Inverse model identification of the thermal dynamics of a Norwegian zero emission house

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Abstract. Dynamical model identification is an essential element in the implementation of a model predictive controller. In this work, a control-oriented first order model was identified in a dedicated experiment on a super-insulated single-family house. First, parameters resulting from CTSM and the MATLAB System Identification toolbox were compared. Then, a comparison of model predictions and measurements showed that this simple model captures well the main dynamics of the building-averaged indoor temperature, after one week of training on rich data with sample time below 15 minutes. It was also observed that this prediction performance was not affected by the configuration of internal doors.

Keywords: Zero emission building, dynamical thermal model identification, control-oriented building modelling

1 Introduction

1.1 Context

Model predictive control (MPC) is a control technique that has gained rising attention from the HVAC sector over the last years, as a way to increase energy efficiency and reduce environmental impact [1]. MPC is also seen as a promising tool to deploy the flexibility of the building heat demand in order to achieve some greater objectives (e.g. reducing the peak load of a cluster of buildings, reducing greenhouse gas emissions from the power consumed) [2].

A central aspect in MPC implementation is the identification of a robust model, which is among the most demanding tasks in the development of such a control. This identification of a dynamical model relies on a well-established theoretical framework [3], and has been extensively studied [4,5]. To allow using well-known optimisation methods with low computational cost, linear models are preferred. A stochastic component is often added to explicitly account for their uncertainty.

1.2 State of the art

Different modelling approaches are possible, depending on the availability of measurement data. If no data is available, a so-called “white-box” model can be built from knowledge of the building structure and materials and physical principles. However, this approach is time consuming and leads to complex models that are often not appropriate for predictive control [4] . On the other hand, when only data is available and no knowledge of physical principles is used, so-called “black-box models” can be used. Examples of such models include ARX, ARMAX, Box-Jenkins models [6], subspace models [7] and neural networks [8]. However, a drawback of this approach is the need for a large amount of data covering the whole range of operating conditions in order to achieve a robust model.

A third approach combining data and physical principles is known as “grey-box modelling” (or “inverse modelling” as it is based upon observations of an actual behaviour). In that case, simplified physical models of the buildings are proposed, and their parameters are identified from experimental data [5]. A method for selecting the best candidate within a set of grey-box models of increasing complexity is presented in [9], where likelihood ratio tests are used as a decision criterion. Furthermore, considerations about the quality of such identified parameters are introduced in [10], where the investigation was made on a simulated building. These works were later extended by a report from IEA EBC Annex 58 providing practical guidance for experimental characterisation of a building’s thermal dynamics [11].

1.3 Contribution

A first contribution of this work is in the comparison of two tools for identification of a simple first order (grey-box) model describing the thermal dynamics of a light-weight super-insulated building: CTSM [12] and the MATLAB System Identification toolbox [13]. A second contribution is in assessing the temperature disparities within the building during an identification experiment. A last contribution is found in the assessment of the prediction capability of a single zone first order model for predicting the future thermal behaviour of the building.

2 Building and Experiments

2.1 The LivingLab

The LivingLab is a zero-emission single family house at the Norwegian University of Science and Technology (NTNU). Here ‘zero-emission’ is used in the sense of compensating the greenhouse gases emissions resulting from operation (including equipment) and most of the materials [14].

The building is made of a highly insulated (rock-wool layer of thickness 35–40cm) wooden structure, with a significant window area (ca. 20% glazed area). Mechanical ventilation with heat recovery is implemented. Local energy production is installed, and consists of solar thermal and PV panels, and a ground source heat pump (the main heating system of the building was disabled in this experiment). Phase change material (PCM) boards are also installed behind the cladding of the ceiling of the building. More detailed information about the building may be found in [15].

The inside of the building consists of several inhabitable rooms of a total area of ca. 100 m^2 (not counting the attendant technical room), as seen on figure 1. Doors can be opened/closed to separate the bathroom and two bedrooms from the main zone.

