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► To cite this version:

Emilio Sassine, Yassine Cherif, Emmanuel Antczak. Parametric identification of thermophysical properties in masonry walls of buildings. Journal of Building Engineering, 2019, 25, pp.100801. 10.1016/j.jobe.2019.100801. hal-03209140

HAL Id: hal-03209140 https://hal.science/hal-03209140

Submitted on 23 Mar 2022

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Parametric identification of thermophysical properties in masonry walls of buildings

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Abstract

The objective of this work is to improve the knowledge on the thermophysical characterization of opaque walls by determining the thermophysical properties of an experimental massive brick wall identical to old buildings walls in the North of Europe.

This method allows the

The approach developed here consists in carrying out a parametric identification of the thermophysical properties of the wall in question (namely the thermal conductivity λ and the heat capacity ρC_p), by comparing and minimizing the difference between the results resulting from the experimental tests and those resulting from the numerical model.

The optimization of the identified parameters is based on the Levenberg-Marquardt algorithm via the Comsol tool. The validation of the algorithm was carried out as well as its use in different ambient conditions (harmonic and random temperature profiles).

The investigated method shows satisfactory results for both λ (0.877, 0.880, and 0.935 W/(m.K)) and pC_p (1,012,400, 944,710, and 1,057,100 J/(m³.K)). The inner heat exchange coefficient h_i was also successfully determined for the three tests with similar values (6.13, 6.53, and 6.03 W/m².K). The results were also confirmed by comparing measured and numerical outer heat fluxes for the optimized values. The second part of this article is devoted to the study of the sensitivity of the results with respect to various parameters: the optimization algorithm, the total simulation time, the simulation time step, and the meshing element size.

NOMENCLATURE

Symbols

| Csurface equivalent heat capacity $(J.m^{-1}.K^{-1})$ C_p specific heat $(J.kg^{-1}.K^{-1})$ P thickness (m) R equivalent thermal resistance $(m^2.K W^{-1})$ T temperature (°C) t time (s) P Laplace transform variable $(-)$ F heat flux $(W m^{-2})$ X component of x direction (m) $Greek$ letters λ thermal conductivity $(W.m^{-1}K^{-1})$ ρ density of the material $(kg.m^{-3})$ $Subscripts$ iinner surface o outer surface w wallexpexperimentally measured valuenumnumerically simulated valueambambient | 2 | |
|--|---------------|--|
| ethickness (m)Requivalent thermal resistance $(m^2.K W^{-1})$ Ttemperature (°C)ttime (s)pLaplace transform variable (-)Fheat flux (W m ⁻²)xcomponent of x direction (m)Greek letters λ thermal conductivity (W.m ⁻¹ K ⁻¹) ρ density of the material (kg.m ⁻³)Subscriptsiinner surface o outer surface w wallexpexperimentally measured valuenumnumerically simulated value | С | surface equivalent heat capacity (J.m ⁻¹ .K ⁻¹) |
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| pLaplace transform variable (-)Fheat flux (W m-2)xcomponent of x direction (m)Greek lettersλthermal conductivity (W.m-1K-1)ρdensity of the material (kg.m-3)Subscriptsiinner surfaceoouter surfacewwallexpexperimentally measured valuenumnumerically simulated value | Т | temperature (°C) |
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| Greek lettersλthermal conductivity (W.m-1K-1)ρdensity of the material (kg.m-3)Subscriptsiinner surfaceοouter surfacewwallexpexperimentally measured valuenumnumerically simulated value | F | heat flux (W m ⁻²) |
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| ρdensity of the material (kg.m-3)Subscriptsiinner surfaceoouter surfacewwallexpexperimentally measured valuenumnumerically simulated value | Greek letters | |
| Subscripts i inner surface o outer surface w wall exp experimentally measured value num numerically simulated value | λ | thermal conductivity (W.m ⁻¹ K ⁻¹) |
| iinner surfaceoouter surfacewwallexpexperimentally measured valuenumnumerically simulated value | ρ | density of the material (kg.m ⁻³) |
| oouter surfacewwallexpexperimentally measured valuenumnumerically simulated value | Subscripts | |
| wwallexpexperimentally measured valuenumnumerically simulated value | i | inner surface |
| exp experimentally measured value num numerically simulated value | 0 | outer surface |
| num numerically simulated value | W | wall |
| · · · · · · · · · · · · · · · · · · · | exp | experimentally measured value |
| amb ambient | num | numerically simulated value |
| | amb | ambient |

<u>Keywords</u>

Building wall, heat transfer, thermal properties, inverse method, energy simulation

1 Introduction

The current energy and environmental issues related to resource limitations of fossil fuels and global warming issues have led to an increasing focus on energy efficiency in many energy sectors. One of the main contributors in the energy efficiency potential is the building sector and particularly the thermal behavior of building envelopes. The thermophysical properties of the building envelope are considered as key parameters in assessing and predicting the energy demand of existing or new buildings.

In order to envelopes to assess the overall thermal performance of buildings and provide a valuable decision tool for energy-efficient building design, some building attributes need to be considered. These attributes include the U-value, the absorptivity of the external surfaces, the shading coefficient (SC) of glass, the external shading coefficient of shading devices,

Solar Heat Gain Coefficient (SHGC) of glass, the building orientation and window-to-wall ratio (WWR) [1].

Many heat transfer formulations utilize steady state thermal network models which require only effective thermal conductivities or associated U- and R-values of the wall material and this approach is still been undertaken in many research studies using either laboratory experimental devices or in-situ measurements. The thermo-flux meter method is used in steady state lab conditions to determine the thermal conductivity of building materials [2]. The ISO 9869 standard requires one heat flux sensor and two thermocouples to determine the thermal resistance of walls using in-situ measurements. Some improvement has been proposed by Rasooli et al. [3] who suggested using an additional heat flux sensor, opposite to the first one for reducing the duration of the measurements and improving the precision of the results.

