ASSESSING THE RELEVANCE OF REDUCED ORDER MODELS FOR BUILDING ENVELOP

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ABSTRACT

The paper focuses on parameter estimation processes for physically meaningful models tuned online and define a process to determine whether a model is relevant or not for GMBA-BEMS tuning purpose. The proposed approach relies on the data coming from the PREDIS/MHI platform. The first step is to calculate realistic parameters with possible intervals because nonlinear optimization, required for physically explicit models, implies initial parameters. The next step is to find the best reduced order model structure using an iterative nonlinear optimization approach using recorded data that leads to parameter estimation. It is based on randomize initial values for parameters to measure the convexity of the search space in studying the convergence. Finally, the last step consists in enhancing the time zones where reduced order model does not fit well with the available data. It points out some non-modeled phenomena. It is based on a weighted iterative estimation method where weights depend on the estimation errors obtain at the previous step.

INTRODUCTION

The energy issue is one of the major challenges of the 21st century. Building related energy consumption accounts for a large part of the total energy bill. Researchers are therefore developing continuous performance monitoring, automatic diagnoses and home energy management systems to improve building consumption. Nevertheless, all these upcoming applications require reduced order models of the building envelop that can be tuned online. Many models are proposed in literature but models are related to specific goals, with specific time scales. Consequently, assessing the relevance of a reduced order model for a specific goal is a key issue. This paper proposes an approach making it possible to determine whether a reduced order model fits a specific goal or not. The paper focuses on models for Global Model Based Anticipative - Building Energy Management System (GMBA-BEMS) such as G-homeTech (Ha et al., 2012) but results can be extended to any usage that requires parameter estimation procedure for physical models by contrast with black box model not directly related to physics.

STATE OF THE ART

When interacting with a system, knowledge about how its variables are related, is needed. With a broad definition, these relationships among observed signals related to a system is called a model of the system (Ljung, 1999). However a model has to be useful i.e. to fit a specific goals. For instance, very detailed models are not useful for a GMBA-BEMS because they contain too much parameters that cannot be properly estimated with a parameter estimation approach. Data are indeed not sufficient and, when using a 1 hour sampling time, it is not meaningful to represent fast dynamics.

The paper focuses on parameter estimation processes for physically meaningful models tuned online and define a process to determine when a model is relevant or not for GMBA-BEMS tuning purpose. Roughly speaking, the simpler the model is, the more imprecise it could becomes and the more complex it is, the more difficult it is to get physically meaning parameters. The target is to find a criterion that points out when a model structure is suitable taking into account physical insights of the system plus identifiability of the dedicated parameters.

Many models have been proposed in scientific literature to represent the thermal behavior of the buildings. Linear regressive models such as ARX (Auto Regressive model with exogenous inputs) have been compared with time scaled identification methods (Malisani et al., 2010) and ARMA (Auto Regressive Moving Average) models for fault detection purposes (Chowdhury and Carrier, 2000). The structures of these models are very general and take into account neither the actual physical relations between variables, nor the existing links between parameters. It makes it difficult to extrapolate to other contexts: for instance, finding a ARX model representing the thermal behavior of a thermal zone is easy when the ventilation flow is constant but extrapolating this model to other levels of ventilation is not possible because physical parameters are distributed into several ARX parameters. These kinds of models may be used in real-time for a given context, using no other information than input-output data, considering the system as a black box. Based on all previous claims, using black box approaches is relevant for GMBA-BEMS purpose.

A physical analogy of thermic with electric circuits has been widely used in literature (G. G. J. Achterbosch, 1985; Hudson and Underwood, 1999; N. Mendes, 2001; G. Fraisse, 2002; M. M. Gouda, 2002; S. Wang, 2006). Most of these building models are based on a heat balance equation. By means of this equation, building thermal parameters such as thermal resistance and thermal capacitance plus indoor/outdoor and adjacent zones temperatures, metabolic heat of occu-

pancies and electric appliances can be adapted to the electric circuit components such as resistor, capacitor, voltage and current source. These models may be used to estimate the internal temperature and the heating/-cooling energy demand of buildings (Park et al., 2011; Deng et al., 2010).
The work of M. M. Gouda (2002) proved that a second order RC network with 3 resistors and 2 capacitors (3R2C) is sufficient to capture the fine conductive dynamic interaction between two spaces connected through a single wall (Deng et al., 2010) for simulation purpose. Deng et al. (2010) suggested a 1R1C lumped parameter circuit which presents a building thermal model using thermal-electric analogy. In order to avoid opinions about model structures and to get tangible conclusions dependent of model usage, a modeling process is going to be defined.

