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## NONLINEAR ARX MODEL ASSOCIATED TO NEURAL NETWORKS TO PREDICT HYGTHERMAL BEHAVIOR OF BUILDING MATERIALS

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**Abstract.** *Moisture presence in building material can significantly affect heat exchanges between indoor and outdoor environments, influencing on both energy consumption and thermal comfort. With the objective of estimating the hygrothermal variations, computational tools, those based on analytical and numerical models, are being used to reduce the energy consumption of new and retrofitting buildings. However, when moisture presence is taken into account, especially when high hygroscopic materials are adopted in building projects, a nonlinear behavior may occur affecting temperature profiles within building structures. This situation is constantly discussed in the literature as a difficult task due to modeling difficulty and highly moisture-dependent properties. Based on these concepts, this work presents a black box system identification approach in order to reproduce the hygrothermal behavior of high hygroscopic materials that are commonly adopted as insulation on building envelopes. By assuming a mixed approach considering both linear and non-linear techniques, a NARX (Nonlinear AutoRegressive with eXogenous input) MIMO (multiple-input, multiple-output) model, where an Artificial Neural Network (ANN) was considered as nonlinear approximation tool, is presented in this work. By using a data set provided by experimental analysis, the model was validated and reasonable results in terms of approximation were obtained. To conclude this paper, remarks about the model performance are presented, including the computational cost.*

**Keywords:** *building simulation, hygroscopic materials, hygrothermal behavior, neural network, system identification.*

### 1. INTRODUCTION

The dynamic behavior of building materials associated to both temperature and humidity variations has significant impacts on thermal engineering design, where the heat flux within building surfaces is affected by several parameters such as solar radiation, air temperature, rain, wind speed, time of the year, shading etc.

Interests on the hygrothermal behavior of buildings has increased in the last decades, as alarming statistics have proved that buildings are responsible for a considerable amount of the total energy demand of emerging and developed countries, including Brazil, Europe and the United States of America (Brazilian Energy Research Company (EPE), 2016; Ciulla, Lo Brano, & D'Amico, 2016; U.S. Energy Information, 2013).

Governments have created regulations and standards in order to reduce the energy consumption of new and retrofitting buildings, and in many cases, Building Performance Simulation (BPS) has been adopted as the main tool for certification when energy consumption is taken into account.

The development of building simulation tools have started with specific computational codes in order to describe the heat transfer through a single building surface. Today, whole-building and energy simulation software are available, where simulation of building structures was integrated to other systems, e.g. Heating, Ventilation and Air Conditioning

(HVAC) and lighting, in order to provide an accurate approximation of the building physics and make available a consistent analysis associated to energy usage (Hamdy, Nguyen, & Hensen, 2016; Loonen, Favoino, Hensen, Overend, & Attia, 2010).

Moisture presence can considerably affect thermal gains or losses in buildings with direct relation to the energy consumption (Santos & Mendes, 2013). However, most of whole-building simulation tools normally do not take into account the moisture effects due to modeling difficulty, divergence caused by nonlinear behavior, and highly moisture-dependent properties (Crawley, Hand, Kummert, & Griffith, 2008). Moreover, humidity accumulation can contribute to mould growth on surfaces, affect occupants' thermal comfort, and both durability and efficiency (in terms of insulation) of building materials.

As an alternative way to include the moisture effects on building simulation, black box models, based on computational intelligence, have proved to be a consistent approach for approximating simulation and reality. In (Ascione, Bianco, De Stasio, Mauro, & Vanoli, 2016), black box models, those composed by different categories of Artificial Neural Network (ANN), were used to predict energy performance and occupants thermal comfort of a specific category of buildings considering low computational times. Another application using ANN is presented in (Deb, Eang, Yang, & Santamouris, 2016), where daily energy consumption variations of three distinct buildings in Singapore were predicted using the previous five days as inputs for the model. Moreover, with the objective of reducing the degree of variation, the energy consumption data was divided into classes, and the class numbers were considered as inputs for the energy performance forecasting model.