However, external thermal boundary conditions on building envelope are not steady due to changing outdoor conditions such as temperature, wind speed, and solar radiation. It can also be induced by indoor factors such as occupant behavior or the use of heating or air conditioning systems. The dynamic behavior of the building envelope is thus gaining increasing importance, as the analysis of buildings energy performance needs to be more and more accurate. While the steady-state conditions hypothesis seem to be acceptable in winter time for moderate and cold regions, it has to be replaced by dynamic conditions in summer conditions especially in hot climates [4]. Several works address the determination of dynamic thermal properties of building walls in dynamic boundary conditions. The approaches include statistical methods such as the Bayesian inference method, the Standard EN ISO 13786, or the analytical solution of Fourier's equation. Berger et al. [4] used a statistical method called Bayesian inference to estimate the thermal conductivities and the internal convective heat transfer coefficient by monitoring a wall in an old historic building. The method seems promising but it only considered the determination of thermal conductivities of three materials composing the wall without taking into consideration dynamic thermal properties, such as the density and the specific heat, which were predetermined based the French standards. The Bayesian inference model has also been used by Gori et al. [5] to compare two physically-informed lumped thermal mass models (the one thermal mass model 1TM and the two thermal mass model 2TM) together with temperature and heat flow measurements on two heavy-weight walls of different construction: a solid brick wall and an aerated clay, plaster, wood fiber insulation and gypsum board wall. The comparison strongly supported the 2TM over the 1TM model to

accurately describe the observed data. On the other hand, the Standard EN ISO 13786 has been adopted by Petojević et al. [6] for determining the dynamic thermal characteristicsof a multilayer wall with unknown thermal properties using thermal impulse response (TIR) functions using data from in-situ experimental measurements and least square estimator. Baldinelli et al. [7] also used the Standard EN ISO 13786 to determine the amplitude and time shift through an experimented wall using a hot box with one-day period sinusoidal solicitations. The method lacks of accuracy with an amplitude difference over 9%, and is limited to the sinusoidal boundary condition which makes it unsuitable when dealing with random boundary conditions such as in the case of in-situ measurements. By comparing the measured heat flux to the analytic solution providing a prediction of the transient surface heat flux, Robinson et al. [8] estimated the thermal diffusivity of an experimental wall. A high temperature thermal ramp boundary condition has been applied to one face with the other exposed to the cooler ambient surroundings. In the same way, the effective thermal conductivity was determined by applying steady surface temperature as boundary condition.

Inverse problems are some of the most important problems in science because they lead to physical parameters that cannot be directly observed. An inverse problem is the process of calculating from a set of observations the causal factors that produced them. Unlike a direct problem that starts with the causes and then calculates the results, inverse problems calculate the causal factors that produced by a set of observations. While inverse problems have been used in various thermal applications, it has not been applied in the building envelope context to determine thermal properties of buildings walls. Indeed, the inverse method has been used to determine the strength and location of a fixed-length heat source on a wall by employing a few selected data points downstream [9], and to reconstruct to boundary condition transient temperature distribution in a whole element based on measured temperatures at selected points [10], and even to predict the state of the lateral refractory brick wall of a melting furnace [11]. Among the very few works used for determining the thermal properties of walls using the inverse method is the work of Chaffar et al. [12] who used a flat heating resistance surface measuring 0.9 m x 1.1 m pressed against the tested wall by an 18 cm thickness polystyrene panel to direct most of the power dissipated by the resistance into the wall being tested. The method consists of thermally examining a wall by applying a heat flux and studying the response in terms of the temperature recorded through infrared thermography on the opposite surface. Although the method gives satisfactory results, it can difficultly be used for onsite measurements since it requires the use of a transient plane source which is not easily transportable.

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For several years, LGCgE's Habitat team has been working on experimental and numerical characterization on different building materials, these methods are generally based on direct measurements of temperatures and heat flux applied either under experimental conditions in the laboratory or in the laboratory. These approaches developed either in the frequency domain via thermal impedances or also by inverse methods in the time domain, aim to propose efficient methods for determining the thermophysical properties of the walls.

This paper investigates the usage of the inverse method for parametric identification of the thermophysical properties of an experimental brick wall (namely the equivalent thermal conductivity λ and the equivalent heat capacity ρC_p), by comparing and minimizing the difference between the results resulting from the experimental tests and those resulting from the numerical model. The brick was specifically chosen since it is one of the most common of architectural similarities of old houses (before 1948) in Northern Europe. Many works have investigated the thermal performance [13-15] and potential insulation of these walls [16]. Walker et al. [17] investigated thermal and moisture behavior of internal thermal insulation applied to historic brick walls by using temperature and RH probes. Several studies have also evaluated the thermal performance of building bricks. Results show that thermal properties of bricks have significant variations even within the same geographical area. This can be clearly observed in the work of Touré et al. [13] who studied compressed stabilized earth bricks (CSEB) produced by eight brickworks in Senegal and found that the thermal conductivity varied between 0.66 and 0.85 W.m⁻¹.K⁻¹ and the heat capacity varied between 939 and 1170 J.kg⁻¹.K⁻¹. Some studies have investigated the effect of modifying the composition the brick on its thermal performance such as the work of Kazmi et al. [14] who evaluated the eco-friendly bricks incorporating waste glass sludge and Raefat et al. [15] who demonstrated the interest of substituting fired clay bricks with plaster-granular cork bricks.

