TRANSIENT SIMULATION CALIBRATION OF AN OLD BUILDING USING AN EXPERIMENTAL DESIGN: EVALUATING UNCERTAINTY RESULTS

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ABSTRACT

Calibration of Building Energy Simulation is an under-determined problem. There can be several correct solutions. The consequences of using the Building Energy Simulation for retrofit design can be significant. In this paper, we will propose a method that identifies different solutions in the entire field that was studied. It enables one to evaluate the uncertainty in energy saving estimations. The method uses an experimental design in order to reduce calculation time. It uses the coefficient of variation of root mean square error. We applied the method on an old building. The same retrofit design can yield a 40 to 60% savings in energy according to the chosen calibrated Building Energy Simulation.

INTRODUCTION

Within the framework of greenhouse gas emissions reduction and increasing energy costs, assessing energy efficiency of buildings becomes an increasingly critical issue. It is not only a matter of customer information, but also a question of enhancing building energy efficiency, energy performance contracting and energy expenditure control.

It is fully acknowledged that Building Energy Simulation (BES) could be very helpfull for Building Energy Efficiency Characterization (Bertagnolio 2010, Coaklay 2011, ASHRAE 2002, etc.). BES should help understanding building behaviour versus measurements and calculations. But as results are influenced by a high number of variables, it still is difficult to assess an accurate representation of a building's energy performance.

In this paper, we are proposing a method for the validation and the uncertainty analysis of a Building Energy Simulation model. It is based on simplified BES performance modelling using an experimental design. The method has first of all, been applied to monitoring a centuries old building, and secondly, validated with a calculated data for this same building.

The goal of this paper is three-fold:

- to provide a method for sucessful calibration,
- to provide indicators to operators in order to evaluate the relevance of the results,
- to provide key elements to reduce measurement time and the number of parameters: amount of data needed, confidence interval that can be obtained, etc.

Goals of using Building Energy Simulation

In metrology, measurement can be defined as the application of chains of traceability made in practice linked to reference standards. This reference depends on the characteristics:

- for customer information or regulatory control, the reference deals with the comparison of performance with other buildings (Barley 2005),
- for new building performance verification, performances have to be compared with the design intent,
- for energy saving estimation, it should be compared before and after retrofitting.

Therefore, there are 2 kinds of references:

- standards references, e.g. that French regulation defines as the energy consumption of a building under standard meteorological conditions and occupancy. Occupancy is defined as internal gains and indoor temperature (CSTB 2006).
- baseline references that IPMVP (2002) and ASHRAE (2002) define as the energy use or demand through a baseline period which is the "period of time selected as representative of facility operations before retrofit".

BES are then used to put the building under reference conditions. BES uses 3 different kinds of input data :

- static ones that correspond to building characteristics (dimensions, material used, systems characteristics, etc.)
- dynamic ones (meteorological conditions, occupancy, indoor temperature, etc.)
- constants that corresponds to theoretical models (specific air heat, Stefan Bolzmann constant, etc.)

LITTERATURE REVIEW

BES are able to calculate several output data. The most common ones used are heating demand or energy consumption.

Subsequently, BES calibration deals with finding the input data that represent the real building the most accurately and its energy performance in terms of the output data. It is a highly under-determined problem (Coakley 2011) that leads to several plausible solutions.

Usual methods start with building model construction by collecting static data (audit). Then several methodologies are used depending on available data and monitoring. They are all based on an iterative process that tends to improve the model (making it the most life-like). These methodologies use sensitivity analysis, evidence, and calculated and monitored output data comparison (Bertagnolio 2010, Raftery 2009).

Sensitivity analysis and measurement uncertainty

In order to be as precise as possible when modeling, the first question asked is what are the parameters that have the greatest impact on the results. The influence can be two-fold:

- the parameter value is very uncertain,
- the model is very sensitive to the modification of the parameter value .

Then substantial research is conducted to reduce the uncertainty of input parameters. As pointed out by ASHRAE and IPMVP (2002), one of the keys to building energy efficiency verification is to control data measurements uncertainties as efficiently as possible.

