Designing a 24-hour perturbation method for the estimation of a building heat transfer coefficient

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Abstract. Verification of the actual thermal performance of a building envelope after renovation is likely to become a useful key for performance contracting in the frame of heavy retrofit operations in buildings. Some existing methods such as the co-heating method, use on-site measurements to estimate the Heat Transfer Coefficient, or its inverse the overall thermal resistance. Although reliable and accurate, they need several days to several weeks of undisturbed measurements which can be rather inconvenient for building occupants and quite expensive in terms of operational costs. This paper investigates perturbation methods to design a 24-h heat input signal that would ensure an accuracy similar to or better than other perturbation methods to estimate an overall thermal resistance of the building envelope. The paper first studies 256 different squared heating signals in a numerical methodology to determine common characteristics of high-scoring 24-h signals. An experimental campaign in a wooden-framed house tested one of the high-scoring signals. The experimental results showed estimation errors higher than expected but consistent with the literature.

1. Introduction
In a world-wide effort to decrease the carbon footprint of the existing building stock, massive and extensive building retrofit operations are to be expected. Performance contracting could benefit the investors by securing an effective thermal performance. Verification of the actual thermal performance of the envelope after renovation from on site measurements such as the estimation of the overall Heat Transfer Coefficient (HTC), or its inverse the overall thermal resistance $R_{eq}$, is then necessary. Reliable and accurate existing methods to estimate the HTC however need several days to several weeks of undisturbed measurements which can be rather inconvenient for building occupants and quite expensive in terms of operational costs.

Oppositely, controlling the indoor conditions can avoid weather-related correlation and can favour accuracy while relying on a shorter experiment. This is done by controlling the heating power in the building, thus creating a perturbation signal. The response of the building to this impulse heating perturbation signal is measured in the indoor air temperature. At building scale, this identification methodology has been applied to estimate the thermal dynamics or estimate the HTC or the thermal resistance $R_{eq}$ in methods such as QUB [1], ISABELE [2] or in Madsen and Schultz [3].

The principle of the QUB method is to perform an estimation of the HTC overnight by heating during the first $n_h$ hours and leaving it for the next $n_h$ hours in free-floating conditions. This induces a rise and decay of the indoor air temperatures which was exploited by means of a quadrupole model in [1]. The authors obtained the most accurate results with $n_h = 4$ h as all
estimations scored within 20% of the reference value. The ISABELE method, as described in [2], sets the indoor temperature at a fixed value during up to 4 days. Satisfactory results were found with shorter durations, from 2 days on. A particularity of the ISABELE method is to propagate measurement uncertainties onto the final estimation to better reflect on systematic errors. After uncertainty propagation and within 2 days of experiment, the error did not exceed 15–20%. In Madsen and Schultz [3], applied in Bacher and Madsen [4], in Andersen et al [5] and used as comparison in Thébault and Bouchié [2], the thermal dynamics of a building are identified by means of a pseudo-random binary heating signal (PRB signal or PRBS). As underlined in [3], PRB signals have the advantage of exciting the building envelope within a desired range of frequencies, here chosen to be representative of the expected time constants of a building. PRB signals shift between two constant levels of heating (for example on–off) and have the very desirable property not to be correlated to the outdoor conditions. In [4], the PRB signal experiment lasted 4 days and provided an identical estimation of the overall thermal resistance of the envelope for all high-likelihood models, although no reference value was given.

In summary, within the existing perturbation methods for estimating the HTC at building scale, the QUB method is short but has moderate accuracy, the ISABELE method scores slightly better but is much longer and the PRBS-based method seems to be a promising option, although its accuracy has not been proven yet.

Given the desirable properties of PRB signals, this paper intends to design a 24-hour PRBS-inspired heating input signal that would enhance the accuracy and precision of the estimation of an overall thermal resistance $R_{eq}$ of a building envelope. In a preliminary framework, the paper proposes a numerical methodology to characterise well-suited binary heating signals to achieve satisfactory estimations of an overall thermal resistance. The results of an experimental validation in a highly insulated wooden frame house is presented to discuss the feasibility of such short experiment. The paper concludes on refinements to be brought to the methodology.

