RECURRENT NEURAL NETWORKS AND NEURO-INVERSE APPROACH FOR ESTIMATING THE THERMAL DIFFUSIVITY OF BUILDING MATERIALS

Stéphane Grieu[1,*], Adama Traoré[1], Olivier Faugeroux[1], Bernard Claudet[1], Frédérik Thiery[1] and Jean-Luc Bodnar[2]
[1]ELIAUS Laboratory, University of Perpignan Via Domitia, 52 avenue Paul Alduy, 66860, Perpignan, France
[2]GRESPI Laboratory, University of Reims Champagne Ardenne, 9 boulevard de la Paix, 51100, Reims, France

ABSTRACT

According to both the actual energy context and the latest laws meeting EU requirements about energy certification schemes for buildings, carrying out an energy performance diagnosis is mandatory, notably when buying or selling buildings. Indeed, invisible defaults could have a detrimental effect on their insulating qualities. An in-situ estimation of thermo-physical properties allowing to locate defaults, the present work focuses on testing in simulation, as a first approach, a new and effective method based on the use of artificial neural networks to characterize building materials i.e. to estimate their thermal diffusivity using thermograms obtained thanks to a non-destructive method.

INTRODUCTION

The actual European energy context reveals that the building sector is one of the largest sectors of energy consumption. In France, about 25% of greenhouse gases emissions and 45% of energy consumption are due to buildings (ADEME, 2007). Consequently, the adopted "Energy Performance of Buildings Directive" (Official Journal of the European Communities, 2002), focusing on energy use in buildings, requires all the European Union (EU) members to enhance their building regulations and to introduce energy certification schemes, with the aim of both reducing energy consumption and improving energy efficiency. Thus, an advanced energy performance diagnostic has to be done, notably when buying or selling buildings (Journal Officiel de la République Française, 2006). Presence of invisible defaults, like non emerging cracks or delaminations, in a wall or a ceiling completely spoils insulating qualities of a building. A future owner would be pleased to locate these defaults. In the same way, during a building renovation, if a precise draught does not exit, it would be useful to know where are the gas or water ducts and electricity cables passages, if an old opening has been blocked up, or if a wall or a ceiling is crossed by a wooden beam. Unfortunately, these defaults are usually hidden. Whatever the situation, the challenge is the same: locate invisible things under a layer of plaster or similar material, which amounts to locate inhomogeneities in homogeneous medium. These defaults locally modify global thermophysical properties of the medium. Thus, an in-situ properties estimation can lead us to locate them by making a properties cartography of the observed medium.

In the present work, properties estimation methods, alternative to classic ones, are proposed using thermograms obtained with a non-destructive photothermal method. In the large domain of Non-Destructive Control (NDC), thermal methods of characterization have known a new development thanks to infrared measurement tools. They are known as photothermal methods. Their principle is as follows: the sample to be characterized is excited by a light source and its thermal response, called thermogram, is recorded. From the obtained thermogram, one can estimate several thermo-physical properties such as the thermal diffusivity and effusivity or the thickness of a layer for a multilayer material. These methods can be classified depending on the time profile of the excitation: pulsed method when the excitation is an impulse, modulated method when the excitation is periodic. But characterization of fragile or ductile material is still a problem because of high excitation solicitations. So, the idea is to submit the studied sample to a weaker thermal excitation. A recent solution is to apply an excitation with a random time profile. Previous studies have shown all the interest of this kind of method. The properties have to be estimated from the sample response to the random excitation. Two ways of doing are possible: rebuilding the impulse response and estimating the properties by usual method, or estimating the properties directly from the response to random excitation. We usually use a correlation analysis method to rebuild the impulse response. The main objective of the present work is to test some tools belonging to the field of artificial intelligence for rebuilding the impulse response of a sample or for estimating directly the properties from a response to a random excitation. Artificial neural networks, a useful tool for modelling and controlling non-linear systems, are known as universal and parsimonious approximators. They present some interesting attributes, mostly their learning and generalization capabilities, to be used for rebuilding impulse responses of building materials (in this case, the thermal diffusivity of the concerned materials is

*Corresponding author. Tel.: +33 4 68 66 22 02; email: grieu@univ-perp.fr.

thereafter determined by means of inverse methods; one could speak of "neuro-inverse" approach) or for directly estimating the above-mentioned thermo-physical property.
First, we will present the photothermal experiment and more particularly the random method. Inverse method for parameters estimation will be described too. Then, we will be interested in the artificial intelligence tool we use i.e. the Elman recurrent neural network. Finally, we will present our main results: rebuilt impulse responses and properties estimations. We will end this paper by a concrete application for buildings, our conclusions and actual prospects.