Sensitivity analysis (Westphal 2005) consists of varying the inputs and verifying the consequences on the model outputs. Complete analysis often requires running a great number of simulations. It can be automated.

Model output and monitoring results comparison

When available, calibration consists of comparing measured and calculated data to improve the model. This process is iterative. It consists of comparing model outputs to monitored data to enhance the building model analysis of the results.

In order to analyse the differences between measurements and calculations, two different and complementary methods are used : graphical and statistical.

Graphical calibration consists of using different graphical technics. It uses, for example (ASHRAE 2002) :

- weather day type 24 hour profile plot,
- binned interquantile analysis,
- three dimensional surfaces,
- three dimensional color plot.

The expertise of the modeler is then used to enhance the BES. The statistical approach consists of calculating mathematical indicators that evaluate BES matches with measurements. ASHRAE proposes 2 main indicators : Normalized Mean Bias Error (NMBE) and Coefficient of Variation of the Root Mean Square Error (CVRSME)

$$NMBE\ (\%) = \frac{\sum_n (m_i - s_i)}{\sum_n m_i} \qquad \text{E1}$$

$$CVRMSE\ (\%) = \frac{\sqrt{\frac{\sum_n (m_i - s_i)^2}{n}}}{\bar{m}} \qquad \text{E2}$$

Where m_i and s_i are measured and simulated values for each i data point, with n being the number of data points.

Evidence-based methodologies

Evidence-based methodologies are iterative methods that consist of improving the BES model by changing input parameters with regards to available evidence in clearly defined priorities (Coakley 2011). It can use both previous described tools.

Conclusions

ASHRAE considers that a BES model is calibrated when "they produce MBEs within ± 10% and CVRMSE within ± 30% when using hourly data or ±- 5% to 15% with monthly data". There are obviously several possibilities to obtain such performance. But there still is not any method that can evaluate the relevance of the results.

METHODOLOGY

As calibration is an under-determined problem, it is often advisable to run thousands of simulations. In order to reduce time and their number, we are proposing a method using an experimental design. It is based on a reduced number of simulations. It is aimed at creating a simplified model representative of BES performance as a function of the input data. As it is simplified, we have to choose the most influent parameters for which the model will be calibrated.

The method consists of 7 steps:

1. audit and BES creation
2. hourly measurements
3. choice of the most influent parameters (based on literature or on a sensitivity analysis),
4. experimental design construction and corresponding BES calculation,
5. automatic identification using simplified model,
6. evaluation of confidence interval results
7. Calculation of BES reference conditions.

Building audit and BES model construction

In order to construct a BES model, input variables and parameters have to be set as accurately as possible. The first step is then to make a strong audit with the lowest uncertainty possible with non-destructive measurements. This uncertainty has to be evaluated.

"The need for certainty must be carrefully balanced with measurement and analysis costs." (ASHRAE 2002). As this study concerns research, a lot of time has been taken for the audit. It has to be adapted for commercial purposes.

For wall composition identification with a non-destructive audit, operator expertise is important. Moreover, some specific tests can be employed :

- visits and geometry measurements,
- construction drawing,
- surveys and interviews,
- blower door test for air tightness evaluation,
- infrared thermography,
- etc.

Uncertainty analysis of the measurement should be kept in mind when auditing.

Hourly measurements

Hourly measurements have to be carried out through a baseline period. ASHRAE and IPMVP recommend establishing a baseline period that is "representative of facility operations. It has to represent the range of conditions encountered by the affected energy using systems." (ASHRAE 2002).

Parameters that must be measured have to correspond to dynamic input and output of the chosen BES such as : meteorological conditions, indoor temperature and heating load. An estimation of their uncertainty has to be assumed. Temperature measurements should corresponds to BES model zoning. In our case the purpose is to evaluate winter energy heating demand.