2. Methodology for mapping suitable perturbation signals

2.1. Overview of the methodology

In overall, as illustrated in Figure 1, the principle is to test numerically multiple PRBS-inspired signals and assess whether the overall thermal resistance $R_{eq}$ inferred is accurate. A wide variety of signals is designed by a maximum length sequence algorithm. Each signal is simulated in a building energy model of a wooden-framed house. The simulated data are used to calibrate an appropriate stochastic RC model. An overall thermal resistance $R_{eq}$ parameter is inferred from the estimated parameters of the RC model and compared to the target value, known analytically from the building energy model. All steps are detailed in the following subsections.

2.2. The case study and its numerical building energy model

The case study used in this paper is a wooden-framed two-storey house on the INCAS platform in Le Bourget du Lac (France). The house served for the experimental campaign and for the numerical study. For the latter, the house was modelled in EnergyPlus as a 5-zone model. It has no air infiltration nor ventilation to keep the focus on the thermal behaviour of the envelope which have longer time characteristics than the thermal losses by air change. The numerical simulations are performed in January using actual weather measured in Le Bourget du Lac in 2019. The boundary conditions during the numerical experiment is given in Figure 2. The building energy model has convective heaters in all zones and in total 3 kW. The building energy model has a theoretical thermal resistance of 23 K/kW.

The experimental campaign has been performed in the house with 4 kW electric convective heaters. A 4-weeks co-heating has been performed late 2020 and established the overall thermal resistance at 15.7 K/kW ($\sigma = 0.5$ K²/kW²). The airtightness has also been measured and
Building Energy Model (BEM) of a wooden-framed house

\textbf{Simulation with BEM (January)}

\textbf{Req estimation} \quad \textbf{Accuracy: good} \quad \textbf{Experimental validation on site}

\textbf{Simulation with BEM (January)}

\textbf{Req estimation} \quad \textbf{Accuracy: poor}

\textbf{Simulation with BEM (January)}

\textbf{Req estimation} \quad \textbf{Accuracy: average}

\textbf{Designing multiple signals}

\textbf{Figure 1.} Overview of the numerical methodology for mapping suitable perturbation signals.

\textbf{Figure 2.} Outdoor temperatures during the experiment in the numerical simulations of the building energy model.

scores at Passiv-Haus level \( n_{50} = 0.54 \) vol/h. Sensitivity of the estimation of the overall thermal resistance to wind speed and outdoor temperatures should therefore be minimal.

\subsection*{2.3. 24-hour Pseudo Random Binary Signals}

To cover a wide variety of 24-hour pseudo-random binary signals, a truncated maximum length sequence (MLS) is used. Originally, the objective of a MLS is to produce a signal which contains all possible frequencies given a specified length, and which has very low auto-correlation. By truncating the signal to 24 h, it concededly annihilates these original properties. However, the pseudo-random nature of the squared signal in the first 24 h remains interesting for model identification. In addition, many squared signals, with a variable number of heating and free-floating periods, can be produced from only three parameters. Parametrisation of multiple heating and free-floating periods would have otherwise been cumbersome.

The MLS is generated with linear feedback shift registers. An algorithm of this generator is implemented in the python library SciPy [7]. The algorithm can be used with physically-scaled parameters which allows to link their values to the shape of the signal. The largest parameter is the first heating period (in h), the difference between the largest and second largest is the first free-floating duration (in h) and the difference between the second largest and last parameter is the immediately next heating period (in h).

Figure 3 shows four examples of 24-hour signals that can be generated with a 3-parameter MLS-generator. As well single heating periods than multiple heating and free-floating periods can be generated which indeed ensures a wide coverage of pseudo-random signal types over a 24-hour timespan.
2.4. Mapping suitable signals

An optimisation routine on the MLS parameters is not guaranteed to be successful. It would indeed rely on a major and unverified hypothesis that there exists a global maximum for the accuracy indicator assessing the quality of the estimation. Instead, there could be many sets of MLS parameters achieving similar outcomes and/or multiple local maxima could also co-exist.

