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Determination Of Relevant Models Structures for Self-Learning Energy Management System

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 performance monitoring, diagnosis and energy management systems to improve building consumption. Nevertheless, all these upcoming applications require reduced order models of the building envelope. Those models have to describe the physics while neglecting irrelevant details of the high order model. Many models are proposed in literature but models are related to a specific goal with a specific time scale. Consequently, assessing the relevance of a reduced order model for a specific goal is a key issue. This paper proposes an approach to determine relevant structures to fit energy management system with one hour time step and 24h as time horizon. Indeed, several methods to determine the dominant parameters for the modelling were tested. . This will help to simplify the model in order to improve the identification results.

Keywords: parametric estimation, white box modelling, sensitivity analysis, parametric scattering

Introduction

Nowadays, the energy estimation methods for building are based on simulation: typical values are introduced in a model. But the variance of the prediction error only based on knowledge is approximately between 50% and 200% (C. Turner et al., 2008). Nevertheless, calibration allows reducing the uncertain values. Reduction thanks to a simplified physics is useful to reduce the number of uncertain variables, and at the same time, it improves the robustness of the calibration. The more parameters a model has, the more it is difficult to identify them. The so-called white-box models are considered for parameters estimation because they are able to establish a link with physics, which is useful for extrapolation to any kind of context, not only the one corresponding to the training datasets. The quality of a parameter estimation process consistent with energy management purpose is highly depending on the dataset but also on the

model structure. A 1h time step allows taking into account the thermal inertia of the building and anticipate its behaviour in the short term to be able to manage energy. Indeed, a model has to be useful to fit specific goals. A very detailed model is not relevant for an energy management system because it contains too many parameters that cannot be properly estimated with a parameter estimation approach (S., Sarabi et al., 2013). The paper proposes a methodology to design a suitable model structure and to assess the consistency with learning purposes.

Many models have been proposed in the scientific literature to represent the thermal behaviour of the buildings. A physical analogy of thermic with electric circuits has been widely used (G.G.J., Achterbosch et al., 1985 ; G. Hudson et al., 1999 ; N. Mendes et al., 2001 ; G. Fraisse et al., 2002 ; M.M. Gouda et al., 2002 ; S. Wang, 2006). These models may be used to estimate the internal temperature and the heating/cooling energy demand of buildings (H. Park et al., 2011; K., Deng et al., 2010).

In order to improve the identification process in simplifying the number of parameters, a sensitivity analysis is conducted. The sensitivity analysis methods deal with the impact of uncertain input parameters on the output variable. Generally, this kind of analysis allows reducing the complexity of a model in eliminating the parameters, which have a negligible effect on the output variable. This hypothesis will be tried to be validated with the PREDIS datasets. Thus, a given nominal value for those parameters is sufficient (A. Saltelli et al., 2008). The method used for sensitivity analysis is the MORRIS method. Thanks to a sensitivity ranking, the parameters will be based on physical estimation in order to improve the identification process in simplifying the complexity of the model. Then, in order to improve the parametric scattering, a second ranking method of parameter to be fixed will be studied too. Both approaches will be compared and validated in order to provide the best

model for a smart identification process, that is to say the results have to be accurate, reproducible and quickly recalibrated.

1. Case Study

The platform

A detailed analysis of a platform, named PREDIS/Smart Building (H-A., Dang et al., 2013), has been done. It is composed of two rooms, an office and a classroom, surrounded by other rooms: corridor, others offices and technical rooms (fig1.a.). The studies room in the following paper will be the classroom but the same kind of study could be done for the office. The classroom is located at the first floor under an empty space which is called the shed.
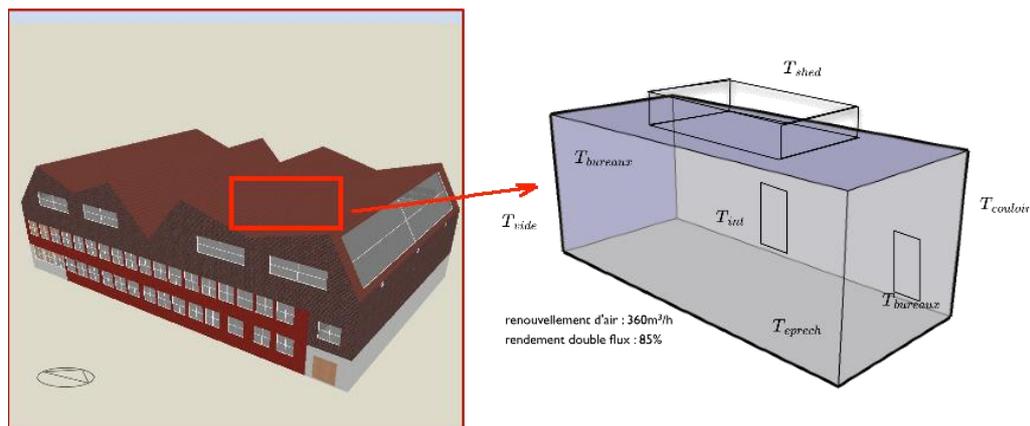

Figure 1 - location and 3D view of the classroom of PREDIS

The floor is composed of concrete slab that absorbs temperature variations. Indeed, the other walls are just thin plates of plasterboard. The thermal inertia of a room depends on the mass of the materials that constitutes it. Thus, the thermal masses of the walls are very low compared to the slab. All the dynamics of the room are considered as related to the slab. That is why a 2R1C structure is next to the T_{down} input in the equivalent electrical circuit. The HVAC resistance stands for the dual flow ventilation system and varies according to the fan speed.
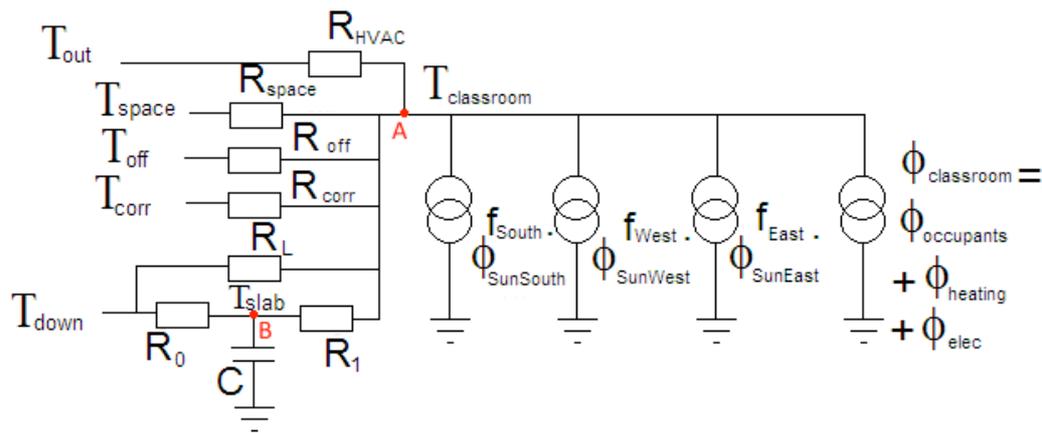
Figure 2 - equivalent electrical circuit of the classroom[CS1]