Choosing influent parameters

This is one of the key steps of the method; the selection of only a few parameters among the hundreds. The most influent parameters have to be selected. The influence of a parameter on the result can be two-fold. The value of the paremeter could have a great uncertainty or the model used is very sensitive to it. So, a complete uncertainty and sensitivity analysis could be very helpful, but analysis of the litterature (Gautier 2012) shows that the most influent parameters are often the same :

- indoor and outdoor temperature,
- conductivity coefficient of walls and windows,
- ventilation flows,
- air tightness of the building,
- internal gains,
- efficiency of HVAC,
- etc.

Moreover, the audit can add greater uncertainty to input parameters, for exemple :

- is there insulation behind the wall ?
- what is the conduction coefficent of a material ?
- etc.

Once the parameters have been chosen, upper and lower limits have to be set. Uncertainty analysis provides a way to choose those limits.

Experimental design construction and corresponding BES calculation

Experimental design methods are mathematical sets of tools that enable one to establish and analyse the relationship between one or several variables and the parameters that make them vary. It can be used for optimization strategies (Vivier 2002).

For each Pi parameter, upper (+1) and lower (-1) limits are set as regards to the studied field. The response is considered to be linear between these two values.

Then the number of experiments that must be conducted depends upon the number of chosen parameters and their interactions between each other. Table 2 is an example of a 7-parameter experimental design with 15 experiments. The type of interaction was determined according to our modelling expertise.

The variable we are interested in is heating load. For each experiment, we calculated the BES daily consumption $C_{calc\_d\_k}$ where d corresponds to the day's number and k the experiment number.

The purpose is to write the equation of the calculated consumption for each day of calculation and for each experiment as a function of parameter value and coefficients. In our example of the experimental design describe in Table 2 :

$$C_{cal\_d\_k} = c_{d\_0} + a_{d\_0} * P_0 + \sum a_{d\_i} * P_i + \sum b_{d\_i} * P_0 * P_i + c_d * P_5 P_6 \quad \text{E3}$$

With P_l, the parameter values, C_{d_0}, $a_{d\_i\_}$, b_{d_i} and c_{d_xx} are the coefficients of the equation. Let C_{cal_d} be the vector of the calculated consumption for each experiment on the d day, and P the matrix of the Pi value. It yields :

$$C_{cal\_d}(P_i) = M_d.P(P_i) \quad \text{E4}$$

where M_d is the vector of coefficient (ai, bi and c). It is possible if P is an invertible matrix and if its determinant is not null. It yields as many matrix M_d as monitored days.

Identification

Monitoring provides the heating load for each day : C_{mon_d}. We use an experimental design and identification method to find parameter values that minimalize the difference beween measured data and simulation output data. The indicators used are Mean Bias Error (MBE) and Root Mean Square Error (RMSE). We used the Excell® solver method.

As the problem is under-determined, several solutions can be achieved. It depends on the parameter values with which we initialize the algorithm. Then in our studied field, we chose different start vectors (V_i) as figured in Table 3.

Evaluation of confidence interval results

Next, we obtain 2 sets of 5 solutions, one with MBE and one for RMSE. Comparison of the solutions in terms of the indicators will help to find an acceptable solution. Then for each parameter, an average value and its standard deviation can be calculated. It is the first step to evaluating the confidence interval of the results. Indeed, the lower the standard deviation, the higher the confidence interval value.

If the solutions present values that are too different, further analysis can be done. The first step is to run BES with the different sets of solutions that have been chosen. Graphical observation can provide an initial indication. It is also necessary to evaluate the results using MBE and CVRMSE on BES real calculation to avoid experimental design errors.

BES calculation with reference conditions

Finally, depending upon the purpose of the audit, BES have to be run with standard conditions or projected baseline data.

If the goal is to improve energy efficiency of a building, a new BES model can be constructed with projected improvement and the results are then compared with the different sets of solutions. This gives an initial uncertainty idea of the results.

CASE STUDY

The building we chose for this study is a manor house near the Loire Valley in Western France. It has 2 levels above a vault and is 240 square meters. It is constructed with tuffeau (a limestone with about 45% porosity). Indeed, among the diversity of existing stones used for construction, limestone represents 10% of the total sedimentary stock. It has been widely used for construction in many countries such as Canada, Belgium and France. Those buildings present a large potential for energy savings. It has to be retrofitted.