In (Freire, Oliveira, & Mendes, 2008a), two ARX (AutoRegressive with eXogenous inputs) models were developed in order to predict temperature and relative humidity variations in an indoor environment. This model was created using data provided by a building simulation software, and both models were used as input for a Model Based Predictive Controller (MBPC) to reduce energy consumption and improve thermal comfort (Freire, Oliveira, & Mendes, 2008b). Fuzzy systems have also been used for predicting control of building HVAC systems as presented in (Killian, Mayer, & Kozek, 2016). The authors propose a Cooperative Fuzzy Model Predictive Control (CFMPC) in order to attend distinct building zones and reduce the energy consumption of the heating and cooling system. Finally, in (Dai, Zhang, Arens, & Lian, 2017), a control method based on a Support Vector Machine (SVM) classifier is proposed. By using as inputs for the model just the building skin temperatures, the model can predict the steady state thermal demands of two distinct buildings.

Based on an experimental data set, collected from an specific device developed for understanding heat and moisture transfer in high hygroscopic materials (Slimani, Trabelsi, & Virgone, 2016a, 2016b), this paper presents an approach to predict temperature and relative humidity in building materials using a Nonlinear AutoRegressive eXogenous (NARX) Multiple-Input, Multiple-Output (MIMO) model. In this case, the nonlinear estimator is composed by a Wavelet Neural Network (WNN).

The next section of this work presents the methodology adopted during this research, followed by the theory about the NARX model, which is presented in section 3. Section 4 describes a quite review about WNN concepts. In the sequence, section 5 presents how the experimental data set was obtained. Section 6 introduces the system identification procedures, simulation parameters and the metric adopted to evaluate the model quality. Section 7 shows the simulation results, and finally, section 6 reports the conclusions and future works.

## 2. METHODOLOGY

This work initiates with a bibliography review about the importance of considering moisture presence in building simulation, showing that one possibility to obtain consistent results in building simulation, when high hygroscopic materials are taken into account, is assuming black box system identification procedures. Additional bibliography review are presented in order to provide scientific arguments related to the usage of black box models in applications related to the hygrothermal variations in both building materials and building systems.

In the sequence, concepts about the system identification technique adopted in this work are presented, showing the model structure and relevant mathematical notation. In order to detect the nonlinear behavior of high hygroscopic materials, a particular variation of an artificial neural network (ANN), known as Wavelet Neural Network (WNN), is introduced.

A data acquisition plant, which is capable to capture hygrothermal variations in building materials, is presented. A data set of a non-isothermal case collected using this plant is presented. In this case, a high hygroscopic material was considered in order to emphasize the nonlinear behavior that this type of material can provide. The data set was divided into two parts, and the first one was adopted to estimate the model proposed in this study. The other part of the data set was used to validate the model. Finally, results about the estimation and validation procedures were addressed.

To conclude, remarks about this study and suggestions for future works are presented.

### 3. SYSTEM IDENTIFICATION STRATEGY

This section describes the model structure adopted in this work followed by the technique for system identification.

An AutoRegressive model with eXogenous input (ARX) can be expressed by a linear difference equation, where the current output can be predicted as a weighted sum of past output values, and current and past input values (Ljung, 1987).

$$y(t) + a_1y(t-1) + \dots + a_{n_a}y(t-n_a) = b_1u(t-n_k) + \dots + b_{n_b}u(t-n_k-n_b+1) + e(t) \quad (1)$$

In the previous equation,  $y(t)$  represents the current output of the model,  $y(t-k)$  is a finite number of past outputs,  $u(t-k)$  the inputs, and  $e(t)$  is a white-noise error that is introduced in the difference equation. The model structure is entirely defined by three integers, where  $n_a$  represents the number of poles,  $(n_b - 1)$  is the number of zeros, and  $n_k$  is the time delay of the systems.

#### 3.1 Nonlinear ARX model

A nonlinear ARX model (NARX) can be defined as an extension of the linear model presented in Eq. (1). If we rewrite it as product (Eq. (2)), this structure can be modified to create a nonlinear form presented in Eq. (3).

$$y(t) = [a_1, a_2, \dots, a_{n_a}, b_1, b_2, \dots, b_{n_b}] * [y(t-1), y(t-2), \dots, y(t-n_a), u(t-n_k-1), u(t-n_k-2), \dots, u(t-n_k-n_b-1)]^T \quad (2)$$

$$y(t) = f(y(t-1), y(t-2), \dots, y(t-n_a), u(t-n_k-1), u(t-n_k-2), \dots, u(t-n_k-n_b-1)) \quad (3)$$

The nonlinear function  $f$  can be expressed in terms of the model regressors, and the nonlinear mapping can be performed using nonlinear estimators. In this work, the Wavelet Neural Network (Zhang & Benveniste, 1992) was adopted as nonlinear estimator, and will be presented in the sequence. Figure 1 presents a block diagram that describes both model and signals. The linear function is obtained using the Least Square Method (Marquardt, 1963).