After a brief presentation of the experimental device, the boundary conditions, and the physical problem, the first part of the paper investigates the accuracy of the inverse method for the determination of the thermal properties (λ and ρC_p) of an experimental wall using as well as the inner heat exchange coefficient h_i in three different boundary conditions data sets. The results were also confirmed by comparing measured and numerical outer heat fluxes for the optimized values. The second part of this paper is devoted to the study of the sensitivity of the results with respect to various parameters: the optimization algorithm, the total simulation time, the simulation time step, and the meshing element size.

2 Methodology

2.1 Experimental setup

The experimental wall that was monitored is a massive brick wall similar to the walls of the old houses in Northern France; it is made of solid bricks of (6 cm x 11 cm x 22 cm) with mortar joints and has a total thickness of 34 cm [17-20].

The wall is subjected to a controlled ambiance through a heating box containing a radiator with a controlled fluid temperature varying in a range of 5°C to 60 °C.

The lateral surfaces of the wall were insulated by 20 cm of Rockwool which makes it possible to assume a one-dimensional heat flow. The heating box was also insulated to reduce heat losses.

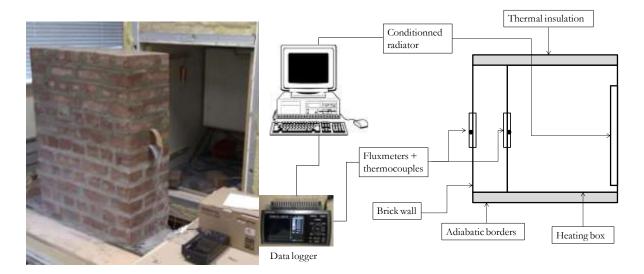


Figure 1- Experimental setup

Fig. 1 shows the experimental device (wall and heating box) before its assembly as well as a schematic cross-sectional drawing of the device and its main components.

Two thermocouples (T-type) give the inside and the outside surface temperature of the wall and two fluxmeters measure the flux passing through the wall at the inside surface of the heating box. All sensors were connected to a data logger.

2.2 Assumptions: Homogeneous wall and unidirectional heat transfer

The masonry wall composed of brick blocks and mortar joints is supposed to be a homogeneous wall having an equivalent thermal conductivity λ and an equivalent heat capacity ρC_p [18].

In addition, the heat flux is supposed to be unidirectional since the lateral boundaries of the wall are very well insulated.

The problem is thus reduced to become a unidirectional heat transfer through a homogeneous equivalent wall having the equivalent thermal properties λ and ρC_p .

2.3 Boundary conditions temperature profiles

Two types of boundary conditions were studied: the harmonic case and the random temperature profile case with two different signals.

The temperature profile of the refrigerant flowing through the radiator is predefined by a set of values generated by the LABVIEW program. This creates in the heating box a temperature T_i , on the inner face of the wall, a temperature T_{wi} , and, on the outer face of the wall, a temperature T_{wo} . These values were used as boundary conditions in the numerical model.

 F_i and F_o are respectively the inner and outer heat flux at the inner and outer wall boundaries.

In the experimental study, the interior of the box represents the external environment of the house, which varies randomly, and the atmosphere of the laboratory (outside the box) represents the interior ambiance of the house where the temperature varies slightly around 22 °C as shown in Figs. 2, 3, and 4.

The heating fluid creates in the heating box a temperature $T_i(t)$ which heats the inner wall face to reach a temperature $T_{wi}(t)$ through convection heat transfer, this heat crosses the wall by conduction and creates at the outer wall surface a temperature $T_{wo}(t)$. The ambient air temperature in the laboratory has a value $T_o(t)$. The four temperature profiles $T_i(t)$, $T_{wi}(t)$, $T_{wo}(t)$, and $T_o(t)$ are represented in Figs. 3-5 for the three case studies.

In the sinusoidal case (Signal 1), the heating fluid temperature profile has a sinusoidal shape with a period of 24 hours, an average temperature of 40 °C and amplitude of 20 °C and temperature was recorded at a regular time interval of 10 minutes through a data logger (Fig. 2).

For the random temperature profile, two different random temperature profiles were generated and the temperature and heat flux data were recorded at regular time intervals (10 min for signal 2 and 30 min for signal 3) as shown in Fig. 3 and Fig. 4.

