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ARX Models Inspired By Physics As a Service For Building's Users

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Abstract – Recently, in the field of building energy efficiency, many works focused on model based energy management services but developing models consistent with a measured reality is still an issue. Fine physical models with many parameters cannot be adjusted while non-physical models cannot extrapolate to situations never met in the training data. In this paper, pure data models will be implemented with ARX models. In a second time, physical knowledge is added in order to improve the accuracy especially in the cross-validation process. These models are applied to a mono-zone study case in order to forecast the indoor CO₂ concentration.

Keywords – building model ; parameter estimation ; energy management ; simulation ; occupants / users

I. INTRODUCTION

Buildings represent 40% of the final energy consumption in the world so it is one of the main levers for energy savings. Several thermal regulations appeared to stop the continuous increase of energy consumptions. Until the 1990s, scientists focused on energy efficiency by working on different equipments operating in buildings. It has led to different labels to classify buildings performance. The next step has been to develop efficient building energy management systems (BEMS). Buildings became more and more automated with controlled rolling shutters, lights and temperature set-points. To operate these controls, researches focused on model based energy management. Despite these new technologies and energy management methods, there is still a big gap between predicted consumptions and real ones. Dujin et al. [1] explained that in these approaches, users are seen as passive actors and have to learn how to do nothing and finally undergo systems not adapted to their rhythms and comfort criteria. In this kind of situation, it can lead users to bypass the systems and those behaviours can be strongly against energy savings purposes because even very efficient appliances can have a significant consumption if they are misused. To avoid these situations and to better manage energy in buildings, many sociologists suggest that users must be involved and empowered. In

this paper, the modelling for model based energy services for occupants is discussed.

The model requirements for energy end-users services are different from those for building design or for energy performance analysis. Indeed, energy demand for an entire year is not needed neither results pointing out the influence of elementary design decisions. Energy management services usually requires the ability to forecast the energy demand with effects for 24 hours with generally hourly time steps. Existing models for energy management services rely on a different set of hypotheses.

The aim of this paper is to investigate the relevancy of black-box models for generating user advice, the final objective being to help them understand their impact on their dwelling. Then, physical knowledge is introduced in the definition of the model and the impact on the accuracy and forecast capacity of the model is quantified. Data from sensors on an occupied study case are used to estimate the parameters of the models.

II. PROBLEM STATEMENT

The general objective and methodology investigated in this paper consist in defining different black-box model structures and then to quantify the gain due to the introduction of physical knowledge. Indeed, if black-box models have the advantage not to require any prior knowledge of the building it induces to select an appropriate structure and a representative data-set for learning. The paper is organized as follows. First, a literature review is led on ARX models in general and in building modelling in particular in Section 3. The office settings are described in Section 4. The principle of ARX models inspired by physics is presented in section 5. Finally, the conclusions are drawn in Section 6.

III. LITERATURE REVIEW

Universal models or black-box models are based on general purpose structures and then do not require any physics expertise. However, even if black-box models are often criticized for lack of physical interpretation [2], Richalet [3] demonstrated that for some kind of these models it is possible to recover some physical information. Universal models can be either linear or non linear and take one or several inputs in consideration. Most

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of the time universal models were used for modelling systems or walls instead of the whole building [4], [5]. Extending these models for describing a model would require to fully know the different systems operating in the building but, most of the time, the description of buildings systems are unknown. Then, this approach cannot be applied with this objective.

More recently, several authors did the exercise to model an entire building with different objectives: predicting the indoor temperature [6], predicting the thermal load [7] or recovering u and g values of buildings [8]. Even if phenomena involved in building physics such as heating, ventilation or occupancy are non linear, authors often chose linear models to represent the building dynamics. However, models taking only one input tend to disappear due to the complexity increase of building integrated systems. On the other hand MISO models (Multi Inputs Single Output) or MIMO (Multi Inputs Multi Outputs) are becoming more and more common. Those two categories can be broken down in different formulations: ARX (Auto Regressive with exogenous inputs), OE (Output Error), ARMAX (Autoregressive moving average with exogenous inputs), BJ (Box-Jenkins). OE was found to provide the best prediction compared to ARX and BJ models while looking for the response of internal temperature in an office building [9]. Mustafaraj et al [10] conclude that BJ models outperform ARX and ARMAX models. Rabl [11] presented an overview of different methods, focusing especially on their physical interpretation. This study, applied to building models, revealed that even with wrong parameters a model may give a good fit to the data because of compensations in errors. It confirms thus that estimated parameters should be interpreted carefully.