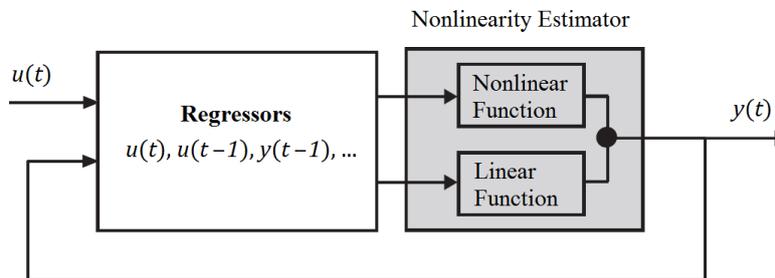


Figure 1. NARX model (Ljung, 2013).

#### 3.2 Nonlinear estimation using Wavelets Neural Networks

Wavelets Neural Networks (WNNs), or Wavenets, are a class of networks which has been used with great success in a wide range of applications (Alexandridis & Zapanis, 2013; Billings & Wei, 2005; Joo & Kim, 2015). The constructive procedures of WNNs allows to efficiently initialize the parameters of the network, providing a fast convergence for the global minimum (Alexandridis & Zapanis, 2013). The Wavelet Neural Network came up as a combination of the ANN concept with the Wavelets transform, as detailed by (Lekutai, 1997).

According to (Veitch, 2005), the Wavelet is the function of a little wave that can grow and reduce in a finite time and is expressed in a continuous way by Eq. (4), being  $x$  the signal and  $g$  the Wavelet, such as:

$$(x, g) = \int_{-\infty}^{\infty} g(u)x(u)du \quad (4)$$

The Wavenet output can be described as presented in Eq. (5), where  $h_j$  is defined in Eq. (6). Equation (6) applies to mother Wavelet  $\psi$  dilation and translation, being  $a$  and  $b$  the dilations and translation parameters, respectively. They are real and  $a$  must be positive. Moreover, the parameter  $\theta$  is the bias and  $m$  is the number of inputs.

$$\hat{y}(x) = \sum_{i=1}^n w_i h_i(x) + \theta \quad (5)$$

$$h_j(x) = a_j^{-\frac{1}{2}} \psi\left(\frac{x - b_j}{a_j}\right) \quad (6)$$

#### 4. ANALYSIS OF HIGH HYGROSCOPIC MATERIALS

Based on an experimental plant presented in (Slimani et al., 2016a, 2016b), a data set was collected and used in the system identification procedure. The main objective of the previous mentioned study was to present an experimental device capable to measure the hygroscopic behavior of hygroscopic materials, permitting the analysis of multi-layered configurations that are commonly found in the building envelop.

The equipment, presented in Fig. 2, is composed by two chambers of  $0.5 \text{ m} \times 1.0 \text{ m} \times 1.0 \text{ m}$ , these representing the indoor and the outdoor environments. The air temperature and relative humidity are controlled, and it is possible to consider both natural and forced convection effects. By using temperature, humidity, heat flux, and mass flow rate sensors, the equipment can improve the understanding of the hygroscopic phenomena involving building materials, these directly related to thermal comfort and energy consumption. The data set collect using this equipment was adopted to estimate the NARX model coefficients, and to validate the model. Additionally, this equipment can also be used for the characterization of transport properties.

#### 5. EXPERIMENTAL PROCEDURES AND SIMULATION PARAMETERS

This work adopts a data set obtained using the plant presented in the previous section, in a non-isothermal experiment. In order to test the potential of the system identification technique described in section 2, a wood fiber panel, which is frequently used for insulation, was adopted as case study. The idea is to consider materials from a particular group that can be classified by their high hygroscopic properties, those that can increase the nonlinear behavior in terms of temperature variations.