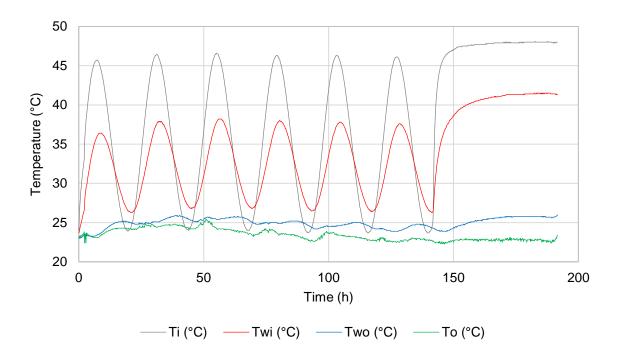


Figure 2- Temperature boundary conditions for harmonic signal 1

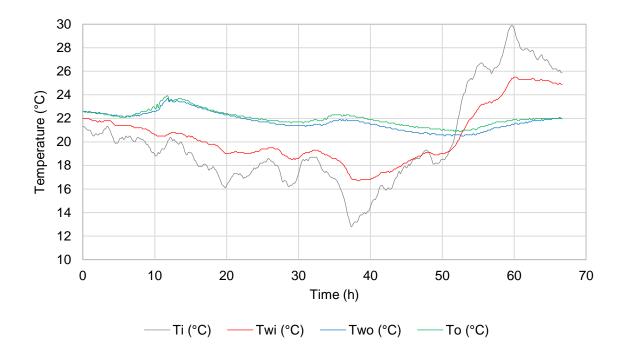


Figure 3- Temperature boundary conditions for random signal 2

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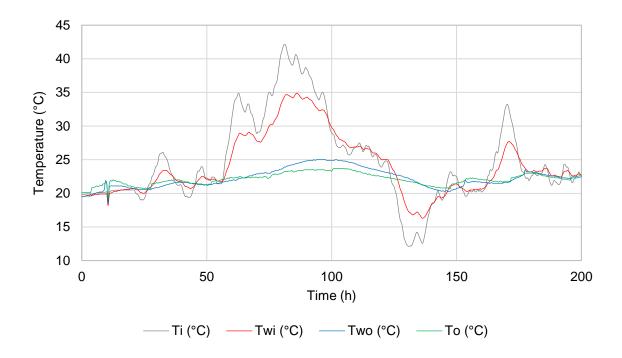


Figure 4- Temperature boundary conditions for random signal 3

2.4 Physical problem

According to Standard EN ISO 13786, the transmission equation relating the temperatures and heat fluxes at both sides of a homogeneous in terms of Laplace variable p, and taking into consideration the two heat transfer coefficients h_i at the inner face of the wall h_o at the outer face of the wall can be expressed in hyperbolic functions form as follows:

$$\begin{bmatrix} T_{wo} \\ F_o \end{bmatrix} = \begin{bmatrix} 1 & \frac{1}{h_i} \\ 0 & 1 \end{bmatrix} \times \begin{bmatrix} ch(\sqrt{pRC}) & \sqrt{\frac{R}{pC}}sh(\sqrt{pRC}) \\ \sqrt{\frac{pC}{R}}sh(\sqrt{pRC}) & ch(\sqrt{pRC}) \end{bmatrix} \times \begin{bmatrix} 1 & \frac{1}{h_e} \\ 0 & 1 \end{bmatrix} \times \begin{bmatrix} T_{wi} \\ F_i \end{bmatrix}$$
(1)

Where, R is the thermal resistance of the layer and C its surface heat capacity.

In direct heat transfer problems, parameters R and C are known and two of the boundary conditions (temperatures and/or heat fluxes) are the unknown to be determined through Eq. 1.

2.5 Description of the optimization methodology (inverse method)

Three physical parameters were optimized in two different optimization calculations using the Levenberg–Marquardt algorithm (LMA). At first, wall thermal properties (λ and ρC_{p} .) were optimized, and then the internal convective heat exchange coefficient h_i was optimized separately.

The LMA algorithm is normally used to solve non-linear least squares problems and is used in many software applications for solving least squares curve fitting problems. It has been chosen for its fast simulation time and its reliability.

The validity of other optimization methods available in COMSOL Multiphysics has also been studied.

a- Methodology for λ and C_p

Three parameters were targeted using the inverse method. At first, the thermal properties specific to the experimented wall were determined by using as boundary conditions the imposed temperatures at the inner (T_{wi}) and outer (T_{wo}) faces of the wall and by minimizing the difference between the measured heat flux on the inner face of the wall F_{i_exp} and the heat flux obtained numerically on the same face F_{i_num} for the objective function F_i . In this case two control variables were simultaneously optimized through an optimization inverse algorithm used in COMSOL Multiphysics Software, the thermal conductivity λ and the heat capacity ρC_p .

The unknown parameters λ and ρC_p are related to the equivalent thermal resistance R and the equivalent surface heat capacity C by the following equations:

$$R = \frac{e}{\lambda} \tag{2}$$

$$C = \rho . C_{p} . e \tag{3}$$

where e is the total wall thickness.

b- Methodology for hi

Afterwards, the determination of the internal convective heat exchange coefficient h_i is carried out using the properties of the wall already determined in the first phase, and using

as boundary conditions the heating box ambient temperature T_{amb} and the inner face wall temperature (T_{wi}). The convective heat flux is thus given by:

$$F_i = h_i \left(T_{amb} - T_{wi} \right) \tag{4}$$

The optimized value of h_i is thus the value that minimizes the difference between the measured heat flux on the inner face of the wall and the heat flux obtained numerically on the same face.

3 Results

3.1 Thermal characterization of the walls and determination of convective exchange coefficient h_i in different regimes using the inverse method

Three different heat fluxes profiles were compared in Figs. 5-7; the experimental heat flux that was measured through the internal thermal fluxmeter F_{i_exp} , the numerical internal heat flux for determining the optimized thermal properties of the wall (λ and ρC_p), F_{i_num} ($\lambda,\rho C_p$), and the numerical internal heat flux for determining the optimized inner heat exchange coefficient h_i , F_{i_num} (h_i). This means that F_{i_num} ($\lambda,\rho C_p$) and F_{i_num} (h_i) come from two different simulations where the first simulation is carried out to determine the optimal thermal properties of the wall (λ and ρC_p), and the second to determine the convective exchange coefficient h_i , inside the heating box.

Results show that numerical and experimental graphs of the objective function F_i match perfectly in the three studied cases (sinusoidal case, random case 1, and random case 2) and for the two optimization cases.

