identification (MRI) methods.

Many papers searching for an adequate process model have been published. Reference [7], [8] from the early 1990s focused on the minimization of the multi-step prediction error - this work was later followed by [9], [10]. These approaches solved the problem of obtaining a model appropriate for the MPC using a pre-filtration of the input-output data. However, this is based on the knowledge of (at least) the structure of the real noise model which handicaps the use of these approaches in the real-world situations. In this paper, in order to obtain a model which satisfies the needs of the MPC, a multi-step prediction error minimization approach is used - this approach is based on an idea presented in [11]. Estimation of the influence of the disturbance variables (outside temperature and solar radiation in our case) requires a special treatment of the input data. The need for special approach is given by the fact that the available data set is of closed loop character. This originates in the presence of the feedback controller acting on the controlled system.

The paper is structured as follows: Section II is fully devoted to the modeling with a full development of the multi-step ahead error minimization framework. A case study, where the proposed approach is tested, is described in Section III. Section IV summarizes the numerical results of the previous sections. An evaluation of the performance of the current and previous control strategies is provided as well. Last section concludes the paper.

II. IDENTIFICATION APROACH

Prediction Error Method (PEM) framework [12] can be counted to one of the most frequently used frameworks when dealing with parameter identification. The main drawback is, however, that it minimizes only a one-step ahead prediction error which does not match MPC cost function and leads to a suboptimal behavior. In the following paragraph, the importance of a model with satisfactory long term prediction properties for the correct predictive controller behavior is showed.

A. Multistep prediction error

Let us consider the following cost function which penalizes the sum of the squared differences of the controlled output y and required reference y_{ref} over the prediction horizon

$$J_{MPC} = \frac{1}{(N-P)\,P} \sum_{k=1}^{N-P} \sum_{i=1}^{P} (y_{ref}(k+i) - y(k+i))^2, \quad (1)$$

where N is the number of samples and P is the length of the prediction horizon. Next, let $y(k+i) = \hat{y}(k+i|k) + e(k+i|k)$, where $\hat{y}(k+i|k)$ denotes the predicted output values at the time $k+i$ using the data until k, $e(k+i|k)$ is the i-step

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prediction error. (1) can be then rewritten as

$$J_{MPC} = \frac{1}{(N-P)\,P}\sum_{k=1}^{N-P}\sum_{i=1}^{P}(y_{ref}(k+i) - \hat{y}(k+i|k))^2 + \frac{1}{(N-P)\,P}\sum_{k=1}^{N-P}\sum_{i=1}^{P}(y(k+i) - \hat{y}(k+i|k))^2 - \frac{2}{(N-P)\,P}\sum_{k=1}^{N-P}\sum_{i=1}^{P}(y_{ref}(k+i) - \hat{y}(k+i|k)) \times (y(k+i) - \hat{y}(k+i|k))\,. \quad (2)$$

The MPC itself minimizes only the first term, but to achieve the optimal solution minimization of the remaining terms is necessary. The last term represents the cross-correlation between the identification and control errors [13]. Now, only the second term remains. Its minimization is performed within the MPC Relevant Identification (MRI) framework. It was shown by [10], [9] and later by [7], [8]) that the pre-filtration of the input and output data sets by a noise model is equivalent to the minimization of the second term in (2). This approach, however, suffers from the fact that the perfect knowledge of the noise model is inevitable, which does not happen very often in practical cases. Therefore, another approach introduced by [14] is to be used. Denoting the second term in the (2) as J_{MRI} a following expression is obtained

$$J_{MRI} = \sum_{k=0}^{N-P}\sum_{i=1}^{P}(y(k+i) - \hat{y}(k+i|k))^2\,, \quad (3)$$