PROBLEM STATEMENT

The PREDIS/MHI (Monitoring et Habitat Intelligent) platform, located at the ENSE3 school of Grenoble Institute of Technology, is used as reference building in this paper. This platform is a tertiary low energy building that is highly instrumented where most of the energy flows are measured using different sensor technologies. The studied thermal zone is a classroom surrounded by 5 adjacent thermal zones (one adjacent thermal zone has been neglected because of its small impact). The classroom is equipped with a CMV (controlled mechanical ventilation) with a static air/air heat exchanger. This CMV may provide heat through air/water exchanger thanks to a fuel boiler. Data set and model quality assessment methodology are proposed in this paper to assess the obtained reduced order model.
The proposed approach relies on the data coming from the PREDIS/MHI platform. The first step is to calculate realistic parameters with possible intervals because nonlinear optimization, required for physically explicit models, implies initial parameters. The next step is to find the best reduced order model structure using an iterative nonlinear optimization approach using recorded data that leads to parameter estimation. It is based on randomize initial values for parameters to measure the convexity of the search space in studying the convergence. Finally, the last step consists in enhancing the time zones where reduced order model does not fit well with the available data. It points out some non-modeled phenomena. It is based on a weighted iterative estimation method where weights depend on the estimation errors obtain at the previous step.

THE PREDIS/MHI PLATFORM

A 3D representation of the PREDIS/MHI platform is given by figure 1. PREDIS/MHI platform is a low consumption building inside another building, which is a kind of warehouse. The typical year consumption are given by(regarding electricity, primary energy is obtained by multiplying by 2.58 the electric kWh, according to French standards):

- ventilation: 43kWhpe/m^2/year (pe=primary energy)
- hot water/air exchanger: 16kWhep/m^2/year
- lighting: 35kWhep/m^2/year
- other usage of electricity (computers): 56kWhep/m^2/year

In this paper, we focus on the thermal zone named *classroom*. It is surrounded by the following thermal zones:

- a space over the ceiling but also on one side of *classroom*, at temperature T_{space}
- a corridor at temperature $T_{corridor}$
- a downstair thermal zone at temperature T_{down}
- a adjacent thermal zone corresponding to an open space with offices at temperature $T_{offices}$
- a technical area named *control panels* in figure 1, which is not considered in the thermal modeling because the temperature inside this area is almost the same that in *classroom* but also because the exchange interface (a wall) is small.

The HVAC system is composed of:

- a double flux ventilation system with a rotative heat exchanger, whose measured efficiency is 50%. It renews air of both zones *classroom* and *offices*. 61% of the injected air is going to *classroom* and 39% is going to *offices*.
- 2 hot water/air heat exchanger, one for each zone of the PREDIS/MHI platform. Hot water is produced by a site fuel oil boiler.

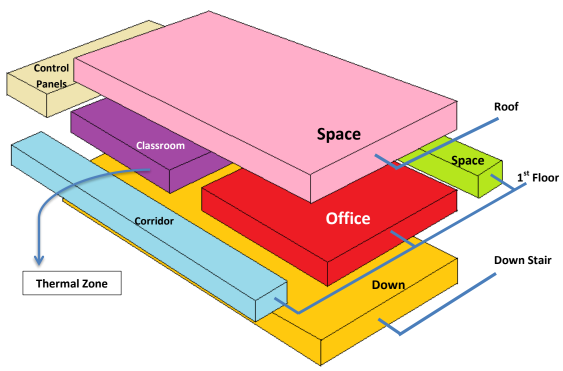

Figure 1: 3D overview of PREDIS/MHI platform

The relation between the rotation speed of a ventilation drive and the electric power consumption has been measured; results are given by figure 2.