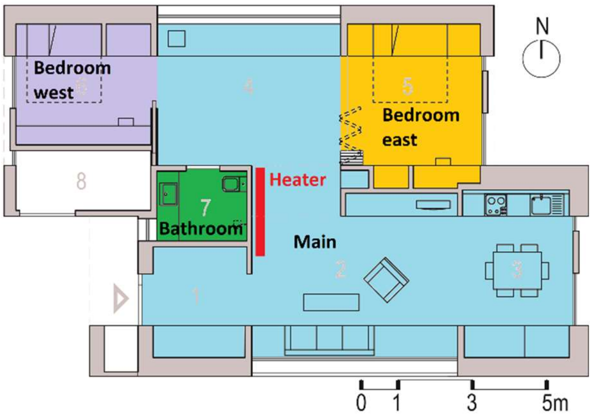

Fig. 1. Layout of the inside of the LivingLab and position of the heat emitter in the experiments (adapted with authorisation from [15] and [16])

2.2 Weather and heating conditions

Three successive experiments were carried out on the unoccupied building. A single heat emitter composed of electric radiators was used to heat the building (the ventilation also contributed in the first experiment, due to a high supply air temperature setpoint). This use of a single source is in line with the aim of a simplification of the heat distribution in zero emission buildings (see chapter 2.8 of [14]).

Data collected included: power to the heater, indoor temperatures, global solar irradiance, ambient temperature, as well as heat gains from appliances/lighting and ventilation. The corresponding data is presented in figure 2 below, and freely available (including details of the measurement instrumentation) on an open platform for further reuse in benchmarking studies [16].

To assess the impact of their configuration, the doors to the bedrooms were opened in the first and the last experiment, and closed in the second. The door to the bathroom was always closed. Ventilation settings were updated during the experiment to increase the variety of conditions. Initially, supply air temperature was regulated to 30°C. It was then lowered to 18°C in the beginning of the second experiment. Finally, it was fully stopped in the last days of the third experiment.

The radiator was mostly operated according to successions of pseudo random binary sequences (PRBS) [9,11], designed to excite the building over a large range of frequencies and yield a rich dataset for model identification. It is however worth noting that this does not allow comfortable occupation of the building — unless specific precautions are taken (which was not the case here).

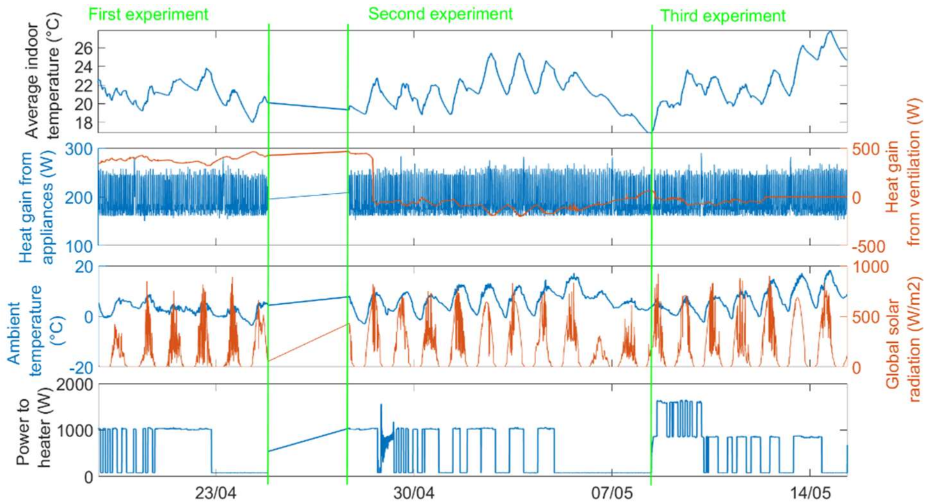

Fig. 2. Experimental data (an interruption happened before the 2nd experiment) [16]

2.3 Model investigated

As the aim is to use the model in future implementation of a model predictive controller, a simple linear formulation was adopted. It turned out that a first order model was sufficient to represent the main thermal dynamics of the building, as will be seen in a later section of this article.

