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An Adaptive Neural Network model for thermal characterization of building components

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Abstract

Building materials are usually characterized in stationary or almost-stationary conditions and mono dimensional heat flow regime. The existing standards (such as ISO 9869 or EN ISO 6946, EN 12664, EN 12667, ISO 8302 etc), require experiments carried out in steady-state conditions, with a very fine control of the measuring parameters with the aim to apply a simple and reproducible procedure for the determination of thermal properties. However, the thermodynamic conditions that lead to a steady-state operating mode and mono dimensional flow are very difficult to obtain (in real conditions) or very expensive and time consuming (in climate chambers). In this paper the authors present the development of a method for thermal characterization of building components, inferring the steady-state conditions, when only measures in transient conditions are available. The method, based on an adaptive linear neural network (ALNN) model also could be have the potentialities to determine the thermal diffusivity from a significant transient behavior ad hoc imposed. The study targets multilayered walls homogeneous and the results are compared with the experimental data measured by a climate chamber that operate according to the standard EN 12667

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Keywords: Transient test conditions; Artificial neural networks; thermal properties identification, inverse problem

1. Introduction

Recently, a growing interest on the adoption of EU Directives in the field of buildings and constructions can be noticed. Consequently, professionals are forced to take care limit performance requirements that the new buildings

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must ensure concerning energy, acoustics, lighting and more in general environmental and economic impacts. The European board has recently issued the EU directive "roadmap for moving to a competitive low carbon economy in 2050 [1,2] which lays down recommendations to achieve, by 2015, the 80% reduction of greenhouse gas emission compared with those of 1990.

Nomenclature

Physical quantities
T Temperature throughout the thickness of the wall, [°C]
T_H Temperature in correspondence of the hot side of the wall, [°C]
T_C Temperature in correspondence of the cold side of the wall, [°C]
T_0 Temperature throughout the thickness of the wall at initial time, [°C]
Q_H Heat flux flowing through the hot side the wall, [W/m2]
Q_C Heat flux flowing through the cold side the wall, [W/m2]

Greek symbol
λ Equivalent thermal conductivity of the wall, [w/mK]
cp Specific heat capacity at constant pressure of heat-transfer fluid, [W/(kgK)]
ρ average density of the wall, [kg/m3]
α Thermal diffusivity, [m2/s]

Simulated quantities
$\dot{Q}_{H,ALNN}$ numerically simulated heat flux by neural Neural Network model [W/m2]

In the light of the above task the EU has also defined a strategy for coherent re-search with these objectives. The Strategic Energy Technology (SET) Plan, [3] and the Communication "Investing in technologies low-carbon [3], represent the technological pillar of European policies on energy and climate change. One of the immediately applicable strategies to reach by the goal is the energy efficiency of buildings, as provided for by [4] which introduces and defines the edifice NZEB "nearly zero energy building". and prescribes a set of calculation procedures [5 - 7] which in turn require input certified data.

Three approaches can be applied o estimate U-value in situ, directly on existing buildings [8]:

1. Estimation based on data obtained by "reference buildings" [9] which represent the characteristics of large groups of buildings, classified according to age, size and other specific features. It suffers the increased uncertainty about availability of statistical data on the historical sample of buildings and the lack of an accurate knowledge of materials and of the layers constituting the wall;
2. Estimation based on the nominal design data according to ISO and ASTM standards [7] and [10 - 13];
3. In situ measurements using heat flux meters, whose main error sources may result from the variation of climatic parameters, heat flow and from the temperature gradients through the investigated component during measurements [14].

A fourth approach involves laboratory measurements on samples taken directly "in situ" or reconstructed on the basis of an endoscope method. For such a purpose, the existing standards require the use of specific equipment as guarded hot plates [15 - 17], calibrated and guarded hot box [18 - 20] or heat flux meters [16, 17] and experiments carried out in steady state conditions with a very fine control of the measuring parameters. The aim to apply a simple and reproducible procedure for determination of thermal properties. These methods rely on efficient control of climate parameters, allowing the achievement of almost steady-state operating mode in test environments; but, on the other hand, they suffer from the thermal inertia of the envelope component under investigation that causes very expensive and time consuming tests.