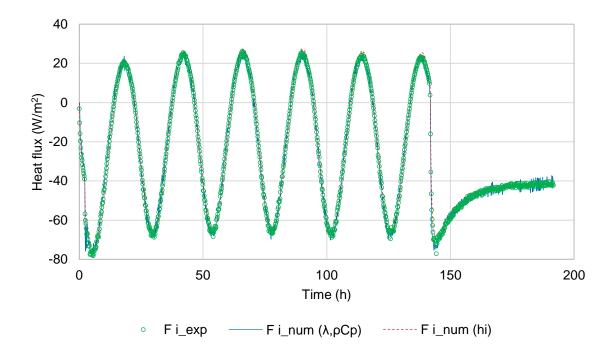


Figure 5- Numerical and experimental inner heat flux in signal 1 for the optimized wall thermal properties λ and ρC_p and for the optimized inner heat exchange coefficient h_i

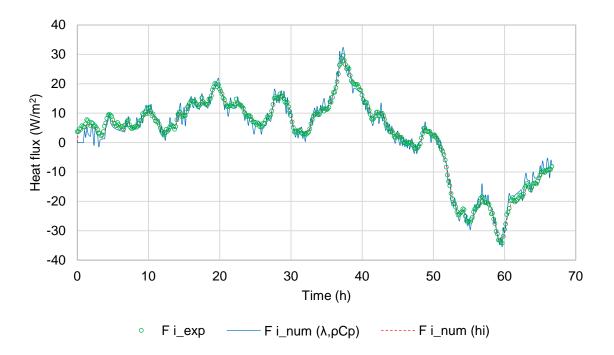


Figure 6- Numerical and experimental inner heat flux in the signal 2 for the optimized wall thermal properties λ and ρC_p and for the optimized inner heat exchange coefficient h_i

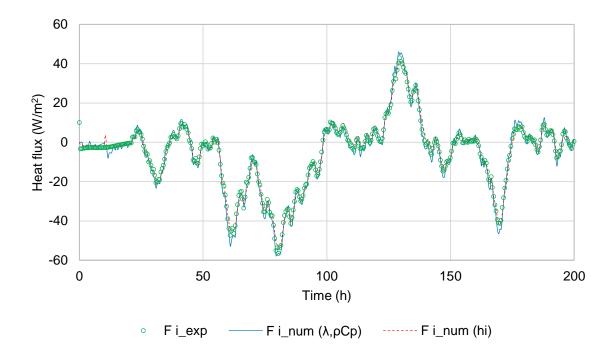


Figure 7- Numerical and experimental inner heat flux in signal 3 for the optimized wall thermal properties λ and ρC_p and for the optimized inner heat exchange coefficient h_i

The inverse method for determining wall thermal properties (λ and ρC_p) showed satisfactory results in harmonic and random boundary conditions and the values obtained were very similar as shown in Table 1. Similarly, the inner heat exchange coefficient h_i was successfully determined for the three tests with close values (6.13, 6.53, and 6.03 W/m².K) reported in Table 1.

| | λ (W/(m.K)) | ρCp (J/(m ³ .K)) | h _i (W/(m².K)) |
|----------|-------------|-----------------------------|---------------------------|
| Signal 1 | 0.877 | 1,012,400 | 6.13 |
| Signal 2 | 0.880 | 944,710 | 6.53 |
| Signal 3 | 0.935 | 1,057,100 | 6.03 |

Table 1- Thermal properties through inverse method for the three experimental tests

* Corresponding authors

3.2 Direct problem solution

For a better proof of the numerical heat transfer model and of the optimized thermal parameters values through the inverse method, the numerical outer heat flux F_{o_num} was compared to the experimentally measured outer heat flux F_{o_exp} for the three case studies. The graphs show a very good match between the numerical and experimental results (Fig. 8, Fig. 9, and Fig. 10).

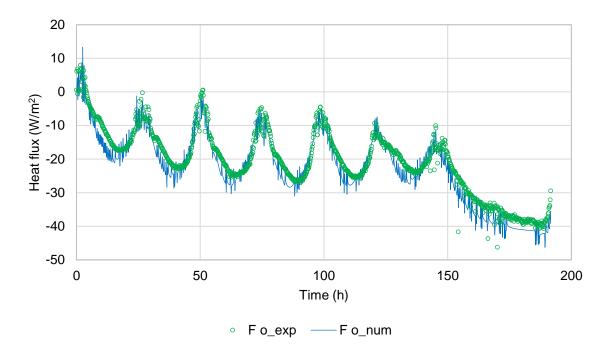


Figure 8- Numerical and experimental outer heat flux in signal 1 for the optimized wall thermal properties λ and ρC_{ρ}

* Corresponding authors

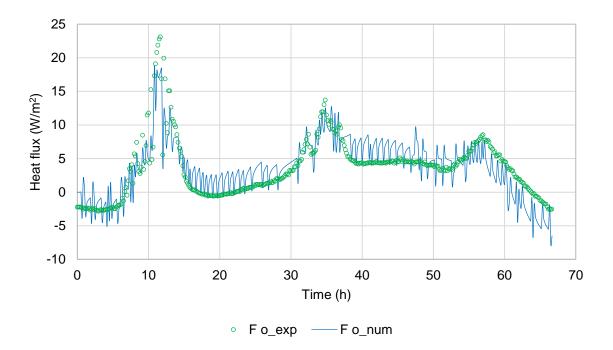


Figure 9- Numerical and experimental outer heat flux in signal 2 for the optimized wall thermal properties λ and ρC_p

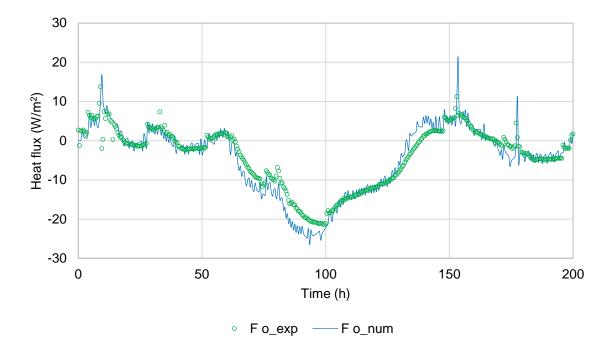


Figure 10- Numerical and experimental outer heat flux in signal 3 for the optimized wall thermal properties λ and ρC_{ρ}

4 Sensitivity analysis and discussion

In order to perform sensitivity assessment for the inverse method, the random test (signal 2) with the unknown parameters λ and ρC_p was adopted and the influence of the initial values of λ and ρC_p , the influence of the optimization algorithm used, the influence of the total simulation time, the influence of the simulation time step, as well as the influence the meshing element size were assessed.