The thickness of the wood fiber panel is  $8 \text{ cm}$ . Temperature and relative humidity sensors were include on both surfaces, and also at 2, 4, and 6  $\text{cm}$  depths. Heat flux and mass flow rate were measured on the internal surface, and just mass flow rate was monitored on the external surface. For additional information about the experimental procedures see (Slimani et al., 2016a, 2016b).

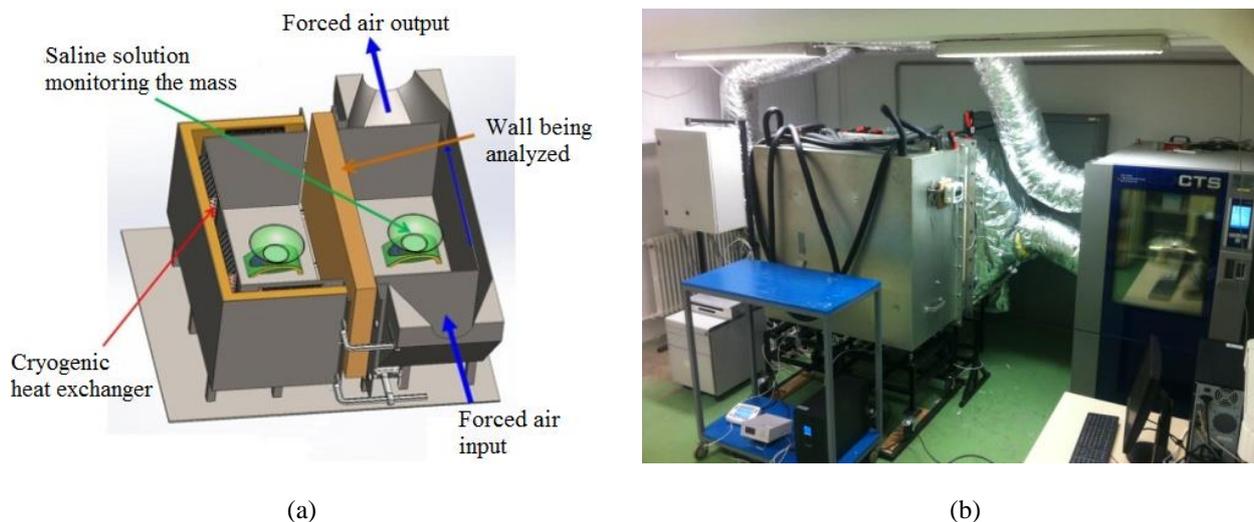


Figure 2. (a) Experimental plant scheme; (b) plant image: data acquisition being performed (Slimani et al., 2016a, 2016b).

Seven variables were considered as inputs for the model, they are the internal and external surfaces temperature and relative humidity, the internal heat flux and both internal and external mass flow rates. The objective of the system identification technique is to predict temperature and relative humidity at 2, 4, and 6  $\text{cm}$  depth (six outputs). Figure 3 shows the input data obtained during the experimental procedure considering  $1.04 \text{ min}$  sample time. It represents almost 8.5  $\text{days}$  of data acquisition and 11,255 samples of each variable.

As it can be verified in Fig. 3 (b), mass flow rates measurements were obtained using a longer sample time. In this case, a linear interpolation was performed. Figure 4 presents the data set considered as the model output. They were used to estimate the model parameters and to evaluate the model response.