This first order model is described by the following differential equation:

$$\mathrm{dT_i} = \frac{1}{C_i}\ (\ UA_i\ [\ T_a(t) - T_i(t)\ ] + \ \mathrm{A_W}\ \Phi_G(t) + P_{app}(t) + Q_{vent}(t) + P_{rad}(t)\ )\ dt + \ d\epsilon_p(t) \qquad (1)$$

where T_a is the ambient temperature, T_i the (lumped) indoor temperature, Φ_G the global solar radiation, P_{rad} the power to the radiator, P_{app} the power to appliances and lighting, Q_{vent} the estimated heat gain from ventilation, and $d\epsilon_p$ a stochastic process (typically assumed to be a Wiener process). Parameters of this model are a global (lumped) heat loss coefficient to the ambient UA_{ia}, a (lumped) heat capacity C_i, and an effective window area A_W (reusing the term from [9], although such a gain to the global horizontal radiation is hard to interpret in physical terms). It is worth noting that numerical values of UA_{ia} and A_W are dependent on the value of C_i, since they only appear in ratios in the input/output dependencies of the above equation. Moreover, the choice to focus solely on the global horizontal radiation for sun modelling is because predictions of it are available from weather forecast services (similarly to T_a), therefore allowing its use in predictive control.

The heat gain from ventilation Q_{vent} was estimated using the approximation:

$$Q_{vent}(t) = M_{air}\ C_{p,air}\rho(t)\ \left(T_{supply}(t) - T_{extract}(t)\right) \qquad (2)$$

where M_{air} is the volume mass of air, $C_{p,air}$ the specific heat of air, ρ the air flow rate, T_{supply} the supply air temperature and $T_{extract}$ the extract air temperature. Infiltration is not included in this, but already integrated in the model (as a part of UA_{ia}).

In the experiments, the building-averaged temperature was used as an observation of this lumped indoor temperature T_i (model output). However, operative temperature measurements could be more physically representative here.

2.4 CTSM and the MATLAB System Identification toolbox

Several tools are available for dynamical modelling using measurement data. In this study, the choice was made to use and compare the CTSM package for R [12] and the MATLAB System Identification Toolbox [13].

CTSM is a software tool interfaced with the free software statistical modelling environment R. It is meant to identify parameters of continuous time stochastic state space models, using a maximum likelihood approach.

On the other hand, the MATLAB System Identification toolbox is a commercial software. It can identify a variety of model types, including both continuous and discrete time grey-box models, with either a stochastic or deterministic approach. A *prediction error method* was used for parameter identification (using the *pem* function — but *greyest* yielded similar results). For consistency of the approach with CTSM, a continuous time stochastic approach was used in the modelling with the toolbox.

It is worth knowing that these two tools use a different formal description of stochasticity, which prevents direct comparison of their noise models (however, these two descriptions have a zero mean — so that they result in the same deterministic description).

3 Experimental Results

3.1 Limits of the single thermal zone approximation

Significant disparities of air temperature were observed within the building, with differences of up to 10°C between the highest and lowest measured temperature during the experiment. This is due to the superposition of 2 effects: vertical stratification within each of the rooms, and horizontal disparities due to zoning (particularly clear in the case of closed doors, as seen in figure 3). In the case of stratification, air temperature measurements taken at several heights showed differences as high as 4 °C in the main zone between floor and ceiling levels.

As reminded by figure 3 below, the indoor air temperatures varied in a large range which was not compatible with comfortable occupation of the building, with the chosen PRBS excitation. In particular, the solar gains in the main (southern) zone led to large excursions of its air temperature.

With these strong inhomogeneities in mind, a single zone approach was adopted in the rest of the work. The building-averaged indoor temperature was computed by averaging the numerous measurements according to volume considerations (to account for combined effects of stratification and zoning). In all 3 experiments, this average included bedroom temperatures and bathroom.