The equivalent electrical circuit stands for the heat exchanges between the classroom and the adjacent rooms and contains all the heat supply of the room. Indeed, on the left, there are the adjacent room's temperatures of the empty space, the corridor, the office and the down temperature. They are relied to the classroom temperature with thermal resistances and capacitance with stand for the insulation and inertia of the wall, respectively. On the right, there are the injected heat inputs which are directly connected to the classroom temperature.[AL2]

The following table lists the parameters identified in Fig. 2 and their description[CS3]

R_{space}, R_{office}, $R_{corridor}$	The thermal resistances of the adjacent rooms
R_L, R_0, R_1	The thermal resistances of the down room
C	The thermal capacitance
efficiency	The efficiency of the dual flow ventilation system
f_{East}, f_{South}, f_{West}	The coefficients of the solar flux
T_{w0}	The initial temperature of the slab
$P_{residual}$	The residual power in order to adjust the uncertainties about power inputs
airLeak	The leakage coefficient of the dual flow ventilation system

Table 1 - List of parameters ~~to be identified~~

Each interface is composed of wall and often of glasses. According to the different layers of materials, the thermal resistances are calculated thanks to the following equation:

$$\frac{1}{R_{interface}} = \frac{S_{wall}}{\frac{1}{h_1^{wall}} + \frac{e_{layer1}^{wall}}{\lambda_{layer1}^{wall}} + \frac{1}{h_{1/2}} + \frac{e_{layer2}^{wall}}{\lambda_{layer2}^{wall}} + \frac{1}{h_2^{wall}}} + \frac{S_{glass}}{\frac{1}{h_1^{glass}} + \frac{e_{layer1}^{glass}}{\lambda_{layer1}^{glass}} + \frac{1}{h_{1/2}} + \frac{e_{layer2}^{glass}}{\lambda_{layer2}^{glass}} + \frac{1}{h_2^{glass}}} \tag{1}$$

Where:

S is the surface;

h is the heat transfer coefficient;

e is the thickness of a layer;

λ is the thermal conductivity of a layer.

The previous equation describes a situation where an interface is composed of wall and glasses and where each area has two layers. If the layers are opaque, then there is not the term $\frac{1}{h_{1/2}}$ between the two layers.

The calculation of the thermal capacitance is done as following:

$$C_{interface} = \sum_{all\ layers} V_{layer} * d_{layer} * C_p^{layer}$$

Where:

V_{layer} is the volume of the layer;

d_{layer} is the density of the layer;

C_p^{layer} is the heat capacity of the layer.

These calculations give the initial values of the parameters. [AL4]Then, uncertainties and the fact that the building is evolving over time are taken into account by the introduction of uncertainty bounds on parameters that delimit the search space. The parameters values are sought in those validity ranges. If the identified values are beyond, it would not be considered as a good result because there is no physical meaning.

The temperatures of adjacent rooms are obtained by sensors. The sensors have a relative accuracy of more or less 0.5 degrees. The heat inputs are obtained by calculation from measured variables. Heating is computed from the temperature difference upstream and downstream of the hot water coil and the water flow. All these variables are the inputs of our model because they all contribute to the temperature of the classroom, which is the output.

To perform this study, a first dataset of thirty days was used. Because of technical problems with the recording of the data, this dataset is the longest that we have without errors and gap. The dataset was recorded between October and November of 2013. [CS5] It was divided in two datasets – one for the identification and one for the validation.[CS6] Hence, they have been recorder under the same kind of conditions.[AL7]

The data obtained from sensors are not always reliable (incorrect or missing values), which has to be taken into account in the parameter estimation process. Furthermore, because of the spectral poverty of the signals, it is even more difficult to identify parameters because of a resulting lack of estimability.
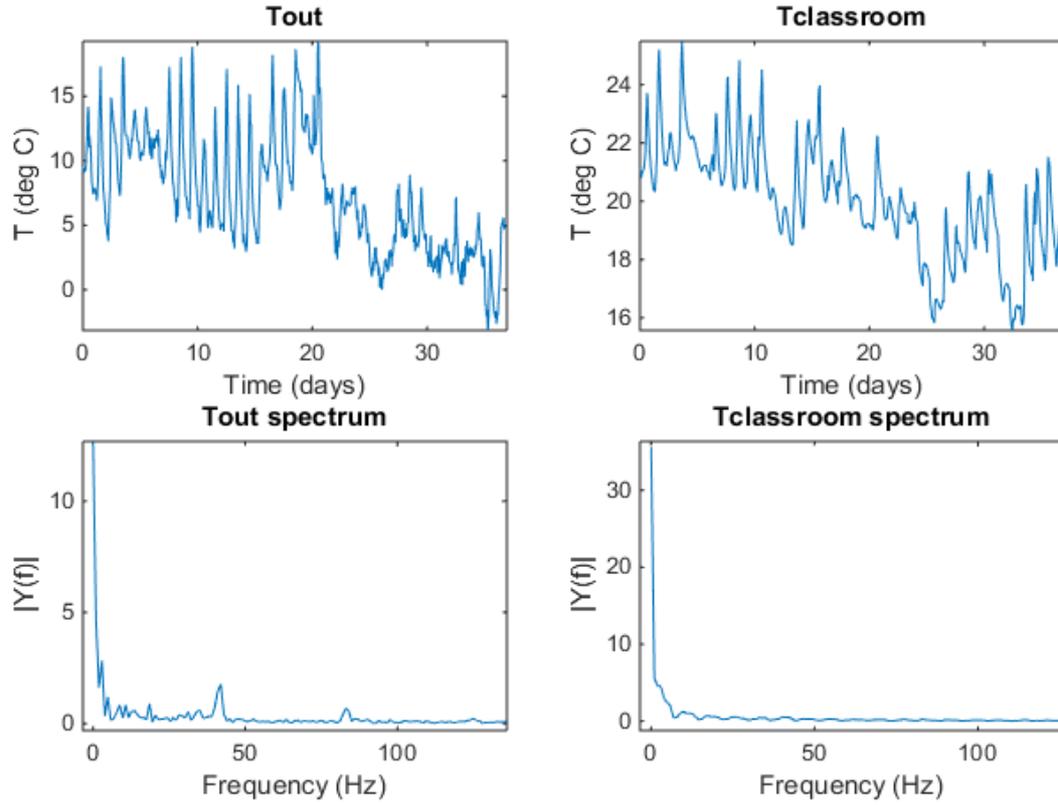
Figure 3 - T_{out} and $T_{classroom}$ spectrum[CS8]