THE PHOTOTHERMAL EXPERIMENT

Presentation

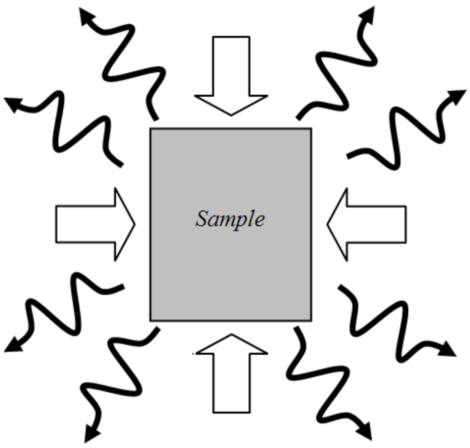

Figure 1. The photothermal experiment. White arrows: light excitation, black arrows: IR response.

This NDC method consists in submitting the sample to be characterized to a light flux. The flux absorption products a local temperature elevation. The IR emission is recorded (Figure 1). With low heating hypothesis, the obtained photothermal signal is proportional to the surface sample temperature. It depends on the observed sample thermophysical properties (thermal effusivity and diffusivity), its structure, the eventual presence of defects or delaminations, etc… The temporal profile of the excitation flux represents one of the photothermal experiment characteristics. If the excitation is a pulse (as close to a Dirac in time as possible), the experiment is called pulsed method, better known as "flash method" (Parker W.J. et al., 1961). This method is very efficient: all frequencies are in the sample response. However, using this technique, a high quantity of energy has to be deposited in a very short instant. Thus, analysing fragile materials with the flash method is not possible. If the excitation is periodic (fixed and known frequency, sinusoidal profile for example), one speaks of modulated method. The sample response is recorded by the way of a lock-in amplifier. Energetic stresses are very smaller but the permanent regime has to be reached to begin measurements. Responses contain only one frequency and the experiment has to be repeated to obtain a complete study of the samples (Gervaise C., 1999). The last born of the photothermal methods is the random method (Bodnar J.L. and Brahim S., 2003), a random excitation (a Pseudo Random Binary Signal) being used.

The random method

This method has been developed by the GRESPI Laboratory from the University of Reims Champagne Ardennes (France). The random method combines elements from both flash and modulated methods. Energetic stresses are very low and if the excitation is perfectly random, the sample responses contain all frequencies. Using correlation analysis techniques, the sample impulse response is recalculated from its response to PRBS. Material properties are identified from the impulse response by well-known techniques (Parker W.J. et al., 1961). The major difficulty is to create experimentally an excitation as close as possible to a real random signal.

- Using the random method

After that several excitation types have been tested, the Pseudo Binary Random Signal (PRBS) has been chosen to excite the samples. The PRBS is a signal composed of low (0) and high (1) states, the duration of which is practically random (Figure 2.1). Construction of pseudo random sequences consists in getting the output signal of a shift register with a feedback via a modulo-2 addition (Auvray J., 1994). Samples can be stressed with a laser diode piloted by a PRBS. IR responses are recorded using an InSb or HgCdTe infrared detector. In parallel, a response model has been developed. Thus, it is possible to simulate the experiment.

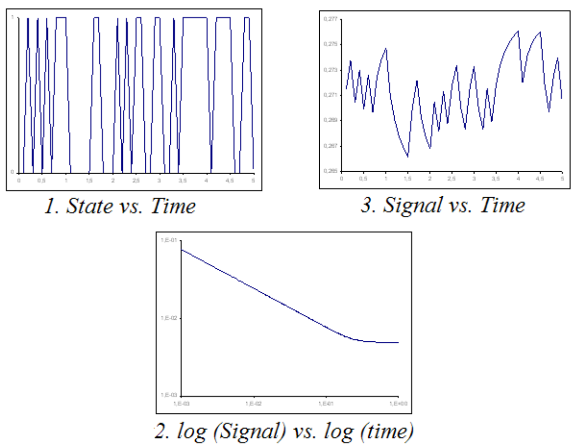

Figure 2. Examples: 1. PRBS, 2. Sample response to a pulsed stress, 3. Sample response to PRBS.