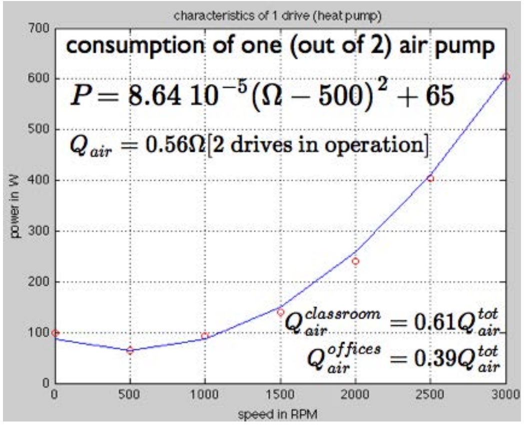

Figure 2: Characteristics of the air treatment unit

Because there are two drives for ventilation, the relation between consumed electric power P_{elec} and air flow Q_{air}^{tot} has been interpolated using a quadratic function:

$$P_{elec} = 1.728\ 10^{-4}(\Omega - 500)^2 + 65 \quad (1)$$
$$Q_{air}^{tot} = 0.56\Omega \quad (2)$$

where Ω stands for the speed of the two drives.

PREDIS/MHI platform is much more than a low consumption building: it is a tool for research. Indeed, it contains lots of sensors to measure all the energy flows, including energy transported by air and hot water. It contains different technologies of sensors: all the measurements can be accessed thanks to a unique RESTful web service connected to many different sensor protocols such as OPC for sensors/actuators controlled by a SCADA, Zigbee, X10, Oregon Scientific protocol, 8-20mA analogic protocol,...

CALCULATION OF PARAMETERS

Calculation of parameters based on physical considerations

In order to calculate parameter values based on physics, 4 interfaces have been defined, each interface is decomposed of parts. Thermal conduction, convection and radiation have been taken into account for each layer of a part within an interface but thermal bridges have been neglected. Because of the uncertainties about the materials and some dimensions, instead of searching average values, surrounding values have also been searched taking into account the minimum and maximum possible values for dimensions and physical characteristics of materials:

1. the equivalent thermal resistor for the classroom/offices interface $R_{offices}^{classroom} = 7.12\ 10^{-3} K/W \in [2.79\ 10^{-3}, 14\ 10^{-3}]$
   (a) wall part with pvc layer, air layer and pvc layer
   (b) glass part with glass layer, air layer and glass layer
2. the equivalent thermal resistor for the classroom/corridor interface $R_{corridor}^{classroom} = 23.2\ 10^{-3} K/W \in [7.91\ 10^{-3}, 52.7\ 10^{-3}]$
   (a) wall part with plaster sheet layer, rock-wool layer and wood layer
   (b) glass part with glass layer, air layer and glass layer
   (c) door part with wood layer, air layer and wood layer
3. the equivalent thermal resistor for the classroom/space interface $R_{space}^{classroom} = 7.12\ 10^{-3} K/W \in [2.79\ 10^{-3}, 14\ 10^{-3}]$
   (a) wall part with plaster sheet layer, rock-wool layer and wood layer
   (b) glass part with glass layer, air layer and glass layer
   (c) ceiling part with plaster sheet layer and rock-wool layer
4. the equivalent thermal resistor for the classroom/down interface $R_{down}^{classroom} = 5.66\ 10^{-3} K/W \in [1.91\ 10^{-3}, 22\ 10^{-3}]$
   (a) floor part with concrete layer, air layer and plastic layer

In order to evaluate the capacity, a cross correlation between the air temperature of the classroom $T_{classroom}$ and the outdoor temperature T_{out} has been done using a 18 days dataset. Figure 3 points out a time lag comprised between 1h and 2h. This result will be used to determined the equivalent capacity in the next section.

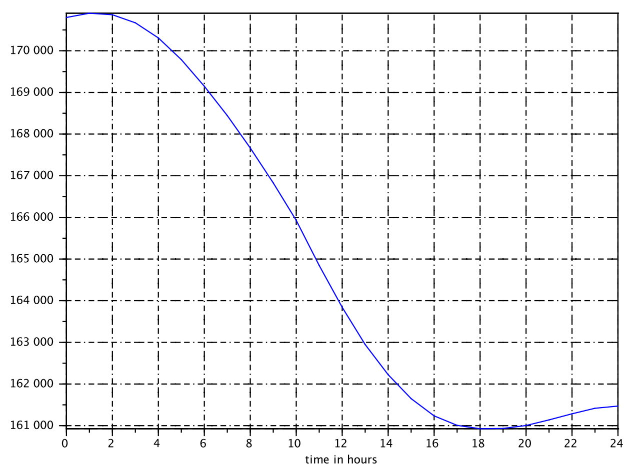

Figure 3: Cross correlation between $T_{classroom}$ and T_{out}

Obviously, all these values are approximation and should be adjusted in order to fit measurements.