ARX models are the most common in thermal modelling. Besides Jimnez and Madsen [8] and Mustafaraj et al. [10] show they are sufficiently efficient to model building thermal behaviour. ARX models were also used by Armstrong [12] and Naveros [13] for building applications. Chen et al. [14] used a fractional version of ARX models in order to describe the overall thermal dynamics of a building. Thus, an ARX structure is implemented in that paper.

IV. MONO-ZONE OFFICE

In order to validate model structure, a real case study has been chosen: an office occupied by 1 to 4 persons. In terms of instrumentation, the office is equipped with 26 sensors measuring temperatures, CO₂ and COV concentrations, illuminance, humidity and power consumption, door and windows contacts, motion and weather (*cf.* figure 1). Only indoor temperature, CO₂ sensors, window and door contacts and weather station for outdoor temperature and nebulosity are used to estimate the parameters of the models. Estimators for occupancy and heating during winter season were defined. For occupancy, power-consumption measurements are used to estimate the num-

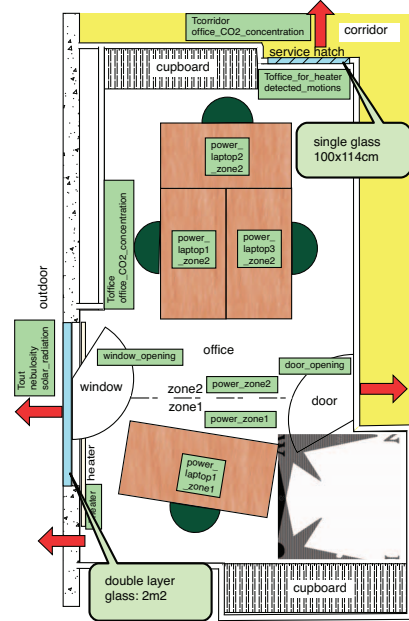


Figure 1: Map of the office with sensors

ber of computers used and thus the number of occupants. Regarding the heating power, a temperature sensor has been placed on the surface of the heater and the power heating is computed using equation 1

$$P_{heat} = K(T_{heater} - T_{office}) \quad (1)$$

where K is estimated.

V. MODEL FORMULATION

The general formulation of an ARX model with one output is illustrated in equation 2 for the temporal description and in equation 3 for the z-form.

$$T_{i,n} = - \sum_{l=1}^p a_l T_{i,n-l} + \sum_k \sum_{j=0}^q b_{k,j} u_{k,n-j} + e_n \quad (2)$$

where b_k are the coefficients for the respective inputs u_k and e represents the error which is assumed to be white noise.

$$A(z^{-1})T_i = \sum_k B_k(e^{-1})u_k + e \quad (3)$$

Lowry and Lee [9] implemented different autoregressive models such as ARX or OE models in order to predict the response of internal temperature in a building under passive conditions. They studied different orders for their models and conclude that even if outdoor and indoor air temperature are highly correlated, simple linear-regression models have a variance of at least 44%. Thus, autoregressive models are interesting. They tested different possibilities of higher-order with respect to any combination of the input and output variables and concluded that no improvement was noticed beyond second-order. The models were able to predict with a good accuracy the indoor air temperature for more than one week.