Up to now, to obtain the impulse response (R_{imp}) (Figure 2.2) from the sample response to a random excitation (R_{rand}) (Figure 2.3), the GRESPI uses the J. Max's technique (Max J., 1993) (Equation 1).

$$R_{imp}(t) = FT^{-1}\left[\frac{R_{rand}(f)\cdot E(f)}{E(f)\cdot E(f)}\right] \quad [Eq.1]$$

with FT^{-1} the inverse Fourier transform, $R_{rand}(f)$ the Fourier transform of $R_{rand}(t)$ and $E(f)$ the Fourier transform of the excitation.

The aim of this paper is to show that correlation analysis can be efficiently replaced by artificial intelligence tools.

- Identifying sample properties by inverse method

The impulse response can be exploited using Parker's technique (Parker W.J. and al., 1961) or by inverse method (Faugeroux O., 2001) to identify thermophysical properties. We usually use inverse method. The principle of an inverse method is to compare a model to experimental measurements.

The model depends on parameters which are usually thermophysical properties combinations. The goal is to minimise a criterion by adjusting the parameters by an iterative process (Figure 3). Calculation is initiated by a priori parameters chosen by the user. Thus, having mathematical model very close to the used experiment is crucial.

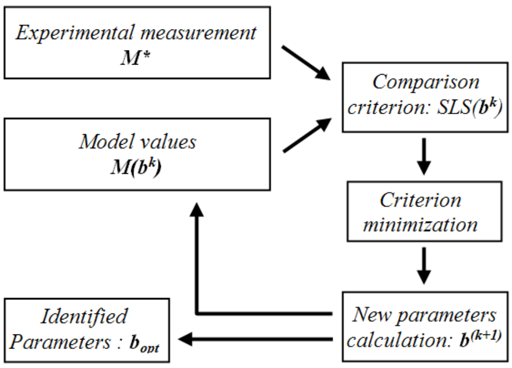

Figure 3. Estimation by inverse method principle.

Bolt characters represent vectorial quantities or matrix. Let, first, $\boldsymbol{M}^* = (M_1^*, \dots, M_k^*, \dots, M_n^*)^T$ be a vector whose components are n experimental measurements uniformly spaced in time between t_1 and t_n and, secondly, $\boldsymbol{M}(\boldsymbol{\beta}) = (M_1, \dots, M_k, \dots, M_n)^T$ be the vector of modelised temperature with $M_k = T_i(t_k, \boldsymbol{\beta})$, $\boldsymbol{\beta}$ being the parameters to be identified and calculated with a model. Finally, let $SLS(\boldsymbol{\beta})$ be an objective function, defined as the sum of the least square of $\boldsymbol{M}^*$ and $\boldsymbol{M}(\boldsymbol{\beta})$, to be minimised with respect to the unknown $\boldsymbol{\beta}$. It could be written:

$$SLS(\boldsymbol{\beta}) = \sum_{k=1}^{n}[M_k^* - M_k]^2 \quad [Eq.2.1]$$

$$SLS(\boldsymbol{\beta}) = [\boldsymbol{M}^* - \boldsymbol{M}(\boldsymbol{\beta})]^T \cdot [\boldsymbol{M}^* - \boldsymbol{M}(\boldsymbol{\beta})] \quad [Eq.2.2]$$

We use the Gauss-Newton's or Box–Kanemasu's iterative method (Beck J.V. and Arnold K., 1977) to seek $\boldsymbol{b_{opt}}$, the best estimate of $\boldsymbol{\beta}$, from an initial estimate $\boldsymbol{b}^{(0)}$. Each iteration requires the inversion of the approximation of the Hessian matrix $\boldsymbol{A}$ given by:

$$\boldsymbol{A} = \boldsymbol{X}^T \cdot \boldsymbol{X} \quad [Eq.3]$$

with $\boldsymbol{X}$ the sensitivity matrix whose component X_{kp} is given by the time discretisation of the sensitivity function related to the parameter β_p. The sensitivity function related to β_p is given by the first derivative of the model with respect to β_p.

$$X_p(t, \boldsymbol{\beta}) = \left(\frac{\partial T_i(t,\beta)}{\partial \beta_p}\right)_{\beta_{q\neq p}} \quad [Eq.4]$$