This figure shows the spectral content of the outdoor temperature and of the classroom temperature of the dataset used for the study. The poverty of the signal spectrum of the classroom temperature could be a reason of the identification difficulty of the model.[AL9]

Problem Statement

The following equations are written for the equivalent electrical circuit:[AL10]

$$
\begin{cases}
\dfrac{dT_{slab}}{dt} = \dfrac{1}{C} * \left(\dfrac{T_{classroom}}{R_1} + \dfrac{T_{down}}{R_0} - T_{slab} * \left(\dfrac{1}{R_1} + \dfrac{1}{R_0} \right) \right) \\
T_{classroom} = R_{eq} * \left(\Phi_{tot} + \dfrac{T_{out}}{R_{HVAC}} + \dfrac{T_{corr}}{R_{corr}} + \dfrac{T_{off}}{R_{off}} + \dfrac{T_{space}}{R_{space}} + \dfrac{T_{down}}{R_L} + \dfrac{T_{slab}}{R_1} \right)
\end{cases}
\tag{1}
$$

With $R_{eq} = \dfrac{1}{\frac{1}{R_{HVAC}} + \frac{1}{R_{corr}} + \frac{1}{R_{off}} + \frac{1}{R_{space}} + \frac{1}{R_L} + \frac{1}{R_1}}$;

$\Phi_{tot} = \Phi_{occupants} + \Phi_{elec} + \Phi_{heating} + f_{East} * \Phi_{SunEast} + f_{South} *$

$\Phi_{SunSouth} + f_{West} * \Phi_{SunWest}$;

$R_{HVAC} = \dfrac{1}{(1-efficiency)*c_{air}*p_{air}*\frac{(airLeak+0.61*Ventil_{mode})}{3600}}$;

Where c_{air} stands for the air specific heat, p_{air} for the air density and $Ventil_{mode}$ corresponds to the ventilation mode among four modes: recycling, low exchange, high exchange and free cooling. All these modes are bearings fixed to discretize the ventilation variable.

For a better understanding of the equations, all the parameters are bolded.

Hence, the A, B, C, D matrix of the state-space system can be calculated as following:

$$\begin{cases} \dot{X} = AX + BU \\ Y = CX + DU \end{cases} \quad (2)$$

With:

X the state space variable which stands for the slab temperature

Y the output which is the classroom temperature

U the matrix of solicitations which gather adjacent rooms temperatures and internal heat flows.

Thanks to the *fmincon* function of Matlab, the model is optimized with an active-set algorithm in order to minimize the gap between the temperature obtained by sensors and the one obtained by the model in adjusting the parameters values.[AL11]

~~The algorithm tries to minimize the average error between the temperature obtained by simulation and the temperature obtained by sensors in adjusting the values of the parameters in the validity ranges.~~[CS12] In order to assess the quality of the model, the identification process is computed several times and each time, the initial parameter values are obtained by random guesses between the validity ranges.

Thus, some statistics about the error behaviour can be done and the parameter scattering between the validity ranges can be observed.

These aspects which will be called "quality criteria" thereafter were observed for the initial model with 14 parameters. [AL13]~~Let us see this kind of results for the initial model~~ [CS14]~~with 14 parameters to be identified.~~
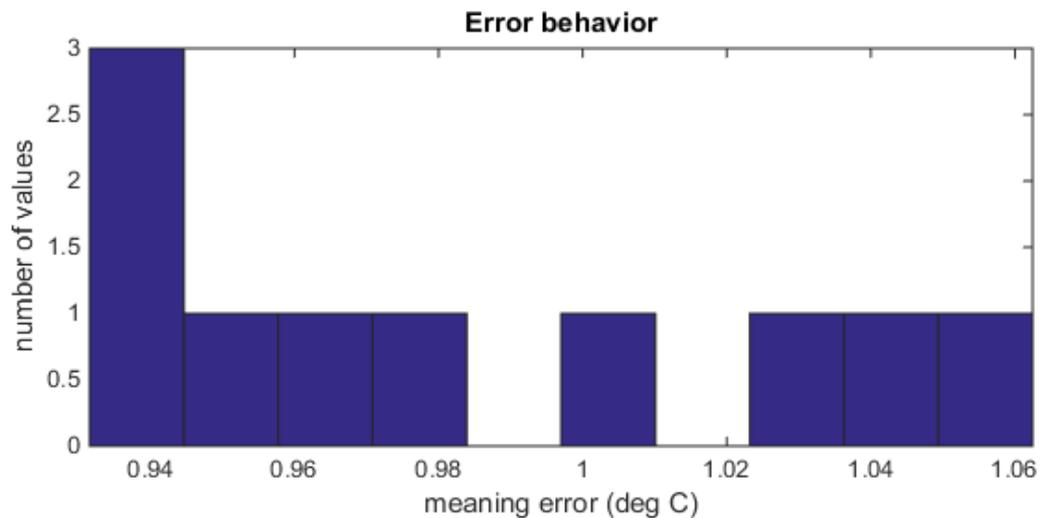