4.1 Influence of initial values of λ and ρC_p

During the simulations, the initial value for the equivalent thermal conductivity λ was chosen to be equal to 0.2 and varying between 0.1 and 2, while the initial value for the equivalent heat capacity ρC_p was chosen to be equal to 200000 and varying between 100000 and 2000000.

Table 2 and Fig. 11 represent, for different initial values of λ and ρC_p , the optimized values of these parameters to verify the convergence of the optimal solution. It was found that the initial values of λ and ρC_p have a very slight influence. Note that it is preferable to choose initial values far from the optimized values to allow a right the convergence of the solution and avoid the solution rapidly to converge as was the case for (1;1000000) as shown in Fig. 12.

| Initial values of λ and ρCp | λ [W/(m.K)] | ρCp [J/(m ³ .K)] |
|---|-------------|-----------------------------|
| (0.2;200000) | 0.88 | 944710 |
| (0.5;500000) | 0.882 | 942570 |
| (1;1000000) | 0.844 | 999980 |
| (1.5;1500000) | 0.874 | 952580 |

Table 2- Optimized values of λ and ρC_{ρ} for different initial values of λ and ρC_{ρ}

* Corresponding authors

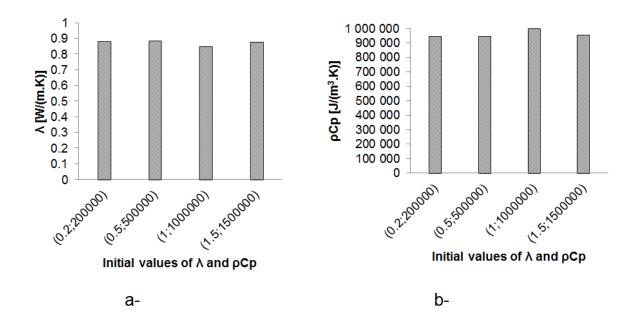


Figure 11- Optimized values of λ (a) and ρC_p (b) for different initial values of λ and ρC_p

4.2 Influence of the optimization method

The Levenberg–Marquardt algorithm (LMA) was used in this paper; however, the validity of other optimization methods available in COMSOL Multiphysics has been studied. These methods include Monte Carlo, Nelder-Mead, BOBYQA, COBYLA, SNOPT, and MMA.

It was found that the MMA algorithm converges to a similar solution as Levernberg-Marqardt with a similar convergence profile (Fig. 12) and a similar simulation time (7 minutes for Levernberg-Marqardt and 8 minutes for MMA).

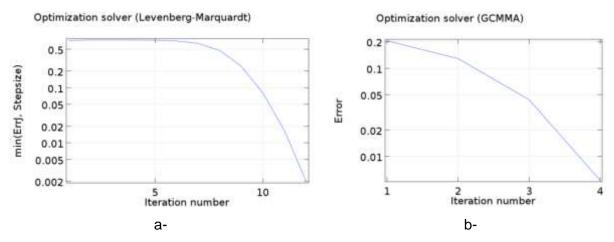


Figure 12- Convergence profile for Levernberg-Marqardt (a) and for MMA (b) algorithms

The SNOPT algorithm also converges to the similar values of λ and ρC_p as Levernberg-Marqardt and MMA but with a different convergence profile (Fig. 13) and a greater simulation time (19 minutes).

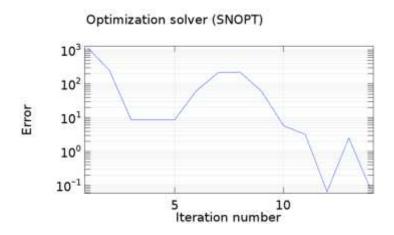
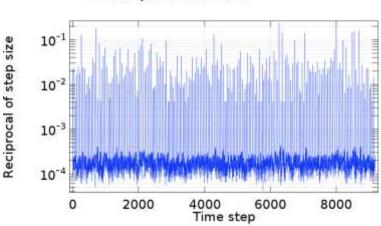


Figure 13- Convergence profile for SNOPT algorithm

The remaining algorithms methods (Monte Carlo, Nelder-Mead, BOBYQA, and COBYLA) do not converge to any solution and run the maximum number of evaluations that was fixed to 200 without any convergence. The convergence profile of the Monte Carlo algorithm is shown in Fig. 14 as example.



Time-Dependent Solver 1

Figure 14- Convergence profile for Monte Carlo algorithm

The optimized values of for the three succeeded optimization methods (Levernberg-Marqardt, MMA, and SNOPT) are summarized in Table 3.

Table 3- Optimized values of λ and ρC_p for different optimization algorithms

| Optimization algorithm | λ [W/(m.K)] | ρCp [J/(m ³ .K)] |
|------------------------|-------------|-----------------------------|
| Levernberg-Marqardt | 0.88 | 944710 |
| MMA | 0.884 | 928080 |
| SNOPT | 0.878 | 947410 |

4.3 Influence of the simulation total time

The total simulation time used for signal 1 was equal to 240000 seconds (66.7 hours). Shorter total simulation time was inspected to study the minimum measurement time required for the use of the considered inverse method.