As far as autoregressive model with external input ARX is considered, 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:

$$\hat{y}(k+i|k) = Z(k+i)\hat{\Theta}, \quad i \in 1, 2, \ldots, P, \quad (4)$$

where $\hat{\Theta} = \begin{bmatrix}\hat{b}_{n_k} & \cdots & \hat{b}_{n_b} & \hat{a}_1 & \cdots & \hat{a}_{na}\end{bmatrix}^{\mathrm{T}}$ and regressor $Z(l) = [u(l-n_k), \cdots, u(l-n_b), y(l-1), \cdots, y(l-n_a)]$ and with $l = k+i$, n_a denoting the number of the delayed inputs in the regressor, n_b is the number of the outputs in the regressor, n_k represents the delay of the outputs compared to the inputs ($n_k = 0$ means the direct input-output connection). Let us mention that in case that a MIMO system is considered then $y(k)$ is the output vector $y(k) = \begin{bmatrix}y_1(k) & \cdots & y_{no}(k)\end{bmatrix}$, where n_o is the number of the outputs. It is important to realize that 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:

$$\hat{y}(k+1|k) = Z(k+1)\hat{\Theta}, \quad (5)$$

where

$$Z(k) = [u(k-n_k) \;\cdots\; u(k-n_b) \; y(k-1) \; y(k-n_a)]\,, \quad (6)$$

$k \geq \max(n_a, n_b)$. 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 optimization task:

$$\arg\min_{\Theta}\sum_{i=1}^{P}\sum_{k=0}^{N-i}(y(k+i) - Z(k+i,\hat{\Theta})\hat{\Theta})^2. \quad (7)$$

As the regressor $Z(k+i)$ is dependent on the regressed parameters Θ, nonlinear optimization methods must be employed. Solving this optimization problem, the parameters of MIMO input-output representation with ARX structure are obtained.

B. Extension for state space model

If the relation for particular input and output is represented by a higher-order transfer function $n_b > 1$ for the same input, $n_b - 1$ auxiliary state variables need to be employed in order to obtain the state-space representation such that it holds:

$$\begin{bmatrix} x_{n_o+1}(k+1) \\ x_{n_o+2}(k+1) \\ \vdots \\ x_{n_o+n_b-1}(k+1)\end{bmatrix} = A_{aux}\begin{bmatrix} x_{n_o+1}(k) \\ x_{n_o+2}(k) \\ \vdots \\ x_{n_o+n_b-1}(k)\end{bmatrix} + B_{aux}u_j, \quad (8)$$

where A_{aux} and B_{aux} are of the following form:

$$A_{aux} = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & 0 & \vdots \\ \vdots & & \ddots & & \vdots \\ 0 & \cdots & & \cdots & 0 \end{bmatrix}, \quad B_{aux} = \begin{bmatrix} \mathbf{0}_{j-1} & \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix} & \mathbf{0}_{n_i-j} \end{bmatrix}. \quad (9)$$

Here, $\mathbf{0}_{j-1}$ and $\mathbf{0}_{ni-j}$ are zero matrices of corresponding size.

Having introduced this notation, the state description of the overall system can be summarized as follows:

$$x(k+1) = \bar{A}x(k) + \bar{B}u(k), \quad (10)$$

where:

$$\bar{A} = \begin{bmatrix} A & \begin{bmatrix} b_{n_b,j} & b_{n_b-1,j} & \cdots & b_{n_2,j} \\ 0 & 0 & \cdots & 0 \\ \vdots & & \ddots & \vdots \\ 0 & \cdots & & 0 \end{bmatrix} \\ \mathbf{0} & A_{aux} \end{bmatrix}, \quad \bar{B} = \begin{bmatrix} B \\ B_{aux} \end{bmatrix}. \quad (11)$$

III. Case study

A. Building description

The building of the CTU in Prague used as an example, utilizes the Critall type ceiling radiant heating and cooling system [15]. In this system, the heating (or cooling) beams are embedded into the concrete ceiling that enables the utilization of the thermal capacity of the building. The required values of the heating water is obtained by mixing the hot water from the heat exchanger with the return water in a three point valve. The valve is operated by a low-level controller (e.g. a PID controller) maintaining the required temperature of the heating water in certain heating circuits which is set by a high-level controller. In the role of the high-level controller, a predictive controller is used in the CTU building. Simplified scheme of the realized heating system for one of the heating blocks is shown in the Fig. 1. More can be found in [1], [16].