Figure 4 - Error scattering

This histogram shows all the average errors obtained for all the identifications. This value is the one that the algorithm tries to minimize. So, a small width and a small average value are the characteristics of a good model which should always converge to the same value. The following curves stand for the best identification obtained among all the identifications and which can be seen on the left side of the previous histogram.
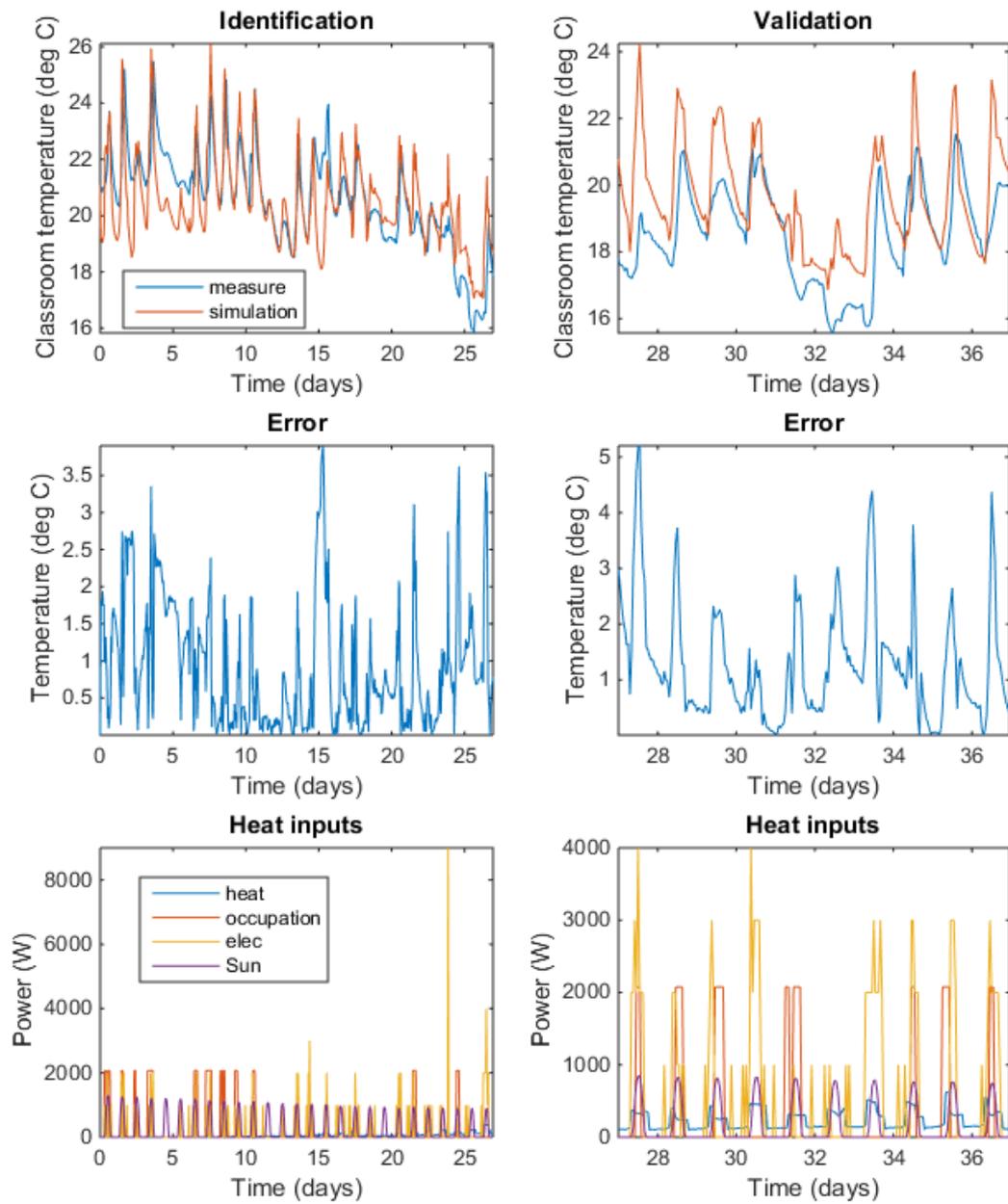
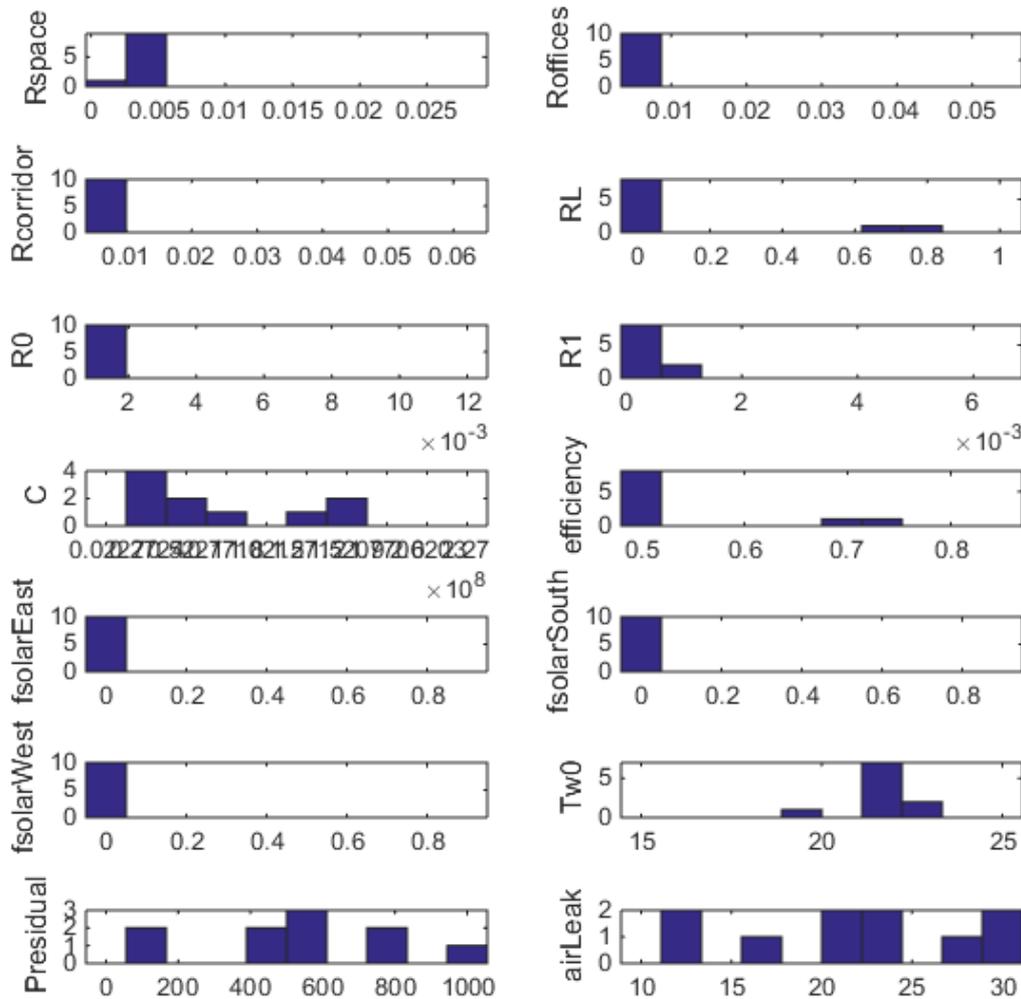Figure 5 – Identification and validation

Figure 6 - parametric scattering

The previous graphic shows the parametric scattering on their respective validity ranges. Several parameters are very scattered. This result reflects a difficulty of the algorithm to identify them.

