Comparison of models to identify thermal characteristics of multi-layer building walls using inverse methods

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Abstract

The objective of this study was to evaluate inverse techniques for estimating the resistance and the capacity of walls in real weather conditions. The inverse techniques were applied on temperatures measured by sensors located in the wall. The performance of four different models were compared.

We demonstrated a high correlation with some parameters. A solution was proposed to limit the number of parameters identified, while allowing the identification of the thermal resistance and thermal capacity of the walls. The high uncertainty applied to some experimental data led to the exclusion of these data from the inverse method to improve its convergence.

Most of the models were highly accurate in estimating thermal resistance and capacity of a lightweight wall using a set of experimental data.

Nomenclature

a	Thermal diffusivity, $\text{m}^2.\text{s}^{-1}$
c	Specific heat capacity, $\text{J.kg}^{-1}.\text{K}^{-1}$
C	Total thermal mass, $\text{J.m}^{-2}.\text{K}^{-1}$
e	Thickness, m
P	Response factor of solar radiation excitation
p	Laplace variable
Q	Heatflux, W.m^{-2}
R	Thermal resistance, $\text{m}^2.\text{K.W}^{-1}$
t	Time, s
T	Temperature, °C
X	Response factor of indoor temperature excitation
Z	Response factor of outdoor temperature excitation
Greek symbols:	
α	Absorptivity
λ	Thermal conductivity, $\text{W.m}^{-1}.\text{K}^{-1}$
θ	Temperature in Laplace domain, °C
φ	Heatflux in Laplace domain, W.m^{-2}
ρ	Density, kg.m^{-3}
Index and exponent:	
in	Indoor
out	Outdoor
s	Surface
SW	Shortwave radiation

Introduction

Of all the factors that influence the energy consumption of buildings, one of the most important is the overall energy performance of the building envelope, mainly because of the heat loss by conduction through opaque walls and windows, air leakages (Meiss and Feijo-Munoz, 2015), and also, because of the degradation of its performance through time (Eleftheriadis and Hamdy, 2017).

The heat loss by conduction can be characterized by the physical properties of each material constituting the wall, such as λ , c and ρ . From these physical and geometrical properties, it is possible to determine the *R-value* and *C-value* of the wall components (Asan and Sancaktar 1998). The material properties are usually evaluated in a laboratory using standard tests as described in (NF EN 12939, 2000) and (EN 12667, 2001). The main drawback of this method is that it cannot be applied on whole implemented building walls.

In order to measure the thermal characteristics of the whole envelope already built or under test, new methods have been developed such as the heat flux meter method (ISO 9869-1, 2014), which consists in calculating the thermal transmittance of walls using three sensors: two temperature sensors (inside and outside) and a heat flux meter. The main drawbacks are that the method takes days or even weeks and the thermal capacity cannot be estimated. Quicker methods such as the dynamic method (ISO 9869-1, 2014) and ARX-modelling are described in (Deconinck and Roels, 2016) and (Gaspar et al., 2016).

The aim of this paper is to compare different models, such as Resistance-Capacitance models, response factor models and quadrupole models in order to determine which one is the most appropriate to identify the thermal characteristics of walls for different types of envelope (lightweight and heavyweight walls). A way to obtain this information is to apply inverse techniques (Beck and Arnold, 1977; Beck et al., 1985) considering a model, boundary conditions and temperature sensors data using a minimization algorithm. Identifying λ and $\rho.c$ of the materials of the wall allows the calculation of *R-value* and *C-value*, which describe the thermal behaviour of an opaque wall.

In this article, the models (Resistance-Capacitance models, quadrupole models and response factor models) are described and the lightweight and heavyweight walls

are briefly presented. Then, the models are validated numerically using real boundary conditions. Next, identification techniques are applied on simulated experimental data, thus allowing an estimation of uncertainties. Finally, identification techniques are applied on experimental data in order to assess the resistance and the thermal mass of the walls.