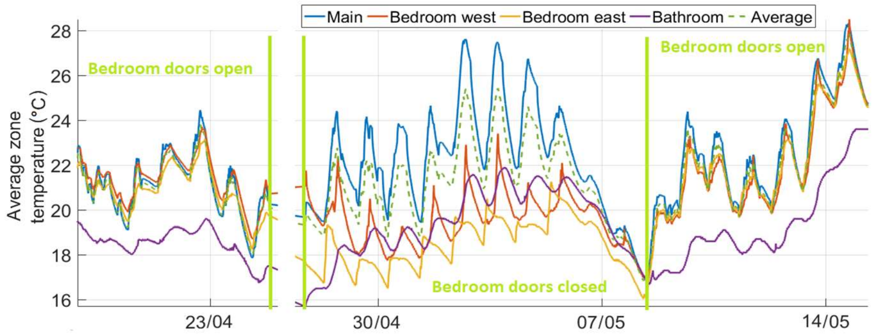

Fig. 3. Zone-averaged air temperatures (an interruption happened before the 2nd experiment)

3.2 Identified model parameters

The first order model parameters of the dynamical model described in Equation (1) were then identified using CTSM and the MATLAB System Identification toolbox. Resulting parameters (and their uncertainties) are plotted in figure 4 below. One may notice the influence of different sample times for the data (values of 5, 15, 30 and 60 minutes were considered).

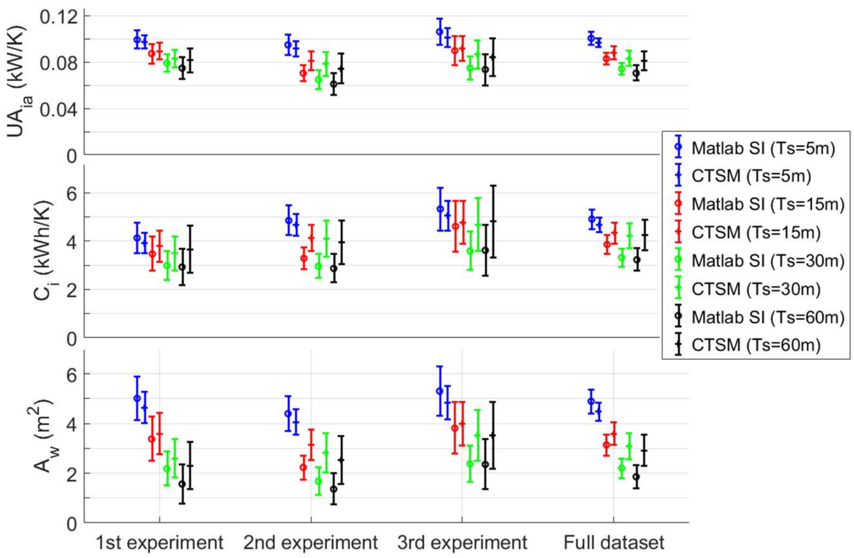

Fig. 4. Values of identified parameters by MATLAB and CTSM (colours correspond to different sample times for the data, uncertainties plotted correspond to 2 standard deviations)

In all cases, common bounds and initial values were used for the parameters. UA_{ia} was initially set to 0.1 kW/K, with allowed range 0–5 kW/K. A_W was initially set to 2 m^2 with allowed range 0–30 m^2. C_i was initially set to 4 kWh/K with bounds 0–100 kWh/K (for the third experiment with CTSM, an initial value of 3 kWh/K was used for allowing convergence of the optimisation).

As expected, the uncertainty of the parameters is significantly reduced by considering the whole period instead of a subperiod. Similarly, uncertainty was increased by higher sample times. These results provide an estimation of the long time constant of the building (estimated by the ratio C_i/UA_{ia}) in the range of two days, which is consistent with its well-insulated lightweight wooden structure. As observed, a period of one week (equal to several long time constants) is sufficient to identify a simple first order model of the building's thermal dynamics. Here, it is however important to bear in mind the use of a PRBS type of excitation, and the relatively clear sky days.