This function allows us to calculate the sensitivity coefficient, the value of the function at time t_k. At iteration k, a new estimate vector is calculated, knowing the $(k-1)^{th}$ estimate and a correction to the $(k-1)^{th}$ estimate:

$$\boldsymbol{b}^{(k)} = \boldsymbol{b}^{(k-1)} + h \cdot \Delta\boldsymbol{b}^{(k-1)} \quad [Eq.5]$$

with h the Box-Kanemasu correction coefficient (h = 1 for Gauss-Newton method), $\Delta\boldsymbol{b}^{(k)} = \boldsymbol{P}^{(k)}\left[\boldsymbol{X}^{T(k)} \cdot \left(\boldsymbol{M}^* - \boldsymbol{M}(\boldsymbol{b})^{(k)}\right)\right]$ and $\boldsymbol{P}(k) = \left[\boldsymbol{X}^{T(k)} \cdot \boldsymbol{X}^{(k)}\right]^{-1}$. Thus, the parameter vector at iteration k is calculated. Let us note that the matrix $\boldsymbol{A}^{(k)}$ has to be inversed and, consequently, needs to be well-conditioned. So, $\boldsymbol{X}^{(k)}$ values have to be maximum because small values lead to an ill-conditioned matrix and the inverse algorithm will not converge. The algorithm is stopped if the $SLS(\boldsymbol{b})$ function value at this iteration reaches a critical value.

ARTIFICIAL NEURAL NETWORKS

Recurrent Neural Networks (RNN)

Feedforward neural networks have been successfully used to solve problems that require the computation of a static function i.e. a function whose output depends only on the current input, and not on any previous inputs. In the real world however, one encounters many problems which cannot be solved by learning a static function because the function being computed changes with each input received. It should be clear from the architecture of feedforward neural networks that past inputs have no way of influencing the processing of future inputs. This situation can be rectified by the introduction of feedback connections in the network (Elman J.L., 1990). Now network activation produced by past inputs can cycle back and affect the processing of future inputs. The class of neural networks, which contain cycles or feedback connections, is called recurrent neural networks.

Elman Neural Network (ENN)

The Elman network used for rebuilding impulse responses and for estimating the thermal diffusivity of materials is a 2-layer network with feedback from the first-layer output to the first layer input (Haykin S., 1994). This recurrent connection allows this kind of network to both detect and generate time-varying patterns. The Elman network has "tansig" neurons (i.e. using tan-sigmoid transfer functions) in its hidden (recurrent) layer and "purelin" neurons (i.e. using linear transfer functions) in its output layer. This kind of networks can approximate any function (with a finite number of discontinuities) with arbitrary accuracy. The only requirement is that its hidden layer must have enough neurons. More hidden neurons are needed as the function being fitted increases in complexity. The Elman network differs only from conventional 2-layer networks in that the first layer has a recurrent connection. The delay in this connection stores values from the previous time step, which can be used in the current time step. Because the network can store information for future reference, it is able to learn temporal patterns as well as spatial patterns. The Elman network can be trained, using an iterative process, to respond to, and to generate, both kinds of patterns (Charalambous C., 1992). At each iteration: (i) The entire input sequence is presented to the network, and its outputs are calculated and compared with the target sequence to generate an error sequence; (ii) For each time step, the error is backpropagated to find gradients of errors for each weight and bias. This gradient is actually an approximation since the contributions of weights and biases to errors via the delayed recurrent connection are ignored; (iii) This gradient is then used to update the weights with a backpropagation training algorithm like the Levenberg-Marquardt algorithm (Demuth H. and Beale M., 1992).

REBUILDING OF IMPULSE RESPONSES AND ESTIMATION OF THERMAL DIFFUSIVITIES

Available database

The used database has been provided by the GRESPI Laboratory. It is composed of responses to PRBS, impulse responses and thermophysical properties for the following seven building materials: glass wool, brick, plaster, stainless steel, granite, concrete and glass. Responses to PRBS and impulse responses are both composed of 255 points (uniformly spaced in time, $\Delta t = 3$s for responses to PRBS while $\Delta t = 3.10^{-2}$s for impulse responses).

Rebuilding of impulse responses using an Elman network and estimation of thermal diffusivities by inverse method (neuro-inverse approach)

A first Elman neural network has been trained using the glass wool, concrete, glass and stainless steel responses to PRBS as network inputs and their respective impulse responses as targets i.e. as desired network outputs. Then, the trained Elman neural network has been used for rebuilding the impulse responses of brick, plaster and granite using their responses to PRBS as new network inputs. It is the validation phase (Grieu et al., 2005).