The goal of the present research is to evaluate an adaptive dynamic model calculation, which leverages on algorithms to neural networks, allowing measurement times very short for determinate the energy performance of the building component. It is important to notice that the goal of the experiments described below at the Lab MAST does not consist in the dynamic characterization of the masonry being tested, but rather in producing reference experimental data, useful for tuning and the first validation of the adaptive model proposed.

Many methods [21] can be applied for the parametric identification of a wall system experiencing an axial temperature gradient during the transient regime, the most successful one are the neural networks [22 - 25].

In the early stage of the present research, an investigation aimed at identifying what architecture among static ones was the best suited to manifest the correct behaviour in the steady state condition has been carried out, (even if the neural model had been trained exclusively with experimental data belonging to the transient regime). Due the poorness of the results obtained with static neural network architecture it was decided to abandon the static architecture and turned the attention to a dynamic network of the adaptive type.

The neural adaptive model proposed by the authors is shown in Figure 1. It is a Dynamic Time Delay Neural Network [26] which uses, as a training set, the values of the thermodynamic coordinates at instant "τ" together with the values assumed at a certain number of instants immediately before, so that the network can exhibit an ability to learn not only the values acquired, but also temporal dynamics with which they occur. The learning algorithm of the neural network follows the Widrow-Hoff rule [27], consistent in the Linear Mean Square based on an approximate steepest descent procedure.

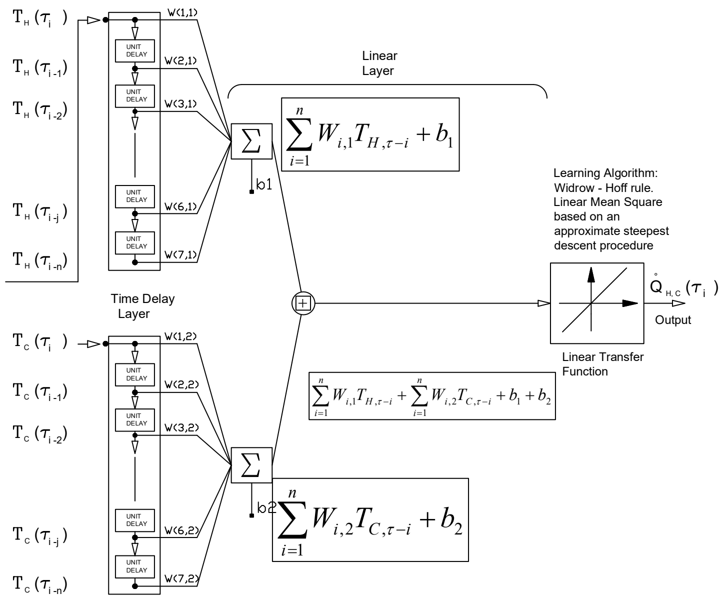

Figure 1 .Structure of the used adaptive neural network

The adaptive artificial neural network has a learning algorithm that allows adaptation of its parameters to re-propose the temporal relation between inputs and output. The training of the network parameters takes place for each sample of the input sequence that is supplied in the network. At each training step, the algorithm acts reducing as much as possible both the overall error between the answer given by the network at the actual instant "τ" and the relative target, and the error of the answer given by the network at a certain number of preceding instants with respect to the relative target results. The number of the delay inputs considered for the training phase is **10**, with a learning rate equal to 0,0018 and a linear transferring function. The choice of considering a **10**- delayed samples derives from having adopted the strategy based on the Lipschitz Quotients criterion proposed for the first time by [28], and later developed by [29], for dynamic neural models of the MISO (Multi Input Single Output) type.

2. The Adaptive model

Let the equations Eq (1) - Eq (6) be the general scheme which describe respectively the linear flow of heat in a homogenous layer bounded by two parallel planes. To fix ideas we will refer to x=0 and x=L indicating the boundary conditions in correspondence of the two parallel planes and τ=0 for the initial condition for. Eq (5) and Eq(6) represent the heat fluxes on the hot and cold side of the wall, [30].

$$\left|\begin{array}{ll}
\dfrac{\partial T}{\partial \tau}=\dfrac{\lambda}{\rho c_p}\dfrac{\partial^2 T}{\partial x^2} \quad (0<x<L),\ \ (\tau>0) & Eq(1) \\
T(x=0,\tau)=T_H(\tau)=\varphi_1(\tau) & Eq(2) \\
T(x=L,\tau)=T_C(\tau)=\varphi_2(\tau) & Eq(3) \\
T(x,0)=T_0(x)=f(x) & Eq(4) \\
Q_H(\tau)=-\lambda\left.\dfrac{\partial T}{\partial x}\right|_{x=0} & Eq(5) \\
Q_C(\tau)=-\lambda\left.\dfrac{\partial T}{\partial x}\right|_{x=L} & Eq(6)
\end{array}\right.$$