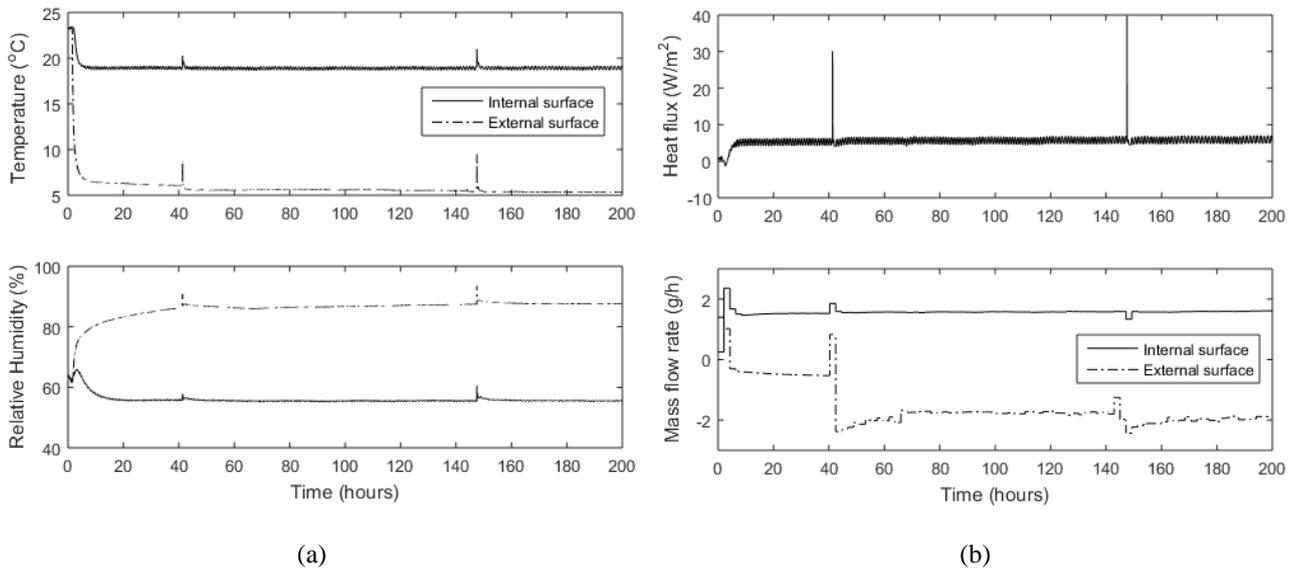


Figure 3. Model inputs: (a) internal and external surfaces – temperature and relative humidity; (b) internal heat flux and internal and external mass flow rates.

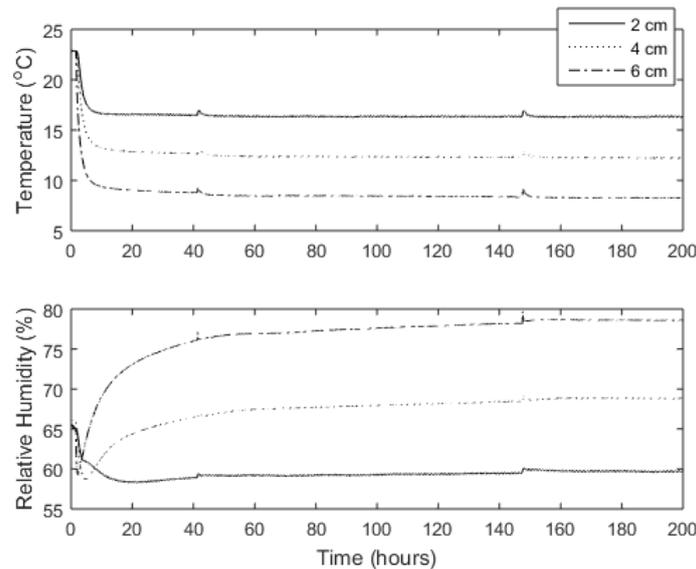


Figure 4. Model output: temperature and relative humidity at 2, 4, and 6 cm depth.

For the nonlinear system identification procedures, simulations were performed in order to evaluate the best set of regressors (the number of past inputs and past outputs adopted in the model structure) and the number of neurons that provides the best approximation. As reference case, data obtained from the experimental analysis were compared to the model response. Tests were also been performed using a maximum number of 20 neurons to each output signal in order to capture the nonlinear behavior. Additionally, 60 % of the data set was used for the estimation phase and 40 % for the validation phase.

In order to evaluate the model performance in predicting temperature and relative humidity in different depths, the multiple correlation coefficient was adopted for both training ( $R_{tr}^2$ ) and validation ( $R_{val}^2$ ) procedures.

$$R^2 = 1 - \frac{\sum_{t=1}^N [y(t) - \hat{y}(t)]^2}{\sum_{t=1}^N [y(t) - \bar{y}]^2} \quad (7)$$

where  $N$  is the number of samples,  $y(t)$  is the output of the real system (experimental data),  $\hat{y}(t)$  is the output estimated by NARX MIMO model, and  $\bar{y}$  is the mean value of the system output set.