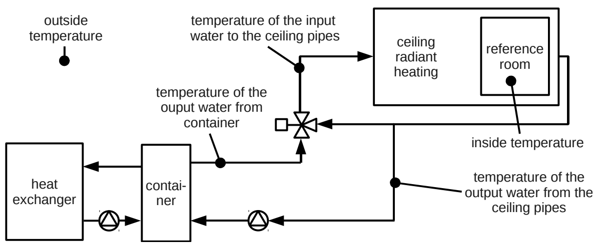

Fig. 1. Ceiling radiant heating system: a schematic view

The ceiling radiant heating system is modeled by a discrete-time linear time-invariant model. For identification, the predictions of some disturbances have been available - namely the solar radiation power predictions taken on the horizontal area I_H and outside temperature predictions ϑ_o. Next, it was possible to set and measure the supply water temperatures in particular heating circuits ϑ_{HWS} and ϑ_{HWN} (the subscripts N and S denote north respective south heating circuits). Then, the reference room temperatures $\vartheta_{INS}, \vartheta_{INN}$ and the return water temperatures $\vartheta_{RWS}, \vartheta_{RWN}$ are measured. The original model structure introduced in [17], [18] has not been able to consider neither the water flow in the pipes nor the fact that the heating control action (heating water step) effects the return water temperature soonest certain time later. Similarly, it takes some time until the heating effort effects the room temperature. Using the correlation analysis, the time lag between $\vartheta_{HWS}, \vartheta_{HWN}$ and $\vartheta_{RWS}, \vartheta_{RWN}$ has been assigned to 30 minutes and the lag between $\vartheta_{HWS}, \vartheta_{HWN}$ and $\vartheta_{INS}, \vartheta_{INN}$ has been estimated as 4 hours. In order to describe the discrete-time linear time-invariant model, let us consider the following state space description:

$$\begin{aligned} x(k+1) &= \bar{A}x(k) + \bar{B}_d d(k) + \bar{B}u(k), \\ y(k) &= Cx(k), \end{aligned} \tag{12}$$

where $\bar{A}, \bar{B}, \bar{B}_d$ are constructed as mentioned in section Section II. Now, choosing the sampling period $T_s = 30\,\text{min}$, the following structure can be used for the simplified description of the thermal exchange in the north heating circuit(which can be analogously applied for the south heating circuits):

$$\begin{aligned} A &= \begin{bmatrix} a_1 & 0 \\ a_2 & 0 \end{bmatrix}, B_d = \begin{bmatrix} b_3 & b_4 \\ 0 & 0 \end{bmatrix} \\ B &= \begin{bmatrix} b_1 & b_2 \end{bmatrix}. \end{aligned} \tag{13}$$

In this case, A_{aux} is a square matrix 7×7 with ones above the main diagonal, in matrix $\bar{A}$, all the elements are zero except of the $b_{n_b,j}$ elements and the matrix B_{aux} is of size 7×1. For the input vector u, disturbance vector d and the output vector y, it holds:

$$\begin{aligned} d(k) &= \begin{bmatrix} I_N(k) & \vartheta_o(k) \end{bmatrix}^{\mathrm{T}}, u(k) = \begin{bmatrix} \vartheta_{HWN}(k) \end{bmatrix}^{\mathrm{T}} \\ y(k) &= \begin{bmatrix} \vartheta_{INN}(k) & \vartheta_{RWN}(k) \end{bmatrix}^{\mathrm{T}}. \end{aligned} \tag{14}$$

Here, it is important to notice that in the role of disturbance variable entering the system, it is not correct to take directly the commonly available predictions I_H which represent the intensity of solar radiation measured on the horizontal area - much more reasonable is to re-calculate the values for the north and south facade, respectively. For the re-calculation, the following relations can be used:

$$I_{N,S} = I_H \frac{\cos\delta}{\sin h} \tag{15}$$

where $\delta = \cos h \cos(\alpha - \gamma)$.Symbol h specifies the position of the Sun above the horizon,α is solar azimuth and γ is the inclination angle of the chosen facade ($\gamma = 0$ rad for north facade and $\gamma = \Phi$ rad for south facade). Identifying the proposed structure parameters, the multi-step ahead prediction error minimizing identification method has been used - this method is described in Section II in more details. The choice of the correct structure of the system matrices turned out to be of the key importance. The incorrectly structured model (e.g. all parameters non-zero) fitted the reference room temperature well but it was absolutely of no use within the control design as it disagreed with the physical nature of the controlled building.