Modelling

Heat transfer through multi-layer walls are modelled on the heat equation:

$$\frac{\partial T}{\partial t} - \alpha \nabla^2 T = 0 \quad (1)$$

The boundary conditions are outdoor and indoor temperatures (T_{out} and T_{in}) and shortwave solar radiation (Q_{sw}) normal to the surface. These boundary conditions are characterized by the internal and external convective and radiative heat transfer coefficients ($R_{in} = 0.125 \text{ m}^2 \cdot \text{K} \cdot \text{W}^{-1}$ and $R_{out} = 0.04 \text{ m}^2 \cdot \text{K} \cdot \text{W}^{-1}$) and the exterior solar surface absorptivity for short wave radiations ($\alpha = 0.24$).

The case studies illustrated in Figure 1 are composed of three different materials, with constant properties. Temperature sensors are located outside of the boundary layer, at the surface and within the wall. They are used to identify the thermal properties.

Figure 1: Sensor locations in the walls.

Quadrupole model

The thermal quadrupole model (*the QR model*) was developed in the 1980s. As mentioned in (Maillet et al., 2000) the « quadrupole method was developed as a tool for developing new techniques of thermal property measurements [...] ». The quadrupole method allows the construction in a very simple way, of an exact and reliable direct model that can be used in the optimal design of the experiment as well as in the 'best fit' inversion process ». In this work, the second possible use of this method is considered.

In Figure 2, a quadrupole model of a three-layer model is presented.

Figure 2: Quadrupole model structure.

Each layer i is symbolized by a matrix.

$$M_i = \begin{bmatrix} A_i & B_i \\ C_i & D_i \end{bmatrix} \quad (2)$$

$$\text{where } \begin{cases} A_i = D_i = \cosh(e_i \sqrt{p/a_i}) \\ B_j = \frac{\sinh(e_j \sqrt{p/a_i})}{\lambda_j \sqrt{p/a_i}} \\ C_j = \lambda_i \sqrt{p/a_i} \sinh(e_i \sqrt{p/a_i}) \end{cases}$$

The boundary conditions are taken into consideration as shown in (Maillet et al., 2000).

Resistance-Capacitance model

The Resistance-Capacitance model (*the RC model*) considers walls as resistances and capacitances. Here, the nodes located at the interface between layers i and j (T_{Li-Lj}) or at the surface ($T_{s,out}$ and $T_{s,in}$) have no capacity. Capacities and resistances are equally distributed in each layer.

Figure 3: RC model structure for the model 6R3C.

If a simple RC model is considered (Figure 3), with one capacity in each layer, the following equations are obtained:

$$\begin{pmatrix} 0 \\ C_{L1} \\ 0 \\ C_{L2} \\ 0 \\ C_{L3} \\ 0 \end{pmatrix} \cdot \begin{pmatrix} T_{s,out} \\ T_{L1,1} \\ T_{L1-L2} \\ T_{L2,1} \\ T_{L2-L3} \\ T_{L3,1} \\ T_{s,in} \end{pmatrix} = \begin{pmatrix} R_{out}^{-1} & 0 & \alpha \\ 0 & \vdots & 0 \\ \vdots & & \vdots \\ 0 & 0 & \vdots \\ \vdots & & \vdots \\ 0 & R_{in}^{-1} & 0 \end{pmatrix} \cdot \begin{pmatrix} T_{out} \\ T_{in} \\ Q_{sw} \end{pmatrix} + \begin{pmatrix} -\frac{1}{R_{in}} - \frac{2}{R_1} & \frac{2}{R_1} & 0 & \dots & \dots & \dots & 0 \\ \frac{2}{R_1} & -\frac{4}{R_1} & \frac{2}{R_1} & \ddots & & & \vdots \\ 0 & \frac{2}{R_1} - \frac{2}{R_1} - \frac{2}{R_2} & \frac{2}{R_2} & \ddots & & & \vdots \\ \vdots & \ddots & \frac{2}{R_2} & -\frac{4}{R_2} & \frac{2}{R_2} & \ddots & \vdots \\ \vdots & & \ddots & \frac{2}{R_2} - \frac{2}{R_1} - \frac{2}{R_3} & \frac{2}{R_3} & 0 & \vdots \\ \vdots & & & \ddots & \frac{2}{R_3} & -\frac{4}{R_3} & \frac{2}{R_3} \\ 0 & \dots & \dots & \dots & 0 & \frac{2}{R_3} - \frac{1}{R_{out}} - \frac{2}{R_3} \end{pmatrix} \cdot \begin{pmatrix} T_{s,out} \\ T_{L1,1} \\ T_{L1-L2} \\ T_{L2,1} \\ T_{L2-L3} \\ T_{L3,1} \\ T_{s,in} \end{pmatrix} \quad (3)$$