A. Reference

In order to quantify the impact of the inclusion of physical knowledge on the forecast ability of the ARX model, a reference structure needs to be defined. For that purpose, an output is chosen: the CO_2 concentration. Then, only the data from variables linked to CO_2 concentration is used as variables of interest: corridor CO_2 concentration, ζ_D and ζ_W representing conversely the door and window openings. Results of the reference model represented by equation 4 for forecasting CO_2 can be seen in figure 2.

$$\Gamma_{in} = b_0\Gamma_{corridor} + b_1\zeta_D + b_2\zeta_W \quad (4)$$

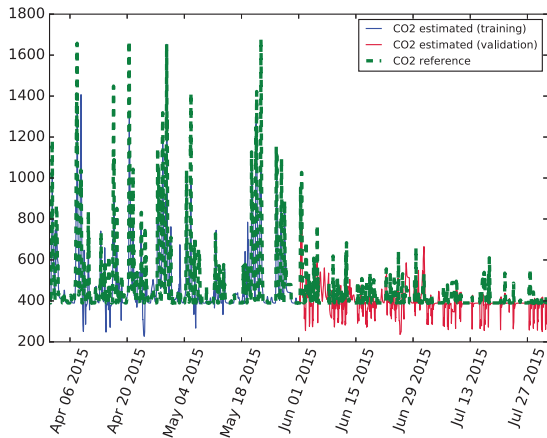


Figure 2: CO_2 concentration of the reference model

It can be observed that the values obtained in the validation part are significantly different from the measures and most of all non-physical. Indeed, the outdoor CO_2 concentration is around 400 ppm and cannot be lower inside a building. With this model, CO_2 concentrations go down until almost 200 ppm.

1) *Training and cross-validation periods:* Contrary to the use of physical or semi-physical models, black-box models require a rich dataset for training the model. It means that the training dataset needs to include several behaviours such as door or window openings and different range of temperatures or more generally it needs to include behaviours occurring during the validation dataset. Indeed, learning the model on a certain period and applying it on a very different period leads to low accuracy. In figure 3, it can be seen that the model has been learned during a winter month. Then, as windows are not frequently opened before the months of June, the training dataset chosen was made with the months June and July and the cross-validation was performed with the months of April and May since August is not very interesting due to the lack of occupancy. Besides, it allows to ensure that the model is then able to forecast

really different scenarios in terms of use of openings and outside temperature.

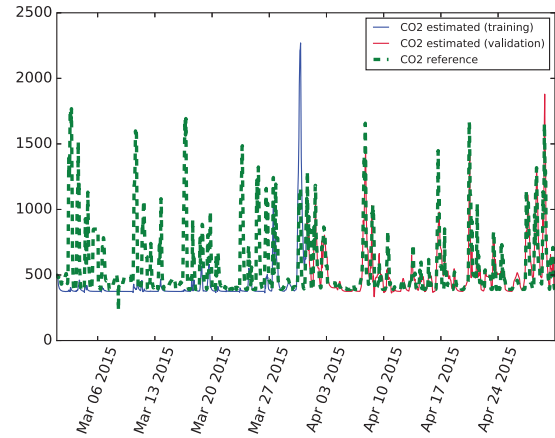


Figure 3: CO_2 concentration of the reference model March / April

B. Liability of the estimated model along the seasons

Then, it was examined how a model estimated in summer or in winter is able to forecast the thermal and aerualic behaviour of the study case during the whole year. Results can be seen in figure 4. Regarding the CO_2 concentration, once again it can be observed that the behaviour of the model during the month of June is physically non-acceptable. But the difference between the model estimated in winter and the one estimated in summer cannot be seen graphically. As previously, the absolute average error and the standard deviations are computed for these new configurations.

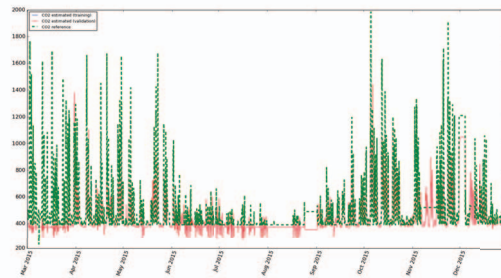


Figure 4: CO_2 concentration of the ARX model estimated in summer

Obviously, it can be observed in table I that the errors are higher. The significant increase in CO_2 errors is mainly due to the period of missing data in November. But, even in that case errors remain in an acceptable range since a difference of 150 ppm is unlikely to be felt by

end-users. Then, it is in agreement with the objective of energy services implementation.