B. MPC problem formulation

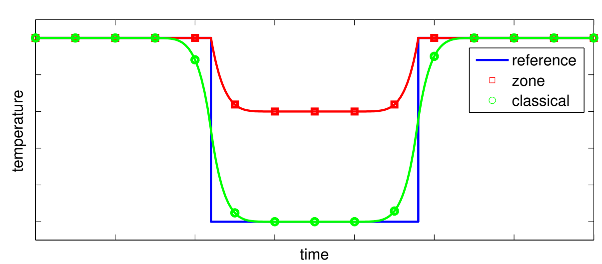

Fig. 2. Classical vs.zone control

The objective of the control is to design a predictive controller primarily maintaining the room temperatures above the desired reference value when the rooms are occupied (during the working days from 8a.m. till 6p.m.) and minimizing the energy consumption which in case of the ceiling radiant heating systems (depicted in the Fig. 1) corresponds proportionally to the difference $\vartheta_{HW} - \vartheta_{RW}$ in the corresponding heating circuits.

In such case, the classical criterion form (1) is not the most suitable (its behavior is shown by the circles marked line in Fig. 2) because the underheating at the beginning of the occupancy intervals can occur. This problem is solved by so called zone control [19] (squares marked line Fig. 2), where the underheating is penalized (the difference between the room temperature and the reference temperature when negative). The aforementioned requirements are satisfied by the criterion in the following form:

$$J = \sum_{k=1}^{P} \|Q_1 a(k)\|_2^2 + \|Q_2 b(k)\|_2^2 \qquad (16)$$

subject to

$$\begin{aligned} y_{ref}(k) - y_1(k) - a(k) \leq 0 \quad a \geq 0 \\ y_2(k) - b(k) \leq 0 \quad b \geq 0 \\ u_{min} \leq u(k) \leq u_{max} \\ |u(k) - u(k-1)| \leq \Delta u_{max} \end{aligned} \qquad (17)$$

where $a(k)$ and $b(k)$ stand for so called slack variables of the same size as $y_1(k)$ and $y_2(k)$, Q_1 and Q_2 are the weighting matrices of the corresponding sizes, u_{min} and u_{max} stand for the lower and upper input bounds, respectively, Δu_{max} is the maximum rate of input signal change, $y_1(k)$ represents controlled variable T_{IN} and $y_2(k)$ is equal to the difference output $y_2(k) = \vartheta_{HW}(k-1) - \vartheta_{RW}(k)$. Then it holds:

$$\begin{aligned} y_1(k) =& A^{k-1}x(0) + \sum_{i=0}^{k-1} C_1 A(k-1-i)(Bu(i) + B_d d(i)) \\ y_2(k) =& A^{k-1}x(0) \\ &+ \sum_{i=0}^{k-1} C_2 A(k-1-i)(Bu(i) + B_d d(i)) + D_2 u(k). \end{aligned} \qquad (18)$$

The sampling period of the controlled system is T_s = 30 min. The length of the prediction horizon is chosen as $P = 96$ (two days). The predictive controller is implemented using YALMIP language, whilst the minimization is performed utilizing SeDuMi solver[1].

C. *Influence of the Solar Radiation*

The model introduced in the previous section involves the solar radiation influence. The solar radiation strongly affects (mostly during midday) the room temperature (especially for the south-oriented rooms) and incorporation of it into the model can both improve the prediction properties of the obtained model and enables the thermal energy of the sun to be used for room heating, which saves a considerable amount of energy.

Only the data corrupted by a noticeable cross-correlation between past outputs and current inputs caused by the presence of the feedback controller eliminating the disturbance variables including the solar radiation (see Fig. 3) were available in our case, which did not allow us to identify the influence of this variable.