Finally, this approach which consists in making several identifications in order to find the best one is a first method to obtain a good model. The aim of this paper is to improve how to find the best model trying to improve both the scattering results and the time calculation. The complexity of the model compared to the poverty of the inputs signals could be a reason for those bad results. So the number of parameters has to be reduced in fixing the parameters which have the less impact on the output variable and which disturb the algorithm during the identification process.

Reduction method

The quality of a model is highly dependent on his structure and the choice of its parameters. Some parameters are scattered in the validity ranges (each identification give a different value). This result reflects the difficulty of the algorithm to identify a parameter. A sensitivity analysis can allow solving the identifiability issues.

This is in order to improve the quality of the model that a local sensitivity analysis was conducted. The purpose of this analysis is to classify the parameters from the less sensitive to the more sensitive and to fix one by one the less sensitive ones. Each new model, which has one parameter less, is computed several times in order to observe the error behaviour and the parametric scattering.

Comparing the results, the best approach has to be found. First of all, a global sensitivity analysis with MORRIS method (A. Saltelli, 2008) was conducted. Then, an approach which will fixed one by one the more scattered parameters in order to improve the global scattering (on error and on parameters) was tested.

The results were compared and the model with less parameters to be identified which give the better result compared to the initial model with 14 parameters will be validated.

2. Sensitivity Analysis

The purpose of a sensitivity analysis is to prioritize the sources of uncertainty in order to reduce the output variability and to simplify the model. The MORRIS method has been use to classify the parameters by sensitivity.

Method description

The MORRIS (M.D. Morris, 1991) method is a qualitative method which allows classifying the parameters in three groups depending on their effects:

- The negligible effects

- The linear effects without interactions

- The non-linear effects with or without interaction

The MORRIS method measure the sensibility of each parameter thanks to the expectancy calculation of the variations: $\mu_i^* = E(|d_{X_i}|)$. If the value is important then the effects are significant (in average) and the model is sensitive to variations.

It also measures interactions and non-linear effects with the standard deviation: $\sigma_i^* = \sigma(d_{X_i})$. If the value is important, then the effects are differents from each others and depends on either the input (then the effect is non-linear) or the others parameters (then there is interaction).

The method has been applied to our parameters. The following figure shows the obtained results.
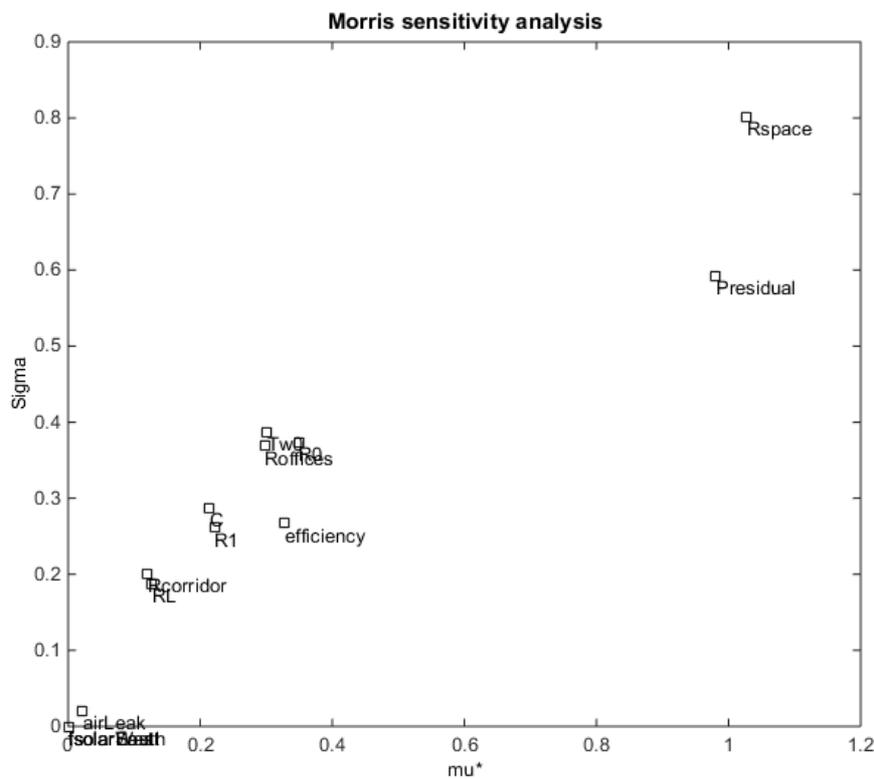

Figure 7 - sensitivity ranking of the parameters with the MORRIS method

This sensitivity analysis implies this ranking of the parameters:

fsolarWest	fsolarSouth	fsolarEast	airLeak	RL	Rcorridor	R1	C	efficiency	Roffices	Tw0	R0	Rspace	Presidual

Table 2 - Sensitivity Ranking (from the least sensitive to the most sensitive) with the MORRIS method

Result of the reduction by the sensitivity analysis order

So, the parameters were kept fixed to their nominal values one by one following the sensitivity ranking. Each time, the algorithm is computed several times and the quality criteria are finally compared.

The following figure allows to observe how evolves the error scattering during the reduction process. Indeed, the horizontal axis stands for the number of parameters that have to be identified – the others are fixed – whereas the meaning error is on the vertical axis. Hence, the largeness of the gap between the horizontal curves shows the ability of the algorithm to converge always toward the same error value or not. If the gap is small, it means that the algorithm is quite stable. The lowest curve gives information about the best accuracy that can be achieved by the model. The best compromise would give an error with a gap as small as possible while maintaining a good precision.