$$C\dot{T} = BU + AT \quad (4)$$

where C is the matrix of capacities, A is the matrix of resistances; B and U are matrices and vectors of boundary conditions; T is the vector of temperatures.

In this paper, the method is applied on two RC models: the first one is called *the 6R3C model* (one capacity in each layer) and the second one is called *the 18R15C model* (five capacities in each layer).

Response factor model

Response factor models (*the RF model*) are described in (Mitalas and Stephenson, 1967).

The objective is to precisely calculate the response given by the simple excitation (triangular pulse) of each boundary condition using a well-described model (here, we used a RC model with a number of capacities higher than 10 per layer). In this case, the temperature response is called factor response for indoor temperature, outdoor temperature or solar radiation. An example is illustrated

in Figure 4. Response factors are calculated for each boundary condition regarding sensor between the first and the second layer (T_{L1-L2}) i.e, X_{L1-L2} , Z_{L1-L2} , and P_{L1-L2} .

Figure 4: Response factor model description.

Once these response factors obtained and the real boundary conditions broken down into a series of triangular functions using a time step Δ , it is possible to express each temperature as follows:

$$T_i(t) = \sum_{j=0}^n Z_{i,j} * T_{out}(t - j\Delta) + \sum_{j=0}^n X_{i,j} * T_{in}(t - j\Delta) + \sum_{j=0}^n P_{i,j} * Q_{SW}(t - j\Delta) \quad (5)$$

where $*$ is the convolution function.

This method is applied to sensors located within the wall and at the surface.

Description of the walls and sensors

The four models described before were applied on two case studies. The first one is related to a lightweight wall installed on a test cell located in TIPEE in La Rochelle, France. The second one is an insulated heavyweight wall located in BESTLab, EDF Lab, near Paris, France.

The lightweight wall

The lightweight wall under test is a wall made up of three homogeneous layers. Its layers and their material's properties are described in Table 1. Only one-dimensional heat transfer is considered.

Table 1: Description of the lightweight wall.

Layers		Properties			
Material	Code	λ	ρ	c	e
Outside					
Plywood	pl	0.13	650	1700	0.021
Polyurethane	PUR	0.023	35	1000	0.12
Plywood	pl	0.13	650	1700	0.021
Inside					

From these data, it is possible to calculate the theoretical R -value and C -value of this wall:

$$R = \sum_i \frac{e_i}{\lambda_i} \quad (6)$$

$$C = \sum_i e_i \rho_i c_i$$

For the lightweight wall, $R_{Light} = 5.5 \text{ m}^2.\text{K}.\text{W}^{-1}$ and $C_{Light} = 51 \text{ kJ}.\text{m}^{-2}.\text{K}^{-1}$.

The heavyweight wall

The heavyweight wall under test is a wall made up of three homogeneous layers. Its layers and their materials' properties are described in Table 2. Only one-dimensional heat conduction is considered.

Table 2: Description of the heavyweight wall.

Layers		Properties			
Material	Code	λ	ρ	c	e
Outside					
Coating+Concrete	conc	1.0	639	920	0.21
EPS	EPS	0.04	14	1400	0.1
Gypsum	gyps	0.31	832	800	0.01
Inside					

Using equation 6: $R_{Heavy} = 2.7 \text{ m}^2.\text{K}.\text{W}^{-1}$ and $C_{Heavy} = 131 \text{ kJ}.\text{m}^{-2}.\text{K}^{-1}$.

Temperature sensors

As shown in Figure 1, temperature sensors (4-wire resistance thermometers) were installed inside the components and on the internal and external surfaces.