| Training month | Absolute Average Error | Standard Deviation |
|----------------|------------------------|--------------------|
| Winter | 68.66 | 138.17 |

Table I: Comparison of absolute average error and standard deviation for the reference model and the ARX model inspired by physics

VI. THE CASE OF JUNE

ARX models have been proved to deliver good performance for forecasting air temperature and CO₂ concentration. However, several limits need to be raised. The case of June regarding the CO₂ requires to be further investigated in order to understand the observed behaviour. For that purpose, environmental inputs are plot in order to identify if a specific phenomena happened that month. Then, window openings, outdoor and indoor air temperatures as well as CO₂ concentrations in the corridor are observed (cf. figure 5). It can be seen that there is a gap between the window openings in May and the ones in June which is consistent with the significant increase in outdoor temperatures. It can explain why the ARX model is not able to forecast the CO₂ concentrations in June.

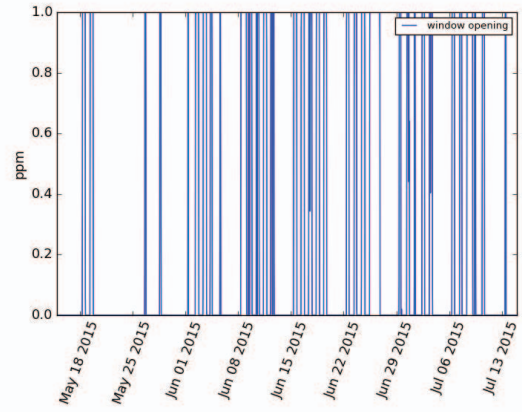
Then, another test is performed, estimating the model parameters with the month of July which also presents a great number of window openings and similar outdoor conditions and validated on the month of June. Results in figure 6 reveal that the prediction is still not as accurate as it was for winter forecasts but there is a significant improvement with an average absolute error of 34.54 ppm against 72.62 ppm and a standard deviation of 64.52 ppm against 96.60. This study highlights that ARX models require rich datasets for learning the coefficient of the variables of interests and cannot ensure a systematic accuracy in the predictions.

VII. ARX INSPIRED FROM PHYSICS

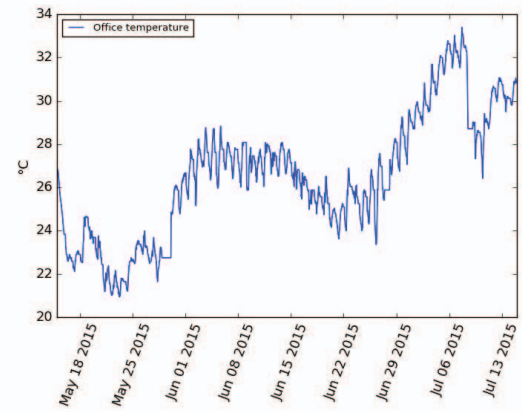
In order to solve problems such as the case studied in the previous section, a lead is explored: how integrating physical knowledge in the ARX model structure can improve the accuracy of the forecasts. Indeed, the low performances observed for the month of June are due to new physical phenomena (absent from the training data) but these phenomena can be represented by physical equations.

A. Principle

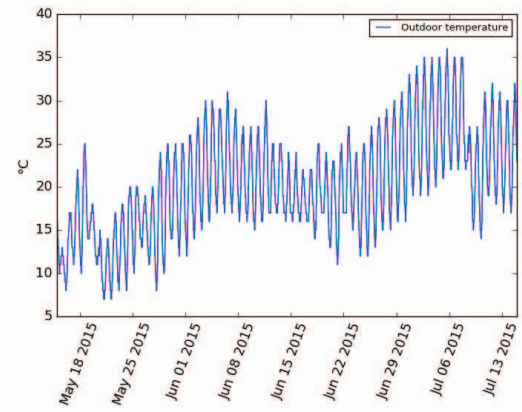
The main idea is to improve the prediction ability of ARX models when they face new dynamics or behaviours and develop an automatic method for determining the inputs and the order to consider. Indeed, if black-box models have the advantage not to require any prior knowledge of the building it induces to select an appropriate structure for the model structure. This step usually generates a great



(a) Window openings



(b) Indoor air temperature



(c) Outdoor temperature

Figure 5: Environmental inputs during the month of June

number of simulations [10]. For that purpose, physical equations can be extracted either from grey-box models such as electric analogy models (RC models) presented in figure 7 for forecasting the temperature or from aeraulic equations for forecasting the CO₂ concentration (see. figure 8 and equation 5).