The network's hidden layer was composed of 8 neurons and 35 iterations have been carried out during the training phase. The learning rate has been set to 0.3. After rebuilding the impulse response, the inversion algorithm has been used for estimating the thermal diffusivity of the concerned materials (Figure 4 up). First, the Gauss-Newton's method has been tried but the inverse problem is very ill-conditioned so we used the Box-Kanemasu's method. A self-made condition has been added, close to the Box-Kanemasu's modified method, to be sure that the criterion to be minimized decreases during calculations. It provided the results presented in Table 1. Figures 5 (linear scale) and 6 (log-log scale) show the rebuilt impulse responses of brick, plaster and granite. Mean relative errors for these rebuilt impulse responses are about 0.7% for brick, 0.5% for plaster and 0.1% for granite.

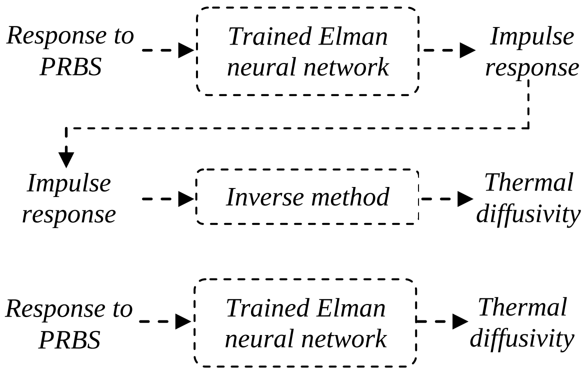

Figure 4. Up: neuro-inverse approach. Down: direct thermal diffusivity estimation.

Table 1
Inverse method results

Materials	**Granite**	**Plaster**	**Brick**
Estimated diffusivity (m.s^{-2})	1.11 x 10^{-5}	5.06 x 10^{-7}	4.63 x 10^{-7}
Real diffusivity (m.s^{-2})	1.10 x 10^{-5}	6.00 x 10^{-7}	5.17 x 10^{-7}
Rel. dif.	< 1%	15%	10%

Table 2
Elman neural network results

Materials	**Granite**	**Plaster**	**Brick**
Estimated diffusivity (m.s^{-2})	1.15 x 10^{-5}	5.6 x 10^{-7}	4.85 x 10^{-7}
Real diffusivity (m.s^{-2})	1.10 x 10^{-5}	6.00 x 10^{-7}	5.17 x 10^{-7}
Rel. dif.	4.5%	6.7%	6.2%

Direct thermal diffusivity estimation using an Elman neural network

A second Elman neural network has been trained using, this time, the glass wool, concrete, glass and stainless steel responses to PRBS as network inputs and their respective thermal diffusivities as targets i.e. as desired network outputs. Then, the trained Elman neural network has been used for estimating the thermal diffusivity of brick, plaster and granite, using their responses to PRBS as new network inputs. It is the validation phase (Figure 4 down). The network hidden (recurrent) layer was now composed of 10 neurons and 30 iterations have been carried out during the training phase. As previously, the learning rate has been set to 0.3. The trained network provided the following results (Table 2).

