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Hygrothermal transfer modelling through a bio-based building material: Validation of a switching-linear model

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Abstract

This research presents a switching linear data-driven model (PWARX) dedicated to predicting the hygrothermal behavior through the building envelope. This model uses a discrete state and a switched detection approach for discrete-time linear switched systems, as well as an additional variable with a discrete value. The bio-based materials are subjected to humidification/drying cycles by the temperature and relative humidity variations. The current study aims to fill the knowledge gap and to address the limitations of data-driven models by (i) providing a realistic explanation of the hygrothermal behavior of bio-based materials, (ii) identifying the hygroscopic mode such as sorption/desorption and transition phase between sorption/desorption modes, and (iii) estimating the process time of each phenomenon, which makes it possible to estimate the rate of moisture propagation. Finally, the proposed method can be faithfully applied to the study of hygrothermal behavior of materials, which is strongly related to the building energy performance and the investigation of their durability.

Keyword: Moisture transport; Hygrothermal behavior, Operating modes; Switching model; PWARX model.

Highlights

- PWARX used to assess the hygrothermal behavior of bio-based building material.
- Several modes were identified and related with sorption state.
- The proposed method shows a good accuracy with convergence time reduced.
- The use of PWARX model in the building energy performance is validated.

1. Introduction

The transport of moisture across the building envelope is responsible for increasing the biological pollution of the indoor air of the building. Moisture results in the development of molds, bacteria and viruses, the main factors causing respiratory problems in the occupants [1,2]. In addition, moisture can also affect the mechanical properties and the sustainability of buildings [3,4]. The transport of water at liquid or vapor state is the primary vector for the transport of chemical species such as sulphates and chlorides leading to the degradation of concrete and the corrosion attack of reinforcement steels [5,6]. In addition, at a medium humidity level, the CO₂ transfer is increased in porous media allowing the degradation of carbon steels [7]. It is noted that this mass transfer mechanism depends on the intrinsic properties of the materials, including porosity, pore size distribution and tortuosity, in addition to the exposed climate [8,9]. Therefore, it is crucial to understand the moisture transfer mechanism in order to prevent these risks. In addition, moisture is a paramount factor that affects the thermal performance of building envelope elements through latent heat exchange coupled with heat transfer [10,11].

The hygrothermal behavior of buildings is related to several parameters that are sometimes uncontrollable. Finding a reliable model describing the hygrothermal behavior of building is a challenging task. Indeed, their dynamics are defined by complex and non-linear processes governing by their environment. However, an accurate hygrothermal model is essential to evaluate and improve the energy performance. Two types of models can be distinguished [12]:

- Physical models based on physical approaches such as conservation of energy, and mass using Comsol Multiphysics®, Fluent®, WUFI® and EnergyPlus® tools.
- Data driven models. Models that depend on the input/out data without any physical interpretation.

For the physical model point of view, several models have been proposed in the literature to predict the physical phenomena of hygrothermal transfer in porous materials [13]. The building envelope is exposed to various parameters of influence. We can cite, for instance, the conditions of the external environment (radiation, rain, temperature, wind, etc.) and the internal environment (heating, ventilation, different sources of heat and humidity, etc.). Numerical modelling is a useful method for assessing building envelope behavior. The modelling of fully coupled heat and mass transfers in envelopes is based on several phenomenological approaches, which differ generally in the transfer potentials used. For heat transfer, for example, the temperature is referred to as a conventional transfer potential. Regarding moisture transfer, there are several models with different mass transfer driving forces as water content [13], vapor pressure [14,15], vapor content [16,17] and relative humidity [18,19].

However, the main difficulty of this model lies in the determination: (i) of the model parameters by separating the transfer of the liquid and vapor phase, (ii) and of the thermal gradient coefficient.

Indeed, the input parameters characterization of these models is very chronological with tests which can last up to one year in the case of the hydric properties, in particular sorption isotherm curves with hysteresis effect and water vapor permeability. In addition, the determination of the sorption isotherm curves, which describe the material's hydric behavior in relation to their environment, also requires heavy experimental means. Then, the Guggenheim–Anderson–de Boer model (GAB) is the most widely used to fitting sorption isotherms in construction materials, but others like the Langmuir, Van Genuchten (VG) have been also used [12]. The Clausius-Clapeyron equation was used in several studies to describe the sorption curves as a function of temperature [12].

In the case of data driven models, three main categories for building thermal prediction were identified in the literature [20], i.e., RC models (resistor-capacitor), TF models (discrete-time transfer functions) [21], AI models with a deep learning approach (Artificial Neural Network, ANN) [22,23]. Indeed, ANN models present a capacity to discern nonlinear correlations among inputs and outputs that are complex [24]. Wang et al. [20] have shown that the ANN model usually beats the RC model and an autoregressive model with exogenous terms (ARX models) [25]. On the other hand, both the ARX and RC models can be used to drive important thermal properties of the house. Several model structure of ARX can be found in the literature [26] such as (1) indexed ARX model, (2) nonlinear auto-regressive network with exogenous inputs (NARX) [27], autoregressive moving average with exogenous input (ARMAX) model and fractional order autoregressive model with exogenous input (FARX). Benzaama et al. [26] explained the interest of these models for the validation and showed that the thermal behavior of the building cannot be explained using these models. However, the RC model is best used for explanatory purposes [26,28,29].

Besides, only three studies highlight the use of data-driven models to investigate the hygrothermal behavior of building materials [30–32]. The authors used ANN, CNN (Convolutional neural networks) and LSTM (Long short term memory) to predict the hygrothermal behavior of buildings component [33]. However, the hygrothermal performance is not carried out on bio-based materials. The materials studied by these authors are: (i) massive masonry wall [31], (ii) timber frame wall [31] and (iii) concrete wall protected by a second foliage skin [30]. The authors conclude that, unlike physical models, ANN modeling is an effective tool to simulate the hygrothermal behavior of building materials with a small number of inputs. When compared to bio-based materials, this material's hygrothermal activity is less noticeable.

Based on the literature, several limitations can be summarized under the following issues:

Physical models:

- The resolution of the partial differential equations governing the coupled heat and mass transfer requires heavy numerical and a long calculation time.

- The complexity of co-simulation between models that consider mass transfer (Comsol for example) and building energy tools (BES) [34–36].
- The experimental characterization (thermal and hydric) for each material is needed to provide the model with inputs.
- A lack of reliable thermophysical input data for various envelope components such as the heritage buildings [37].

Due to the complexity of the dynamic hygrothermal response of bio-based materials, most of the mathematical models used in simulations are simplified.