Tuning of the calculated parameters

Adjusting parameters by identification requires a model. Because our aim is to configure a GMBA-

BEMS whose sampling time is 1 hour, dynamics lower than one hour would not appear. The model represented in figure 4 has been selected but this choice will be discussed in the next section. Reduced order physically explicit model is given by:

$$\begin{aligned} \frac{d}{dt}T_{wall}^{classroom} &= A(t)T_{wall}^{classroom} + B(t)u(t) \\ T_{classroom} &= C(t)T_{wall}^{classroom} + D(t)u(t) \end{aligned}$$

with:

$$A(t) = -\frac{\frac{1}{R_{down}^{classroom}} + \frac{1}{R_{office}^{classroom}} + \dots \frac{1}{R_{space}^{classroom}} + \frac{1}{R_{corridor}^{classroom}} + \dots \frac{1}{R_{wall}^{classroom}+R_{out}^{classroom}(t)}}{C^{classroom}}$$

$$B(t) = \frac{\begin{bmatrix} \frac{1}{R_{down}^{classroom}} \\ \frac{1}{R_{office}^{classroom}} \\ \frac{1}{R_{space}^{classroom}} \\ \frac{1}{R_{corridor}^{classroom}} \\ \frac{1}{R_{wall}^{classroom}+R_{out}^{classroom}(t)} \\ 1 \end{bmatrix}^T}{C^{classroom}}$$

$$C(t) = \frac{R_{out}^{classroom}(t)}{R_{wall}^{classroom} + R_{out}^{classroom}(t)}$$

$$D(t) = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \frac{R_{out}^{classroom}(t)}{R_{wall}^{classroom}+R_{out}^{classroom}(t)} \\ 0 \end{bmatrix}^T$$

$$u(t) = \begin{bmatrix} T_{down}T_{offices}T_{space}\dots \\ \dots T_{corridor}T_{out}\phi_{classroom} \end{bmatrix}^T$$

and:

- $T_{wall}^{classroom}$, the average temperature of the classroom walls
- T_{down}, the temperature of the 'down' zone
- $T_{offices}$, the temperature of the 'offices' zone
- T_{space}, the temperature of the 'space' zone
- $T_{corridor}$, the temperature of the 'corridor' zone
- $\phi_{classroom}$, the heat injected into the 'classroom' zone
- Q_{air}, the air flow provided by the CMV
- Q_{leaks}, the leakage constant air flow
- $R_{out}^{classroom}$, the equivalent thermal resistor representing the air flow exchanged with outide

The discrete time model for $T_s = 3600s$, is then given by:

$$\begin{aligned} T_{wall}^{classroom} &= e^{A(t)T_s}T_{wall}^{classroom} + \dots \\ & (e^{A(t)T_s} - 1)A(t)^{-1}Bu(t) \end{aligned}$$

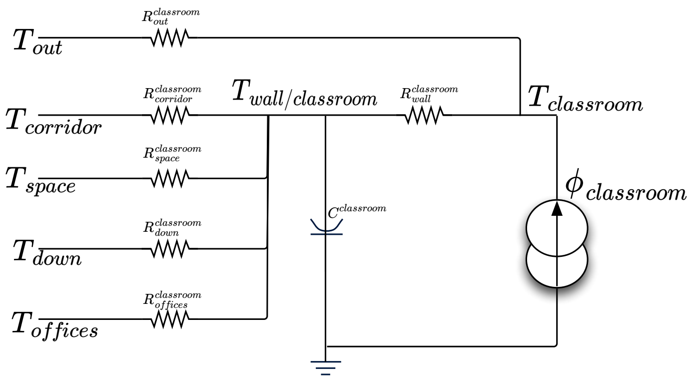

Figure 4: Selected model for PREDIS/MHI classroom

Nevertheless, calculated parameters cannot be directly used in the selected model. The transformation illustrated by figure 5 has been used to obtain model parameters. This transformation relies on the idea that heat fluxes have to remain identical if T_{int} and T_{out} are identical.