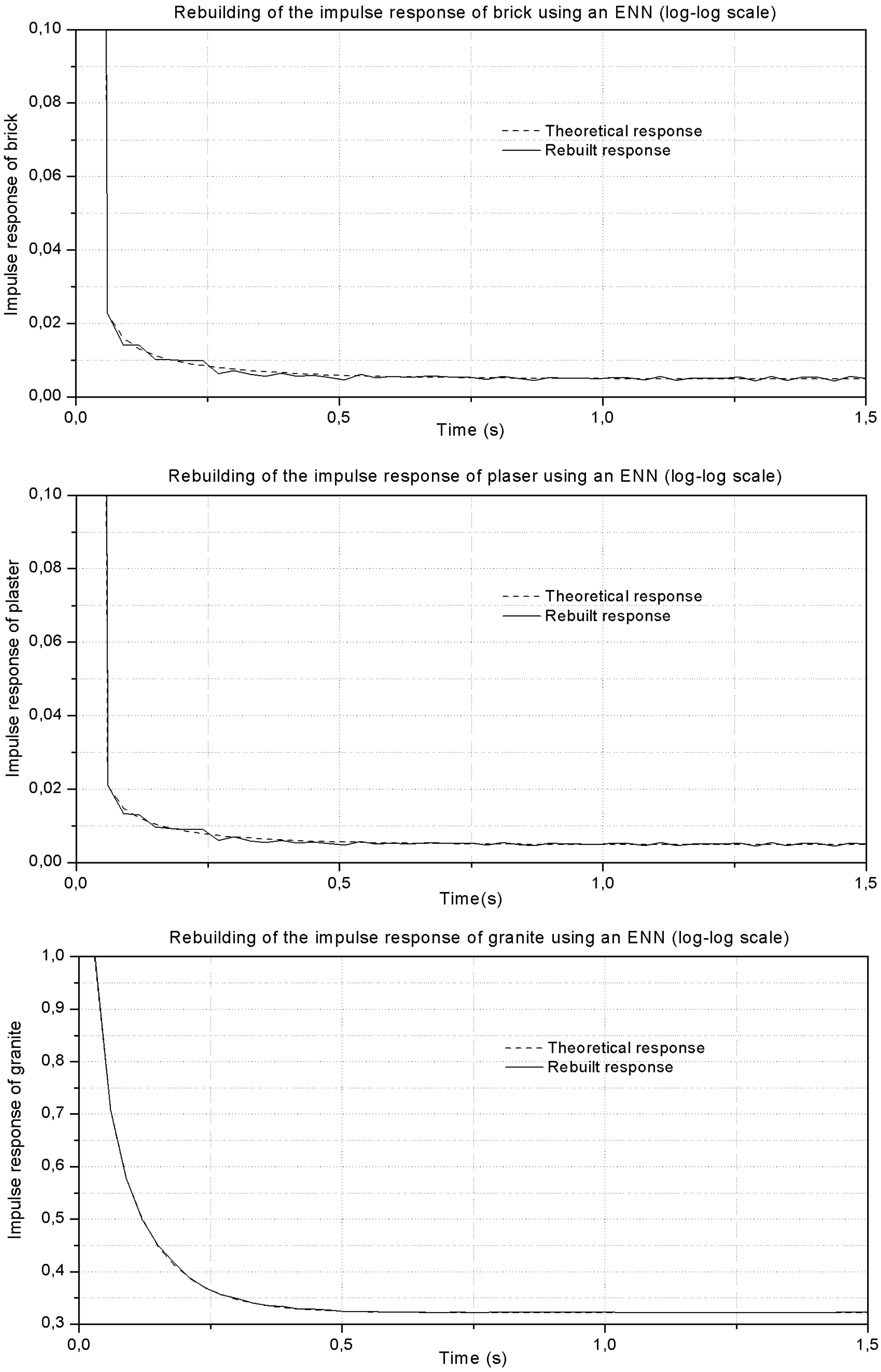

Figure 5. Rebuilt impulse responses of brick, plaster and granite (linear scale).