AI models:

The main limitations of artificial neural network models are:

- The models don't need a physical explanation (black box). In other terms, the results obtained by neural networks are derived from mathematics that are largely unknown and poorly understood. The models lack transparency and access to high-quality data [38]. As a result, determining how distinctive occurrences are related using this class of models is extremely difficult.

The aim of neural networks was initially to generate classification hierarchies – the main plan is to identify classes of things, then classes of classes of things, and so on up a hierarchy. The limitations listed above indicate that there is a knowledge gap that needs to be filled. Neural networks were originally developed to create classification hierarchies - their main goal is to identify classes of things, then classes of classes of things, and so on up to the top of a hierarchy. The constraints listed above imply a knowledge gap that needs to be filled. By overcoming these constraints, we will be able to develop a reliable model that can predict the hygrothermal behavior for a variety of materials and at different setting. This research aims to develop an efficient switching linear model (PWARX) for bio-based material. The main objective is to reduce the knowledge gap and provide a hybrid model able to resolve the limitations such as (i) the reduction of the number of inputs and calculation time compared to physical models and (ii) having a physical understanding compared to AI models. The following are the research questions that correspond to the objectives:

- The switching linear model should be able to simulate the real hygrothermal behavior of the bio-based material?
- The switching linear model should be able to identify the moment and the duration of mass absorbed and mass released by the material?
- The switching linear model should be able to identify the transition phenomenon between sorption and desorption?

Table 1: Comparison between three most used numerical tools

Software	HAM model	Approach	Benefits	Limit
Comsol Multiphysics®	Models based on model of: Luikov [54], Kenzel [55] and Philips & De vries [56]	Finite element Method	Ability to couple several phenomena	Paying software
EnergyPlus®	Kenzel model [55]	Simplified (EMPD)Finite Difference Method	Open access, ability to module develop by the users, BIM Database: building envelope material properties and climates.	Lack of a formal and effective user interface
WUFI Plus®	Kenzel model [55]	Implicit Finite Volume Method		Constant input, paying software, high computing time,

Table 2: Summary of work using ANN, LSTM and CNN models

Study	Approach	Materials	Validation
May Tzuc et al. [30]	ANN	Double-skin green facades	RMSE / MAPE / R ²
Tijskens et al. [31]	CNN	Timber frame wall with brick veneer and sidings	RMSE / MAPE
Tijskens et al. [32]	CNN and LSTM	Massive masonry wall	RMSE / MAPE / R ²

Furthermore, for the tools used in the investigation of hygrothermal behavior point of view, a normalization of ambiguous keywords was necessary. After this process, six keywords were researched, namely, “hygrothermal”, “transfer”, “building”, “material”, “heat and mass” and “modeling”. This research was carried out on this three software, i.e., “Comsol Multiphysics®”, “WUFI ®” and “EnergyPlus ®”. Regarding the source of publications, only peer-reviewed journals were considered. A total of 184 scientific publications were identified between 2009 and 2022 as shown in Figure 3. The identified publications are all in journals edited by Elsevier and can be considered as references regarding the study of hygrothermal transfer through building envelopes. We particularly notice the use of Comsol Multiphysics® tool by 117 researchers throughout the world and particularly in France, China, Sweden, Brazil, Belgium, Viet Nam...

Concerning WUFI® and EnergyPlus ® tools, they are used in 39 studies throughout eight countries i.e., France, Portugal, Spain, United State, Finland, Belgium, and 28 research from Italy, United States, France, Spain, and Canada. For more background information, Tables 1 and 2 show a summary of the works on physical and data AI models, respectively.

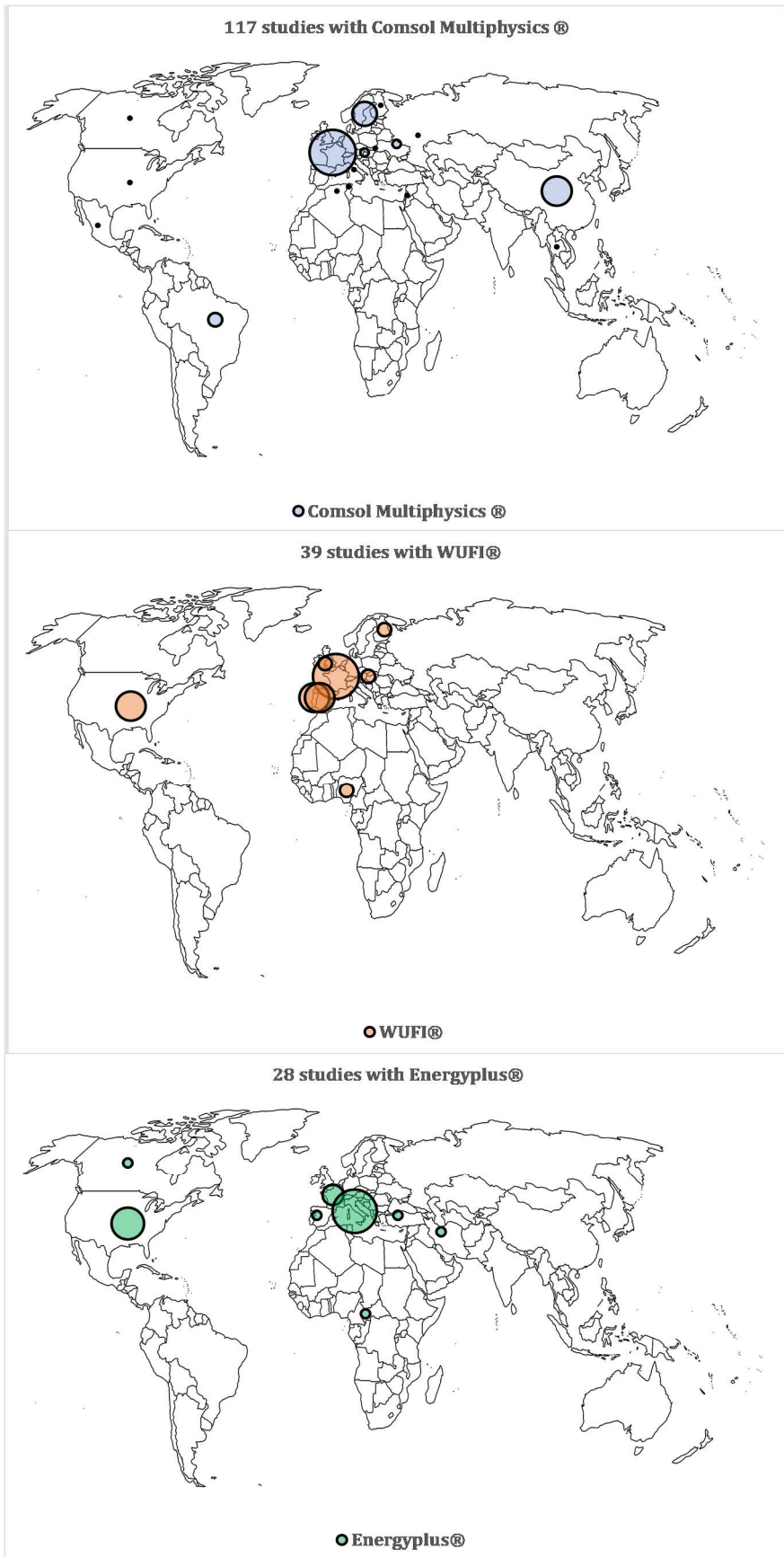


Figure 3: Publication distribution by country using Comsol Multiphysics®, WUFI® and EnergyPlus® tools.

