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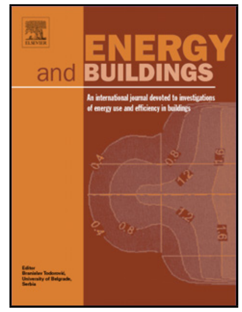

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On site characterisation of the overall heat loss coefficient: comparison of different assessment methods by a blind validation exercise on a round robin test box

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Abstract

Several studies have shown that the actual thermal performance of buildings after construction may deviate significantly from its performance anticipated at design stage. As a result, there is growing interest in on site testing as a means to assess real performance. The IEA EBC Annex 58-project 'Reliable Building Energy Performance Characterisation Based on Full Scale Dynamic Measurements' focused on on site testing and dynamic data analysis methods that can be used to characterise the actual thermal performance and energy efficiency of building components and whole buildings. The research within this project was driven by case studies. The current paper describes one of them: the thermal characterisation of a round robin test box. This test box can be seen as a scale model of a building, and was built by one of the participants. During the project, its fabric properties remained unknown to all other participants. Full scale measurements have been performed on the test box in different countries under real climatic conditions. The obtained dynamic data has been distributed to all participants who had to characterise the thermal performance of the test box's fabric based on the provided data. The paper compares the result of different techniques,

ranging from a simple quasi-stationary analysis to advanced dynamic data analysis methods, which can be used to characterise the thermal performance based on on-site collected data.

Keywords*:* overall heat loss coefficient, averaging method, state space models, ARX-models, round robin test

Introduction

The rise of living standards, the scarcity of natural resources and the awareness of climate change resulted in an international pressure to significantly reduce the energy consumption of buildings and communities. In several countries more stringent requirements are imposed by energy performance legislation and also in building codes an increased awareness for environmental issues can be noticed. Thick insulation layers and more efficient heating systems and appliances are becoming common practice. Most often, requirements and labelling of the energy performances of buildings is done in the design phase by calculating the theoretical energy use. Several studies, however, showed that the actual performance after realisation of the building can deviate significantly from this theoretically designed performance [Marchio and Rabl 1991, Branco et al 2004, Majcen et al 2013 amongst others]. Part of the deviations can be explained by user behaviour [Santin 2010], but the other part has to be attributed to the physical features of the building and its systems. Several authors [e.g. Hens et al 2007, Lowe et al 2007, Roels and Langmans 2016] showed that despite regulation and policy enforcement, the actual as built thermal performance of the building fabric often differs significantly from the requirements. Figure 1 compares predicted and measured overall heat losses of 18 houses in the UK [Wingfield et al. 2009]. None of them realises the intended performance. In some cases, actual performance even rises up to twice that value. Similarly, Houvenaghel and Hens [2003] mention discrepancies for pitched roof components ranging from 10% for carefully crafted details, up to 200%-300% for cases with questionable workmanship quality. Some governments acknowledge the issue (e.g. in the UK a safety factor with regard to party wall heat losses is introduced (bre.co.uk)), however, overall it is not widely recognized nor appreciated for its potential environmental and economic impact [Concerted Action EPBD 2015].

The awareness of a gap between theoretically predicted and real life achieved performance of buildings, is one of the reasons, why, together with an increased application of numerical simulations, a renewed interest in full scale testing is observed [INIVE, 2011]. Despite best efforts, however, practice shows that the outcome of many on site activities can be questioned in terms of accuracy and reliability. Full scale testing requires quality on both the test environment and the experimental set-up as well as on the (dynamic) data analysis methods to come to a characterization that is reliable and accurate. As soon as the required quality fails on one of the topics, the results become inconclusive or might even be wrong. To this extent an international collaboration in the framework of the 'Energy in Buildings and Communities'-programme (former ECBCS) of the International Energy Agency has been set up [Roels, 2017]. From September 2011 till June 2015, the IEA EBC Annex 58-project worked with international experts from all over the world on the topic of 'Reliable building energy performance characterisation based on full scale dynamic measurements'. The global objective of Annex 58 was to develop the necessary knowledge, tools and network to achieve reliable on site dynamic testing and data analysis methods that can be used to characterise the actual energy performance of building components and whole buildings. The present paper focuses on a round robin experiment performed within the framework of this project. In this experiment, a test box – a scale model of a building – has been built by one of the participants, with fabric properties unknown to all other participants. The test box has been shipped to different institutes (different climatic conditions) with the aim to perform a full scale measurement of the box under real climatic conditions. The obtained dynamic data was distributed amongst all partners who had to use the provided data to characterise the thermal performance of the test box.

The current study focuses on the determination of the overall heat loss coefficient of the test box. On site experiments to determine the overall heat loss coefficient are usually based on specific heating experiments performed on vacant buildings. They can be roughly subdivided in two types: the first ones try to keep the conditions as stationary as possible, typically by heating the indoor environment to a fixed elevated temperature. Heating energy, as well as indoor and outdoor conditions are monitored throughout the experiment. This quasi steady-state procedure, i.e. steady-state indoor and dynamic outdoor conditions, came to be known as the co-heating test. A review of the method and corresponding data analysis methods can be found in Bauwens and Roels [2014]. Disadvantages of the co-heating test methodology are that it is intrusive, costly and takes several days to weeks to complete. Alternatives to the co-heating test generally propose tailored dynamic heating experiments, e.g. heating power following a pre-determined Pseudo-Random Binary Sequence (PRBS), and tailored dynamic analysis methods, e.g. lumped state-space modeling, to limit duration to a number of days [Madsen and Holst 1995, Bacher and Madsen 2011, Gutschker 2008, Jimenez and Madsen, 2008, Lethé et al. 2014].

In the first section of this paper an overview is given of the data analysis methods that can be used to deduce the heat loss coefficient on the basis of this kind of on site collected quasi stationary or dynamic data. The next section gives a description of the round robin test box, including its designed heat loss coefficient, and two on site measurement campaigns. In the first one the test box was measured under winter conditions in Belgium, while in the second one the box was measured in south of Spain under summer conditions. The last section compares and discusses the heat loss coefficient of the test box as obtained by different teams, using different data analyzing techniques.

Overview of data analysis methods

Different analysis methods can be used to determine the overall heat loss coefficient of a (vacant) building starting from dedicated heating experiments. The techniques vary from simple stationary methods to advanced dynamic data analysis methods. In the next paragraphs a short description of the most important characterisation methods is given together with their main possibilities and limitations.

Averaging method

Averaging methods are typically used in winter conditions to estimate the thermal resistance of building elements from in situ surface temperature and heat flux measurements [ISO 9869, 1994].