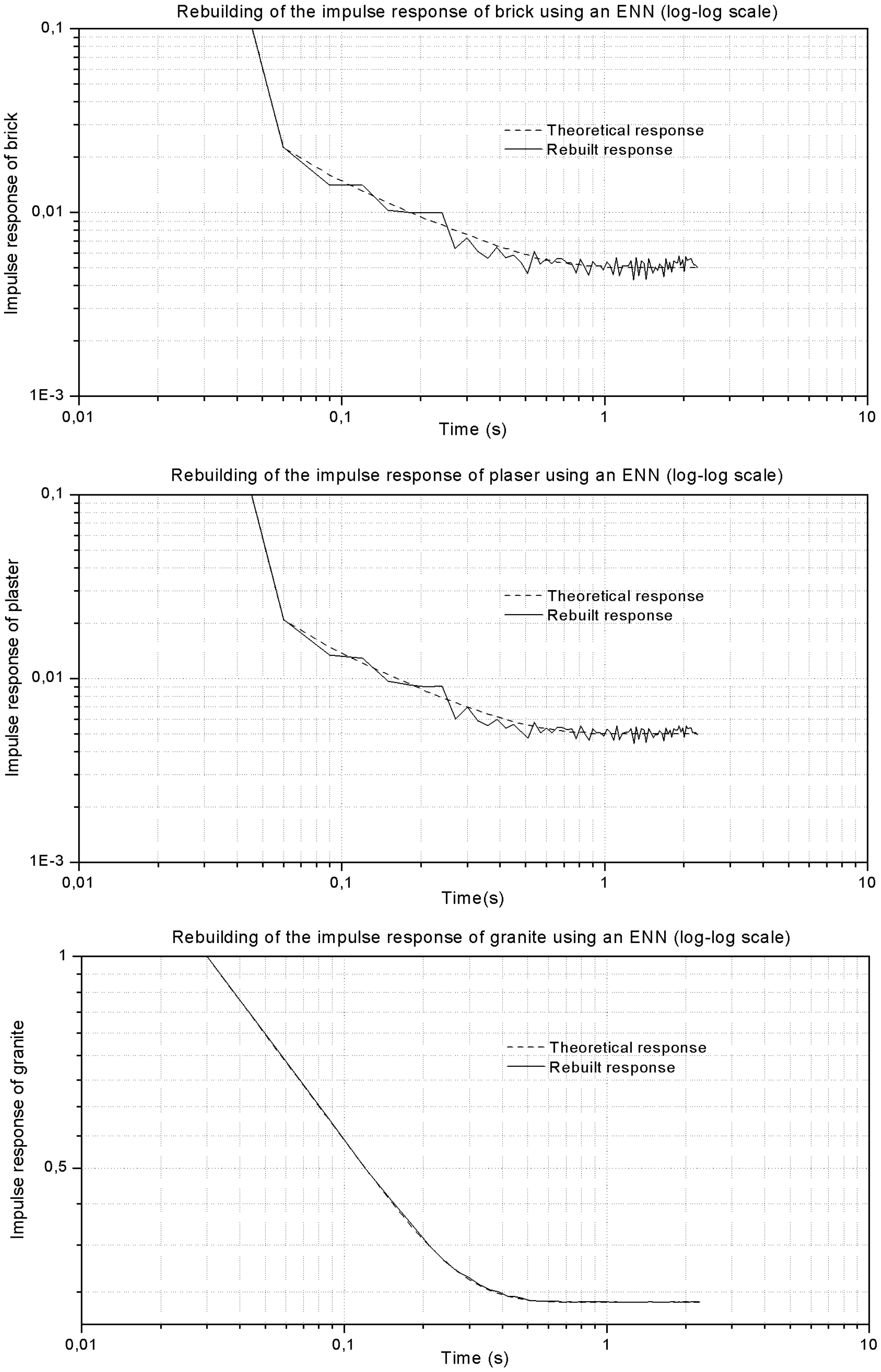

Figure 6. Rebuilt impulse responses of brick, plaster and granite (log-log scale).

RESULTS AND DISCUSSION

With the aim of characterizing building materials and contributing to the necessary energetic performance diagnosis of buildings, the present work focuces mainly on being able to differentiate materials by estimation of their respective thermal diffusivities. So, the first conclusion of the work is that both used methods (an Elman recurrent neural network and the neuro-inverse approach) are usable for rebuilding impulse responses and estimating the thermal diffusivity of materials. They provided correct to very good, indeed excellent, results and proved to be a valid option for characterizing building materials after being trained by means of a database composed of responses to PRBS, impulse responses and thermal diffusivities of various materials. Estimating the thermal diffusivity of building materials using only recurrent neural networks (Elman networks) provided better results than using the neuro-inverse approach, (4.5%, 6.7%, 6.2%) vs. (1%, 15%, 10 %), except for granite. Considering the rebuilt impulse responses of brick, plaster and granite (let us remember that mean relative errors of these rebuilt responses are about 0.7 % for brick, 0.5% for plaster and 0.1% for granite; Figures 5 & 6), one could be surprised when analyzing these results but it is well-known that inverse methods are less efficient when the sensitivity coefficients are weak because ill-conditioned matrix (close to singular) cannot be well-inversed. Indeed, both theoretical and rebuilt impulse responses contain very few points in the high sensitivity area. One can conclude, and this is a very interesting result, that artificial neural networks are able to provide very good estimations of the thermal diffusivity of materials, better than using a more classical approach such as inverse method, even if sensitivity is weak. Concerning granite, a much more diffusive material than brick and plaster, sensitivity coefficients are weak in the used identification area, but high enough to obtain a very good estimation of its thermal diffusivity even from its rebuilt impulse response.

Finally, one can notice, and again this is a very interesting and useful result, that whatever the relative differences between real values and estimated values, the materials stay classed, i.e. the lowest diffusivity is actually estimated as the lowest, the intermediate one as the intermediate and the highest one as the highest. This result is very important to find out the diffusivity contrast between building materials.