The values of the investigated total simulation time were: 10, 20, 30, 40, 50 and 60 hours and the results are reported in Table 4 and Fig. 15.

The results remain accurate (relative deviation below 15%) for the thermal conductivity λ for a total simulation time above 20 hours. The heat capacity (ρC_p) seems to be more sensitive to the total simulation time where the relative deviation exceeds 15% from the initial case (66.7 hours) for a total simulation time below 50 hours.

Table 4- Optimized values of λ and ρC_{ρ} for different simulation durations

| Simulation duration (h) | λ [W/(m.K)] | ρCp [J/(m³.K)] |
|-------------------------|-------------|----------------|
| 67 | 0.88 | 944 710 |
| 60 | 0.895 | 989 930 |
| 50 | 0.936 | 771 110 |
| 40 | 0.991 | 681 590 |
| 30 | 1.001 | 688 130 |
| 20 | 0.951 | 734 180 |
| 10 | 1.998 | 114 100 |

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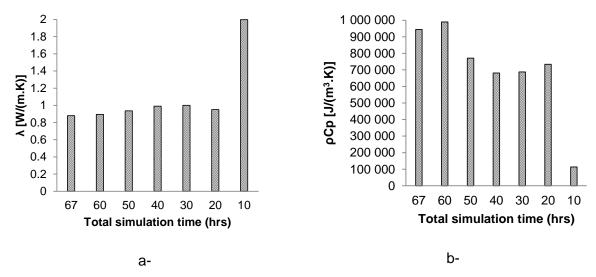


Figure 15- Optimized values of λ (a) and ρC_{P} (b) for different simulation durations

4.4 Influence of time step

The time step investigated in signal 1 was 10 minutes (600 s). The values of time step that were evaluated are: 20, 30, 40, 50 and 60 minutes. The results reported in Table 5 and Fig. 16 show a very good accuracy for both λ and ρC_p for all investigated time steps where the relative deviation of the optimized values from the initial case study (10 mins time step) remains below 2%.

| Time step (min) | λ [W/(m.K)] | ρC _p [J/(m ³ .K)] |
|-----------------|-------------|---|
| 10 | 0.88 | 944 710 |
| 20 | 0.879 | 946 900 |
| 30 | 0.886 | 952 040 |
| 40 | 0.888 | 947 090 |
| 50 | 0.889 | 928 180 |
| 60 | 0.878 | 937 960 |
| | | |

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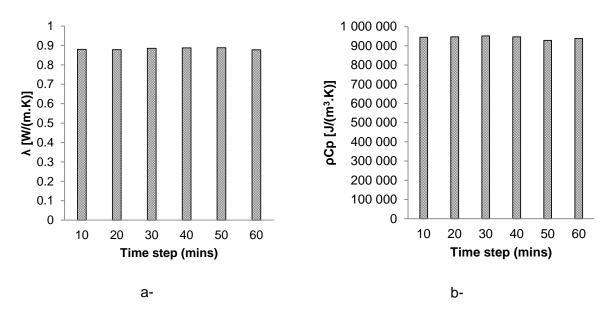


Figure 16- Optimized values of λ (a) and ρC_{ρ} (b) for different time steps

4.5 Influence of element size in meshing

The automatic meshing allows the user to choose between the following size of mesh elements: extremely fine, extra fine, finer, fine, normal, coarse, coarser, extra coarse extremely coarse with their respective maximum meshing element size varying between 0.0033 and 0.109 as shown in Table 6. Normal meshing elements were considered as the default value in the simulations.

The results reported in Table 6 and Fig. 17 show a very good accuracy for both λ and ρC_p for all investigated meshing sizes where the relative deviation of the optimized values from the initial case study remains below 5%.

| Meshing size | Maximum element size | λ [W/(m.K)] | ρCp [J/(m³.K)] |
|------------------|----------------------|-------------|----------------|
| Extremely fine | 0.0033 | 0.88 | 944940 |
| Extra fine | 0.0066 | 0.88 | 945050 |
| Finer | 0.0122 | 0.88 | 945430 |
| Fine | 0.0175 | 0.88 | 944880 |
| Normal | 0.0221 | 0.88 | 944710 |
| Coarse | 0.033 | 0.881 | 942240 |
| Coarser | 0.0429 | 0.881 | 943490 |
| Extra coarse | 0.066 | 0.888 | 935460 |
| Extremely coarse | 0.109 | 0.916 | 898760 |

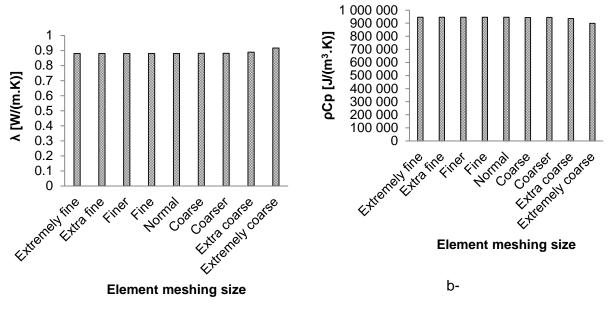
Table 6- Optimized values of λ and ρC_{ρ} for different elements meshing size

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a-

Figure 17- Optimized values of λ (a) and ρC_{ρ} (b) for different elements meshing size

5 Conclusion and summary remarks

A method to derive the thermophysical properties of a building wall from in situ temperature and heat flux measurements using the inverse method has been developed in two different types of boundary conditions: the harmonic case and the random temperature profile case with two different signals.