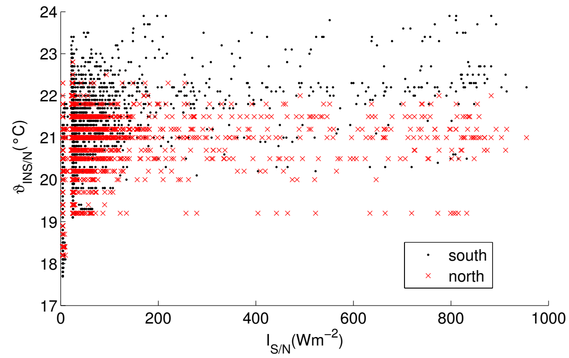

Fig. 3. Correlation between ϑ_{IN} and I (with controller)

To solve the problem, we have introduced a two-step procedure:

1) **Removing the cross-correlation in data**
In the first step, only data-set gathered outside the heating season were used for identification. Thanks to such a choice no cross-correlation due to feedback controller was brought into the data as the heating was switched off during this period, moreover the heating water temperature does not change during this period. The term $Bu(k)$ in (12) can be treated as constant and the model is identified in the form:

$$x(k+1) = Ax(k) + B_d d(k) + aff, \qquad (19)$$

where aff stands for the affine term. Thanks to the affine character of (19) the identification considering the difference of the data sets can be used to eliminate the affine term influence

$$y(k) = x_a(k) - x_b(k), \quad u(k) = d_a(k) - d_b(k) \qquad (20)$$

where x_a, d_a a x_b, d_b represent the data gathered during two periods outside of the heating season where the heating water temperature was constant.

2) **Constrained identification**
In the second step, model parameters corresponding to A, B, B_d are identified using the data-set coming from the heating season satisfying the parameters of the matrix B_d identified in the first step of the algorithm representing the influence of the disturbance variables (solar radiation and outside temperature. The parameters of B_d matrix were searched only inside the interval with the variance of $\pm 5\%$ around the values obtained in the first step.

IV. Results

We will provide here the results of the proposed methods here and compare the behavior of RBC and MPC. For the needs of this demonstration, the block B1 of CTU building consisting of two independent heating circuits is considered.

[1] $http://sedumi.ie.lehigh.edu/$

A. Identification

For the identification purposes, a two-weeks period of the real-operation data from the beginning of the year 2011 has been used while for validation purposes, a data-set from the beginning of the year 2012 has been considered. The obtained models have been intended to provide accurate predictions of the zone temperatures over a 48 h horizon (having $T_s = 30$ min, this represents $P = 96$). To compare the performance of the models, the i-hours prediction error variance $var_p(i)$ and fit factor $fit_p(i)$ are used:

$$fit_p(i) = \left(1 - \frac{\|y_p(k+i) - \hat{y}_p(k+i|k)\|_2}{\|y_p(k+i) - E(y_p(k+i))\|_2}\right) 100\%, \quad (21)$$

where $i \in \{1 \dots 96\}$, N is the number of the data-points, $P \in \{N, S\}$ refers to the north and the south reference room respectively, and E stands for the mean value operator. Symbol i refers to the number of hours fit factor and variance have been computed from. The following pictures compare the quality of the identified models. The first of the compared models denoted as model$_1$ represents the case when the structure proposed in the previous section. The second model, model$_2$, has the structure similar to that of the previous model, however, correlated data are used to identify the influence of the disturbance variables. The last of the models, model$_3$, represents the model which does not involve the solar radiation intensity I as the input variable. The results clearly show that the best prediction behavior recorded the model obtained by the method introduced in Section III-C. Next, it was shown that without a special de-correlation procedure, the ability to identify the influence of the disturbance variables correctly is much restricted - this is supported by the fact that despite that model$_2$ takes the solar radiation intensity into account its behavior is not significantly better than that of model$_3$.