Figure 5: Sensitivity analysis of model 18R15C during a sunny winter's day – parameters R_{out} , R_{in} and α .

There were five sensors:

- Sensor S_1 , on the external surface,
- Sensor S_2 , between the external layer and the insulation,
- Sensor S_3 , in the middle of the insulation,
- Sensor S_4 , between the internal layer and the insulation,
- Sensor S_5 , on the internal surface.

Among these sensor locations, some of them were highly dependent on the modelling hypothesis since the

uncertainty on several parameters was high, such as R_{in} , R_{out} and α .

R_{in} and R_{out} are standard values defined in (NF EN ISO 6946, 2017). According to Annex A of this standard, R_{in} varies between 0.11 and 0.13 m².K/W between 20 and 50°C and R_{out} varies between 0.04 and 0.06 m².K/W when the wind speed varies between 2 and 6 m/s. α is a property derived from a measure performed on a spectrophotometer with an integrating sphere. α varies between 0.18 and 0.35 depending on the cleanliness of the material and the solar spectral distribution.

Figure 5 shows a sensitivity analysis that takes into account these possible variations during a sunny winter's day. It seems clear that sensor S_1 and S_2 are highly sensitive to α and R_{out} variations for both walls. However, in the case of the heavyweight wall, the impact is reduced. It was preferable to reject the results from sensors S_1 and S_2 as R_{out} and α were not known with great accuracy. The uncertainty could have had a negative impact on the identification. Sensor S_5 were also excluded since measurement of the surface temperatures is more challenging and bear a higher experimental uncertainty. In fact, the temperature difference between the air and the wall surface is so small that it is lower than the temperature measurement uncertainty ($\pm 0.15^\circ\text{C}$) most of the time. Only sensors S_3 and S_4 are selected for identification.

Model validation

The models were validated for cases encountered in experimental tests. These cases were classified into two categories for the winter season: cloudy days and sunny days. A model was validated if it succeeded in accurately reproducing the thermal behaviour of the wall during these two typical days.

Figure 6: Boundary conditions for ROLBS case.

Boundary conditions

The typical sunny and cloudy winter's days came from a larger case, called *the ROLBS case*, as shown in the Figure 6. Real boundary conditions were measured by a weather station located near La Rochelle, France. The ROLBS

case lasted 9 days during the winter season with a measurement time step of 120s.

This case was used to identify the *R*- and *C*-values numerically and experimentally as described below.

As illustrated in Figure 7, during the cloudy winter's day, indoor temperature was almost constant. Outdoor temperature and solar radiation were those of a cloudy winter's day. During the sunny winter's day, indoor temperature was almost constant. Outdoor temperature and solar radiation were those of a sunny winter's day. Both cases lasted 24h with a measurement time step of 120s.

Figure 7: Boundary conditions for the cloudy and the sunny winter's day.

The initial conditions were the temperature values obtained assuming that the steady state was reached at the first time step.

Validation of the direct models for the lightweight wall

The results obtained by simulation of *the 6R3C model*, *the 18R15C model*, *the QR model* and *the RF model*, i.e. the reduced models were compared to the results obtained with finite element calculation using Comsol© software (COMSOL, 2019), namely the simulated experimental data.

The comparison of models was based on the study of their residuals, i.e. the absolute value of the difference between the simulated experimental data and each reduced model. The means of residuals of each model for a cloudy day and for a sunny day for the lightweight wall are presented in Figure 8.

Regarding the results for *the RC models*, it seems obvious that the more capacities there are, the lower the residuals are.

Almost all the residuals are under 0.1°C for both sensors. The residuals for sensor S_3 are higher for *the 6R3C model*.

Best models are *the 18R15C model*, *the RF model* and *the QR model* since their residuals are the lowest, mostly for sensor S_3 .

Figure 8: Mean of residuals of each model for sensors S_3 and S_4 .

Validation of the direct models for the heavyweight wall

The same method was applied to the heavyweight wall. The results are presented in Figure 9.

Figure 9: Mean of residuals of each model for sensors S_3 and S_4 .