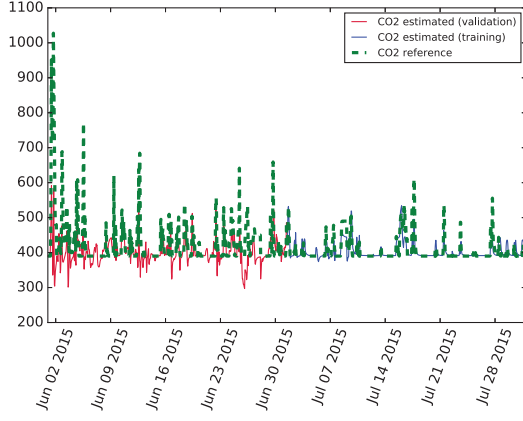


Figure 6: CO₂ concentrations of the ARX model estimated during the month of July and cross-validated in June

In the RC-model, T_n , T_{in} and T_{out} represent respectively the temperatures of the neighbouring room, the room considered and the outdoor
 R_n and R_{out} represent the resistors of the wall between the room and respectively the corridor and outdoor
 R_D and R_W represent respectively the resistors of the door and the window
 ζ_D and ζ_W represent respectively the opening rate of the door and the window
 R_i and C_i represent respectively the resistor and the capacitor of the fictive wall
 ϕ_{in} represents the internal gains: solar gains, electric gains and occupancy gains

Wu and Sun [15] tackled the same questions but using thermodynamics equations to enrich ARMAX models. They predict indoor air temperature in the Science and Engineering (SE) building of UC Merced. They succeeded to precisely forecast the room temperature in both short and long-terms from models trained with the data over a relatively short time.

In this section, only the prediction of CO₂ concentration is investigated since it is the one presenting the most significant difficulty to predict with accuracy. For that purpose, a simple aeraulic model presented schematically in figure 8 and mathematically in equations 5-7.

$$V \frac{d\Gamma_{in}}{dt} = - (Q_W + Q_D)\Gamma_{in} + Q_W\Gamma_{out} + Q_D\Gamma_n + S_{CO_2}^{body} n \quad (5)$$

$$Q_{out}(t) = Q_{out}^0 + \zeta_W(t)Q_W \quad (6)$$

$$Q_{corridor}(t) = Q_{corridor}^0 + \zeta_D(t)Q_D \quad (7)$$

where Γ_{in} , Γ_{out} and Γ_n represent the CO₂ concentrations of the office, the outdoor and the neighbourhood, Q_W

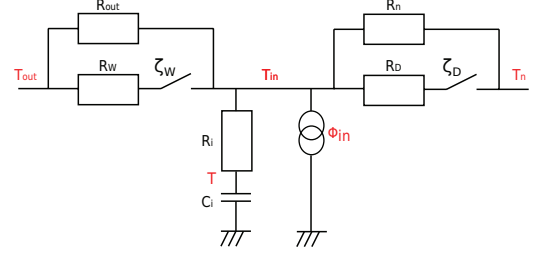


Figure 7: RC model

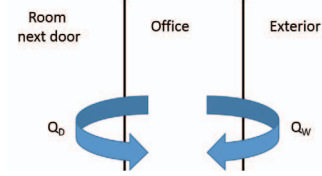


Figure 8: Aeraulic model

and Q_D the air flows coming from the window and the door, ζ_W and ζ_D the state of the window and the door, V the volume of the mono-zone office, $S_{CO_2}^{body}$ the CO₂ concentration expelled by one person and n the number of occupants in the room.