The house presents 3 types of windows : double-glazing windows in the living room, single-glazing in the kitchen and double-glazing roof windows on the first floor. We notice 2 periods of construction. The main part, corresponding to the living room was built in the XVI century. Its walls are 70 cm thick. The kitchen part was built in the XIX century with a 22 cm wall thickness.

As in most old houses, there is a fireplace. Occupants use it only for weekends.

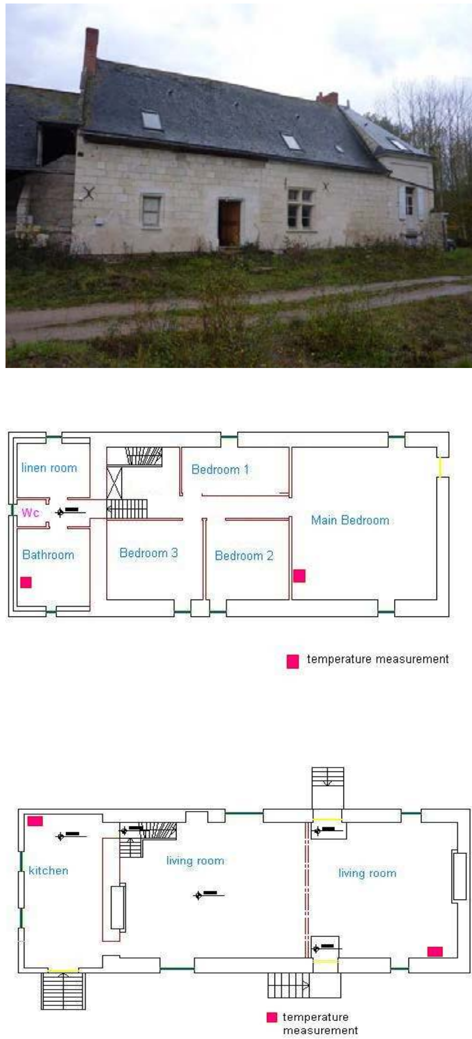

Figure 1. Picture and ground blueprint

BES creation

We used TRNsys v17 in order to model this house with Type 56. We defined 4 living zones corresponding to our 4 temperature measurements (see monitoring further on below). We added 2 zones for the cellar, 2 zones for the attic and 1 zone for the adjoined barn.

We coupled TRNsys with Contam for air flow modelling. The model is made with mechanical ventilation (in bathroom and toilets), natural ventilation, infiltration and door and window opening.

Infiltration rates have been measured with a blower door. We observed that most of the leaks occur around the windows, mainly the kitchen ones. So we distributed the infiltration leaks not only proportionally to wall dimensions but also taking into account the number and quality of windows.

Internal gains are estimated from interviews with the occupants about their habits. This was corrected with temperature and humidity monitoring observations. For example, the use of the bathroom or kitchen are well identified connected with the increase of humidity. Fireplace gains was not initially taken into account (because of its high uncertainty).

Characteristics of tuffeau have been found in litterature (Stephan 2012) and compared with laboratory measurements. As tuffeau is a very porous material, its conductivity can double between a dry stone and a saturated stone.

A strong non-destructive audit was carried out for all the characteristics of the house. High uncertainty still concerns roof insulation since as the attic was not visited.

Monitoring

Monitoring was set up in November 2011 :

- indoor temperature and humidity (4 places),
- meteorological data (wind speed and direction, temperature, humidity and global horizontal radiation) for 2 months,
- heating load for 14 days in December 2011 : energy given by the gas boiler was monitored with ultrasound waterflow and 2 water temperature measurements. Uncertainty of such measurement has been evaluated in our laboratory at 20%.

Choosing influent parameters

As found in the litterrature, and in terms of the audit, the most uncertain and/or sensitive parameters are indoor and outdoor temperatures, roof insulation, ventilation rate, infiltration rate, stone conductivity, internal gain, solar gain and windows conductivity.

An initial sensitivity analysis on these parameters showed that the windows conductivity coefficient and solar gains do not have a great impact on the results because of the small surfaces of the windows.