The method assumes that averages of heat flow rate and temperatures over a sufficient long period of time are representative for their values in stationary conditions. By averaging the (dynamic) measured data, steady state values are calculated. This way, making use of the measured heat input and indoor/outdoor temperature difference, the overall (stationary) heat loss coefficient of a simple building, in this case the test box, can be calculated as:

$$HLC = \frac{\sum Q}{\sum \Delta T} = \frac{\sum_{t_k=1}^{n} Q_{t_k}}{\sum_{t_k=1}^{n} (T_{i,t_k} - T_{e,t_k})} \quad (1)$$

with *HLC* the overall heat loss coefficient of the building (W/K), Q_{t_k} (W) the heat flux introduced at reading t_k to keep the interior temperature at T_{i,t_k}, T_{e,t_k} the exterior temperature at reading t_k and n the number of measured data points (-).

The method is only valid if the thermal properties and heat transfer coefficients can be treated constant over the test period and if the effect of heat storage is negligible. As a result, it is clear that the method can be of use for the quasi steady state experiments, in which the indoor temperature is kept constant and solar gains can be considered as negligible, but that the method loses his applicability for other heat inputs and highly variable outdoor conditions. Furthermore, only the stationary thermal properties can be determined.

Simple and multiple linear regression

Apart from the averaging method, linear regression techniques are commonly used to determine the stationary thermal properties. Where in the averaging method detailed (short interval data) can be used and the stationary values follow from the averaging technique, the linear regression typically makes use of (daily) averaged values, to cancel out short-term effects of thermal mass [Bauwens and Roels, 2014]. For the averaged measurement readings at t_k the simple linear regression model is formulated as

$$Q_{t_k} = HLC.\left(T_{i,t_k} - T_{e,t_k}\right) + \varepsilon_{t_k} \quad (2)$$

with ε_{t_k} the error between the measured and modelled heat input, which is minimized by the regression analysis. If a proper averaging period is used, the sequence of errors will be uncorrelated, i.e. the error sequence corresponds to white noise. Applying multiple linear regression allows to determine not only the overall heat loss coefficient, but also to gain some information on the solar transmittance. Certain climatic conditions or heavy constructions could require longer integration periods (typically multiple of 24h as demonstrated by [Modera et al. 1985]). [Naveros et al, 2012; Castillo et al, 2014] demonstrated that the method can be generalized to systems with increased complexity. Major drawback remains though, that again only stationary properties can be determined and no characterisation of the dynamic thermal behaviour of the building can be made.

ARX- and ARMAX-models

Compared to the previous methods, ARX and ARMAX -models allow to include the dynamics of a linear time invariant (LTI) system. In the abbreviation AR stands for AutoRegressive: the current output is related to the previous values of the output; MA (Moving Average) refers to the noise model used, and X refers to the fact that eXternal inputs are used: the system relies not only on the current input value, but also on the history of the input. For identifying LTI-systems AR(MA)X-models are a standard methodology. The most common ARX-model structure is the simple linear difference equation which relates the current output at time *t* to a finite number of past outputs and inputs. For the estimation of the overall heat loss coefficient, the heat input Q_{t_k} could for instance be taken as output and the indoor and outdoor temperatures T_{i,t_k}, T_{e,t_k} as inputs. This corresponds to a multiple input, single output ARX-model, represented as:

$$\Phi(B)Q_{t_k} = \omega_i(B)T_{i,t_k} + \omega_e(B)T_{e,t_k} + \varepsilon_{t_k} \quad (3)$$

in which $\Phi(B)$ is the model output (AR) polynomial, and $\omega_i(B)$ and $\omega_e(B)$are the model input (X) polynomials. The order of the polynomials basically indicates how many data points from the past are involved in the description of the heat input Q_{t_k} at reading t_k. ARX and ARMAX models have among others been applied by Norlén (1994), and were further developed by Jimenez and Heras (2005) and Jimenez et al. (2008) for modelling the heat dynamics of buildings and building components. A main problem when applying AR(MA)X-models is first of all the selection and validation of the model, but then also the extraction of physical information from the model parameters. In an ARX-model, each individual parameter lacks a direct physical meaning. However, steady-state physical parameters can be obtained by calculating the stationary gain of the transfer function from each input to the output. Comparing Eq. (3) for B=1 to the general steady state heat balance, two stationary gains can be distilled: one heat loss coefficient HLC_i related to the interior temperature and one HLC_e related to the exterior temperature:

$$HLC_i = \frac{\omega_i(1)}{\Phi(1)} \;\; ; \; HLC_e = \frac{-\omega_e(1)}{\Phi(1)} \tag{4}$$

Based on minimum variance weighting, these two estimates can be combined in one estimate for the overall heat loss coefficient [Norlén, 1994].

An important step in ARX-modelling is to select a suitable model with the appropriate orders of input and output polynomials. Madsen et al. [2016] showed that by stepwise increasing the model order until most significant autocorrelation and crosscorrelation are removed, a reliable modeling of both stationary and dynamic properties of buildings is feasible. Other physical criteria that are relevant to this approach are reported by [Jiménez 2016].

State space models

A final methodology to characterise the heat loss coefficient of a building is the use of state space models or so-called grey box models. State space models consisting of simple resistance/capacitance schemes can be used to model the thermal dynamics of a building as a linear time-invariant system. The parameters are readily estimated with e.g. the maximum likelihood technique and most often a suitable model is identified with a forward model selection approach. In this approach the analysis starts with fitting a very simple model, which is then stepwise extended until the loglikelihood no longer increases significantly compared to the previous model and the residuals (the difference between the measured and predicted output) correspond to white noise. Both the initial model and possible extensions thereof simplify the building's thermal behavior; their parameters have a direct physical interpretation. Defining them thus requires – in contrast to the ARMAX-model – some prior physical knowledge. That is why state space models are often referred to as grey box models. Figure 2 shows as an example a two-state grey box model for a one zone building, taking into account heat input by heater and solar radiation, capacity of the interior and walls and (conductive) heat flow through the walls. The continuous-time system equations are two coupled stochastic differential equations:

$$dT_i = \frac{1}{C_i}\left(\frac{1}{R_{iw}}(T_w - T_i) + gA_{sol}I_{sol} + \phi_h\right)dt + \sigma_i d\omega_i(t) \quad (5)$$

$$dT_w = \frac{1}{C_w}\left(\frac{1}{R_{iw}}(T_i - T_w) + \frac{1}{R_{we}}(T_e - T_w)\right)dt + \sigma_w d\omega_w(t) \quad (6)$$

and the discrete-time measurement equation is:

$$T_{r,t_k} = T_i(t_k) + \epsilon_{t_k} \quad (7)$$

For more details, see (Madsen and Holst, 1995). To identify all relevant dynamic characteristics, preferably a predetermined heating power signal (e.g. ROLBS- or PRBS-signal) can be imposed to excite the building around its expected time constants, whilst remaining uncorrelated with outdoor weather conditions.