3. Methodology

We built a conceptual framework that describes and visualizes our study methods after reviewing the relevant current literature. This research's conceptual study plan is divided into two components, as shown in Figure 4. Each phase is composed of several steps, as explained in detail in the following sections. These phases are summarized below:

- 1) Collecting data: The experimental data explored in this study is those reported by T. Alioua et al. [43]. In this cited paper, the purpose is to determine the hygrothermal properties of a concrete wall incorporating date palm. The temperature and relative humidity (RH) profiles at three different thicknesses exposed to outside boundary conditions were measured using a specialized test setup.
- 2) Model estimation: Setting all the parameters necessary for the execution of the algorithm, such as the initial number of operating modes, the system orders, and the convergence rate.
- 3) Classification of operating modes: Training a classification algorithm to learn the relationship between the input variables and the operating mode.
- 5) Model validation: In this step, we compare the water content predicted by the PWARX model and the measured water content.

3.1 Switching linear model

When modelling and comprehending a nonlinear complex system, switched and piecewise affine models are interesting. Indeed, by characterizing their behaviours using the interplay of continuous and discrete dynamics, they may define and explain this class of systems [60]. Variables taking values from a continuous set have been used to describe steady dynamics. Discrete dynamics, on the other hand, are characterized by variables (or events) drawn from a discrete, usually finite, collection. Switched and piecewise affine models are sets of linear/affine models connected by switches and indexed by this discrete variable, designated as discrete state [62]. Models in which the discrete state is governed by a polyhedral input/output domain partition (cf. Figure 5). As a result, they can be described using a linear connection between the input/output pair.

The piecewise-ARX model is made up of several ARX sub-models, each of which corresponds to a discrete state (cf. Figure 6). The ARX model analytic expression is depicted below:

$$y(t) = -a_1 y(t-1) - \dots - a_{n_a} y(t-n_a) + b_1 u(t-1) + \dots + b_{n_b} u(t-n_b) + e(t) \quad (19)$$

where n_a and n_b are the model order, a_i and b_i are the model coefficients, and $e(t) \in \mathbb{R}^{n_e}$ is a white noise process. n_e is the noise system order. y and u are the dependent variable and u is the exogenous variable.

A novel moisture transport identification via a switching-linear model:
application on the bio-based building material

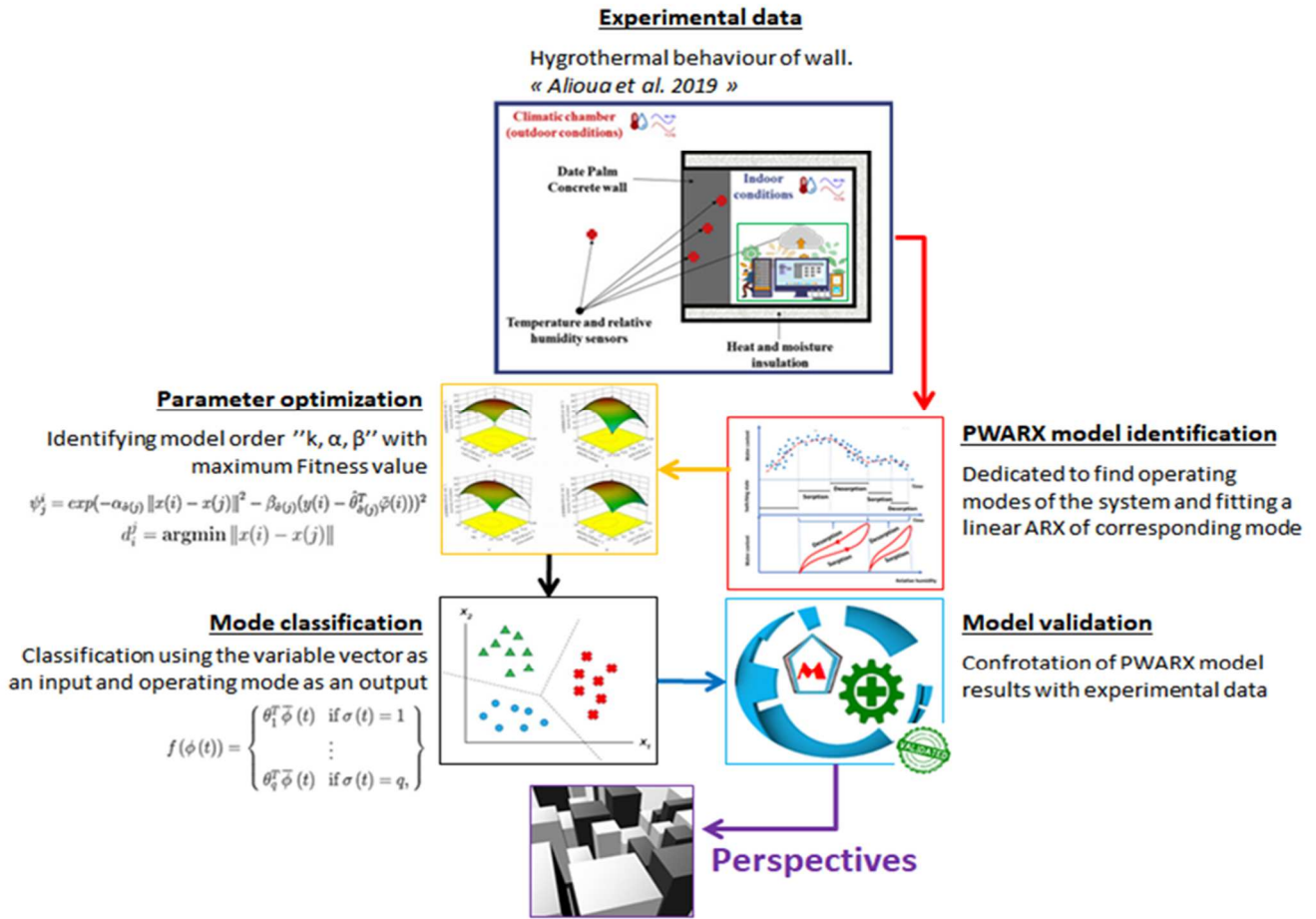


Figure 4: Conceptual study plan.