A1

We can consider the general scheme A1 as a - differential equation system that supports the behaviour of a system made of 2 outputs and 2 inputs: the outputs are the heat-flux measured on the hot and cold side of the wall. The inputs are the two mean surface temperatures TC and TH on both side of the façade at the instant time "τ". _ -

The knowledge of scheme A1 is restricted only to the mathematical structure of the relation between inputs and outputs, therefore all the parameters that appear in A1 (λ, cp ρ,) remain to be estimated. The value of such parameters determines the output of the system for any operating condition (steady-state and transient regime), imposed by the set of inputs, according to boundary and starting conditions. The knowledge of the structure of the relation between inputs and output allows us to qualify the problem of estimating in the graybox model class [31]. Knowing that the relation between inputs and output is imposed by scheme A1, the main question concerns estimating the values of the thermal properties, in terms of λ, cp α,, which make the experimental measures of the output (heat-flux) as a consequence of the experimental measures of the inputs (surface temperatures), boundary and initial conditions. The boundary conditions consist of the time trend of the surface temperatures on both sides of the wall, TH(x=0,τ≥0) and TC(x=L,τ≥0), while the initial conditions represent the temperature distribution throughout the thickness of the slab at initial time, T0(x,τ=0). Adopting in this research the ALNN model we will treat the heat transfer problem prevalently in terms of black box model. We may refer to the general scheme of a parametric identification method shown in Figure 2

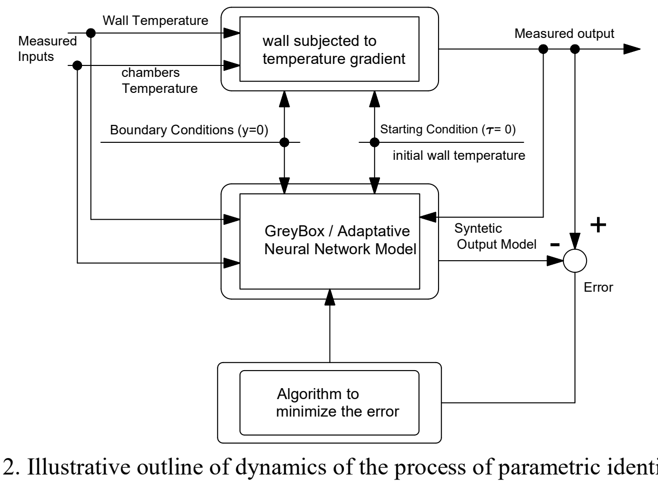

Figure 2. Illustrative outline of dynamics of the process of parametric identification.

First, a model is proposed, to establish a relation between inputs and output of the same structure and order as the real system, but with the starting values of its parameters having a certain degree of approximation. Alternatively, a different mathematical relation that (anyway) re-proposes the same mechanism of data generation of the actual system can be adopted; afterwards the simulation model (the synthetic system) receives the same thermodynamic inputs that have stimulated the real system and its results are compared with the real ones. The error value between the two results is used, as “input” in a dedicated algorithm, to modify the parameters values of the model, in order to minimize the difference between the two output vectors [32, 33].

3. The experimental apparatus

The experimental investigations have been performed in the climatic chamber of the Laboratory for Materials and Traditional Historic Architecture (Lab MAST) of the University of Cagliari (Italy), located in a 200 m^3 room using a heat pump system to guarantee constant thermo-hygrometric conditions: temperature and humidity were kept constant at 20 ± 5 °C and 50 ± 10% RH, respectively. The apparatus was designed according to [UNI. 1999 and UNI. 2000] with the main metrological features (measuring range and the relative accuracy of the hot and cold chambers) summarized in Table 1

The frame can accommodate a specimen 2,5x2,5x0,7 m and is internally framed by a ring of insulating material of high density and low thermal conductivity, better than 0,04 W/(mK), as to ensure an unbalancing thermal flow less than 4% of the main thermal flow.