Round robin experiment

To compare the applicability and reliability of the different methods, and to determine the state of the art on full scale measurements and dynamic data analysis a round robin experiment was set up in the framework of Annex 58. The global objective of the round robin experiment was to perform a well-controlled comparative experiment on testing and data analysis. To this extent, a test box (a scale model of a simplified building) has been built by KU Leuven. KU Leuven was the only partner within the Annex 58-project aware of the exact composition of the test box. After construction, the box has been shipped to different partners (different climatic conditions and different acquisition equipment) with the aim to perform a full scale measurement of the test box under real climatic conditions. The obtained dynamic data has been distributed to different institutes who had to characterize the test box based on the provided experimental data. The current section describes the exact composition of the box and its target value of the overall heat loss coefficient. Thereafter;

two on site experiments are described: one at the BBRI-premises in Belgium under winter conditions and one at CIEMAT, Spain under summer conditions.

Description and exact composition of the test box

The investigated test box has a cubic form, with exterior dimensions of 120x120x120 cm³. The floor, roof and wall components of the box are all identical and have a thickness of 12cm, resulting in an inner volume of 96x96x96cm³. One wall contains an operable wooden window with overall dimensions of 71x71 cm² and a glazed part of 52x52 cm². The double glazing (4-15-4) has a U-value of 1.1 W/m²K (according to EN 673, in a vertical position and with ΔT=15°C) and g-value of 0.63. The air gap (15 mm) between both glass layers (4 mm) is 90% argon filled. Solar absorptance of outer and inner glass layer are 7% and 8% respectively. The solar transmittance of the glazing system is 56%. The outdoor and indoor solar reflection coefficients are 29% and 28% respectively.

To avoid thermal bridges and local effects as much as possible, no inner structure is foreseen in the walls. To realise this, the box consists of an inner box of double layered fibre cement boards. Insulation boards are then glued to the inner box, whereupon an outer box is constructed consisting of fibre cement construction board, finished with a white coloured fibre cement cladding board. The inner walls of the box are painted in a mat black paint. After finishing the box, a steel structure is provided around the box, so that the box remains free from the thermal influence of the ground. This simplifies characterisation assumptions as the box can be considered as floating in free air. Figure 3 presents a horizontal section of the design of the round robin test box, while in Figure 4 the subsequent construction steps are shown.

1. 2. 3.

Table 1 gives the material properties of the different layers of the box, as provided by manufacturers. Based on these values the one-dimensional thermal resistance of the test box fabric is calculated as 1.927 m²K/W. Taking into account the surface resistances (corresponding ISO 6946:2007) this corresponds to a U-value of 0.476 W/(m².K). Note that this value does not take into account the possible presence of a thin air and/or glue layer between the different material layers. The presence of such a layer might slightly increase the actual thermal resistance of the fabric, and hence decrease the obtained U-value. To get an idea of the impact, let us assume a thin air layer of 2.0 mm at the interface between two layers. Knowing that the fabric contains four interfaces, the extra resistance could theoretically count up to 0.32 m²K/W, raising the overall resistance to 2.25 m²K/W.

Determination of the target value of the overall HLC of the box

The theoretical goal value of the overall heat loss coefficient of the box has also been determined with TRISCO, a 3D steady state heat transfer model for the thermal analysis of building components (www.physibel.be). By imposing different indoor and outdoor temperatures the overall heat loss through the fabric of the box can be calculated. Figure 5 presents a vertical and horizontal section through the box, showing the isotherms when an indoor temperature of 25°C and outdoor temperature of 0°C is imposed. On the contour plots the edge effects and thermal bridging at the window façade junction is clearly visible. Taking standard surface resistances (R_{si}=0.13 and R_{se}=0.04 m²K/W) into account [ISO 6946:2007] a theoretical heat loss coefficient of 4.08 W/K is obtained .

Description of the on-site experiments

Winter 2012-2013 the test box has been tested at the premises of the Belgian Building Research Institute in Limelette, Belgium (50°41’ N, 4°31’ E). Afterwards the box has been shipped to Spain, where it was measured under summer conditions in Almeria (37.1° N, 2.4° W). In general, the weather conditions in Belgium are temperate, with a mild, but rainy, humid and cloudy winter. The weather at Almeria on the other hand is dry and extremely hot in summer, with large temperature amplitudes between day and night. During day time, solar radiation is very high on horizontal surfaces and the sky is usually very clear. Figure 6 shows the test box at both sites.

At both sites, different experiments have been performed, ranging from co-heating tests with constant indoor temperature, over free floating temperature runs, to imposed dynamic heating sequences (ROLBS-signals). During the experiments, heat fluxes on all internal surfaces, together with internal and external surface temperatures, indoor temperature and delivered heating energy within the box have been measured. In addition, both test sites are equipped with an outdoor weather station, measuring all relevant boundary conditions (temperature, relative humidity, wind direction and speed, diffuse and direct solar radiation, long wave radiation,…).

The following list summarises the measurement transducers and sensors as used in Almeria:

- Air temperature: Platinum thermoresistance, PT100, 1/10 DIN, with solar radiation shield (Figure 7a, Figure 7b and Figure 7c).
- Surface temperature: Platinum thermoresistance, PT100, 1/10 DIN embedded in a very slim semi-transparent substrate, glued to the measured surfaces and covered with a tape of same colour as the surface (Figure 7d and Figure 7e).
- Heat flux density: Sensor model HFP01 (Hukseflux), glued to the centre of each internal face of the box and covered with a tape of the same colour as the surface (Figure 7d).
- Horizontal and vertical global solar irradiance on the horizontal and south vertical surfaces respectively: Pyranometers, model CM11 (Kipp and Zonen. Analogous devices used for diffuse solar irradiance but installed in a two-axis sun tracker SOLYS 2 (Figure 7f).
- Beam solar irradiance: Pyrheliometer, model CHP1 (Kipp and Zonen), installed in a two-axis sun tracker SOLYS 2 (Figure 7f).
- Horizontal and vertical long wave radiation on the horizontal and south vertical surfaces respectively: Pyrgeometers, model CGR-4 (Kipp and Zonen).
- Heating power: Power transducer, model SINEAX DME 440 (Camille Bauer Ltd).
- Wind velocity: Sensor model WindSonic manufactured by (Gill instruments Ltd.) (Figure 7g).
- Outdoors relative humidity. Sensor model HMP45A/D (VAISALA).