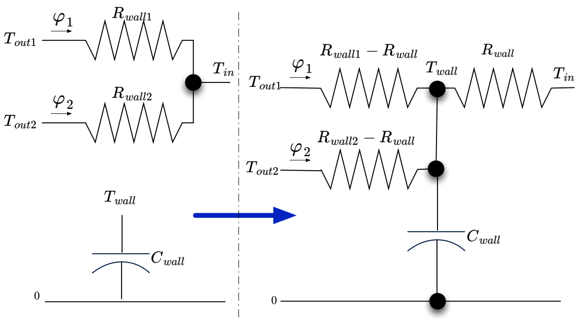

Figure 5: Model transformation used to adapt calculated parameter values

Consequently, the resistor R_{wall} has to be determined. Assuming symmetricity, we used:

$$\begin{aligned} R_{wall} &= \frac{1}{\frac{2}{R_{corridor}} + \frac{2}{R_{space}} + \frac{2}{R_{down}} + \frac{2}{R_{offices}}} \\ &= 1.23\ 10^{-3}K/W \end{aligned}$$

It yields:

$$\begin{aligned} R_{corridor}^{classroom} &= 22\ 10^{-3}K/W \in [6.7\ 10^{-3}, 51.5\ 10^{-3}] \\ R_{space}^{classroom} &= 5.89\ 10^{-3}K/W \in [1.5\ 10^{-3}, 12.8\ 10^{-3}] \\ R_{down}^{classroom} &= 4.4\ 10^{-3}K/W \in [0.7\ 10^{-3}, 20.8\ 10^{-3}] \\ R_{offices}^{classroom} &= 20.1\ 10^{-3}K/W \in [5.2\ 10^{-3}, 137\ 10^{-3}] \end{aligned}$$

The resistor $R_{out}^{classroom}$ has actually a time varying value because it depends on the ventilation air flow.

Because the air flow is known, this resistance can easily be calculated thanks to physics. It yields:

$$
\begin{aligned}
R^{classroom}_{out} &= \frac{1}{0.61(1-\zeta)c_{air}\rho_{air}(Q_{air}+Q_{leaks})} \\
& with \\
\zeta &= 0.5, \text{efficiency of the heat exchanger} \\
c_{air} &= 1006 J/kg.K \\
\rho_{air} &= 1.204 kg/m^3 \\
Q_{leaks} &= 10.03 m^3/s \\
Q_{air} & \; in \; \; m^3/S
\end{aligned}
$$

In the previous section, a time lag of 1 to 2 hours has been observed between $T_{classroom}$ and T_{out}. In order to estimate the value of the equivalent capacity, let's study the theoretical time lag Δ. Considering the first harmonic whose period in 24h, the delay between curves can be calculated because the model is 1st order. It yields:

$$\Delta = \frac{tan^{-1}\left(\frac{2\pi\tau}{T}\right)}{360} T$$

where $T = 24h$ and:

$$\tau = \frac{C^{classroom}}{\frac{1}{R^{classroom}_{down}} + \frac{1}{R^{classroom}_{office}} + \frac{1}{R^{classroom}_{space}} \cdots + \frac{1}{R^{classroom}_{corridor}} + \frac{1}{R^{classroom}_{wall} + R^{classroom}_{out}(t)}}$$

It can be reformulated as:

$$
C^{classroom} = \frac{T \times tan\left(\frac{360\Delta}{T}\right)}{2\pi} \times \ldots
\left(\begin{array}{c}
\frac{1}{R^{classroom}_{down}} + \ldots \\
\frac{1}{R^{classroom}_{office}} \cdots \\
+ \frac{1}{R^{classroom}_{space}} + \ldots \\
\frac{1}{R^{classroom}_{corridor}} + \ldots \\
\frac{1}{R^{classroom}_{wall} + R^{classroom}_{out}(t)}
\end{array} \right)
$$