B. Application

To apply that principle to the ARX model defined in section V, firstly, from the aeraulic model the relevant variables to consider in the ARX inspired by physics were identified. Then, the training and validation periods must be properly defined to ensure that the dataset is sufficiently rich.

1) *Determination of coefficients:* From equation 5, the different variables encountered were used in order to configure the ARX model. As the structure of an ARX model is linear, terms with Γ_{in} are not considered here. Then, only the coefficients of Γ_{cor} are considered in this work. This yields to the variables listed below:

- $\Gamma_{corridor}$: the CO₂ concentration of the corridor
- ζ_D : the rate of door openings
- ζ_W : the rate of window openings
- $\Gamma_{corridor}\zeta_D$: the product between the rate of door openings and the CO₂ concentration of the corridor
- $\Gamma_{out}\zeta_W$: the product between the rate of window openings and the outdoor CO₂ concentration
- n : the occupancy

$$\Gamma_{office} = \alpha_0 + \alpha_1\Gamma_{corridor} + \alpha_2\zeta_D + \alpha_3\zeta_W + \alpha_4\Gamma_{corridor}\zeta_D + \alpha_5\Gamma_{out}\zeta_W + \alpha_6n \quad (8)$$

2) *Implementation:* Once the model is defined, the coefficients of the variables of interests of the ARX model inspired by physics can be estimated and the resulting model can be simulated. Results can be seen in figure 9 and values of the absolute average error and standard deviation in table II. It can be seen that both the absolute

average error and the standard deviation are decreased which allows to improve the forecast ability of the model and to increase the trust that end-users can put in the forecast. Especially, it can be seen that the values forecast with the ARX model inspired by physics stay most of the time in the physical fields which represents a great advantage in terms of trust.

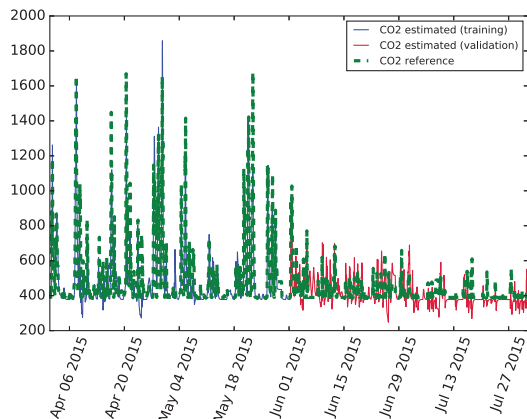


Figure 9: CO₂ concentration of the ARX model inspired by physics

| Model | Average Error | Standard Deviation |
|-------------------------|---------------|--------------------|
| ARX standard | 57.2248 | 78.3289 |
| ARX inspired by physics | 48.9711 | 66.0473 |

Table II: Comparison of absolute average error and standard deviation for the reference model and the ARX model inspired by physics

VIII. LIMITS

It has been observed that under certain conditions, ARX models can deliver good performance for forecasting CO₂ concentration. However some limits must be stated. The most important one is that ARX models require a sufficiently rich training dataset in order to forecast CO₂ concentrations otherwise performance of the model cannot be ensured.

IX. CONCLUSION

In this paper, ARX models of CO₂ concentration for energy services have been explored. They have been applied to a mono-zone study case located in Grenoble. It has been shown that for most of the situations, they have proved to be quite accurate with absolute average errors under 100 ppm. However, in some cases, the ARX model failed to predict precisely the CO₂ concentration as shown with the month of June. This can be explained by the specificities of this month which is the first of the year including a significant use of openings as well

as the heating system off. Then, as ARX models require a rich data-set, they are not reliable in every situation. Indeed, when new physical phenomena appear in the cross-validation period, it can be seen that ARX model does not properly forecast CO₂ concentration. For fixing this problem, a new structure has been proposed and implemented using physical equations to determine the variables of interest of the ARX structure. A simple aerualic model of the study case has been implemented and parsed in order to identify which variable of interests should be considered in the ARX structure. This ARX model inspired by physics has been applied again with the month of June. Results were concluding since it has greatly improved the CO₂ prediction and excluding the most majority of the unrealistic values.

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