Measurement campaigns

Three series of measurements took place at BBRI in Belgium in winter 2013 consisting of:

- A coheating test with the indoor temperature set at 25°C, running from 25.01.2013 till 08.02.2013

- A free floating temperature test (no additional heat input) from 08.02.2013 till 22.02.2013
- An imposed ROLBS power sequence test, running from 25.02.2013 till 28.02.2013

Summer 2013 three additional tests took place at CIEMAT in Spain:

- A co-heating test with an indoor air temperature set point of 40°C, running from 17.06.2013 till 26.06.2013
- A ROLBS power sequence test, running from 28.06.2013 till 01.07.2013
- A free floating temperature test from 02.07.2013 till 10.07.2013

A preliminary observation of the measurements gives very relevant information to construct candidate models. As an example Figure 8 plots the global vertical and horizontal solar radiation during both measurement campaigns. A clear difference is observed. Where in winter conditions in Belgium the vertical solar radiations (impinging on the walls) is much higher than the horizontal one, this is the other way around in summer in Spain: horizontal solar radiation impinging the roof of the box is now significantly higher. But notwithstanding the high levels of solar radiation and the differences between the different orientations, the heat fluxes through all opaque walls remain very similar (results not shown here, but can be found in Jimenez, 2016).

Characterisation of the test box – discussion of the results

The measured data collected as described in the previous section, has been provided to all participants in the Annex 58-project. They were asked to characterise the thermal performance of the round robin test box as precise as possible based on the provided dynamic data. Both stationary properties, e.g. the overall heat loss coefficient, and dynamic properties of the test box were aimed for. Here, only the results on the overall heat loss coefficient will be presented. For the current round robin test, free running tests were not found to give accurate parameter estimates, as equations become over-parameterised when there was no heating power supplied. The exact instruction document of the round robin test as well as all other results can be found in [Jiménez, 2016].

Comparison of the results submitted by participants

Table 1 summarises and compares the obtained overall heat loss coefficient as determined by different participants. Note that several participants have been using different methods and/or investigated different sampling times to determine the overall heat loss coefficient. Considering the heat loss coefficient, some spread is observed in the results based on each data set. Differences are observed not only in the mathematical modelling approach but also in the physical assumptions used to build the models and concerning pre-processing issues.

Comparing the results, it can be seen that most methods result in an overall heat loss coefficient around 4 W/K. This is in close agreement with the target value of 4.08 W/K. Participants that have analysed both test campaigns (recorded in Belgium and Spain), give slightly higher values of the heat loss coefficient for the data recorded in Spain. The dependencies of the heat loss coefficient on the boundary climatic conditions, do not explain this tendency. An important part of this difference is likely explained by the different temperatures of the building fabric along both tests and the temperature dependency of the thermal conductivity. However, information to carry out a theoretical study of this dependence is not available. Considering that the estimates overlap when their uncertainty is taken into account, it is difficult to discern whether the observed differences are due to a typical experimental spread around the true value, or due to a systematic tendency.

Observing all reported estimates, results in line with the target value have been reported using different methods such as stochastic state space, ARX, ARMAX, linear regression models, and averaging methods. The most deviating results (assumed more inaccurate) are those given by models that ignore dynamics, or apply assumptions, which are not valid under the given circumstances. To illustrate this, Figure 9 compares all estimates for the overall heat loss coefficient obtained by different teams using the averaging or linear regression method. The figure plots the estimates as a function of test duration. Smaller test durations are obtained by only considering part of the measurement campaign. The estimates are additionally coloured according to the sampling time. Larger sampling times are obtained by averaging the high frequency data. Finally, the estimates for both the Belgian BBRI and Spanish CIEMAT measurements are grouped. CIEMAT estimates are depicted graphically as hollow dots.

Although *averaging methods* collect a much smaller number of estimates, they seem to yield more consistent estimates than *linear regression methods*. As mentioned above, the CIEMAT case results in slightly higher estimates of the overall heat loss coefficient. Looking at the *linear regression* estimates, two estimates give a value lower than 3 W/K, a deviation of more than 25% from the target value. The leftmost result is low due to the fact only nighttime measurements were considered for the analysis. However, during the day, the building fabric is charged by solar gains. The overnight discharge of solar gains is not considered as an additional heat input, leading to an underestimation of the heat loss coefficient. The large spread of points around measurement duration of 170 hours is due to different assumptions on the same data. One can conclude that only when the linear regression curve is fitted through the origin, we get results that are close to the target value. Having a non-zero intercept, or only taking only night measurements into account, leads to underestimations.

The impact of sampling time and measurement campaign duration on the outcomes for the averaging and linear regression models have been investigated by taking subsets of the data sets. Figure 10 shows the estimates for both the BBRI and CIEMAT test campaigns. The original dataset is subdived in subsets with shorter duration. To avoid correlated estimates, subsets that overlap are avoided. The analysis is performed for different sampling times (indicated by their colour in Figure 10). Overall with increasing duration of the test (from left to right on the x-axis) the results become more consistent. This is most pronounced for the averaging method. The averaging method, however, is unable to explicitly account for solar radiation. This leads to an underestimation of the overall heat loss coefficient, especially for the CIEMAT-measurements that have significant solar irradiation. Multiple linear regression models are able to take solar radiation into account. However, for cases with high solar gains (see CIEMAT-results at bottom row of Figure 10) very high (and unrealistic) estimates for the overall heat loss coefficient are obtained unless a sampling time of 1440 hours (one day) is taken.

An explanation for this sudden shift in estimates when going from higher sampling times (5 minutes up to 6 hours) to daily averages, can be found when analyzing the measurement data in more detail. Figure 11 compares the data of both measurement campaigns when aggregating the data to different sampling times. Where aggregating the winter data of BBRI in Belgium (left column of Figure 11) hardly influences the global trends in the data, this is definitely not true for the summer data collected in Spain (Figure 11, right column). The latter indeed reveals that the daily averaged data shows very different behavior as opposed to data averaged over 5 minutes to 6 hours. The daily fluctuating behavior is completely filtered away. These graphs illustrate that in the case of a stationary heating experiment, where measurements are significantly influenced by a daily recurring solar irradation pulse and that lack a significant trend spanning several days, we should consider at least daily averaged data. Only then can we reliably fit stationary models. As a result, long measurement campaigns are needed to obtain enough data points.

As an alternative, AR(MA)X and stochastic state space models can be used, which do take into account the dynamic behaviour. Moreover, aside from the stationary properties of the box, these models allow a characterisation of its dynamic behaviour. Hence, the models can be used to predict the expected dynamic behaviour of the box. As an example, Figure 12 plots the difference between measured and predicted indoor temperature for part of the test campaign in Spain. Note, that the measured indoor temperatures was in this case not available for the participants and hence, models were identified on the basis of data corresponding to a different test period. Both models identified on the basis of BBRI and CIEMAT data have been used. For the current case, it was found that the models identified on similar summer data in Spain (right figure) perform better. This is attributed to the improved time resolution and accuracy of the measured heating power in the data used to identify the model. More details can be found in [Jiménez 2016].

Based on the outcomes guidelines have been developed, both regarding the physical aspects of performing identification experiments as well as the statistical aspects for the data analysis techniques (Jimenez 2016, Madsen et al. 2016).