Residuals of the 6R3C model are extremely high. This can be explained by the fact that this model is not able to simulate high capacities and that sensor S_3 is the sensor that is the most affected by the solar radiations since it is located closer to the external surface. Regarding the three other models, residuals are close to the residuals calculated for the lightweight wall.

As a conclusion of this validation part, the forecasts of the 6R3C model are far from expected values. Consequently, the 6R3C model is not validated.

Identification

Identification technique

On the one hand, measured values were available (simulated experimental data or experimental data) and on the other hand, outputs from the reduced models defined above were generated. The aim was to find the values of the physical parameters entered in the models so that the

outputs from the reduced models were as close as possible to the experimental values.

The inverse method consists in minimizing the objective function defined as:

$$f_{obj} = \frac{1}{n \cdot m} \sum_{j=1}^m \sum_{i=1}^n (T_{i,j}^{sensor} - T_{i,j}^{model})^2 \quad (7)$$

Where m is the number of time steps, n the number of sensor, $T_{i,j}^{sensor}$ is simulated experimental data or experimental data and $T_{i,j}^{model}$ is data obtained from the chosen model among the 18R15C model, the RF model and the QR model.

The Nelder-Mead algorithm was used to minimize this function (Nelder and Mead, 1965). The function `optimize.minimize` in `Scipy` Python's library was used.

The physical parameters (λ and $\rho \cdot c$) of each layer were estimated. Then, it was possible to calculate the R - and C -values of the studied wall with equation 6.

In order to avoid local minima, different initial values were used.

Sensitivity analysis

As shown by (Remy and Degiovanni, 2005), minimizing f_{obj} is equivalent to calculate its derivatives and find when it is equal to zero. The derivatives are called the sensitivity coefficients. A sensitivity analysis was carried out to study the variation of the response of sensors regarding the variation of unknown physical parameters (λ and $\rho \cdot c$).

Figure 10: Sensitivity analysis of the 18R15C model for the lightweight wall during the cloudy day.

In the case of the lightweight wall, variations of λ_{pl} , λ_{PUR} , $(p.c)_{pl}$ and $(p.c)_{PUR}$ were studied. The reduced sensitivities against time are plotted in Figure 10 and Figure 11 for the 18R15C model during the cloudy and the sunny day described above. The results obtained for other models are similar since all models are based on Equation 1.

It seems clear that the reduced sensitivity is high for the four thermal properties, mainly for sensor S_3 . The dataset for identification should therefore contain sunny days to identify both R - and C -values.

Figure 11: Sensitivity analysis of the 18R15C model for the lightweight wall during the sunny day.

Figure 12: Sensitivity analysis of the 18R15C model for the heavyweight wall during the sunny day.

Regarding the sensitivity analysis for the heavyweight wall in Figure 12, λ_{conc} and $(p.c)_{conc}$ show high sensitivities but they seem correlated. The sensitivity of λ_{conc} is not negligible.

Correlation matrices

The analysis of correlation matrices gives useful information for identification: if the parameters are strongly correlated, it will be impossible to identify all of them at the same time.

Table 3 shows the correlation matrices of the 18R15C model for the lightweight wall during the sunny day. The results for the QR model and the RF model are close to those shown in Table 3. The results of correlation matrices show that parameters are strongly correlated since values are close to ± 1 , mainly for sensor S4 (cells are coloured in light grey when absolute value is above 0.8). Since correlation was strong between parameters, it was impossible to estimate all the parameters at the same time. That is the reason why at least two sensors need to be used to possibly decorrelate the parameters. Moreover,

it was intended to carry out a partial identification of the R - and C -values.

Table 3: Correlation matrix for the sunny day (18R15C model) – Lightweight wall.