It leads to $C = 7.1\ 10^6[3\ 10^6, 17.8\ 10^6]$.
Using a 18 days dataset, a interior point optimization algorithm has then been used to adjust the parameters according to their respective intervals. However it appears that the results where very sensitive to the proposed initial parameters. Moreover, most of the time, results are not physically meaningful. The phenomena is due to the fact that some parameters are not identifiable because of the dataset. It can be understood with a sensitivity analysis.
The measurements of a typical winter day have been used and the energy needs in kWh have been estimated according to different simulations when changing independently each parameter to its minimum and maximum values (average value is 14.2kWh):

parameter	min	max	variation
$R^{classroom}_{corridor}$	12.8	18.3	39%
$R^{classroom}_{space}$	14.2	38	168%
$R^{classroom}_{down}$	8	193	1302%
$R^{classroom}_{offices}$	12.7	18	37%
$R^{classroom}_{wall}$	14.2	39	175%
$C^{classroom}$	12.9	18.6	40%

It appears that the impact of $R^{classroom}_{corridor}$, $R^{classroom}_{offices}$ and $C^{classroom}$ is little and that these parameter values will be more difficult to identify. Therefore, to avoid weird values, the following optimization criterion has been used because norm 1 does not give more importance to larger error:

$$
\begin{aligned}
J &= \sum_i |T^{measured}_{classroom,i} - Tclassroom, i^{model}| + \ldots \\
& \cdots + \xi|\theta_{calculated} - \theta|
\end{aligned}
$$

where sample time is one hour.

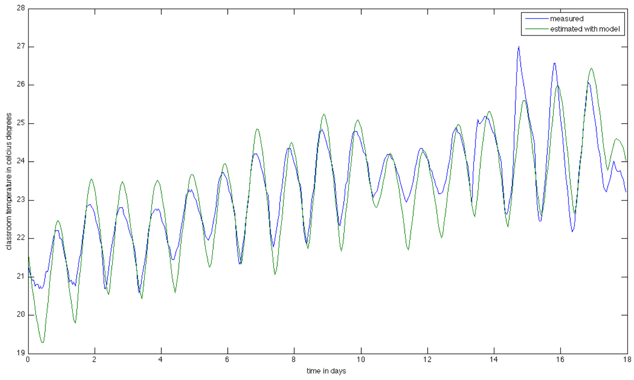

Figure 6: measured and simulated temperature for $Tclassroom$

Thanks to this objective, the optimization will modify a parameter value only if it reduces the optimization error. Consequently, if a parameter is not identifiable, it will be kept at its calculated value.
Based on the measurements for 18 days, the optimization process led to the following values:

$$
\begin{aligned}
R^{classroom}_{corridor} &= 22\ 10^{-3} K/W \rightarrow 22\ 10^{-3} K/W \\
R^{classroom}_{space} &= 5.89\ 10^{-3} K/W \rightarrow 6.4\ 10^{-3} K/W \\
R^{classroom}_{down} &= 4.4\ 10^{-3} K/W \rightarrow 4.4\ 10^{-3} K/W \\
R^{classroom}_{offices} &= 20.1\ 10^{-3} K/W \rightarrow 20.1\ 10^{-3} K/W \\
R^{classroom}_{wall} &= 1.23\ 10^{-3} K/W \rightarrow 1.2\ 10^{-3} \\
C_{classroom} &= 7.1\ 10^{6} K/W \rightarrow 15.3\ 10^{6} K/W
\end{aligned}
$$

The error between the measured temperature for $T_{classroom}$ and the one deduced from the model with optimal parameters is given by figure 6.

ASSESSMENT OF THE MODEL

Before assessing whether a model is suitable or not for a given goal, the quality of a model has to be defined:

- a good model has to explain relations between observed phenomena according to expected precision i.e. estimation error has to be small enough, especially during the validation process

- for BEMS, a good model has links with physics in order to be able extrapolate behaviors like modification of the ventilation

- the parameters of a good model has to be identifiable

The first point is easy to check but the second point is much more difficult. Sensitivity analysis may be used but the link is not direct with identifiability of physical models. In this section, a process is proposed to assess the quality of a model.

The second point leads to the approach that has been followed in this paper regarding the physics based modeling.

Regarding the third point, the basic idea is to check whether identification processes are ergodic. Therefore, the proposed process is to draw randomly initial parameters within their possible value set and check whether identification process leads to the same best parameters.

The curve of figure 7 is the main indicator to assess the quality of a model. It has to be as little as possible to yield good explanation capacity but also as flat as possible to guarantee ergodicity. In the PREDIS/MHI model, same value of criterion is obtained for 60% of the optimizations. It increases a lot for 30% of the optimizations.