Conclusions

The Annex 58-project of the IEA EBC-programme showed that there is currently a large international interest in full scale testing and dynamic data analysis. This can be explained by the fact that full scale testing allows evaluation and characterisation of the real thermal performance of building components and whole buildings. To investigate the current state of the art of onsite testing and data analysis, a round robin test box experiment has been performed within the framework of Annex 58. The global objective of the round robin experiment was to perform a well-controlled comparative experiment on testing and data analysis. It is shown how different techniques can be applied to characterise the thermal performance of the test box ranging from (quasi)stationary techniques towards dynamic system identification. Where the first ones are only able to estimate the steady state properties of the box (e.g. overall heat loss coefficient), the latter can give additional information on the dynamic behaviour of the box and can be used to simulate the dynamic response of the box in a simplified way.

When it comes to steady state methods, it was found that the averaging method overall yields more consistent estimates than the linear regression methods. The method was found to be less sensitive to the sampling time and to nicely converge to the target value with increasing test duration. Major drawback of the averaging method, though, is the fact that it is unable to explicitly account for solar radiation. This led to a systematic underestimation of the overall heat loss coefficient for measurements that have significant solar irradiation. Multiple linear regression models are able to take solar radiation into account. But, a good preprocessing of the measurement data was found to be a prerequisite for realistic estimates. Short term dynamics, such as daily recurring solar irradiation need to be filtered out, as they might hamper a reliable fit when using stationary models. As a result, long measurement campaigns are needed to obtain enough data points.

Finally, it should be emphasized that the current results are based on a measurement campaign on a simplified scale model of a real building. This allowed to investigate the possibilities and limitation of the different methods under well-controlled conditions, but neglects additional challenges that could be encountered when measuring real buildings of normal size and consisting of multiple zones. In a next step of the Annex 58-project more complicated configurations have been studied. The outcomes of the current round robin experiment as well as of other common exercises resulted in physical and statistical guidelines to perform and analyse dynamic experimental measurement campaigns (Jiminez 2016, Madsen et al. 2016).

Acknowledgement

This paper summarizes and highlights main research activities, outcomes and findings from Annex 58, drawing content from Annex 58's final reports and related publications. The authors appreciate strong leadership and technical contribution of subtask leaders, as well as contributions from all participants of Annex 58. In particular for the current paper, the financial support by Knauf Insulation to construct the Annex 58 round robin test box, as well as the input from the different Annex 58 members who participated in the common exercises and of the ST3-taskforce members is valued.

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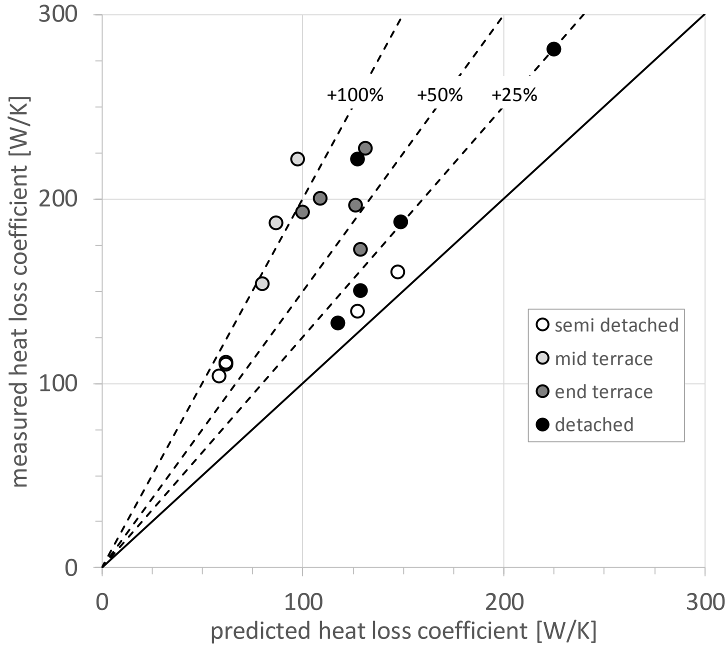


Figure 1 - Illustration of the performance gap: on site measured vs. predicted values of the overall heat loss coefficients [W/K] of different buildings. Discrepancies up to 100% are observed. Figure from Bauwens [2015], based on data from Wingfield et al. [2009].

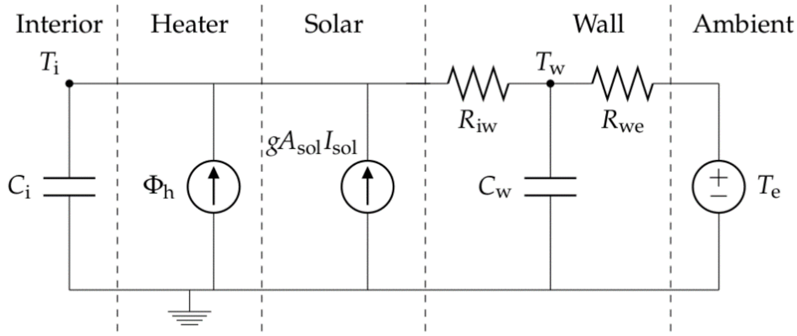


Figure 2.Example of a two-state grey box model applied by one of the participants to characterise the round robin test box (Madsen et al. 2016)