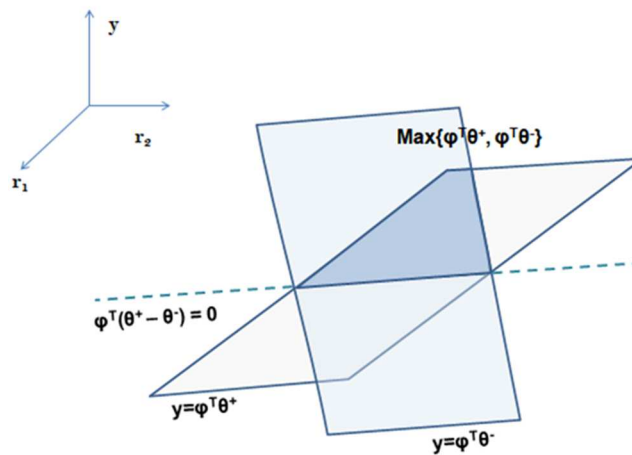


Figure 5: Polyhedral partition defined by $(y = \varphi^T \theta^+ \theta^-)$ and $(y = \varphi^T \theta^-)$, with its hinge corresponding functions $\max(\varphi^T \theta^+, \varphi^T \theta^-)$, where $\varphi = [r_1 \ r_2 \ 1]^T$

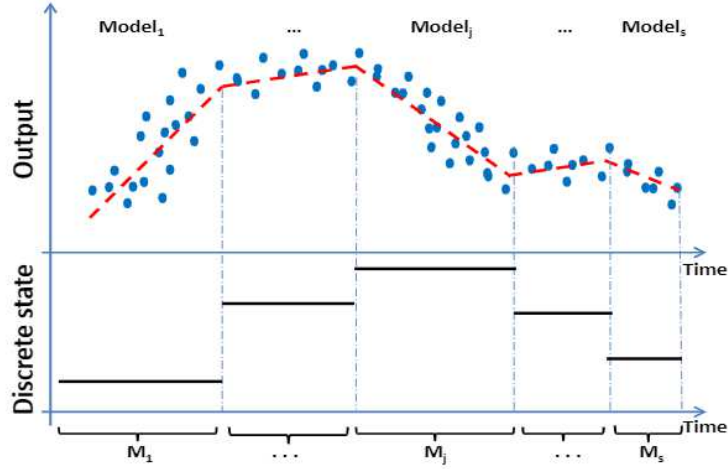


Figure 6: Switched piecewise linear models (Benzaama et al., 2021 [63]).

The general structure of the switched ARX model can be written as [63] :

$$y(t) = f(\varphi(t)) + e(t) \quad (20)$$

with f as a piecewise affine map of the following form:

$$f(\varphi(t)) \begin{cases} \theta_1^T \bar{\varphi}(t) & \text{if } \sigma(t) = 1 \\ \vdots \\ \theta_q^T \bar{\varphi}(t) & \text{if } \sigma(t) = q \end{cases} \quad (21)$$

Where $\bar{\varphi} = [\varphi^T \ 1]^T$ the extended regression vector. $\sigma(t)$ is the switching rule defined by:

$$\sigma(t) = i \quad \text{iff } \varphi(t) \in R_i, \text{ for } i = 1, \dots, q; \quad (22)$$

and $\{\theta_i\}_{i=1}^q$ are the parameter vectors that define the sub models. $\{R_i\}_{i=1}^q$ represent a complete partition of the region $R \subset R^n$, with $n = n_e n_a + (n_b + 1)$, and each region is a convex polyhedron with:

$$R_i = \{\varphi \in R^n: H_i \varphi \leq 0\} \quad (23)$$

where H_i and 0 are the matrix of appropriate dimensions defining the limit of the region partitioning the set of regression vector and the null vector, respectively.

As shown in the synopsis (cf. Figure 7), the proposed approach consists of three basic steps: (i) Initialization phase, (ii) Data reallocation, and (iii) Convergence test.

Thus, the identification algorithm of the PWARX model has as inputs the input-output data and number c fixing the number of nearest neighbours. It has as output: the number of ARX sub-models s , the classes C_i and the parameter vectors θ_i , with $i=\{1,\dots,s\}$.

We noticed that at initialization, the data are used to create N classes, and then are reassigned by successive iterations until the stopping criterion is verified and the data reassignment procedure is stopped. The algorithm convergence test is performed by minimizing the obtained prediction errors at each iteration.

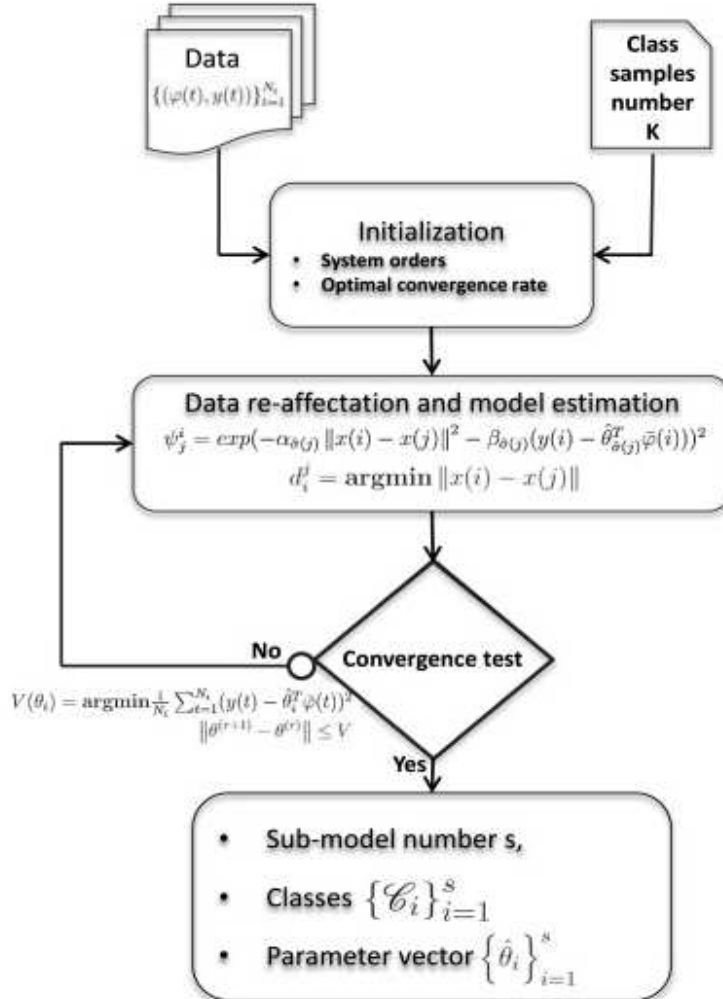


Figure 7: Parameter estimation and data classification algorithm

All the information on parameter identification and the estimation for this class of models is given by Benzaama et al. [26].