## 6. RESULTS

This section presents the simulation results using the NARX MIMO model to predict temperature and relative humidity profiles in a wood fiber board. Temperature and relative humidity in distinct depths (2, 4, and 6 cm) were measured and used to evaluate the model approximation performance. Table 1 shows the multiple correlation indices obtained for training and validation procedures, and the regressors  $i$  and  $j$ . Previous simulations revealed that three was the best set of delayed regressors that should be considered for the inputs, while two delayed regressors were taken into account for the outputs. The numbers of neurons related to each output, those that represent the best model convergence between 1 and 20 units, were also presented in Tab. 1.

Table 1. Model parameters for the best solution found during identification procedures.

Outputs	Number of Neurons	Regressors $u(t - i) : [i]$	Regressors $y(t - j) : [j]$	NARX Model	
				$R_{tr}^2$	$R_{val}^2$
Temperature 2 cm	3	1, 2, 3	1, 2	0.99991	0.96792
Relative Humidity 2 cm	7	1, 2, 3	1, 2	0.99871	0.80815
Temperature 4 cm	5	1, 2, 3	1, 2	0.99995	0.95327
Relative Humidity 4 cm	14	1, 2, 3	1, 2	0.99869	0.96262
Temperature 6 cm	10	1, 2, 3	1, 2	0.99996	0.96712
Relative Humidity 6 cm	18	1, 2, 3	1, 2	0.99954	0.95806

Figure 5 presents the results obtained during the validation procedures for predicting temperature and relative humidity in different depths, and comparisons to the experimental results. As it can be observed in Fig. 5, even opening the chamber for adjusts during the data acquisition procedures, the model was capable to identify the system dynamics and to capture its behavior. By performing a more detailed analysis, Fig. 6 presents the absolute error during the validation procedures. As it can be verified, the maximum error occur when the chamber was open. This situation does not represent a normal behavior of high hygroscopic and high capacity materials submitted to normal weather conditions. Even so, the model presented a maximum absolute errors of 0.04°C, 0.11°C, and 0.17°C for temperature, and 0.22 %, 0.15 %, and 0.23 % for relative humidity predictions at 2, 4, and 6 cm depths, respectively.

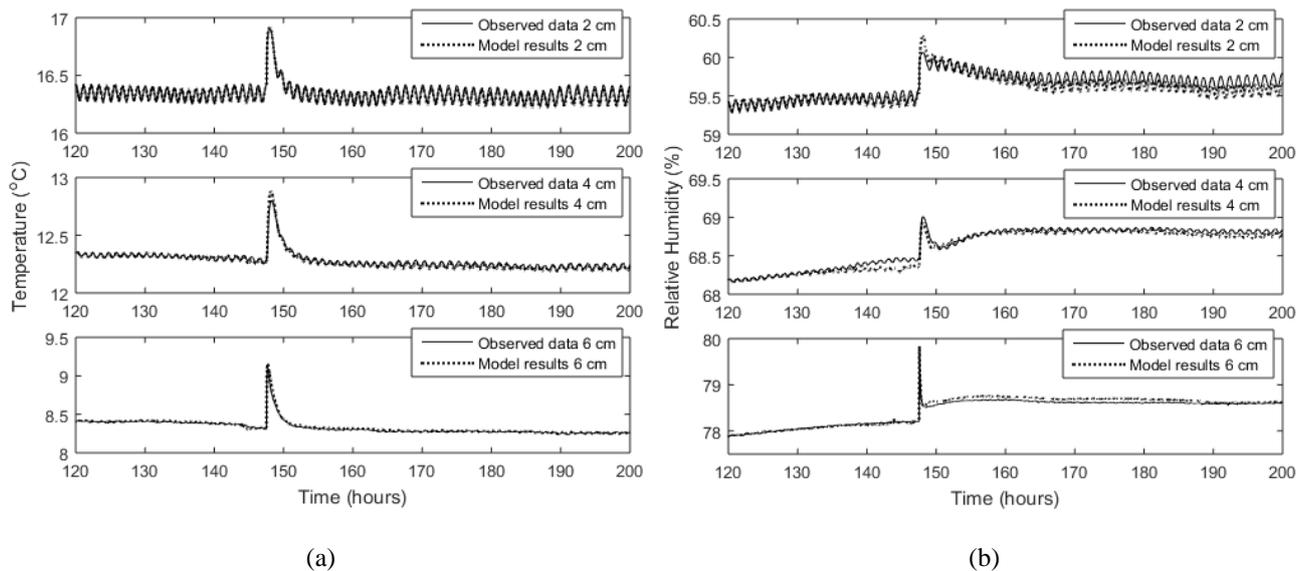


Figure 5. Model results – prediction at 2, 4, and 6 cm depth: (a) temperature; (b) relative humidity.