The measurement campaign was carried out on two side by side samples (Figure 3a), one made of clay blocks ("Bio THERMOTEK Sismic Acoustic"), the other using bricks made with a mixture of clay and straw. Both walls are coated with a uniform layer of plaster having a thickness of 2 cm per side. Finally, the two samples are separated and topped by blocks of insulating material (polystyrene) of 50 mm thickness, to contain edge heat flux distortions.

The instrumentation used for the measurement of heat flux through the walls under test consists, for each side, (Figure 3b) of:

- n. 4 surface platinum temperature sensors (class A);
- n. 2 heat flux meters (accuracy not better than ± 5%@T=20°C).
- The measurements are acquired via wireless with the ISM band of 2.4 GHz and recorded by a specific data logger with an integrated RAM memory.

Table 1. Main metrological parameters of experimental apparatus.

	Air temperature	Relative Humidity	Air velocity
Hot chamber	+15°C … +40°C ± 0,5°C in 15÷26°C ± 2,0°C out	30% … 98% ± 5 %	0,1 …1 m/s ± 0,15 m/s
Cold chamber	-10°C … +80°C ± 0,5°C in 10÷20°C ± 2,0°C out	30% … 98% ± 5 %	0,1 …10 m/s ± 0,15 m/s
Control instrumentation	PID electronic regulator with USB interface Weekly dynamic adjustment of 96 daily temperature step Thermal gradient 0,15 °C/min		

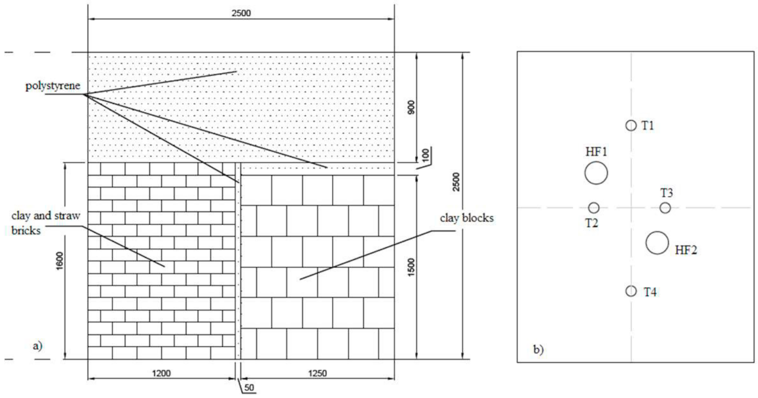

Figure 3– a) Scheme of the walls realized in the laboratory (dimensions in mm); b) Sensor placement on the specimen surface: T = surface temperature sensors; HF = heat flux sensors

3.1 Experimental Results

Before starting the tests, all the specimens were left drying with temperature and humidity controlled, for at least 7 days. Then, 4 different tests were performed, all starting from the initial conditions in the environment until the stabilization of the test parameters. The set values are respectively equal to 22 °C, 40% R.H. and 0,5 m/s for the hot chamber and 2 °C, 60% R.H. and 1,0 m/s for the cold chamber. In all tests, steady state conditions were considered achieved when the progressive mean value is maintained within ±2,5% for at least 24 consecutive hours. This resulted in test times generally higher than 80 hours for clay and straw bricks, and even higher than 100 h for the clay blocks. The transient conditions for the progressive mean value settles within ±5,0% is slightly lower: on average 50 hours for clay and straw bricks, and 70 h for the clay blocks.

3.2 Learning and validation of the adaptive neural network model

The experimental data carried out in the above mentioned tests have been used to identify the ALNN model. The input of the Adaptive Neural Model is composed of the columns of a 150x2 matrix "I_{NN}". The columns of "I_{NN}" incorporate the time trend of the surface temperatures $T_{S,H}$ and $T_{S,C}$ on both, hot and cold, sides of the wall. The output of the Adaptive Neural Model is composed of the columns of a 150x1 matrix, denoted as "Y_{NN}". The column incorporates the time trend of the heat flux crossing the wall and acquired on the hot side of the wall. The lines of the matrix "I_{NN}" and "Y_{NN}" are composed of 150 samples measured in time of the above-mentioned parameters, during the transient regime.

$$I_{NN}(1,j)=T_H(\tau_i);\ \ I_{NN}(2,J)=T_C(\tau_i);\quad with\ J=1,...150\ ;\ Y_{NN}(i,1)=Q_H(\tau_i);\qquad with\ i=1,...150$$