4. Results and discussion

We used the collected data at different depths to estimate the switching linear model parameters as well as the operating modes defined in Eq. (22). Hence, the measured water content is compared with the predicted water content as shown in Figure 8.

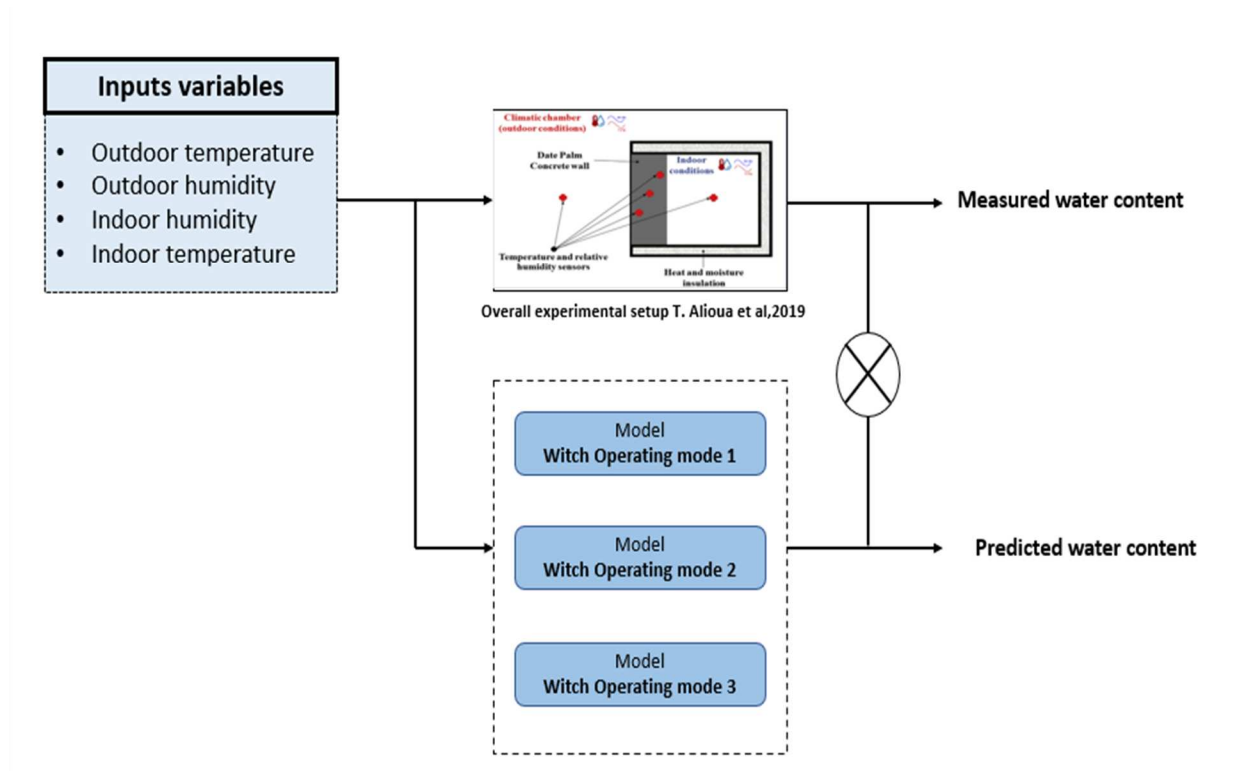


Figure 8: Hygroscopic behavior model identification

Table 3: Model performance at the considered depth

Performance indicator	Depth	At 7,5cm	At 12,5cm
FIT [%]		78,46	88,36
RMSE		0,224	0,0071
R2		0,9536	0,9865
MAPE		515,67	171,01

The experimental data given by Alioua et al, [43] are used to calculate the water content with the GAB model. The results of the GAB model were compared with PWARX results. Figure 9 shows the comparison between the two models.

The results showed a good agreement between the switching linear model and the experimental results given by Alioua, et al. [43] for both depths 12.5 and 7.5 cm (cf. Table 3). The algorithm estimates three operating modes describing the hygroscopic behavior of the bio-based material (cf. Figure 9). According to Promis et al. [64] and for very low moisture contents, a phase called chemical adsorption or chemisorption is observed. This phase corresponds to mode 1 in our case (cf. Figure 9). Indeed, chemisorption, is an irreversible process. This irreversible phase explains why the initial dry mass cannot be recovered during the desorption process, which leads to structural modifications [64].

The second sub-model (second mode) appear when the water content increases which corresponds to the sorption of the material. In the opposite case (decrease in water content) we observe the