Mapping the input parameter space for optimal areas is therefore a safer option and allows for a global glance at all signals which should help uncover common characteristics. To efficiently explore the 3-dimensional parameter space, a Latin Hypercube Sampling is performed to draw samples under a uniform distribution: $U(4, 22)$ for the first parameter and $U(0.25, 22)$ for the other two parameters.

Not all samples initially drawn are, however, implemented in the numerical building energy model. Some parameter combinations induce indeed heating or free-floating periods shorter than 15 minutes as is shown in the upper right part of Figure 3. Such signals have been found unfeasible in practice, due to the technical limitations of the electric heating systems. In the end, after clearing out the inapplicable signals, a set of 256 parameter triplets are used in the study.

2.5. Stochastic RC model calibration

To exploit the dynamic response of an entire building to a pseudo-random signal, stochastic RC models have been proven to be efficient [4]. The model used in this paper is the 3-states $T_w T_i T_m R_o R_i$. As shown in Figure 4, it has three thermal capacities: $C_w$ for the envelope, $C_i$ for the indoor air and $C_m$ for the internal mass. It has no solar aperture coefficients as multiple calibrations showed these were repeatedly insignificant.

A stochastic formulation of the model is used in agreement with [3], to account for model prediction discrepancy. Model calibration is performed with the pySIP python package [8]. Adequacy of the model to the data has been verified by checking the white noise property of the unfiltered prediction residuals. Calculation of the overall thermal resistance $R_{eq}$ with model $T_w T_i T_m R_o R_i$ is straightforward with $R_{eq} = R_o + R_i$.
2.6. Judging the acceptability of an estimation: the interpretability score

In the numerical part, once an estimation of $R_{eq}$ is provided by the calibrated RC model with a given heat input signal, this estimation can be compared to the target value analytically calculated from the building energy model. To account for both the absolute error to the target value and the uncertainty of the estimation, an interpretability score is used. As illustrated in Figure 5, this score is defined as the area (hatched surfaces in the figure) under the estimation curve (coloured curves in the figure) that is between a ±10% error range to the target value (grey area in the figure). Interpretability scores can also be defined with larger or smaller error ranges, but in this case, ±10% should allow a clear discrimination among all results.

As shown in Figure 5, the interpretability score takes values between 0 and 1. A 0-score means that the estimation is completely outside the ±10% error range whereas a score close to 1 means that the estimation and its uncertainty is entirely within the ±10% bounds. Scores higher than 0.5 can be considered as acceptable as it means that half of the area under the curve is within the ±10% error range.

3. Results on common characteristics of suitable signals

This section presents the results of the numerical study of 256 pseudo-random binary signals and how they affect the accuracy of the estimation of the thermal resistance $R_{eq}$ of a building envelope. The most intuitive way to describe and map the 256 signals is to differentiate them by the length of their heating and free-floating periods. For this reason, the interpretability assessments are illustrated in Figure 6 as functions of the longest and second longest heating periods and as a function of the longest and second longest free-floating periods. Each dot therefore represents the estimation from one signal, coloured according to its interpretability score.

Figure 6 shows in all sub-figures distinctive areas of highly accurate $R_{eq}$ estimations and other areas of poorly interpretable $R_{eq}$ estimations. The sub-figures in the left row show on the x-axis the longest heating period and suggest that signals with a 5–12 h longest heating period score higher provided the longest and second longest free-floating periods are both longer than 3 h. Should there be only one heating and one free-floating period, the heating period should not exceed 16–17 h.

The top middle and top right sub-figures offer a complementary view on the high scoring signals. The single heating single free-floating high scoring signals are easily identified along the x-axis in the top middle sub-figure. As for the multiple heating and free-floating figures, both the top middle and top right sub-figures confirm that the longest and second longest free-floating
Figure 6. Numerical results: interpretability scores of the $R_{eq}$ estimations as a function of the longest and second longest heating and free-floating periods in the 24-h heat input signal. Highest-scoring signals, in deep green, share common characteristics: 5–12-hour heating duration and over 4-hour free-floating duration.

periods should be longer than 4 h. Among these signals, a second longest heating period shorter than 2 h scores higher.