Figure 8 points out how the parameters are distributed. If the model is good and if the dataset used for parameter estimation is rich enough, identified parameters should be gathered around a single best value. If the variance is important, it means that the parameter cannot be found either because the model contains to many parameters or because the data set is too poor. Regarding PREDIS/MHI, the parameters are from top to bottom: $R_{wall}^{classroom}$, $C_{classroom}$, $R_{down}^{classroom}$, $R_{space}^{classroom}$, $R_{offices}^{classroom}$, $R_{corridor}^{classroom}$, ζ and $T_{classroom}(0)$. Figure 8 stresses that parameters $C_{classroom}$ and $R_{space}^{classroom}$ are difficult to identify. Sensitivity analysis already pointed out that response is very insensitive to the value of $C_{classroom}$. Nevertheless, the result concerning $R_{space}^{classroom}$ points out that sensitivity analysis is not relevant to evaluate the quality of a model.

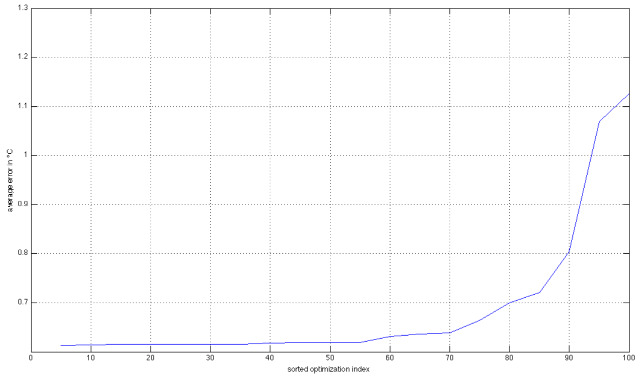

Figure 7: Ascendent values of obtained criteria for 20 optimizations

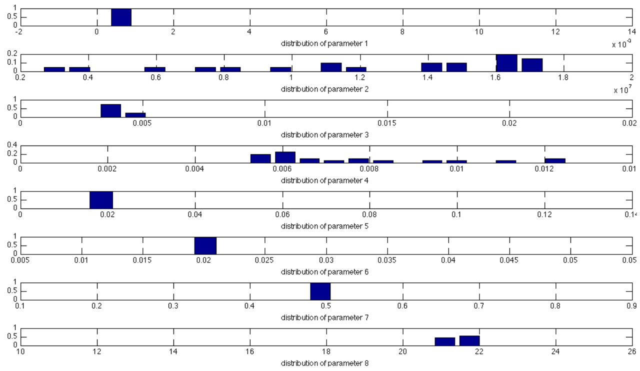

Figure 8: Distribution of parameters for 20 optimizations

CONSIDERING UNKNOWN PHENOMENA

In practical situations, adjusting parameters of a model in order to fit measurements is difficult because of the presence of unknown phenomena. Indeed, in the available data for PREDIS/MHI, there is no information about occupancy, neither about the solar gain or about the position of doors. It means that in practical situations, we have to cope with unknown phenomena. The problem to be solved is to give more important to period where there is not much unknown phenomena. It amounts to enhance the time periods where reduced order model does not fit well with the available data. This mismatch points out some non-modeled phenomena. An algorithm based on a weighted iterative estimation method where weights depend on the estimation errors obtain at the previous step is introduced. This weighting function is supposed to magnify the importance of well-matched intervals and minimize the importance of poor-matched intervals during optimization process of parameter estimation. If the estimation error becomes high, it means that there are some phenomena that have not been taken into consideration. Here is the function definition:

$$\omega(t) = |e(t)| \tag{3}$$

$$W(t) = 1 - \frac{\omega(t) - \min\ \omega(t)}{\max\ \omega(t) - \min\ \omega(t)} \tag{4}$$

where $\omega(t)$ is the absolute estimation error and $W(t)$ is the normalized reversed estimation error which is the weighting function in this case. The procedure of applying this weighting factor is shown in figure 9.