The results were observed with a validation dataset. For each model, the identified parameters were used to compute the output variable without identification.
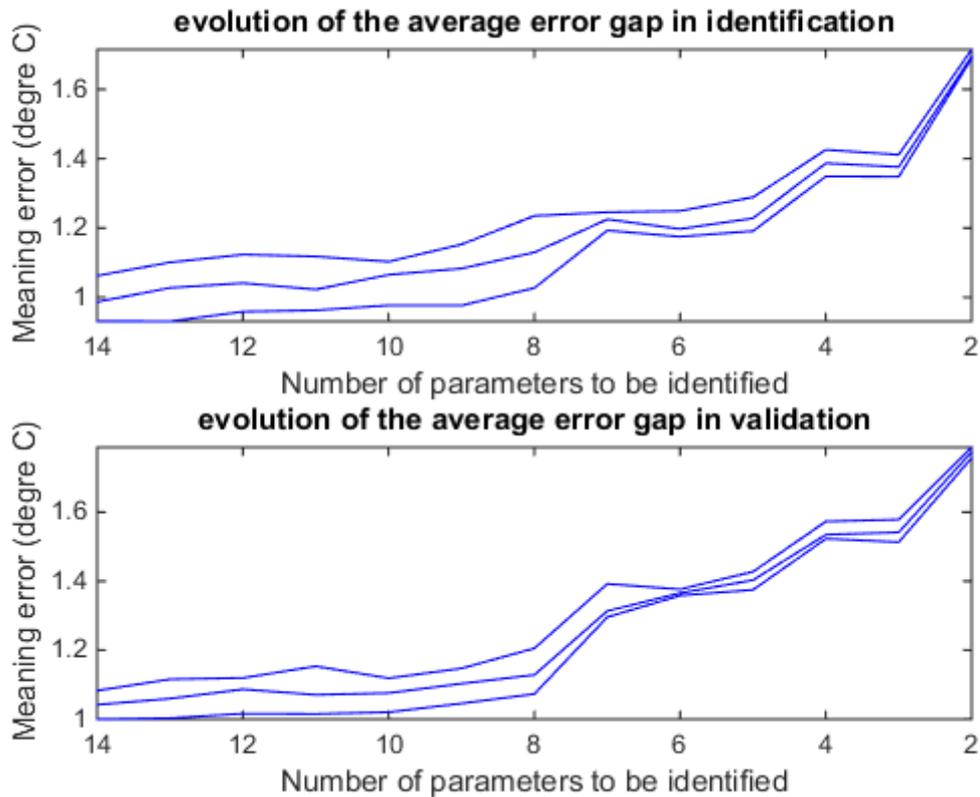
Figure 8 - evolution of the meaning error scattering for the reduction by the MORRIS sensitivity analysis method

By looking at the curves, there is no optimal configuration of fixed parameters. Indeed, despite a decrease of the scattering, the accuracy is rising.

The following figure shows the evolution of the normalized standard deviation for each parameter. The red curve stands for the average normalized standard deviation.

A good reduction would improve the global scattering of the parameters and the red curve should decrease.
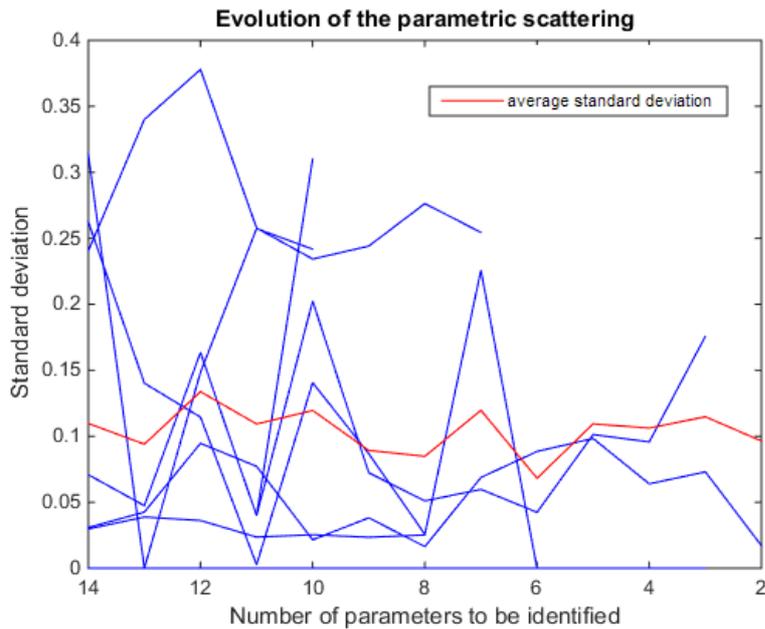
Figure 9 - Evolution of the parametric scattering for the reduction by the MORRIS sensitivity analysis method

Conclusions

Because the sensitivity analysis did not give satisfying results, another way of fixing the parameters was studied. Indeed, the parameters were fixed according to their scattering and classifying by their standard deviation.

3. Reduction of the number of parameters by reduction of the scattering

Let us see if the simplification of the model according to the scattering parameters value gives better results than previously.

Method

The following process was used:

Step 1 – The identification algorithm is computed n times which a different initial set of parameters obtained by random guesses between the validity ranges

Step 2 – The identified parameters values are observed between the validity ranges

and classify by normalized standard deviation

Step 3 – The more scattered parameter is fixed

The steps 1, 2 and 3 are repeated until it remains only two parameters. Then, the quality criteria are observed in order to choose the best model – the one which offers the best compromise between scattering, reliability and precision.

This approach gives a new ranking for the parameters to be fixed which becomes as following:

MORRIS	scattering method
fsolarWest	airLeak
fsolarSouth	C
fsolarEast	Presidual
airLeak	efficiency
RL	RL
Rcorridor	Rspace
R1	Tw0
C	Rcorridor
efficiency	R1
Roffices	R0
Tw0	fsolarEast
R0	fsolarSouth
Rspace	fsolarWest
Presidual	Roffices

Table 3 - Ranking of the parameters for being fixed

Results of the reduction

As previously, the error behaviour and the parametric scattering evolution are observed and compared to the previous results.
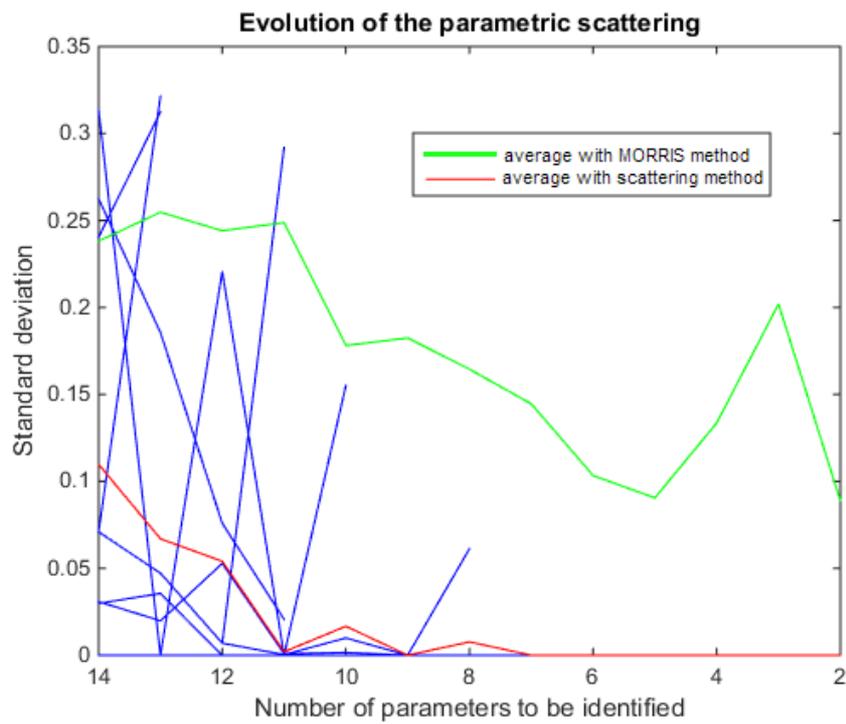
Figure 10 - Evolution of the parametric scattering for the reduction by the scattering method