Overall, these results seem to indicate that signals providing accurate $R_{eq}$ estimations within 24 hours share some common characteristics: (1) they either have one single heating period which should last less than 17 hours; (2) they have multiple heating and free-floating periods, among which at least two free-floating periods longer than 4 hours. This seems to indicate that the stochastic RC model learns appropriately when it is fed with several long-lasting temperature rises and decays. This is consistent with the fact that long heating and long free-floating periods excite the building envelope beyond the shortest time constants.

These numerical results and the inferred preferable duration of heating and free-floating periods are naturally a function of the duration of the entire signal, here 24 h. It makes no doubt that other signal durations will highlight other types of signals.

4. Experimental campaign for validation
Among all suitable signals identified in the numerical part of this study, signal 7.010 / 1.055 / 0.577 has been implemented in the wooden-framed house of the INCAS platform. Figure 3 shows on the bottom right how the signal looks like. As can be seen in Figure 5, this particular signal has a very high interpretability score in the numerical results. In order to assess the reproducibility in different weather conditions, the experiment has been repeated 5
times in autumn and winter conditions. The outdoor temperatures during each test are shown in Figure 7. Similarly to the numerical study, model $T_w,T_i,T_m R_o R_i$ has been calibrated. All residuals showed white noise properties.

Figure 8 compares all five estimations the overall thermal resistance $R_{eq}$ by each dataset to the target co-heating value $R_{eq}^*$. The $R_{eq}$ estimations are significantly higher than the target value. All 5 estimations overestimate the thermal resistance by 15 to 25 \%, except the repetition 5 which overestimates $R_{eq}$ by 33 \%. The estimations also suggest that there is a significant variability, most probably due to the weather conditions, given that only the outdoor conditions varied. Noteworthy is that experiment 5 started at noon, whereas all other experiments started at night fall. This might indicate an unfortunate correlation of the heating signal with other boundary conditions and that the starting time in influential on the accuracy of the method.

5. Discussion

The experimental results are in line with the order of magnitudes found in the literature. This 24-h signal scores better than the 48-h ISABELE signal and has absolute errors similar to that from the QUB method.

However, the experimental results are less conclusive than what was expected from the numerical results. One reason could be that the time constants of the actual house are larger than what is modelled in the BEM. The longest heating period of signal 7.010 / 1.055 / 0.577 is a little over 7 h, which may be insufficient if the actual time constants are actually higher.
In addition, the overall thermal resistance of the numerical model is 30 % higher than that of the actual INCAS house. Given that the experimental results are not as accurate as expected, it might suggest that the outcomes of the numerical mapping methodology are sensitive to the building type and its thermal performance.

The experimental results call therefore for a refinement of the numerical mapping methodology. At this stage, a few significant steps are considered: (1) perform the mapping procedure under actually measured weather data for easier comparison to the experimental results, (2) include RC model selection in the mapping procedure to dismiss the possibility of a bias of inferring $R_{eq}$ from a non-adapted model, (3) investigate how the interpretability improves or worsens with longer or shorter experiments and with the starting time, (4) investigate the robustness of the high scoring signals to building thermal characteristics or building types, with a particular focus on time constants and (5) pursue the experimental campaign to assess the accuracy on site of other high- and low-scoring signals.

6. Conclusion
This paper has investigated heat input signals to create a 24-hour perturbation method for the estimation of the overall thermal resistance of a building. A numerical study of 256 different pseudo-random signals has uncovered common characteristics of signals providing accurate estimations. An experimental validation campaign implemented one of the high-scoring signals and tested its reproducibility under variable weather conditions with 5 repetitions. The thermal resistance estimations were all overestimated by 15 to 33 %. Starting time seems to play a role in accuracy, as do the weather conditions. The numerical methodology is currently being refined to account for weather variability, building type and experimental duration in an attempt to draw a finer mapping of suitable and highly accurate heat input signals for on site short thermal resistance estimations.

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