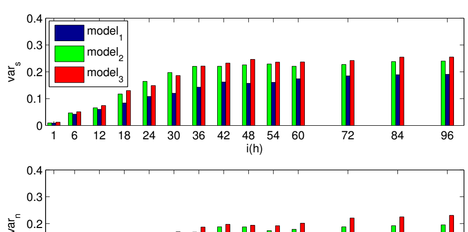

Fig. 4. variance of prediction error $var_p(i)$

B. Controller behavior

In order to be able to compare the classical Rule Based Controller (RBC) (or weather-compensated controller) used to heat the block B1 at the beginning of 2010 to the implemented MPC tested at the beginning of 2012 in spite of the different weather conditions let us define Heating Degree

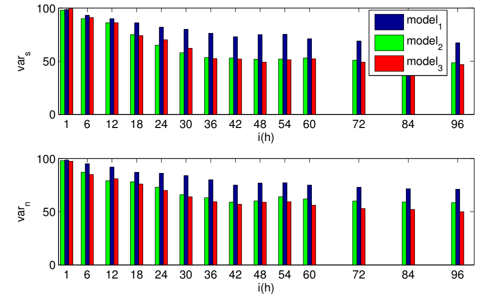

Fig. 5. Fit factor $fit_p(i)$

Days (HDD) and Energy Consumption (E_{CM}) as follows:

$$HDD = \sum_{i=T_{start}}^{T_{end}} y_{ref}(i) - \vartheta_o(i), \quad (22)$$

and

$$E_{CM} = \sum_{p=1}^{2} \sum_{i=T_{start}}^{T_{end}} (\vartheta_{HWp}(i) - \vartheta_{RWp}(i)), \quad (23)$$

where T_{start} and T_{end} specify the beginning and the end of the compared periods. A ratio E_{CM}/HDD representing the energy consumed for heating divided by HDD is used to compare the RBC to the MPC. Fig. 6 and Fig. 7 show the difference between the energy fed into the heating by the RBC and the energy consumed by the MPC and noticeable savings can be seen. Much higher energetic advantages of MPC are supported by a comparison based on the ratio $E_{CM/HDD}$ (see Table I) according to which the savings thanks to MPC during the compared periods are slightly higher than 30%.

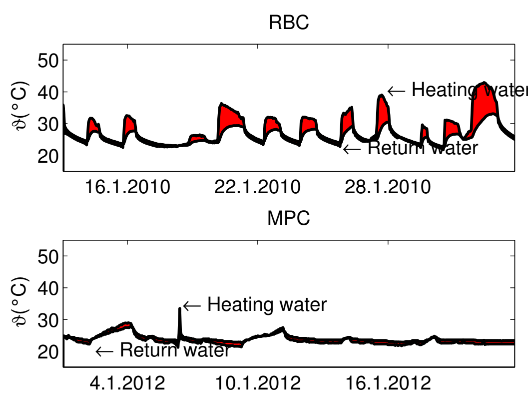

Fig. 6. Savings comparison south room

	E_{CM}/HDD	days	relative savings
MPC	0.5662	102	31.8%
RBC	0.8304	59	

TABLE I
ENERGY SAVING.

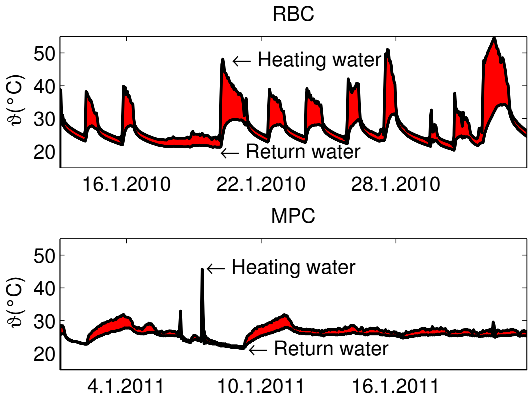

Fig. 7. Savings comparison north room

V. Conclusion

In this paper, building modeling and identification approach based on multi-step prediction error minimization has been discussed and examined on a case study of CTU building in Prague. It was shown that this approach was able to obtain models which were appropriate for MPC use. Resulting controller combining the proposed identification method and predictive framework reached approximately 30% savings of consumed energy compared to the classical RBC strategy. The correlation tests had shown, that the inclusion of the solar radiation to the model's inputs is of great importance for having good prediction properties.

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