Then the choice of parameters and their upper and lower limits are :

- indoor temperature (T, °C) as there are only 4 measurement points for big spaces; there is a great uncertainty on the average temperature for the whole zone. So in the experimental design, we made T vary from -2 °C to + 2°C from its value. This variation was applied to the 4 temperature measurements at the same time.
- roof insulation - we chose mineral wool with a conduction coefficient of 0.04 W/m.K. We made the thickness vary from 5 cm to 20 cm. We noted that the influence of the thickness is not linear to consumption. Only the conduction coefficient is.
- tuffeau conduction coefficient varies with humidity from 0.37 to 0.79 W/mK,
- internal gains are not well known, we applied a multiplier coefficient of 0.5 to 2,
- in the bath-room, it is the only place in the house where tuffeau does not appear. But it is impossible to know if there is insulation behind wall or not. The next parameter corresponds to bathroom wall insulation from no insulation to 10 cm.
- as one measurement gives about 25 m^3 per hour, ventilation rate varies from 10 to 50 m^3 per hour.
- infiltration rate was measured, we applied a coefficient of 0.5 to 2 to its value.

Table 1 summarises the chosen parameters and their limits. We calculated the global influence of each parameter. It is the difference between upper and lower limit consumption divided by the lower limit consumption. The value of all the other parameters are set to 0.

$$I = [C(-1) - C(+1)] / C(-1) \quad \text{E5}$$

Table 1
Choice of parameters and their limits

	PARAMETERS	LOWER LIMIT	UPPER LIMIT	INFLUENCE
P0	temperature (°C)	T - 2	T + 2	70%
P1	roof insulation (cm)	5	20	10%
P2	tuffeau conduction coefficient (W/mK)	0.37	0.79	31%
P3	multiplier coefficient of internal gains	*0.5	*2	7%
P4	wall insulation (cm)	0	10	4%
P5	ventilation rate (m^3 / h)	10	50	3%
P6	infiltrations, multiplier coefficient	*0.5	*2	12%

Experimental design construction

In terms of the chosen parameters, Table 2 presents the experimental design we made. It is a 7-parameter with 15 experiments design. Interactions are : P_0 and P_1, P_0 and P_2, P_0 and P_3, P_0 and P_4, P_0 and P_5, P_0 and P_6, P_5 and P_6.

Table 3 presents the choice of the starting vectors. The first one starts from one limit (-1) another from the other (+1) and one in the middle (0). The 2 others start from the limits that give the highest and the lowest consumption.

Then, BES calculations are done on 15 days. It corresponds to consumption measurement. The first day is calculated twice in order to calibrate the model for the right dynamic temperature.

Table 2
Experimental design

	P_0	P_1	P_2	P_3	P_4	P_5	P_6
Exp 1	1	1	1	1	1	1	1
Exp 2	-1	1	1	1	1	1	1
Exp 3	1	-1	1	1	1	1	1
Exp 4	1	1	-1	1	1	1	1
Exp 5	1	1	1	-1	1	1	1
Exp 6	1	1	1	1	-1	1	1
Exp 7	1	1	1	1	1	-1	1
Exp 8	1	1	1	1	1	1	-1
Exp 9	-1	-1	1	1	1	1	1
Exp 10	-1	1	-1	1	1	1	1
Exp 11	-1	1	1	-1	1	1	1
Exp 12	-1	1	1	1	-1	1	1
Exp 13	-1	1	1	1	1	-1	1
Exp 14	-1	1	1	1	1	1	-1
Exp 15	-1	1	1	1	1	-1	-1

Table 3
identification algorithm start parameters vectors

	P_0	P_1	P_2	P_3	P_4	P_5	P_6
V1	-1	-1	-1	-1	-1	-1	-1
V2	-1	1	1	1	1	-1	-1
V3	0	0	0	0	0	0	0
V4	1	-1	-1	-1	-1	1	1
V5	1	1	1	1	1	1	1

Identification

For identification, we worked on 11 days. Indeed, the fireplace was used for 2 days. Optimising with the MBE indicator yields results close to the starting vector. Table 4 presents the identification results for the 5 starting vectors with the CVRMSE indicator and the standard deviation for each parameter (SD)