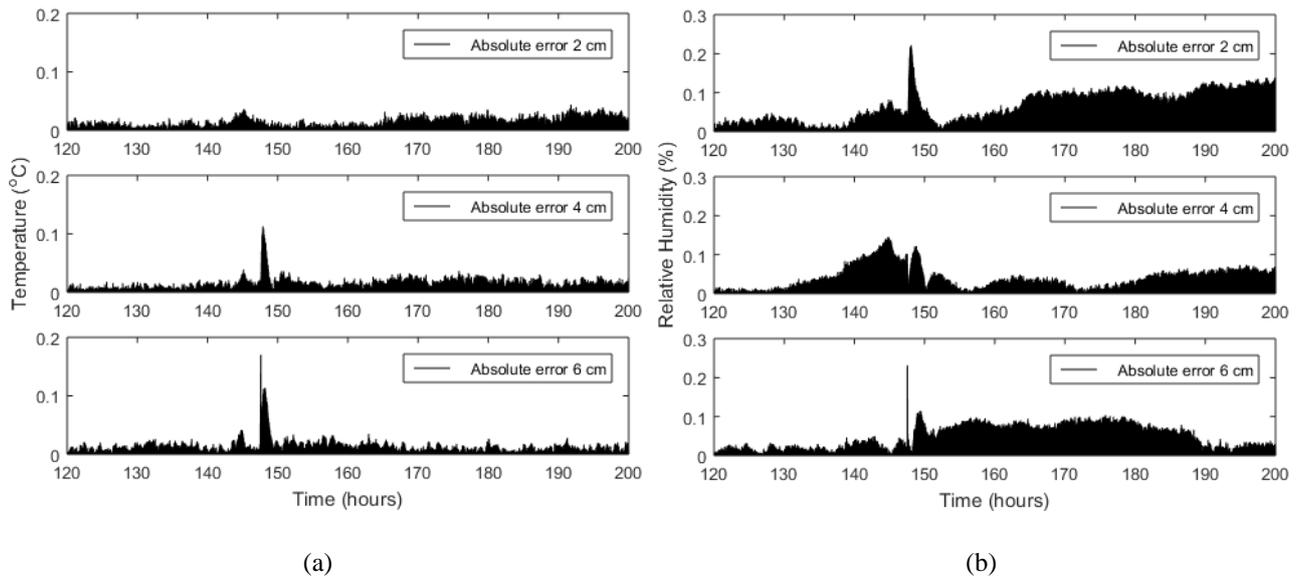


Figure 6. Absolute error at 2, 4, and 6 cm depth: (a) temperature; (b) relative humidity.

## 7. CONCLUSION

This work presented a system identification approach applied on the prediction of temperature and relative humidity profiles of high hygroscopic materials. In this study, a wood fiber board material was adopted, which is commonly used in building envelopes as insulation. Based on the integration of both linear and nonlinear techniques, this work adopted a Wavelet Neural Network in order to capture the nonlinear behavior caused by the moisture accumulation on the hydrothermal variations in distinct depths of the board. As input parameters, seven variables were taken into account, including temperature, relative humidity, and mass flow rates on the internal and external surfaces, and heat flux on the internal surface.

Results presented in this work indicate that a NARX MIMO model can be used as a reasonable approach to predict temperature and relative humidity profiles in high hygroscopic materials. Once the estimation phase was performed, the prediction of the next output can be obtained with low computational cost.

For future works, the NARX models presented in this paper will be compared to numerical models in terms of computational effort and performance related to the experimental data approximation. Additionally, distinct techniques, also based on black box system identification will be considered. Finally, a novel model approach considering less input parameters, e.g. internal and external air temperature and relative humidity, will be considered to evaluate temperature and relative humidity profiles.

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