In Figures 4, 5 and 6 are depicted the time trend of the thermodynamic quantities listed above. The graphs exhibit the whole time period of acquisition, from the transient regime up to the full achievement of the steady state regime. The input and the output vectors "I_{NN}" and "Y_{NN}" of the neural network model include only the first 150 samples of the whole acquisition time period (composed by 1460 samples). We point out that "I_{NN}" and "Y_{NN}" exclusively incorporate sample rather distant from steady state conditions, indeed as can be seen from figures 4 and 5, the surface temperatures as well as the heat flux are characterized by an ample transitoriness over the period included by "I_{NN}" and "Y_{NN}". According to [ISO 1991b] and [ISO 2007a] no time interval before the sample labelled in figure 4, 5 and 6 as 150th sample could be considered valid in characterizing the wall in steady-state and not even in quasi-state conditions.

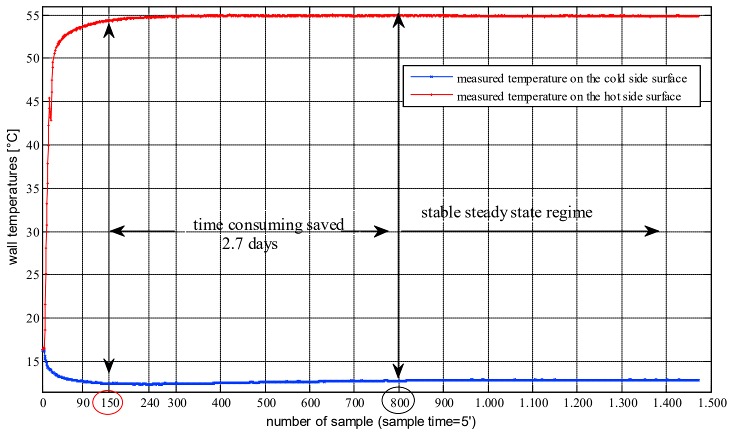

Figure 4. Temperatures on the surfaces of the wall under test. Trend during the 5 days of acquisition.

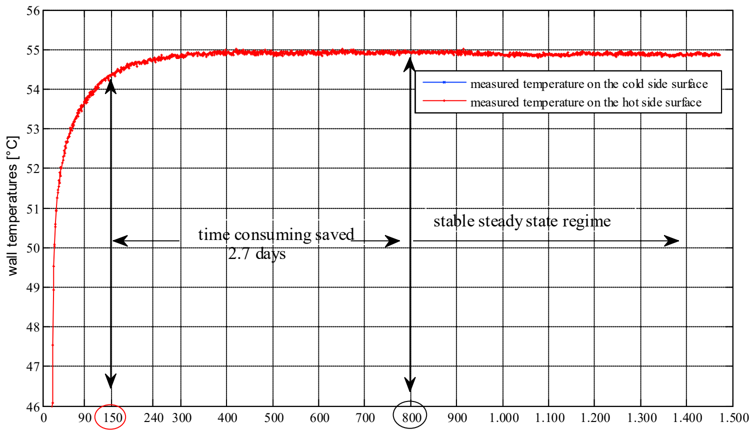

Figure 5. Temperature on the hot surface of the wall under test. Trend during the 5 days of acquisition. The trend before 150th sample is characterized by ample transitoriness.

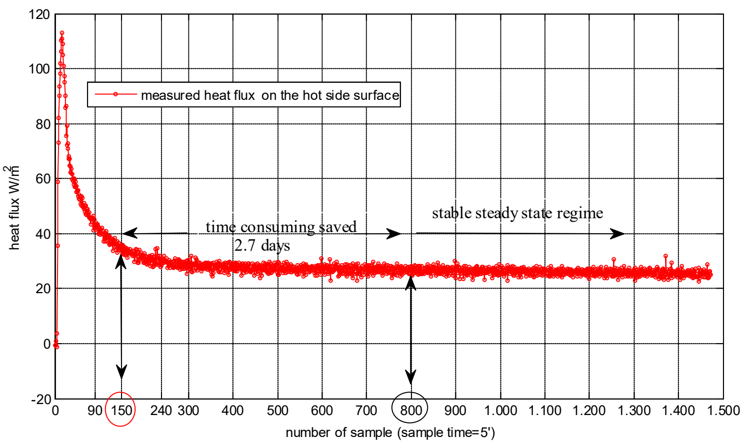

Figure 6. Heat flux on the hot surface of the wall under test. Trend during the 5 days of acquisition.

