Estimation of disturbance heat flux in buildings

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***Abstract*— This paper investigates estimation of disturbance heat flux in a zone using autoregressive integrated moving average model with exogenous inputs (ARIMAX). The model is derived from simple continuous zone model. Data used for estimation is obtained from building simulation in IDA ICE. The procedure exhibits fast detection of the disturbance heat flux which opens several possible applications in energy-efficient buildings control, like possibility of instantaneous on-off reaction on the zone actuators or better building climate prediction for predictive control.**

Keywords—Grey box linear model, Disturbance estimation, Parameter identification

I. Introduction

It is estimated that building sector is responsible for approximately 40% of total energy consumed in Europe [1]. That makes it one of the key energy consumers. It is not surprising that substantial research efforts are being put into achieving better energy efficiency. One way of achieving energy efficiency is trough model predictive control (MPC) of the building climate [2]. In order to develop MPC algorithms, models describing building temperature behavior and energy consumption must be developed.

There are three main ways of modelling technical processes like buildings. One is a full physical model. Examples of such building thermal models are the ones obtained by using professional simulation tools like IDA ICE [3], Trnsys [4] etc. They require substantial knowledge of the building layout and materials used in building. Usually, materials used in buildings are unknown and that is especially true for older buildings. Even if the construction parameters are known, adding furniture into the room can change physical characteristics of the building. That and the fact that these models are usually of high order and nonlinear is the reason why they are not suitable for implementation in MPC.

Another approach to process modeling is usage of so called black box models. In contrast to full physical models, these do not require any knowledge of the process, only thing that needs to be known is which inputs affect model output. ARX and ARMAX models are examples of such approach [5], [6].

Third approach is gray box modelling. Physical knowledge of the process is used to some extent in order to model the process. Again, ARX and ARMAX models are examples of such models, but physical knowledge of the building is used in order to develop such models. Examples of such building modelling can be found in [7].

In this paper gray box approach is used to develop ARIMAX model of the building. The goal is to develop a model that can be used for estimation of disturbance heat fluxes in buildings such as window opening. That can be further used for window opening detection, thus preventing energy losses by shutting down the heating or cooling if window is opened.

The estimation procedure was performed on simulation data from IDA ICE. Data from various zones were used and one of the results is shown here.

The paper is divided in six sections. In Section II data used in the estimation procedure are describe while Section III introduces the grey-box ARIMAX model structure for the building zone. Section IV presents algorithm used for model identification and disturbance heat flux estimation. Results that verify the appropriateness of the procedure are presented in Section V and conclusions are given in Section VI.

II. FER Skyscraper and Data Collection

FER (Faculty of Electrical Engineering and Computing) skyscraper has 12 floors. Floor 9 and 10 are modelled and simulated in IDA ICA. Data is obtained from one of the zones on 9th floor. The zone has one large window and one fan coil used for heating and cooling. Considered zone has three adjacent zones, one of which is hallway. Measured variables are:

- T_o – ambient air temperature;
- T_r – zone air temperature;
- Q_{fc} – fan coil heating power;
- Q_{swin} – solar radiation transmitted through the window;
- T_h – hallway air temperature;
- Q_{dist} – disturbance heat flux.

Although the considered zone has three adjacent zones, only hallway temperature is used in identification. Reason for that is that the wall separating considered zone and hallway has a single glass pane so the energy exchange between hallway and considered zone is greater than exchange between other adjacent zones. Only solar radiation transmitted through the window is considered because solar radiation that heats up the wall and the one transmitted through window are almost linearly dependent. Figure 1 shows the layout of the considered zone (red doors), and its adjacent zones. The disturbance heat flux Q_{dist} is the result of window opening, people occupying the zone and equipment running in the zone. The disturbance heat flux is measured in IDA ICE in order to compare estimated disturbance heat flux with the real one. Data sampling time was 57.6 seconds. The rationale for selecting the sampling time is the following: in order to estimate disturbance heat flux faster sampling time must be low and transient dynamics of fan coil would be lost if greater sampling time is used.

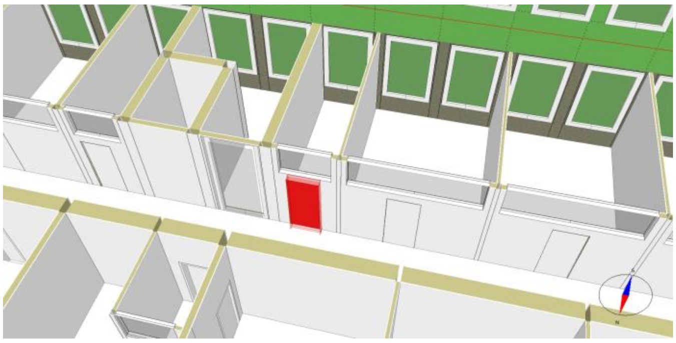

Figure 1 – IDA ICE building layout.