In red, this is the meaning standard deviation of all the remaining parameters with the

reduction method with the parametric scattering. The green one corresponds to the average
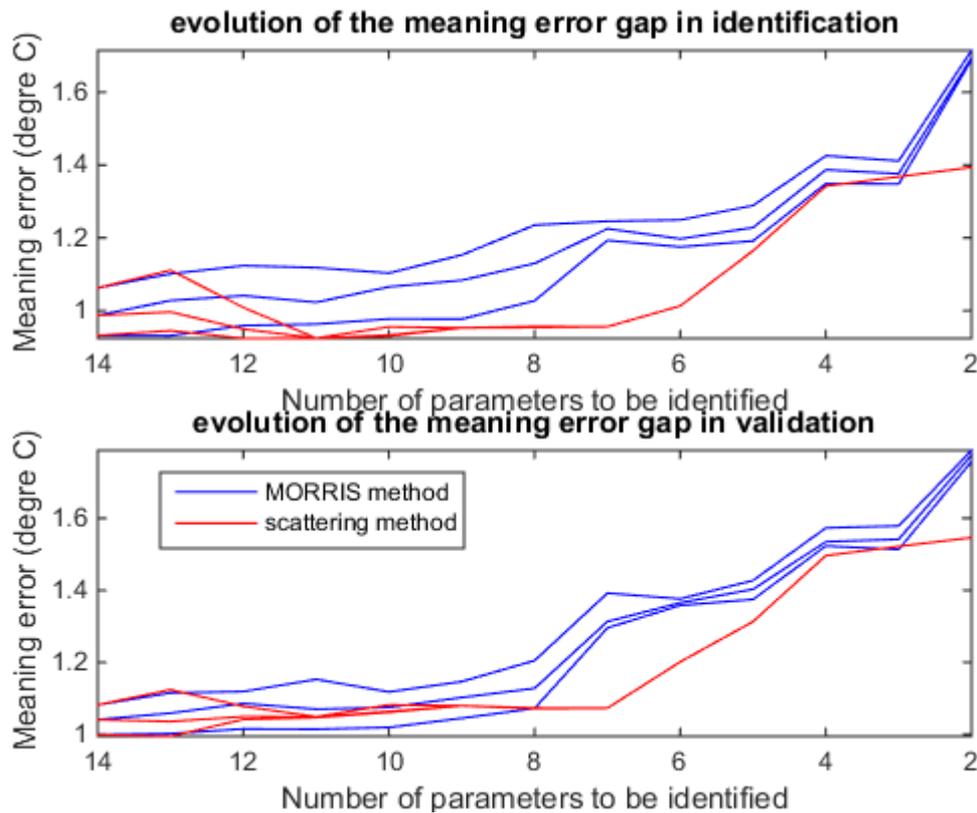
obtained with the MORRIS method.

Figure 11 - evolution of the average error gap in identification and in validation, comparison of the two reduction methods

The results given by the scattering reduction (in red) are much more relevant than the previous one (in blue). Indeed, two models seem to give good results, both in term of precision, stability and parametric scattering: the model with 11 parameters and the model with 9 parameters to be identified.

Conclusion

Thus, the method provides a model which presents several advantages compared to the first identification process which computed several optimizations and give the best one among all the identifications.

Thereafter, the two models with 11 and 9 parameters will be tested on other datasets and will be called respectively: the *9-parameters-model* and the *11-parameters-model*.

4. Validation

In order to validate the previous models, some tests have to be done with others datasets: one in winter, with heating and one in summer without heating.

First of all, the same process was tested on new datasets of PREDIS. This step will allow seeing if the same kind of results is obtained. Then the best models would be the 11 or the 9-parameters-model and the fixed parameters would be the same. If this is not the case, it would however allow seeing if a better model that the initial one can be found. Finally, the 9 and 11-parameters-model will be tested in order to know if those models can work with most datasets or not.

Reduction of the number of parameters to be identified

As previously, for each model, n optimisations are computed and the parameter with the biggest standard deviation was fixed. The following table shows the order obtained for the new datasets compared to the old one:

Initial dataset	February's dataset	June's dataset
airLeak	RL	Rcorridor
C	Tw0	R1
Presidual	Presidual	Tw0
efficiency	C	C
RL	airLeak	Presidual
Rspace	fsolarEast	efficiency
Tw0	R1	RL
Rcorridor	R0	R0
R1	fsolarSouth	Rspace
R0	Rspace	airLeak
fsolarEast	efficiency	Roffices
fsolarSouth	Rcorridor	fsolarWest
fsolarWest	fsolarWest	fsolarEast
Roffices	Roffices	fsolarSouth

Table 4 - ranking of the parameters to be fixed for the new datasets

The results are closed but not exactly the same. Let us see the quality criteria. The results are always compared to the initial dataset results.
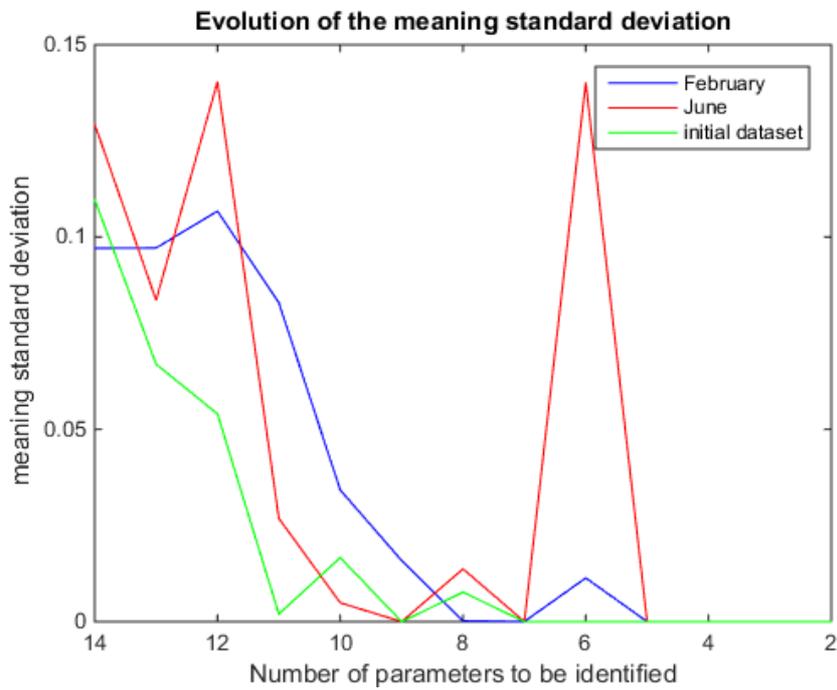