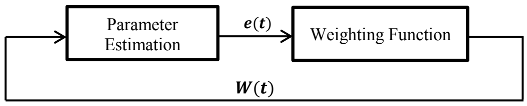

Figure 9: Weighting function algorithm

The idea is to repeat this loop for a certain amount of time (in our case 20 times) to finally assess the error sensitivity and analyze the model's behavior.
Figure 10 is the results of 20 weighted iterative estimations for a set of 6 days captured data. A good model should be able to reduce the error by the help of this weighting function. Studying step by step the results indicates some periods where there is neither significant change in error nor reduction and even some times the errors has increased in further estimations. In this experiment, by the help of two other available information the non-modeled phenomena are introducing.

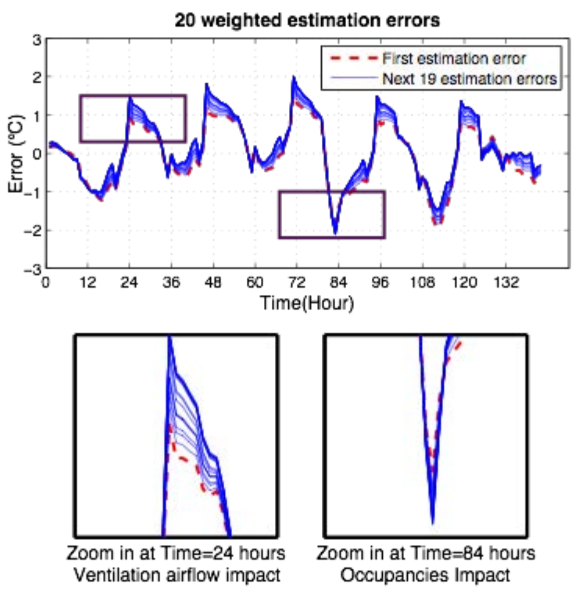

Figure 10: Results of 20 weighted iterative estimation with two samples of non-modeled phenomena

Estimated numbers of occupants from emitted CO2 and airflow rate of ventilation system have been correlated by the results of estimations in figure 11. Five peaks over midnights are correlated at the same time of maximum airflow during midnight. Indeed, two negative peaks occur at the same time of high occupancy in fourth and fifth days. Consequently, it is feasible that the model does not take into consideration the presence of occupants and also air flow variation of ventilation system.

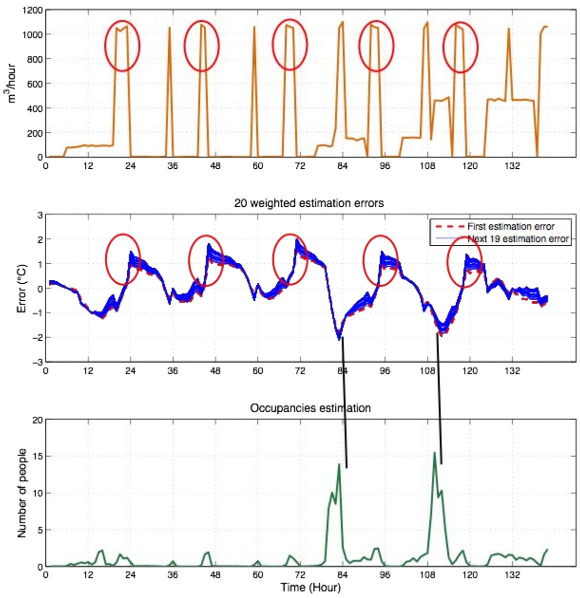

Figure 11: Upper plot: airflow of ventilation system captured by sensors, Middle plot: weighted estimation errors, Lower plot: number of estimated occupancy

CONCLUSION

This paper proposes a methodology to assess reduced order physically explicit models. It relies different steps. First step consists in calculating parameters with bounds from physics and to proposed a relevant model structure according to the expected usage (paper focuses on models for GMBA-BEMS). The second step relies on a nonlinear optimization algorithm that both minimize the error between estimations and measurements but also keeps parameters close to the values calculated using physics in order to avoid weird values for non identifiable parameters. The third step consists in the assessment of the model quality using 2 curves: one points out whether best parameters can be found whatever the initial parameters are (ergodicity) and the other represents the parameter distribution in order to appreciate parameter identifiability which depends both on the selected model and on the used dataset. This procedure has been applied to the PREDIS/MHI platform. Physically explicit parameter values have been found but it turns out that it is still difficult to identify some parameters. Finally, a procedure based on a recursive weighted parameter estimation procedure has been proposed. It makes it possible to automatically give more important to time periods where there are few unknown phenomena.

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