A parametric identification of the thermophysical properties of an experimental brick wall (namely the equivalent thermal conductivity λ and the equivalent heat capacity ρC_p) by comparing and minimizing the difference between the results resulting from the experimental tests and those resulting from the numerical model is presented in this study.

The investigated method showed satisfactory results for both λ (0.877, 0.880, and 0.935 W/(m.K)) and ρC_p (1012400, 944710, and 1057100 J/(m³.K)). The inner heat exchange coefficient h_i was also successfully determined for the three tests with similar values (6.13, 6.53, and 6.03 W/m².K).

The results show that the inverse method can provide satisfactory results in the determination of static (λ) but also dynamic (ρC_p) thermal parameters using random

boundary conditions. This method can thus be used on existing walls by using a fairly simple experimental device consisting of two thermocouples and a single fluxmeter.

The results were also confirmed by comparing measured and numerical outer heat fluxes using the direct method with the optimized values of λ and ρC_p .

The second part of this article is devoted to the study of the sensitivity of the results with respect to various parameters: the optimization algorithm, the total simulation time, the simulation time step, and the meshing element size.

6 References

- [1] Worawan Natephra, Nobuyoshi Yabuki, Tomohiro Fukuda, Optimizing the evaluation of building envelope design for thermal performance using a BIM-based overall thermal transfer value calculation, Building and Environment 136 (2018) 128-145
- [2] Roberto Bruno, Piero Bevilacqua, Giorgio Cuconati, Natale Arcuri, An innovative compact facility for the measurement of the thermal properties of building materials: first experimental results, Applied Thermal Engineering 143 (2018) 947-954
- [3] Arash Rasooli, Laure Itard, In-situ characterization of walls' thermal resistance: An extension to the ISO 9869 standard method, Energy & Buildings 179 (2018) 374–383
- [4] Julien Berger, Helcio R.B. Orlande, Nathan Mendes, Sihem Guernouti, Bayesian inference for estimating thermal properties of a historic building wall, Building and Environment 106 (2016) 327-339
- [5] Virginia Gori, Valentina Marincioni, Phillip Biddulph, Clifford A. Elwell, Inferring the thermal resistance and effective thermal massdistribution of a wall from in situ measurements to characterise heattransfer at both the interior and exterior surfaces, Energy and Buildings 135 (2017) 398–409
- [6] Zorana Petojević, Radovan Gospavić, Goran Todorović, Estimation of thermal impulse response of a multi-layer building wall through in-situ experimental measurements in a dynamic regime with applications, Applied Energy 228 (2018) 468–486
- [7] Giorgio Baldinelli ,, Francesco Bianchi, Agnieszka A. Lechowska, Jacek A. Schnotale, Dynamic thermal properties of building components: Hot box experimental assessment under different solicitations, Energy & Buildings 168 (2018) 1–8
- [8] A.J.Robinson, F.J.Lesage, A.Reilly, G.McGranaghan, G.Byrne, R.O'Hegarty, O.Kinnane, A new transient method for determining thermal properties of wall sections, Energy and Buildings 142 (2017) 139-146

* Corresponding authors

- [9] Ardeshir Bangian-Tabrizi, Yogesh Jaluria, An optimization strategy for the inverse solution of a convection heat transfer problem, International Journal of Heat and Mass Transfer 124 (2018) 1147–1155
- [10] Piotr Duda, A general method for solving transient multidimensional inverse heat transfer problems, International Journal of Heat and Mass Transfer 93 (2016) 665–673
- [11] Mohamed Hafid, Marcel Lacroix, Inverse heat transfer prediction of the state of the brick wall of a melting furnace, Applied Thermal Engineering 110 (2017) 265–274
- [12] Chaffar, Khaled, Alexis Chauchois, Didier Defer, et Laurent Zalewski, Thermal characterization of homogeneous walls using inverse method, Energy and Buildings 78 (2014) 248-255
- [13] E. Sassine, Z. Younsi, Y. Cherif, A. Chauchois, E. Antczak, Experimental determination of thermal properties of brick wall for existing construction in the north of France, Journal of Building Engineering 14 (2017) 15–23
- [14] Emilio Sassine, A practical method for in-situ thermal characterization of walls, Case Studies in Thermal Engineering 8 (2016) 84–93
- [15] Emilio Sassine, Zohir Younsi, Yassine Cherif, Emmanuel Antczak, Thermal performance evaluation of a massive brick wall under real weather conditions via the Conduction Transfer function method, Case Studies in Construction Materials 7 (2017) 56–65
- [16] Emilio Sassine, Zohir Younsi, Yassine Cherif, Emmanuel Antczak, Frequency domain regression method to predict thermal behavior of brick wall of existing buildings, Applied Thermal Engineering 114 (2017) 24–35
- [17] R.Walker, S.Pavía, Thermal and moisture monitoring of an internally insulated historic brick wall, Building and Environment 133 (2018) 178-186
- [18] Pape Moussa Touré, Vincent Sambou, Mactar Faye, Ababacar Thiam, Mamadou Adj, Dorothé Azilinon, Mechanical and hygrothermal properties of compressed stabilized earth bricks (CSEB), Journal of Building Engineering 13 (2017) 266–271
- [19] Syed Minhaj Saleem Kazmi, Muhammad Junaid Munir, Yu-Fei Wu, Asad Hanif, Indubhushan Patnaikuni, Thermal performance evaluation of eco-friendly bricks incorporating waste glass sludge, Journal of Cleaner Production 172 (2018) 1867-1880
- [20] S. Raefat, M. Garoum, M. Souihel, N. Laaroussi, Thermal transmittance comparison between multilayer walls made from hollow fired clay and plaster-granular cork bricks using electrical analogy, Energy Procedia 139 (2017) 596–601