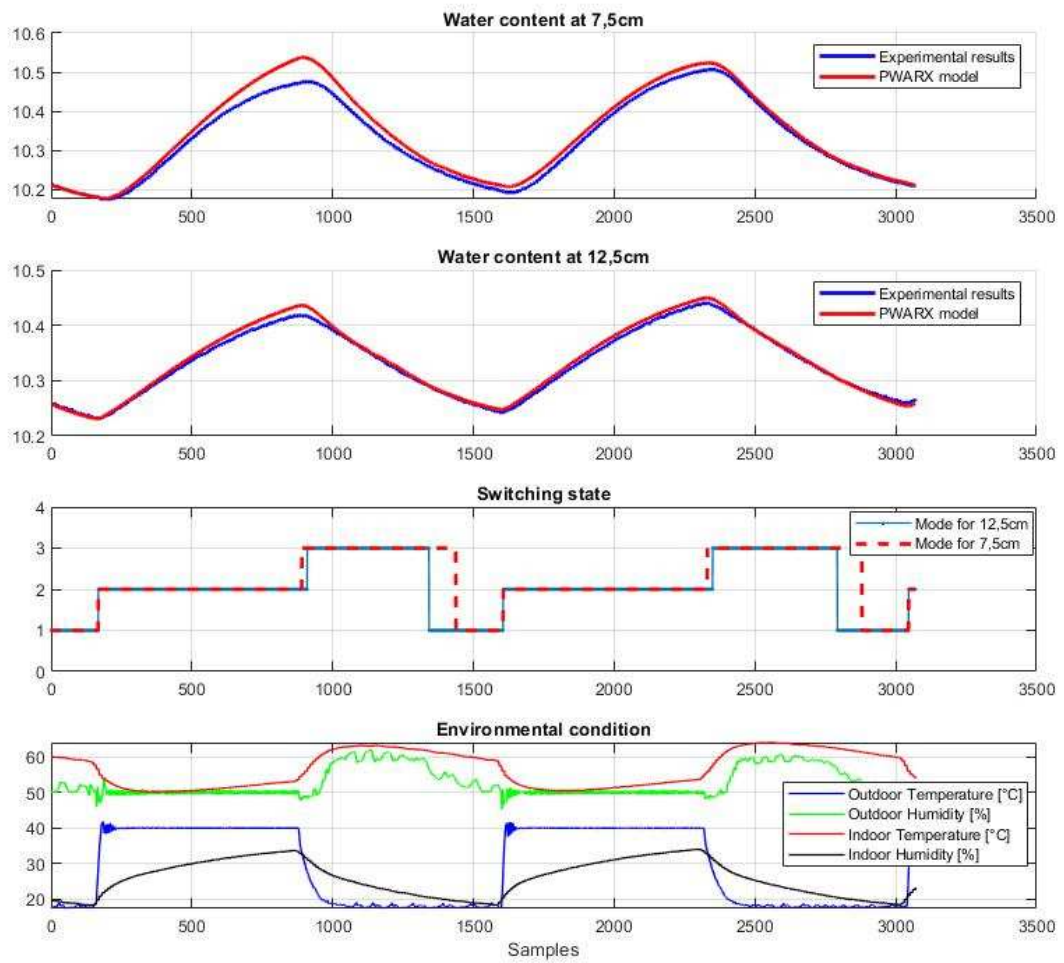


Figure 9: Water content validation and operating modes

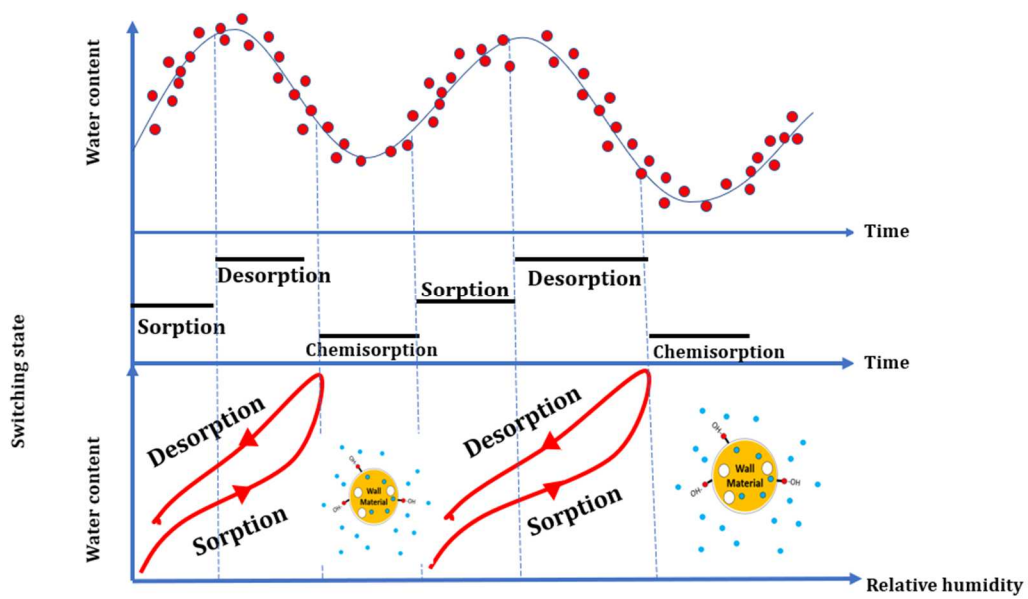


Figure 10: Explanation of physical phenomena

appearance of the third sub-model (third mode), which corresponds to the desorption of the material. With the PWARX model, it is easy to explain the physical processes. As can be observed, the PWARX-hygroscopic model allows us to understand the behavior of the bio-based building materials (cf. Figure 10).

The switching state (cf. Figure 11) shows that the sorption mechanism takes longer (mode 2) than the desorption mechanism (mode 3), which is consistent with the phenomenon of hysteresis. Furthermore, the model confirms that we don't have the same sorption/desorption time for the second cycle. Comparing the two depths of 7.5 and 12.5 cm, the model shows that we have almost the same sorption time but not the same desorption time for both cycles. Furthermore, the results show that the mode 1 time becomes almost double at the depth of 12.5cm (Figure 11). To summarize, the two measurement points (7.5 and 12.5 cm) don't have the same desorption and chemisorption time. This difference generates a phase shift time (Table 4) observed at 1400 and 2800 steps, which allows us to estimate the mass transfer kinetics.