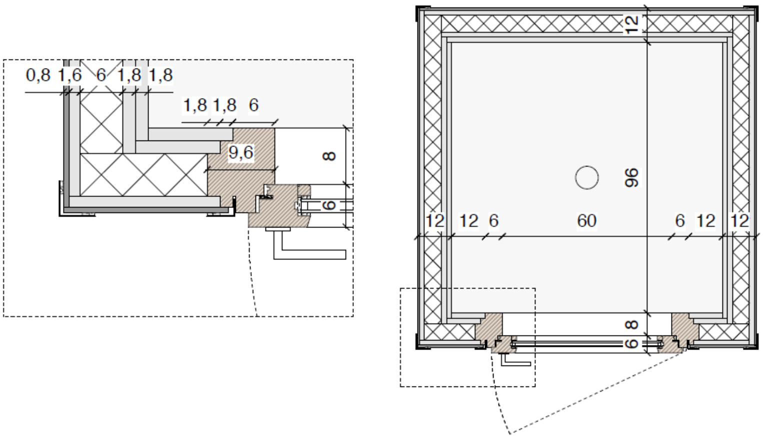


Figure 3 – Horizontal section of the round robin test box

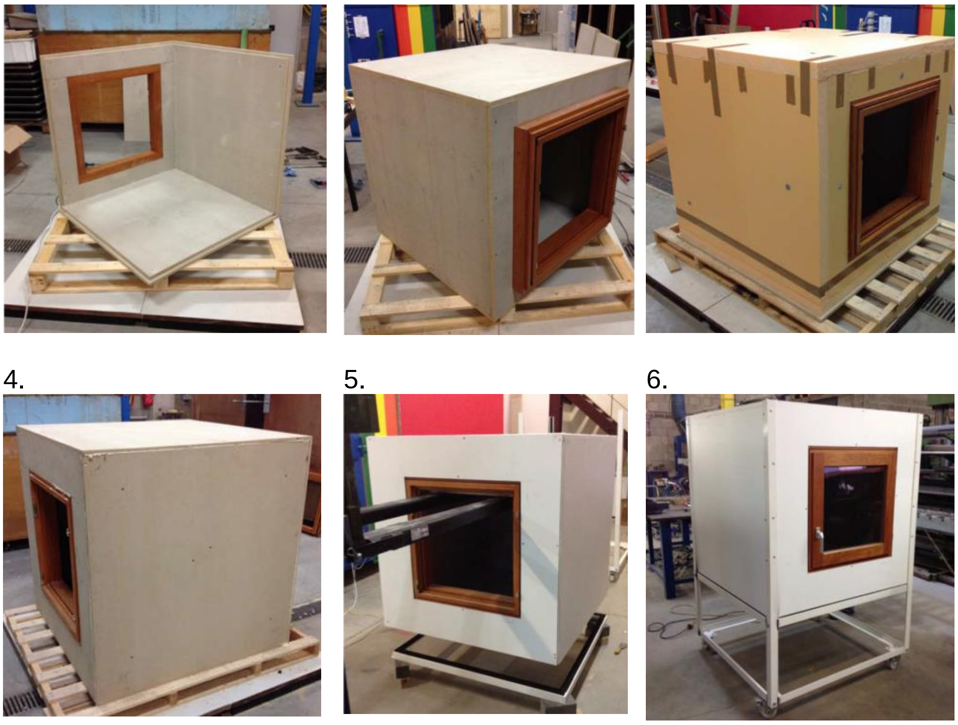


Figure 4: Subsequent steps in the construction of the round robin test box: 1. Inner box of double layered fibre cement boards, 2. Operable window in one façade, 3. Insulation glued to the inner box, 4. Outer box of fibre cement board, 5. White fibre cement cladding, 6. Steel structure supporting the box

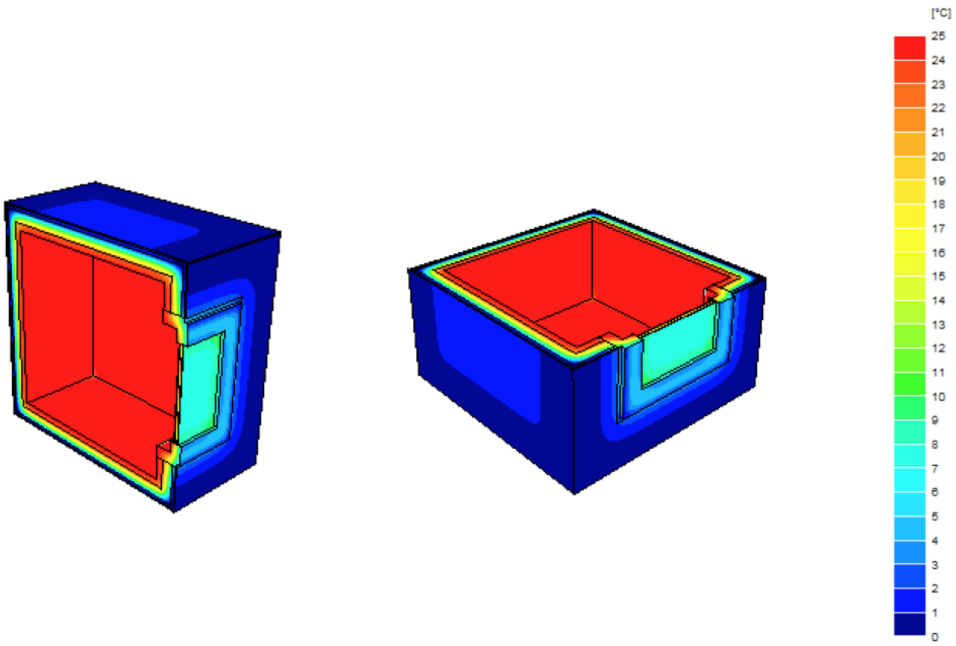
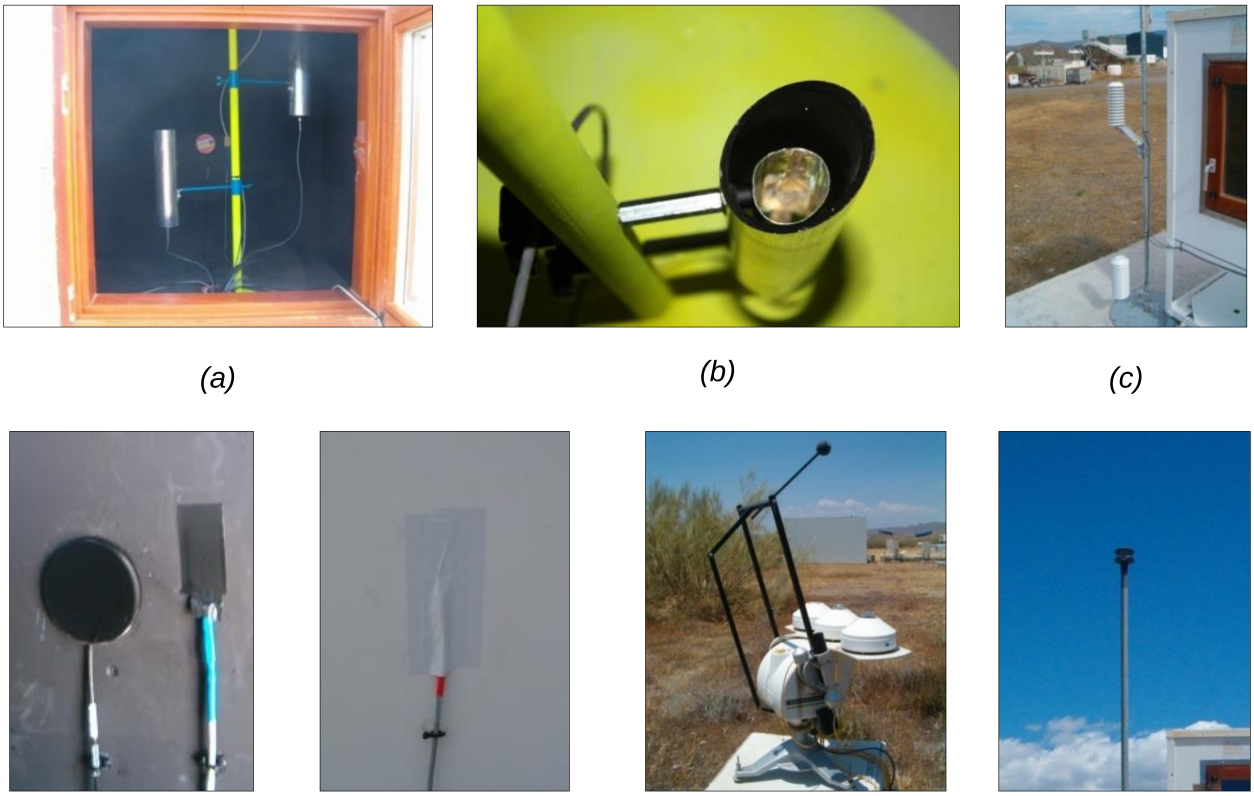


Figure 5: Temperature plots as obtained in the numerical simulation of the thermal performance of the round robin box. The edge effects and thermal bridging at the window perimeter are clearly visible.