A comparison of the experimental data of the measured heat flux with respect to that simulated by the ALNN model is shown in Figure 7. The difference between the two trends is limited by a maximum value lower than 6%.

$$max\left|\frac{\dot{Q}_{H,ALNN}-\dot{Q}_{H,measured}}{\dot{Q}_{H,measured}}\right|_{\tau\leq 150} \leq 6\%$$

An effective treatment of the behaviour of the neural model in transient regime, involving a wide range of inputs stimulus ad hoc selected, for the estimation of the thermal diffusivity and capacity, is currently under development and will be the subject of a forthcoming paper.

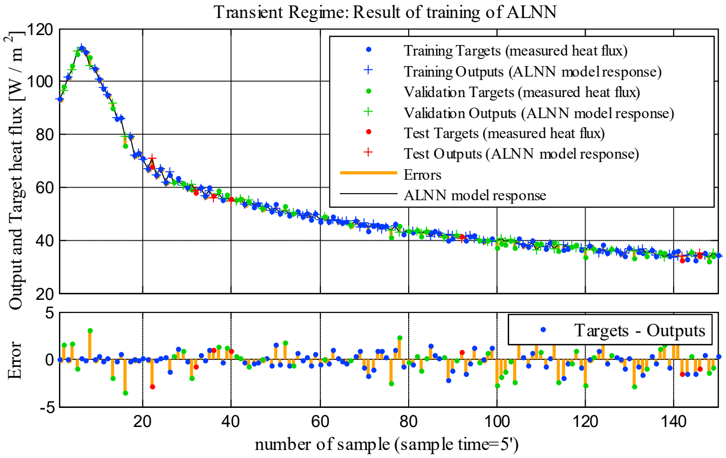

Figure 7. Transient regime: comparison of the measured heat flux data respect to the numerical data simulated by the ALNN model.

Once the ALNN model has been trained with the transient regime it was tested under new synthetic inputs simulating the wall temperatures to verify its behaviour in steady state conditions. In this regard, the constant values in the time representing the temperatures on both sides of the wall were selected with the aim of scanning the thermal steady state condition of the wall under test.

Clearly, the application of constant inputs allows to obtain, starting from a given instant, a thermal response of the wall supplied only by the forced response, (the response of the wall system in a steady state condition), therefore without the natural response, whose presence due to thermal capacity, determines the presence of the transient regime. By means of Matlab software [Matlab 2013] the authors have considered an input vector representing the surface temperatures on both side of the wall, whose trend remains constant for simulating the stationary condition. Constant temperature plotted in Figure 8, representing the hot and cold side of the wall simulate the boundary conditions in steady state regime and represent the input data of ALNN model for its validation

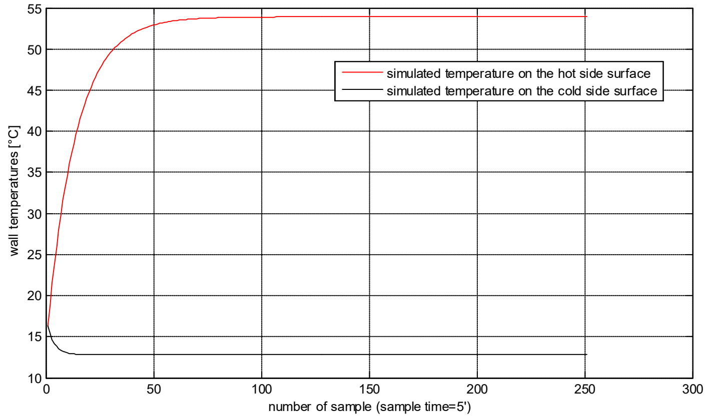

Figure 8. Trend simulation of the temperature on both side of the wall. Simulation of the boundary conditions in steady state regime. Representing the input data of ALNN model for its validation.