Sensor S3				
	λ_{PUR}	λ_{pl}	$(p.c)_{PUR}$	$(p.c)_{pl}$
λ_{PUR}	1	0.15	0.02	0.47
λ_{pl}	0.15	1	0.96	0.87
$(p.c)_{PUR}$	0.02	0.96	1	0.73
$(p.c)_{pl}$	0.47	0.87	0.73	1

Sensor S4				
	λ_{PUR}	λ_{pl}	$(p.c)_{PUR}$	$(p.c)_{pl}$
λ_{PUR}	1	1	1	1
λ_{pl}	1	1	1	1
$(p.c)_{PUR}$	1	1	1	1
$(p.c)_{pl}$	1	1	1	1

In the case of the lightweight wall, we assumed that R -value is mostly impacted by λ_{PUR} (about 94% of total) and C -value is largely impacted by $(p.c)_{pl}$ (about 91% of total).

In the case of the heavyweight wall, we assumed that R -value is mostly impacted by λ_{EPS} (about 93% of total) and C -value is largely impacted by $(p.c)_{conc}$ (about 93% of total).

Estimation of uncertainties

Different sources of uncertainties were analysed:

- the uncertainty due to the inverse technique,
- the uncertainty due to the measurement noise of temperature sensors and the measurement of boundary conditions.

In order to evaluate these uncertainties, a white noise and an offset were applied to all boundary conditions and temperature measurements. The standard deviation of the white noise for temperature measurements is $\pm 0.15^\circ\text{C}$ (two times the standard deviation evaluated during calibration). The standard deviation of the white noise for the solar radiation measurement is $\pm 5 \text{ W.m}^{-2}$. As an initial approach, the offset of both types of measurements are included in a range smaller than the one of standard deviations, i.e., $\pm 0.1^\circ\text{C}$ for temperature measurements and $\pm 1 \text{ W.m}^{-2}$ for the solar radiation measurement. More than 100 tests were performed for which offsets were randomly selected.

The difference between the theoretical R - and C -values and the estimated R - and C -values were considered as the uncertainty due to the inverse technique, the model and the measurement noise.

Application to simulated data of a lightweight wall

In this part, values of T_{sensor} in equation 7 were simulated experimental data with or without noise. Boundary conditions during this test are shown in Figure 6. Identification was applied on sensors S3 and S4. The R - and C -values were estimated at the same time by identifying λ_{PUR} and $(p.c)_{pl}$.

The accuracy of the identification technique using a given model was assessed by comparing differences between the identified values and R_{Light} and C_{Light} . Results are plotted in Figure 13.

Regarding identification applied to simulated experimental data without noise, the *QR model* is the most accurate in estimating both *R*- and *C*-values. When applying the measurement noise, the difference between the identified values and the theoretical values is in $\pm 0.4 \text{ m}^2.\text{K}.\text{W}^{-1}$ for the *R*-value and in $\pm 5 \text{ kJ}.\text{m}^{-2}.\text{K}^{-1}$ for the *C*-value for all the models. In this case, the standard deviation of the difference is lower the *QR model*.

To conclude on the uncertainty due to the inverse technique, the noise related to model choices and measurement is defined as the mean of the difference between the theoretical values and the identified values in the case of noised measurements plus two times its standard deviation so that 95% of future estimations are included. This uncertainty equals $0.29 \text{ m}^2.\text{K}.\text{W}^{-1}$ for the *R*-value and $8 \text{ kJ}.\text{m}^{-2}.\text{K}^{-1}$ for the *C*-value for the *18R15C model*, $0.30 \text{ m}^2.\text{K}.\text{W}^{-1}$ for the *R*-value and $6 \text{ kJ}.\text{m}^{-2}.\text{K}^{-1}$ for the *C*-value for the *RF model* and $0.33 \text{ m}^2.\text{K}.\text{W}^{-1}$ for the *R*-value and $3 \text{ kJ}.\text{m}^{-2}.\text{K}^{-1}$ for the *C*-value for the *QR model*.

Figure 13: Estimation of *R*- and *C*-values for the lightweight wall – data with and without noise.

Application to simulated data of a heavyweight wall

In this part, values of T^{sensor} in equation 7 were simulated experimental data with or without noise. Boundary conditions during this test are shown in Figure 6. Identification was applied on sensors S_3 and S_4 . The *R*- and *C*-values were estimated at the same time by identifying λ_{EPS} and $(\rho.c)_{conc}$.