Figure 6.Test box during winter at the measuring site at BBRI, Belgium (left) and during summer at the Plataforma Solar de Almeria, Spain (right).



(a) (b) (c)

(d) (e) (f) (g)

Figure 7: Installed measurement devices in Almería: (a) Indoor air temperature, (b) shielding devices for indoor air temperature, (c) outdoor air temperature, (d) heat flux and internal surface temperature, (e) external surface temperature, (f) beam, diffuse and global solar radiation, (g) wind speed and direction.

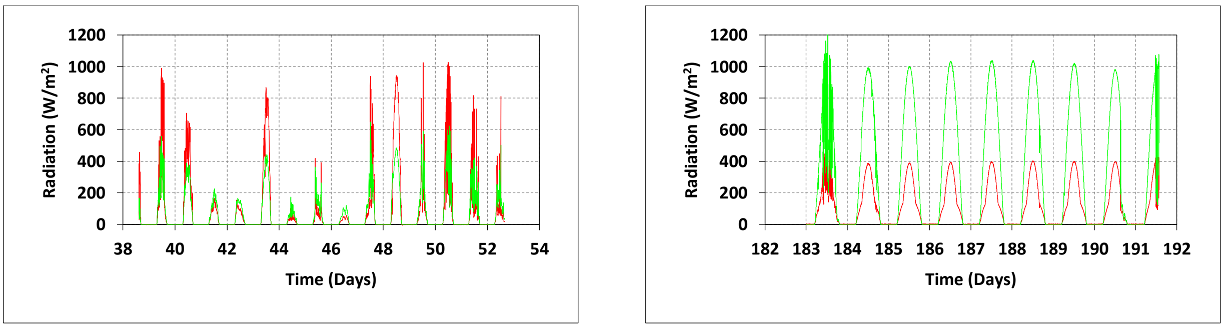


Figure 8: Global vertical (red) and horizontal (green) solar radiation during the winter measurement campaign in Belgim (left figure) and the summer campaign in Spain (right figure)

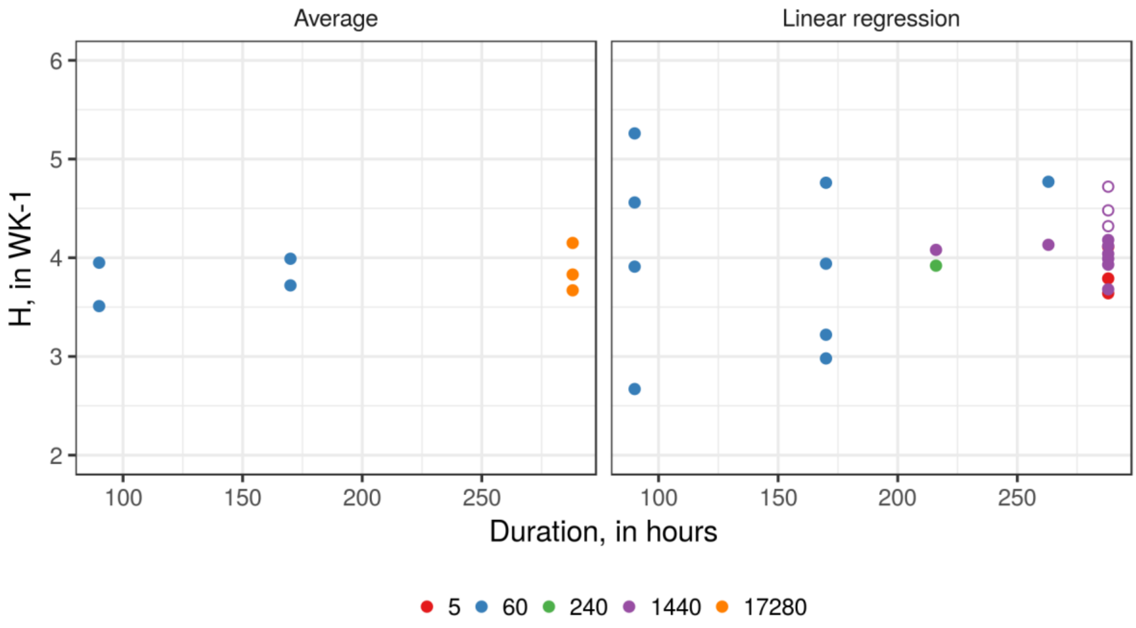


Figure 9: Comparing estimates based on the averaging methods (left hand side) and linear regression methods (right hand sides). The obtained overall heat loss coefficient is plotted as a function of the measurement duration. The dots are colored according to the sampling time (in minutes). Estimates based on the summer data in Spain are presented as hollow dots.

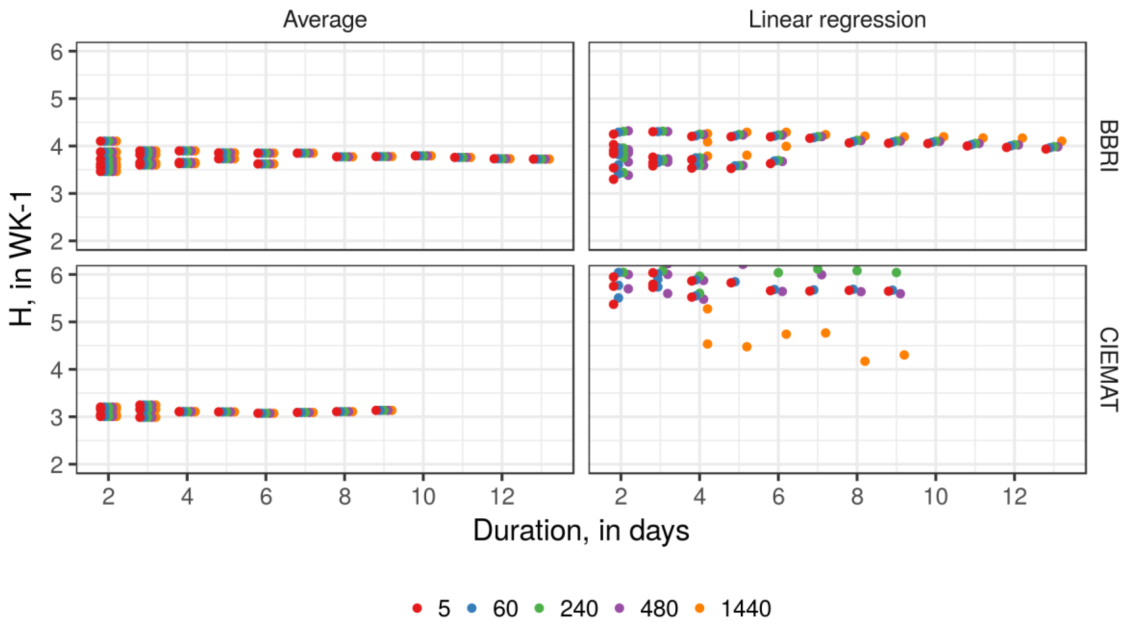


Figure 10: Investigating the effect of sampling time and measurement duration on the obtained estimates making use of the averaging methods (left hand side) and linear regression methods