Table 4
Identification results

	V1	V2	V3	V4	V5	SD
P0	1	1	1	0.93	1	0.03
P1	-1	0.59	-0.03	-0.93	0.84	0.85
P2	0.58	-0.10	0.53	0.99	0.43	0.39
P3	1	0.86	0.30	0.16	0.91	0.39
P4	-1	0.75	-0.07	-1	0.93	0.92
P5	1	-0.91	-0.04	0.80	1	0.83
P6	-1	-0.60	0.03	0.36	1	0.79
CVRMSE (%)	5.34	5.96	5.77	5.59	5.84	

For all starting vectors, the CVRMSE coefficient is good (ASHRAE considers that a model is calibrated when this indicator is under 15% (for 12 monthly measurements). But there is a big variation in the value of each parameter that yields high standard deviations.

Figure 2 presents the standard deviation as a function of the influence of the parameter. The more influent the parameter is, the lower the standard deviation. Furthermore, the more influent the parameter is, the more precise the identification is.

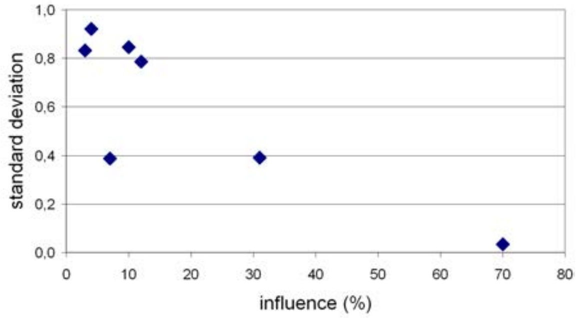

Figure 2: Standard deviation as a function of the parameter's influence

We can observe that the parameter which seems to have a different performance than the others is the internal gains. Indeed, identification is made only with the application of a coefficient. But it still presents great uncertainty in its hourly dynamic.

Evaluation of the confidence interval results

Figure 3 and 4 show that the different solutions give very close simulation results.

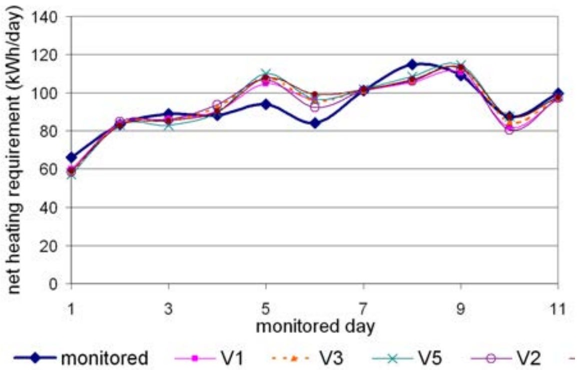

Figure 3: Daily consumption of monitored and BES calculated data for each starting vector

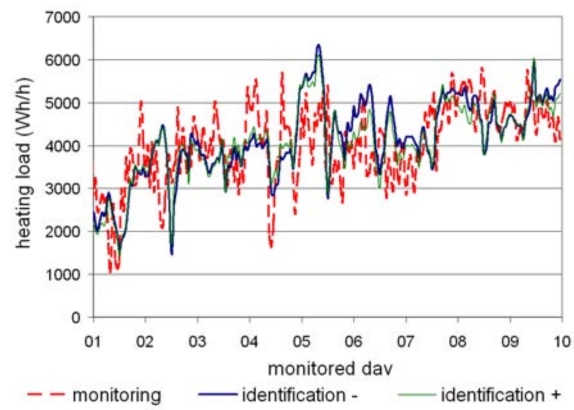

Figure 4: Hourly consumption of monitored and BES calculated data

The houly observed differences can come from internal gains that have not been monitored.

Conclusions and reference calculation

Our case study proposes only 12 days of heating load measurement with high uncertainty. Therefore, the proposed solution still presents high uncertainty.

Further monitoring has been scheduled for early 2013 with more precise heating load and electric consumption.