APPLICATIONS

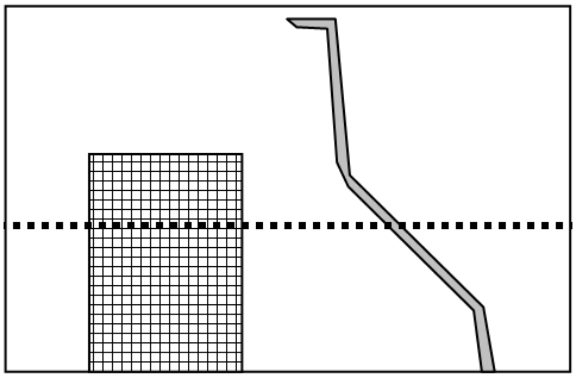

Figure 7. Wall with blocked up door and non-emerging crack. Analysis line is materialised by dotted line.

Let us consider a breeze block wall, covered in plaster, in which a door has been blocked up with bricks and a crack has been filled in with concrete (Figure 7). This wall appears locally as a 2-layer body: plaster-breeze block, plaster-brick and plaster-concrete. The impulse response of a 2-layer body is related to the materials constituting the layers. During short times $[0, t_s]$, considering the thermal diffusivity, the body behaves like the upper layer while during long times $[t_l, +\infty[$, it behaves like the deeper layer. Intermediate times $[t_s, t_l]$ characterize the interface quality (Figure 8).

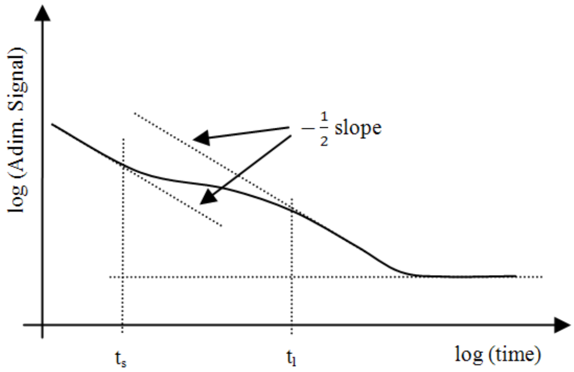

Figure 8. The impulse response of a 2-layer body.

So, getting the response to a random excitation of such a wall and using the presented estimation method allow locating the blocked up door and the crack by analysing the thermal diffusivity contrast (Figure 9), estimated directly or using the $[t_l, +\infty[$ part of the rebuilt impulse response.

Door and crack presence clearly appears because of the thermal diffusivity difference between breeze blocks and bricks or concrete.

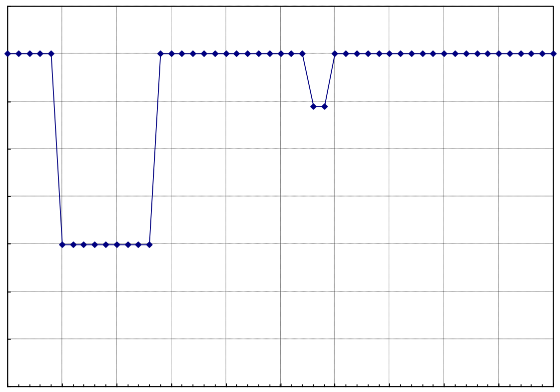

Figure 9. Adimentionnal diffusivity along the dotted line (Figure 7)

CONCLUSION

The objective of the present work was to test in simulation some tools belonging to the field of artificial intelligence for the characterization of building materials. So, recurrent neural networks were, first and jointly to inverse methods, used for rebuilding impulse responses and estimating the thermal diffusivity of materials (neuro-inverse approach). Then, a recurrent neural network was used for directly estimating the above-mentioned thermophysical property.

The main conclusion of the present work is that all the used tools and methodologies are usable for rebuilding impulse responses and estimating the thermal diffusivity of materials. They provide very good results and prove to be a valid option for characterizing building materials. Indeed, the relative difference between the real and the estimated thermal diffusivity ranges between 1% and 15%.

The most significant result is the powerful capability of recurrent neural networks for estimating properties, even if sensitivity related to a property is very weak. Recurrent neural networks are able to estimate the property with good accuracy (relative difference of about 5 %) where inverse method hardly reaches 10%.

Let us note that in case of using inverse methods for estimating the thermal diffusivity of building materials, using more points in the high sensitivity window of the rebuilt impulse responses reduces the property estimation uncertainty. So, more detailed impulse responses will soon be used for training and validating recurrent neural networks.

Finally, future work will also focus on considering not only a PRBS for exciting materials but also others kind of random signals like, for example, a sweep signal.

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