In correspondence to each of the inputs set, the ALNN model returns an output vector $Q_{H,ALNN.}(\tau)$, whose values contain the simulation of the heat flux. Figure 9 shows the simulated output representing the heat flux, up to the reaching of the steady state condition, depending on the forcing inputs applied to the ALNN model. In the same figure a comparison of the experimental data of the measured heat flux with respect to that simulated by the ALNN model is shown. The difference between the two trends once the steady state is achieved (τ > 800), is limited by a maximum value lower than 3%.

$$max\left|\frac{\dot{Q}_{H,ALNN} - \dot{Q}_{H,measured}}{\dot{Q}_{H,measured}}\right|_{\tau\leq 800} \leq 3\%$$

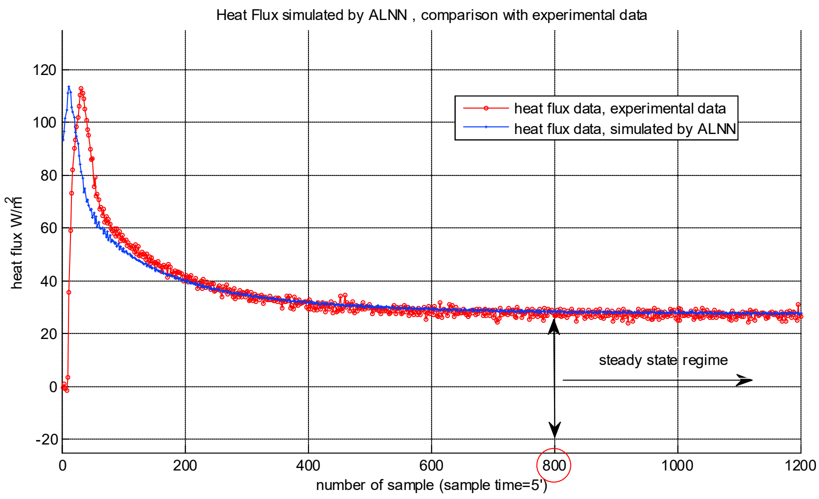

Figure 9. Transient and steady state regime: comparison of experimental data of heat flux trend with respect to the those simulated by Neural Model.

It is worthwhile noting that, starting from the sample corresponding to that labeled as τ = 800, the simulated heat flux of ALNN model remains constant in correspondence to the constant input. Therefore, it may be possible to calculate the thermal resistance of the simulated wall by means the correspondent temperature difference between the hot and the cold side, based on the following expression:

$$R_{sim',j} = \left.\frac{\dot{Q}_{sim,j}}{\left(T_{j,H,sim} - T_{j,C,sim}\right)}\right|_{\tau>800};$$

The behaviour of the model was observed to be sensitive only to the temperature difference values and not to the absolute values of the single wall temperature, in line with the hypothesis of linearity assumed previously and the hypotheses that lead to the Fourier equation in steady state condition.

The methods presented herein, the adaptive neural linear model, is an attempt to overcome the strict limitation inherent the fulfilment of the steady state regime and the one dimensional heat flux. The authors note that, on the one hand, suitable boundary conditions offer substantial and valuable simplification of the physical-mathematical model as for example the steady regime for which the thermal resistance appear in a very simple form: the ratio of a heat flux respect to a temperature difference. However, on the other hand the same boundary conditions raise the problem of their fulfilment, a problem that calls for the addition of special accessory equipment that inevitably increases the cost of the chain of measurements and a very large time consuming procedure.

4 Conclusions

In this paper an adaptive neural model has been selected and trained to learn the complete temporal structure of the process concerning the evolution of the heat flux of the wall system subjected to a temperature gradient. For this reason, the neural network was provided with a set of delay elements connected in cascade to constitute a shift register that stores the last 10 samples of the input sequence. The neural models has been identified by using the experimental data of heat flux and temperature measured on both side of the wall, over a period of 12 hours with no limitation on the range of the transient regimes.

The authors demonstrate that the use of instruments for parametric identification, such as the Dynamic Adapatative Neural Network, makes it possible to infer the steady state performances of a wall, when only experimental data acquired in the transient regime are available.

A data acquisition set during full transient regime was sufficient to rebuild with an ALNN model the steady state behaviour with an error below 3% compared to the experimental data measured with a climatic chamber operating according to [UNI. 1999 and UNI. 2000].

The results obtained suggest that it would be convenient and fruitful to perform further refinement of the research on different composition of layered walls and in different transitory regimes. They could confirm that the proposed method, besides, having the potential for success in providing a characterization of building material starting from environmental data more general than those required by the standards, can be applied, with relative uncertainty, even without a conditioning system to keep constant the thermodynamic conditions.

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