Figure 2 shows a sample of responses of zone, ambient and hallway temperatures. Effect of window opening can be seen in the figure as a temperature drop. Zone temperature is controlled by fan coil equipped with PI regulator.

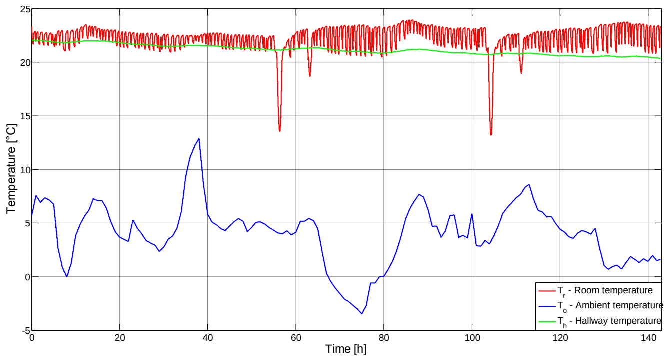

Figure 2 – Zone temperature, ambient temperature and hallway temperature.

Figure 3 shows heating power of the fan coil and solar radiation transmitted through the window in the zone. In order for data to be informative, fan coil controller temperature setpoint was altered frequently. This resulted in temperature response similar to the response of hysteresis regulator, which are common in fan coil control.

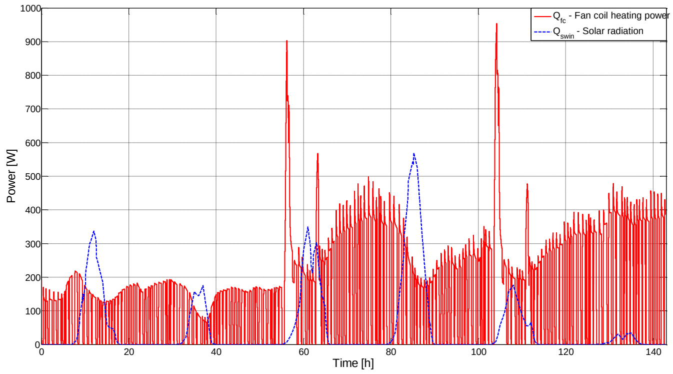

Figure 3 – Fan coil heating power and solar radiation transmitted through the window in the zone.

Disturbance heat flux due to window opening is shown in Figure 4. Difference in heat flux power is a result of partial window opening.

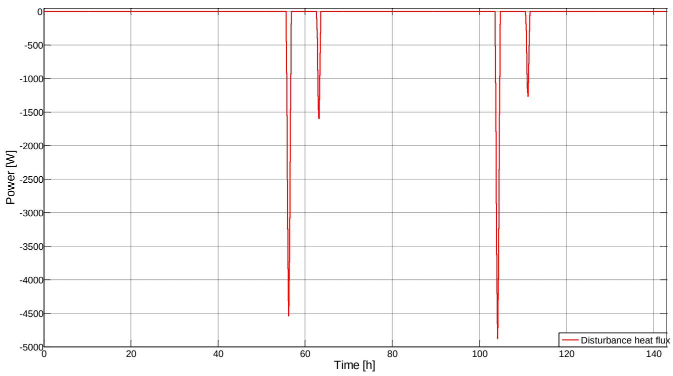

Figure 4 – Disturbance heat flux due to window opening.

III. MODEL DESCRIPTION

In order to capture zone temperature dynamics ARIMAX model is used. Model is derived from the following differential equation describing the zone dynamics:

$$C_r \frac{dT_r}{dt} = \frac{T_o - T_r}{R_o} + \frac{T_h - T_r}{R_h} + \lambda Q_{swin} + Q_{fc} + \varepsilon. \qquad (1)$$

As it can be seen from the equation, we assume that adjacent zones, except for hallway, do not influence the temperature in the considered zone since those zones have fan coils for temperature control. Temperature differences between all zones equipped with fan coils are small, thus energy exchange with those zones is negligible. In equation (1) R_o and R_h represent thermal resistances between the considered zone and ambient and the zone and hallway, respectively. Coefficient λ is used to scale solar radiation entering the zone. This is due to the fact that all of the solar radiation entering the zone does not heat the zone air directly, but instead heats up walls, floor and furniture in the zone, and heat is then transferred to the air by means of convection.