The accuracy of the identification technique using a given model was assessed by comparing differences between the identified values and R_{Heavy} and C_{Heavy} . Results are plotted in Figure 14. Accuracy of the *R*- and *C*-values assessment is high for the *QR model* regarding simulated experimental data without noise. As in the lightweight wall case, the *18R15C model* is better in identifying the *R*-value than the *C*-value.

In the case of the heavyweight wall, the uncertainty due to the inverse technique, the model and the measurement noise equals $\pm 0.19 \text{ m}^2.\text{K}.\text{W}^{-1}$ for the *R*-value and ± 15

$\text{kJ}.\text{m}^{-2}.\text{K}^{-1}$ for the *C*-value for the *18R15C model*, $\pm 0.21 \text{ m}^2.\text{K}.\text{W}^{-1}$ for the *R*-value and $\pm 10 \text{ kJ}.\text{m}^{-2}.\text{K}^{-1}$ for the *C*-value for the *RF model* and $\pm 0.30 \text{ m}^2.\text{K}.\text{W}^{-1}$ for the *R*-value and $\pm 10 \text{ kJ}.\text{m}^{-2}.\text{K}^{-1}$ for the *C*-value for the *QR model*.

Figure 14: Estimation of *R* and *C*-values for the heavyweight wall – data with and without noise.

Comparing the lightweight wall and the heavyweight wall studies, the estimation of the *R*-value is better in the heavyweight wall case whereas the estimation the *C*-value is better in the lightweight wall case.

Application to experimental data from the first component

Figure 15: Estimation of *R* and *C*-values of the lightweight component from experimental data.

In this part, values of T^{sensor} in equation 7 and boundary conditions were experimental data measured during the *ROLBS case* by temperature sensors and the weather station located in La Rochelle, France. Boundary conditions during this test are shown in Figure 6. The first

38 hours were used as initialization period. Identification techniques were applied on data of the next 184 hours.

Figure 15 shows the estimation of R - and C -values of the lightweight wall. The R -value is estimated at around $5.2 \text{ m}^2\text{K.W}^{-1}$ by all models and the C -value is estimated between 63 and $67 \text{ kJ.m}^{-2}\text{K}^{-1}$. If the uncertainty defined above is taken into consideration, the R -value is estimated between 4.9 and $5.5 \text{ m}^2\text{K.W}^{-1}$ and the C -value is estimated between 55 and $72 \text{ kJ.m}^{-2}\text{K}^{-1}$.

Conclusion

In this article, the one-dimensional heat transfer in a multilayer wall instrumented with temperature sensors under real weather conditions was studied. A comparison of the performance in identifying thermal characteristics of walls of different models were proposed.

First, the *6R3C* model was rejected since its accuracy was not satisfying. Concerning the temperature sensors, a sensitivity analysis was completed with the aim of rejecting the sensors that were too sensitive to parameters defined with a low accuracy, such as the internal and external convective and radiative heat transfer coefficients and the exterior solar surface absorptivity. Only 2 sensors out of 5 were finally useful. Then, inverse techniques were applied on two walls. Their objective was to precisely assess the thermal characteristics of walls on site and on experimental data. A first approach was presented to take into consideration the noise of measurements. This point is fundamental to determine the quality of the estimation. Regarding results on the lightweight wall, all the models could estimate the R -value with an uncertainty lower than $\pm 0.33 \text{ m}^2\text{K.W}^{-1}$ and the C -value with an accuracy lower than $\pm 8 \text{ kJ.m}^{-2}\text{K}^{-1}$. For the heavyweight wall, all the models could estimate the R -value with an uncertainty lower than $\pm 0.3 \text{ m}^2\text{K.W}^{-1}$ and the C -value with an accuracy lower than $\pm 15 \text{ kJ.m}^{-2}\text{K}^{-1}$.

This method was applied on experimental data. The estimated R -value is 20% lower than the theoretical value. The estimated C -value is 30% higher than the theoretical value. This can be explained by the risk that the wall built does not fully correspond to the design choices. This method could also be applied on heavyweight walls since a satisfying accuracy was obtained on the estimation of the R - and C -values.

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