Figure 12- Evolution of the parametric scattering for two new datasets
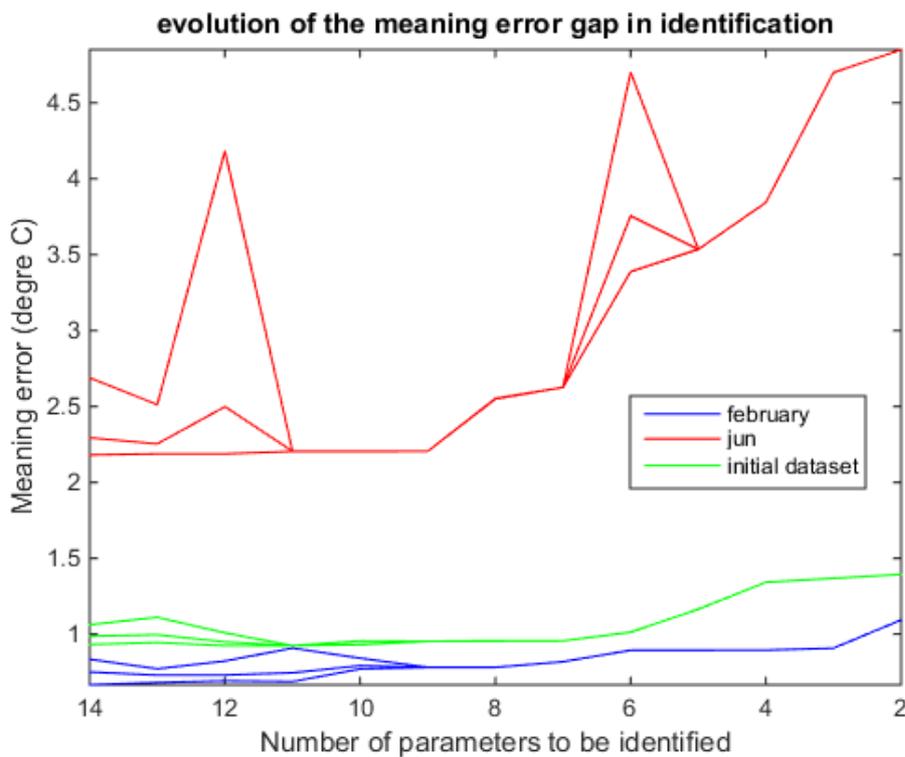

Figure 13 - Evolution of the meaning error gap for two new datasets

For the dataset of June, the best model seems to be the model with 9 parameters to be

identified whereas the best model for the dataset of February seems to be the model with 8 parameters to be identified.

Thus, despite the fact that the best model for this dataset does not match the best model of the initial dataset, this process nonetheless shows that a better model that the initial one with all the parameters and several identification exist for most datasets.

Thereafter, we will call this new model which stands for promptly the best model for this dataset will be called the « x-parameters-model ». This model will be compared to the others models in order to find the better compromise.

Tests of the 9 and 11-parameters-model

Because the process is obviously too long to give the best model, let us see if the models obtained with the initial dataset could give satisfying results.

For the model with 11 parameters to be identified, three parameters have been fixed: $P_{residual}$, airLeak and the capacitance. As to the model with 9 parameters, efficiency and R_L has been fixed in addition.

For each model, the identification is computed several times in order to make statistics. Then, the results are compared to several situations:

- The initial model with all the parameters

- The *11-parameters-model* : obtained with the initial dataset

- The *9-parameters-model* : obtained with the initial dataset

- The *x-parameters-model* : the best model obtained with the studied dataset

The table below shows the results taking into account the error behaviour with precision and scattering, the parametric scattering, the error for a validation dataset and the time calculation.

JUNE	All parameters	11-parameters	9-parameters	x-parameters
meaning error (deg C)	2,29	2,43	2,66	2,2
standard deviation of all the identification errors (deg C)	0,17	1,41E-04	7,19E-11	5,33E-10
meaning standard deviation of all the identified parameters	0,13	6,40E-03	6,34E-10	1,64E-08
time calculation (s)	medium	fast	fast	long

Figure 14 - results comparison for the dataset of June

FEBRUARY	All parameters	11-parameters	9-parameters	x-parameters
meaning error (deg C)	0,75	0,77	0,78	0,78
standard deviation of all the identification errors (deg C)	0,05	0,006	1,28E-04	4,80E-06
meaning standard deviation of all the identified parameters	0,1	0,04	0,0034	2,00E-04
time calculation (s)	medium	fast	fast	Long*

Figure 15 - Results comparison for the dataset of February

* The time calculation of the x-parameters-model would be long because in order to find the best model for one precise dataset, all the reduction method describe above would be computed – that means several identifications by model.

Or all the others models have already their number of parameters to be identified and there is just several identifications to be done for one model.

Furthermore, the 9 and 11-parameters model would be very fast because the standard deviations of all the identification errors are very low, so just one identification would be sufficient.

Conclusion

Although there is a small loss of accuracy, the *9* and *11-parameters-models* give a good compromise between precision, reliability, parametric scattering and time calculation. Furthermore, because the error and the parametric scattering remain very low, one identification would be sufficient so the time calculation would be very fast.

Obviously, the less parameters to be identified a model has, the low precision becomes. But, taking into account the gain in reliability and time calculation, while maintaining acceptable accuracy, the *9-parameters-model* seems to be the best model.

Conclusion and Perspectives

This approach gives encouraging results about the best way of modelling the building envelops. Indeed, it is interesting to take notice that in fixing the more scattered parameters, with the "scattering method", the global scattering reduce, which is quite logical but thoses results are better than the method which fixed the less sensitive parameters. It would be interesting to test this model in energy management in order to check that it gives good temperatures forecast.

Beyond this application on the PREDIS rooms, this approach gives a robust identification method which has to been tested on other buildings in order to validate it.

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