Applying Eulers forward discretization with sampling time ΔT we obtain the discrete-time model:

$$T_r(k+1) = T_r(k) + \frac{\Delta T}{C_r}\left[\frac{T_o(\mathrm{k}) - T_r(\mathrm{k})}{R_o} + \frac{T_h(\mathrm{k}) - T_r(\mathrm{k})}{R_h} + \lambda Q_{swin}(\mathrm{k}) + Q_{fc}(\mathrm{k})\right] + \varepsilon(\mathrm{k}). \quad (2)$$

From that model presented in equation(2) ARIMAX model can be derived:

$$T_r(k+1) - T_r(k) = b_1\left[T_o(k) - T_r(k)\right] + b_2\left[T_h(k) - T_r(k)\right] + b_3 Q_{swin}(k) + b_4 Q_{fc}(k) + \frac{C(\mathrm{q})}{1-q^{-1}}\varepsilon(k). \quad (3)$$

The term $\varepsilon(k)$ represents discrete white noise signal. Polynomial C is equal to:

$$C(q) = 1 + c_1 q^{-1} + c_2 q^{-2} + c_3 q^{-3}; \quad (4)$$

The q in equation (4) represents shift operator, that is $q^{-1}\varepsilon(\mathrm{k}) = \varepsilon(\mathrm{k}-1)$. There are overall 7 parameters that need to be identified in equations (3) and (4).

Model can be rewritten in pseudo-regression matrix form as:

$$T_r(k) = \varphi(\mathrm{k})\theta. \quad (5)$$

In this case $\varphi(\mathrm{k})$ is regression vector containing past values of model inputs, outputs and errors and θ is parameter vector. This form will be used in model identification and disturbance estimation.

IV. Model identification and disturbance estimation

Model identification and disturbance estimation is done simultaneously by implementing recursive least squares algorithm. Equations of the algorithm used are as follows:

$$\begin{aligned}
&\hat{\varepsilon}(k+1) = T_r(\mathrm{k}+1) - T_r(\mathrm{k}) - \varphi^T(\mathrm{k}+1)\hat{\theta}(\mathrm{k}) - v(\mathrm{k});\\
&v(\mathrm{k}+1) = v(\mathrm{k}) + \hat{\varepsilon}(k+1);\\
&d(\mathrm{k}+1) = P(\mathrm{k})\varphi(\mathrm{k}+1)\left[1 + \varphi^T(\mathrm{k}+1)P(\mathrm{k})\varphi(\mathrm{k}+1)\right]^{-1};\\
&\hat{\theta}(\mathrm{k}+1) = \hat{\theta}(\mathrm{k}) + d(\mathrm{k}+1)\hat{\varepsilon}(k+1);\\
&P(\mathrm{k}+1) = P(\mathrm{k}) - d(\mathrm{k}+1)\varphi^T(\mathrm{k}+1)P(\mathrm{k}).
\end{aligned} \quad (6)$$

The term $d(\mathrm{k}+1)$ and $P(\mathrm{k}+1)$ are Kalman gain vector and covariance matrix, respectively.

Vectors in the above algorithm contain:

$$\begin{aligned}
&\varphi^T(\mathrm{k}+1) = [T_o(\mathrm{k}) - T_r(\mathrm{k}), T_h(\mathrm{k}) - T_r(\mathrm{k}), Q_{swin}(\mathrm{k}),\\
&Q_{fc}(\mathrm{k}), \varepsilon(\mathrm{k}), \varepsilon(\mathrm{k}-1), \varepsilon(\mathrm{k}-2)];\\
&\hat{\theta}(\mathrm{k}) = [\mathrm{b}_1, \mathrm{b}_2, \mathrm{b}_3, \mathrm{b}_4, \mathrm{c}_1, \mathrm{c}_2, \mathrm{c}_3]^T;
\end{aligned} \quad (7)$$

Variable $v(\mathrm{k})$ represents the disturbance that we want to estimate. That disturbance must be scaled by some factor in order to obtain disturbance in watts (average disturbance heat flux during the sampling interval). Since data on fan coil average power is scaled by coefficient b_4, the same coefficient is used to scale the estimated disturbance to enable it to be additive with the average fan coil power and thus be representable in watts. Past model errors are calculated as follows:

$$\hat{\varepsilon}(k-i) = T_r(\mathrm{k}-\mathrm{i}) - T_r(\mathrm{k}-\mathrm{i}-1) - \varphi^T(\mathrm{k}-i)\hat{\theta}(\mathrm{k}) - v(\mathrm{k}-\mathrm{i}-1); \quad (8)$$

In order to estimate the disturbance heat flux it was necessary to let the algorithm work on some amount of undisturbed data in order to estimate model parameters first. The issue of sampling time selection requires a special attention. Small sampling time is necessary to capture fan coil dynamics, and to detect disturbance as soon as possible. At the same time, small sampling time might result in higher variance of model parameters due to small difference in zone temperature between neighboring samples.