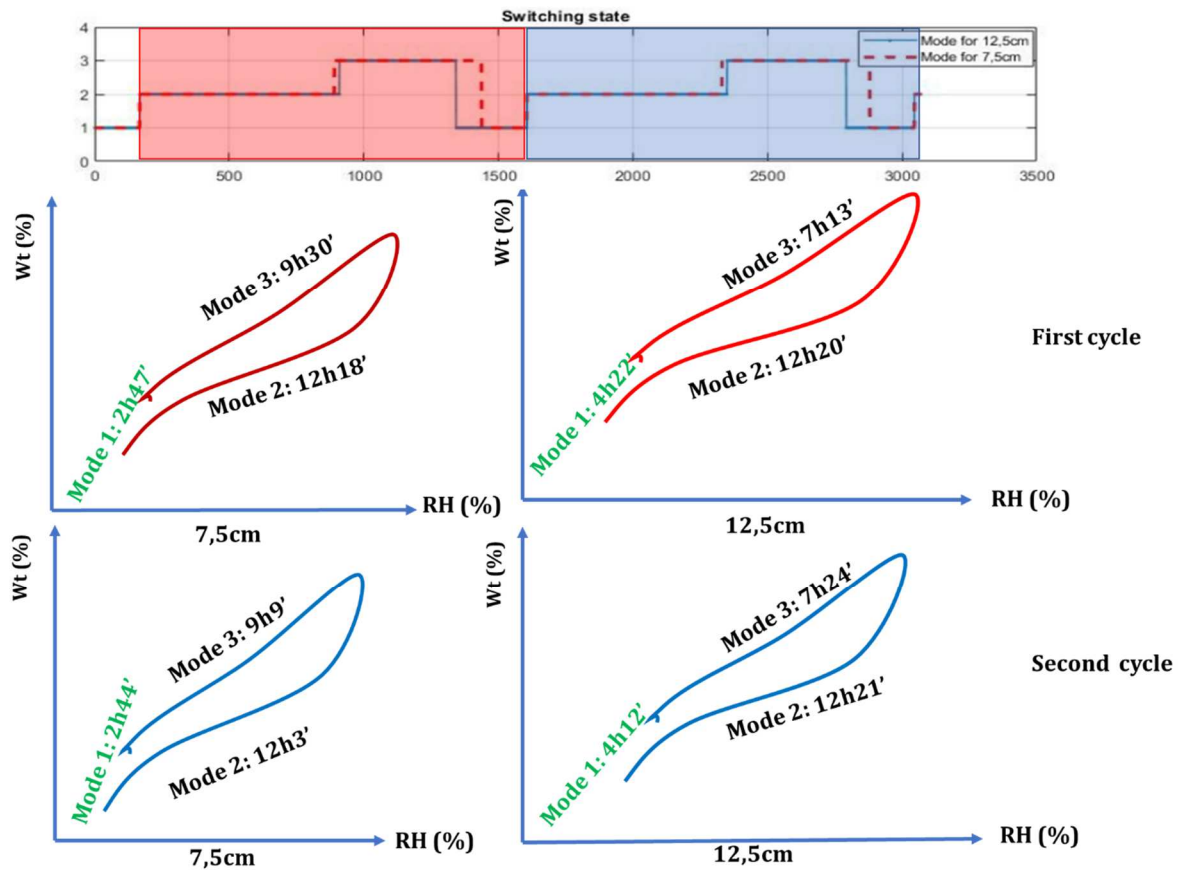


Figure 11: Identification of the hygroscopic mode time

Table 4: Mass transfer kinetics

Cycle	Phase shift time (Hr)	Mass transfer kinetics (m/s)
First cycle	1h34	8.86e-6
Second cycle	1h26	9.68e-6

The model described in this paper enables for sensitive identification of the two processes (absorption/desorption) and the time taken for each cycle across a lengthy measurement period. The results demonstrate that the moisture in the wall material is not totally released, implying that part of the water (moisture) is not completely desorbed and is bonded to the material in a manner apart from adsorption. Because the original material mass is not achieved at the conclusion of the desorption, the water may be bonded to the material not only by physisorption but also by chemisorption, resulting in a structural alteration of the host wall material. Another phenomenon that can lead to this incomplete release is that moisture is blocked in pores with narrow openings (Nano-micro-porosities). This phenomenon is called the ink-bottle or pore-blocking effect representing the hysteresis between the sorption and desorption isotherm curves in porous materials [8].

A variety of mathematical models have been developed to account for sorption isotherms, including linearity or non-linearity models with partial coefficients as parameters. A model well suited for one kind of hygroscopic material is not always suitable for another, and the model only has a suitable predictive value for a limited range of moisture activity [12]. For this purpose, to simulate the hygrothermal behavior by physical models, it will be necessary to inform the thermal and hydric properties and the appropriate mesh size for each material. The type of mesh has a significant influence on the calculation time. Alioua et al. [18] presented the results of the simulations in terms of the computation time required by the two models (Kunzel and Mendes) to solve the heat and moisture transfer problems as shown in Table 5:

Table 5: Dependence of computation time on the number of layers of the mesh. Modified from [18].

Number of mesh layers		2	5	10	50	100	500	1000	2500
Kunzel's model	Calculation time for heat transfer [s]	1.7	1.7	2.1	2.4	2.9	8	14.9	29.1
	Calculation time for moisture transfer [s]	2.4	2.9	2.8	4.6	6.1	17.1	36.6	144.8
Mendes model	Calculation time for heat transfer [s]	2.4	2.1	2.1	2.3	3.8	9.5	17	29.7
	Calculation time for moisture transfer [s]	2.6	2.4	2.5	3.3	4.3	14.9	30.9	102.9
Switching model	No mesh layers	Immediate convergence							

Due mainly to the long calculation times, it is hard to model all physical phenomena using physical models. In this case, for too large calculation times, and for the case of a complex building, the switching linear model allows solving this problem, and making a quick diagnosis of the building envelope. The model could be applied to all materials, just the inputs related to the weather conditions that change.

5. Conclusion

This article presents a linear switching model PWARX used to study the hygrothermal behavior of bio-based material. The given model can help to build thermal engineers and decision-makers to achieve more accurate building performance analyses and thus to estimate the real impact of moisture transfer on thermal comfort. In addition, the proposed model enables building thermal engineers to quickly diagnose the various operating modes and to evaluate the hygrothermal and energy gain provided by bio-based materials. In order to validate the present model, an experimental data from the literature was used.

To our knowledge, a lack of study in relation with the data-driven models has been identified on the literature review of hygrothermal studies. The following issues can be drawn:

- Explaining the physical behavior of the bio-based materials.
- Identify the absorption / desorption modes.
- Estimating the processing time of each phenomenon, which makes it possible to estimate the rate of moisture propagation.

Finally, three operating modes were identified notably, adsorption, desorption, and chemisorption. The switching state demonstrates that the sorption mechanism (mode 2) is longer than the desorption mechanism (mode 3). Furthermore, the model reveals that the second cycle does not have the same sorption/desorption time. The switching modes were also tested for two depths "7.5 cm and 12.5 cm". The results of the present model show that for these different depths, almost the same sorption time was found for both humidification cycles. Nevertheless, in drying phases the time differs between the two cycles. Moreover, the result shows that the time of mode 1 corresponding to chemisorption increases and becomes almost doubled especially at the depth of 12.5 cm. This last one could be related to an indicator of the degradation of the materials and merits further investigation in future studies.

The linear switching model presented in this work has not only enriched the database of hygrothermal modeling tools but has also provided an alternative numerical simulation model that does not require a reliable input data from experimental characterization campaigns to input the physical models for predicting hygrothermal behavior. Therefore, further numerical study will be conducted to highlight the benefits of using the linear switching model in terms of energy performance, durability and environmental impacts.

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Appendix

A.1. Experimental data

The inputs used for the model are outdoor temperature, outdoor relative humidity, indoor temperature and indoor relative humidity (Taken from [43]). Furthermore, the predicted outputs are water content at different depths at 7.5 cm and 12.5 cm as shown in Figure 14.