(right hand side) for the winter measurements in Belgium (top row) and summer measurements in Spain (bottom row). The dots are colored according to the sampling time (minutes).

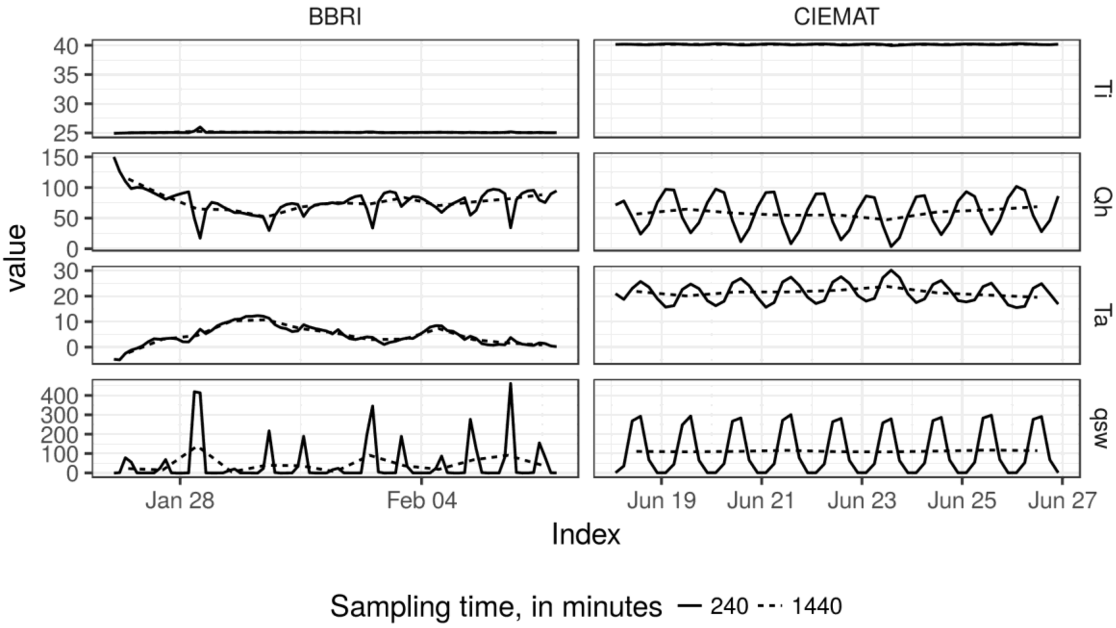


Figure 11: Impact of aggregating the input data for the measurement campaign in Belgium (left hand side) and Spain (right hand side).

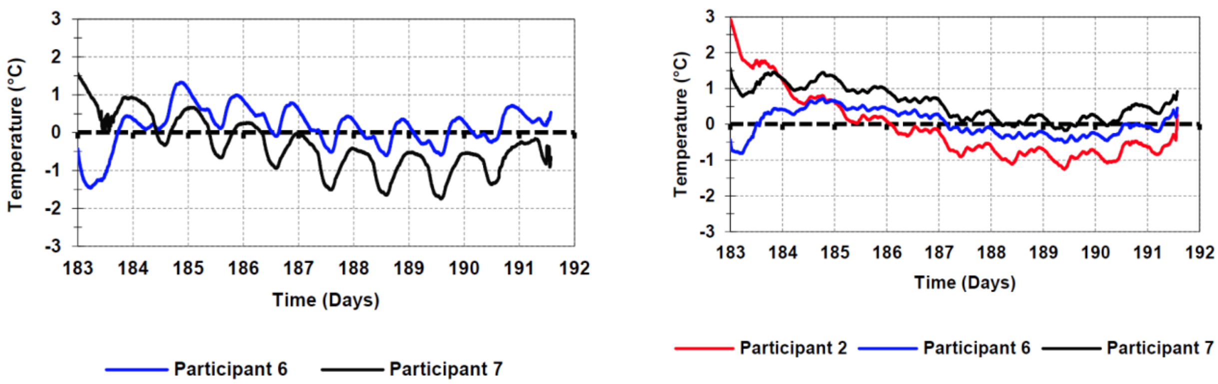


Figure 12: Differences between predicted and measured indoor air temperature of the box, predicted by the participants using dynamic models. Left, using models based on winter data. Right, models based on summer data. Predicted indoor temperatures corresponds to a test period in Spain in summer, different from the ones used for identification.

Table 1: material properties of the different layers of the box as provided by the manufacturer.

	thermal cond. [W/(mK)]	density [kg/m³]	heat capacity [J/(kg/K)]
Fibre cement boards (inner box)	0.35	1250	1470
XPS insulation	0.034	25	1450
Fibre cement board (outer box)	0.35	1250	1470
Fibre cement cladding	0.60	1925	1018
Window frame (wood)	0.17	700	2070

Table 2: Determined overall heat loss coefficient (W/K) of the round robin test box by different modelling teams and making use of different data analysis methods and sampling times.

Team		Winter data Belgium	Summer data Spain
1	Averaging method State space model (RC using LORD)	3.77-3.92 3.07-3.42	
2	Averaging method Linear regression (5'-data) Linear regression (daily averaged data) AR(MA)X-models State space models (RC using LORD)	2.86-4.15 2.84-4.11 3.68-4.12 3.79-4.06 3.93	 4.32-4.48 4.07-4.20 4.23
3	Multiple linear regression (hourly data) Multiple linear regression (daily data)	4.77-5.24 3.73-4.39	
4	State space models	4.27-4.56	
5	Linear regression (daily averaged data) State space models (RC using CTSM-R)	3.99-4.08 3.99	
6	State space models (RC using Matlab)	3.97	4.1-4.46
7	ARX-models State space models (RC using CTSM-R)	3.95 3.84	4.05-4.10 3.96
8	Averaging method Linear regression (5'-data) AR(MA)X-models State space models (RC using CTSM-R)	3.72-3.99 2.98-3.94 4.01-4.08 4.48	