The change in the configuration of internal doors to bedrooms resulted in small reductions of the global heat loss (UA_{ia}) and effective window area (A_W) parameters. The value identified for the global heat loss were in a similar range to the expected value from previous modelling in the simulation software *IDA Indoor Climate and Energy* as part of previous independent work on the LivingLab [17] (0.07 kWh/K — estimated by a product of average U value by envelope area). On the other hand, the heat capacity observed was an order of magnitude above the total indoor air heat capacity (0.12 kWh/K). This confirms usage of the thermal mass of the building that is lumped together with air capacity in the model. Lastly, the identified value of the effective window area was an order of magnitude below the glazed area (36 m^2).

Changes in the sample time of the dataset did affect the value of the identified parameters. A downward trend was observed for the value of the global heat loss (UA_{ia}) and effective window area (A_W) parameters as the sample time increased. This may potentially reflect a tendency to convert some of the solar gains in reduced heat losses, with a similar overall effect on the indoor temperature.

Moreover, it was observed that the System Identification toolbox generally yielded lower values of the parameters for sample times of 15, 30 and 60 minutes in all three experiments (and their aggregation), compared to CTSM.

3.3 Prediction capability of the first order model

For the sake of conciseness, the analysis of this paragraph is reduced to the models identified by the MATLAB toolbox over the first experiment and the whole dataset. The prediction capability of the models identified for each sample time were evaluated by predicting the evolution of the indoor temperature over each of the 3 experiments. In every case, prediction was made starting from the initial temperature and assuming perfect knowledge of the disturbances and inputs (namely T_a, Φ_G, P_{app}, P_{rad}, and Q_{vent}). The resulting predictions are presented in figure 5.

As seen in these results, a simple first order model trained on one week of data was sufficient for predicting the main slow thermal dynamics of this lightweight building over several days. This is supported by figure 6 presenting the evolution of root mean square error (RMSE) over the prediction horizon for sample times of 5, 15, 30 and 60 minutes. It was observed that short sample times of 5 and 15 minutes appeared to provide better overall prediction capability.

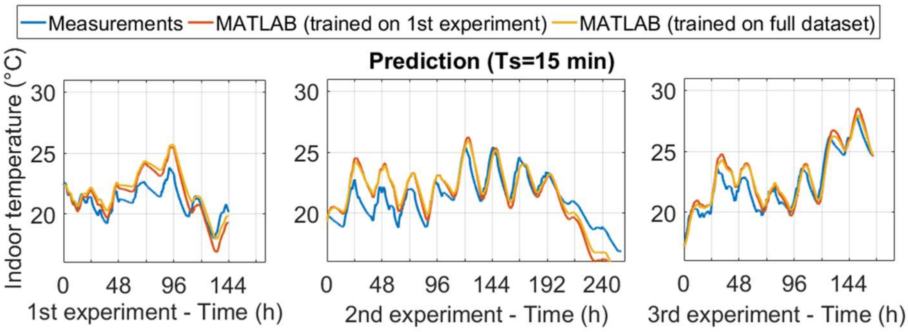

Fig. 5. Prediction of the evolution of the indoor temperature (starting from the initial value) for a model trained on data from the first (red) or all 3 experiments (yellow)