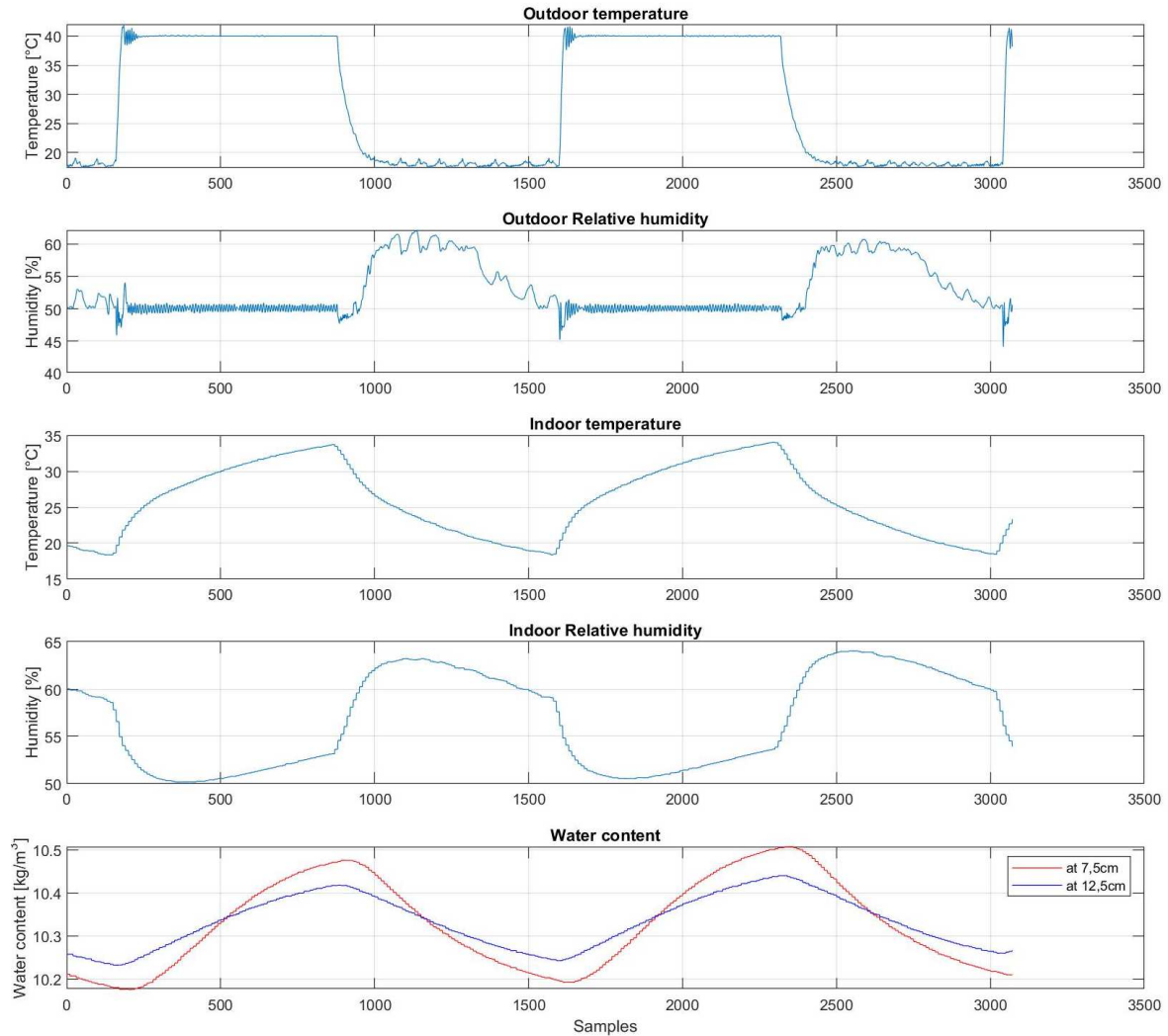


Figure 14: The inputs and outputs used for the classification and model parameters identification

A.2. Identification procedure example

Let suppose that we have the collected data as illustrated in Figure 14 from our system. To start the identification procedure we first plot this data into the state-space domain and apply a separate vector machine (SVM) method to search automatically different classes defining the relationship between the input-output pair. This algorithm can identify for example two-class classification (Figure 15a) or multi-class classification (Figure 15b) according to the data. In order to find the best number of class

(resp. operating modes), we do this procedure iteratively until a performance index will not be reached. We call this step by the classification and data re-affectation phase.

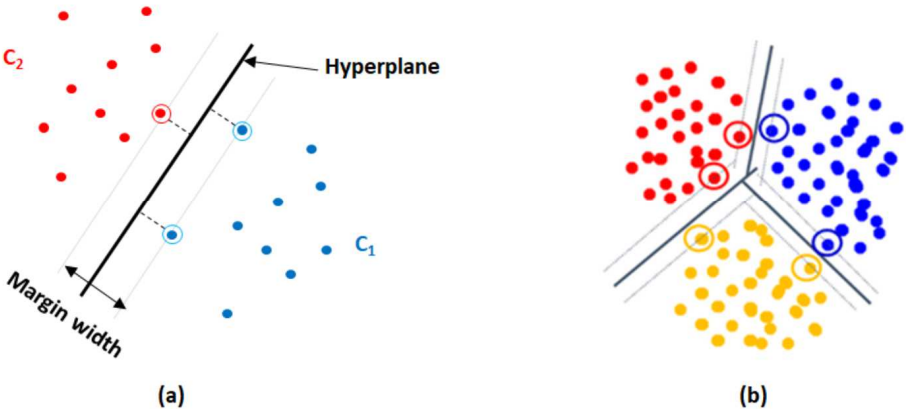


Figure 15: (a) Example of two-class classification and (b) multi-class classification with SVM method

Since the number of operating modes is stable (i.e. we recover the best classes defining the behaviour of our system), we proceed to the identification of each sub-model associated to each operating mode identified (Figure 16). In this case, we regroup all data defining each operating mode and apply a least square method to identify the parameters of each sub-model.

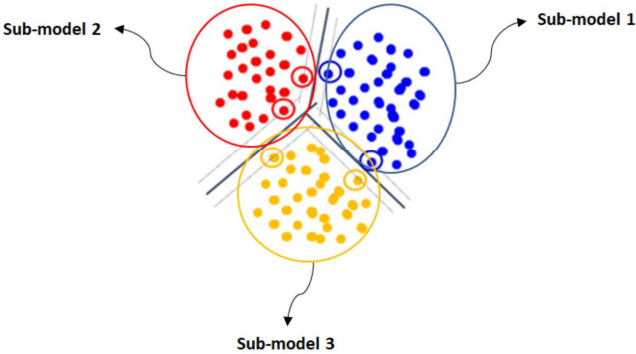


Figure 16: Identification of sub-model parameters using least square approach

To validate each model, we use finally some performance index (FIT, MSE, R2, and MAPE). Let notice if the identified operating modes are not suitable for the system we will have systematically bad parameters for each sub-model. In this case we perform our algorithm iteratively in order to reach the best parameters for each sub-model associated to the best classification of the data. The rest of the procedure is the explanation of the results according to the studied system.