V. Results

Figure 6 shows the result of the estimation procedure. Blue line shows estimated disturbance heat flux and red dotted line shows real disturbance heat flux. In the middle picture estimation procedure for whole data set is shown. Zero disturbance in first 55 hours is the part where only parameters where estimated and $v(\mathrm{k})$ was set to zero the whole time. After that estimation of the disturbance heat flux starts. As it can be seen from the figure, algorithm is successful in getting the dynamics of the disturbance, but it is not successful in determining power of the disturbance. Most likely cause of that is the inaccurate modelling of the influence of solar irradiance on the zone temperature. Upper picture shows estimation of positive heat flux. That heat flux is consequence of zone occupancy and equipment usage. Small oscillations of about 200 W can be seen in the picture. They appear every time when fan coil heating power rises or drops significantly. Figure 5 shows estimated parameters. In approximately 50 hours of data parameters converge to their value.

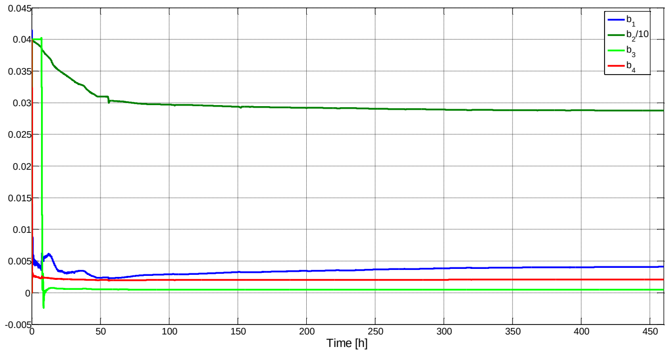

Figure 5 – Estimated parameters.

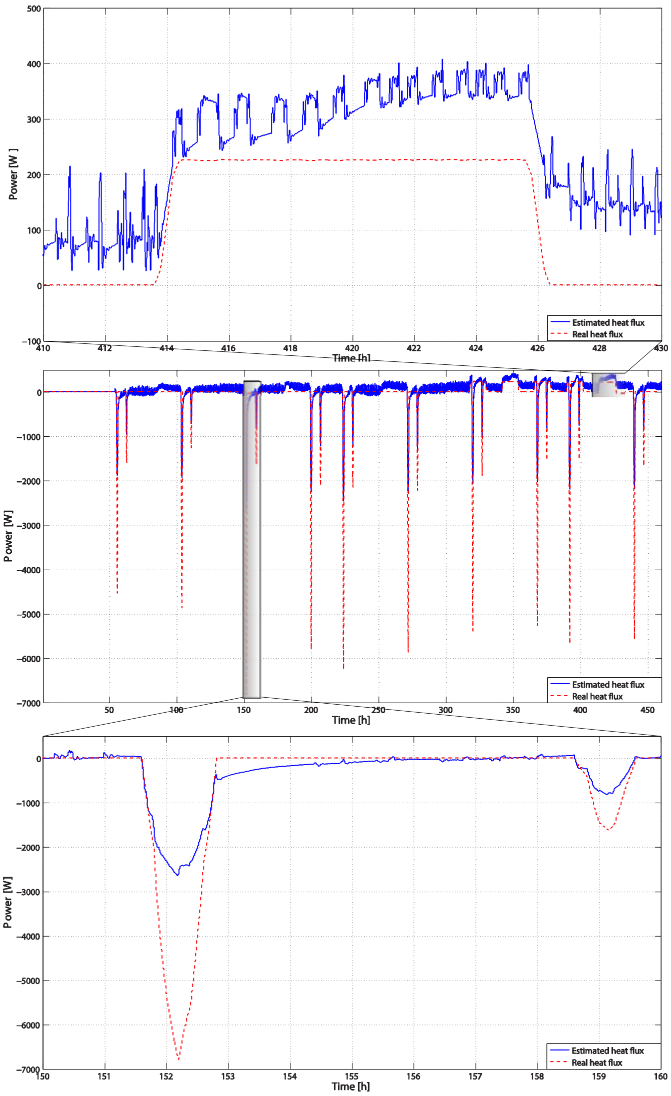

Figure 6 – Estimated and real disturbance heat flux.

VI. Conclusion and Future Work

This study has investigated possibility of disturbance heat flux estimation in buildings using grey-box model. It was shown that simple ARIMAX model can be used for that task. The algorithm used is computationally very efficient, resultant model is stable and does not require much data for parameter identification.

Future work will include using this model for window opening detection, prediction of zone temperature and possible application of this model to predictive control of fan coil. Also, the derived disturbance flux estimation procedure will be tested in real environment as part of ENHEMS-Buildings project.

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