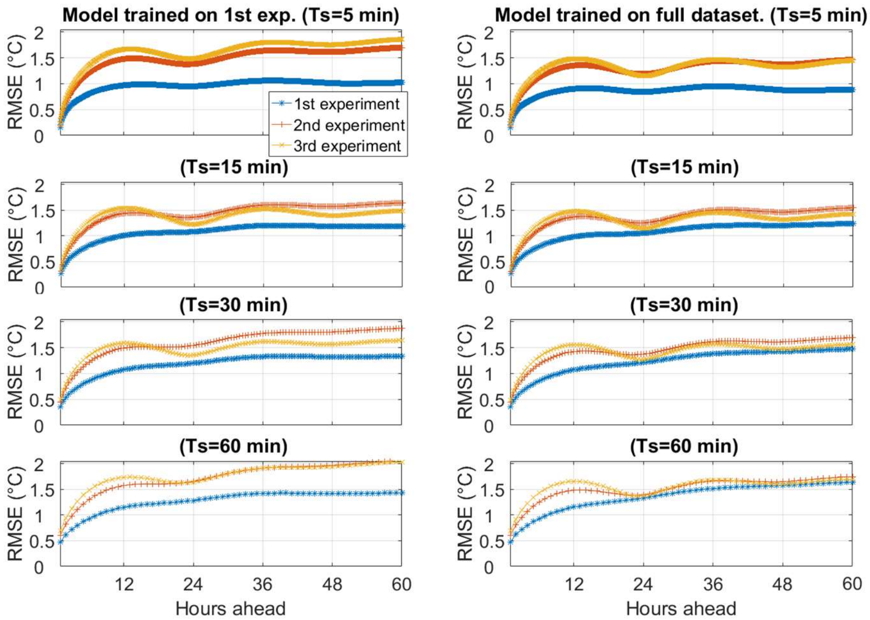

Fig. 6. Evolution of RMSE over prediction horizon for the 3 experiments and different sample times for the model identified on the first experiment (left) and the whole dataset (right). On the left-hand side, blue corresponds to fit to the training data, while red and yellow correspond to validation data, while on the right-hand side all 3 curves correspond to training data.

As also seen on figure 6, the prediction performance is increased by considering more data than just the first experiment. In other words, one week of data was not sufficient for obtaining the best possible fitting to all experiments, as cross validation did show a gap between training and validation data (see left column, as opposed to right column). Yet the improvement of RMSE resulting from training upon the 2 later experiments was small in the case of 5 and 15 minutes data.

It is also important to note that the performance of the model identified on the first experiment was similar on validation data with open and closed bedroom doors. This can be explained physically by higher heat transfer between rooms (both through walls and infiltration through doors) than losses to the ambient through the envelope in such a super-insulated building.

4 Conclusion

This work presented experiments to identify the thermal dynamics of an actual super-insulated building. The heating was operated according to a predetermined rich excitation sequence (PRBS) on a single electrical heat emitter. The experiments showed that large disparities of air temperature happened in the building, due to the combination of zoning (using doors) and air stratification.

The model investigated was a first order model, with 3 parameters to be identified: a lumped heat loss to ambient, a heat capacity and a solar gain. Two software packages were compared for achieving the model fitting: CTSM and the MATLAB System Identification toolbox. These two software packages yielded different values (and uncertainties) of the model parameters, despite identical initial values and bounds in the optimisation. Increase of the sample time of the measurements decreased the values of all 3 model parameters (especially for the MATLAB toolbox), while increasing the uncertainty on each of them. In any case, none of the software packages was found to attain a significantly higher performance than the other.

The prediction capability of the first order model identified in MATLAB was analysed, revealing better short-term performances for measurement sample times within 5–15 minutes, which are therefore recommended in future works.

One week of data under PRBS excitation with an electric radiator allowed identifying such a simple single zone model. This model represents well the main slow thermal dynamics of the building-averaged temperature in this lightweight building case (a different conclusion may be reached on a heavier one). Moreover, this prediction performance was observed to be unaffected by the configuration of internal doors.

Further work should investigate more detailed dynamical models (exploiting the open dataset of the experiment [16] for benchmarking purposes), improvement of the solar radiation modelling (using e.g. a time variating parameter for A_W), and assess the potential of the model for operation of the heating using model predictive control.

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[1] Project links: http://www.zeb.no/ | http://www.fp7-advantage.eu/ | http://www.annex67.org/