THEORETICAL STUDY

In order to evaluate the method, we used the same BES model to create data that corresponds to a "measured" heating load. We randomly chose parameters "true value" in the studied field. This method has often been used to validate calibration algorithms. Therefore hourly measurements correspond to 56 days of BES calculation without uncertainty. The selected influent parameters and the experimental design are the same (See Tables 1 to 3).

Identification

For the identification, two indicators were used. MBE at 56 days and CVRMSE at 14, 21, 28 and 56 days of monitoring. The same 5 starting vectors have been used (table 3).

When using MBE at 56 days, all identification results yield no error (MBE = 0%), regardless of the starting vectors. The total consumption is the same. However, as the parmeters varying from "-1" to "+1", the results give very high standard deviations (Table 5). According to ASHRAE recomendations, that is not the good indicator to calibrate a model.

Table 5
Standard deviation for all identified parameters for the MBE 56-day indicator

	P_0	P_1	P_2	P_3	P_4	P_5	P_6
Standard deviation	0.65	0.82	0.58	0.88	1	0.96	0.80

The CVRMSE results obtained with identification, regardless of the starting vectors and the number of days, are under 1% for 21 days and under 0.5% for 56 days. As seen previously, the more influent the parameter is, the lower the standard deviation is (Figure 5). It appears that standard deviation decreases as the number of days taken into account increases : the average standard deviation for the 7 parameters is from 0.42 at 14 days to 0.31 at 56 days.

Hence, the number of monitored days for calibration is linked to confidence interval results especially for less influent parameters. The less influent the parameter is, the greater the number of monitored days are required for evaluation to achieve good precision in identification (low standard deviation).

Figure 6 presents the evolution of the identified value for 4 parameters with the number of days taken into account. For the most influent parameter (Temperature), a constant value is achieved from 14 days to 56. For the other parameters, a constant value seems to be achieved at different times.

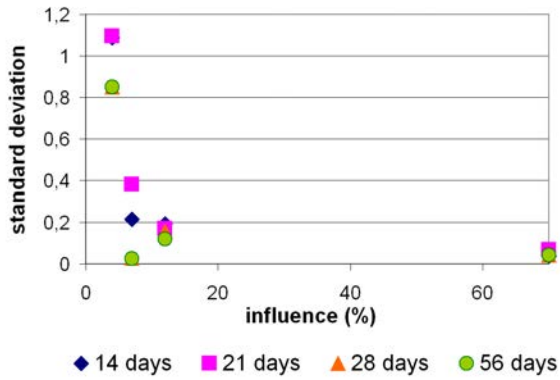

Figure 5: Standard deviation as a function of the parameter's influence

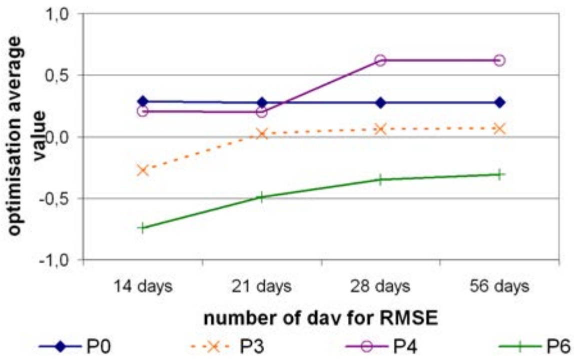

Figure 6: Evolution of identified values

Table 6 presents the achieved parameter value for 4 start vectors. Two vectors come from identification with MBE at 56 days. It corresponds to the two most distant values for each parameter (MBE - and MBE +). Then the two other vectors are the average value for identification with CVRMSE at 21 and 56 days (RMSE 21 and RMSE 56). It has been compared to the true values. For parameters P1 to P5, identification can be considered as very good. But for P0 (temperature) and P6 (infiltration), there still is an error made. Indeed, the 2 parameters influence tend to offset each other.

Table 6
Identified parameters values

	P0 (K)	P1 (CM)	P2 (W/MK)	P3 -	P4 (CM)	P5 (M^3/H)	P6 -
"true values"	0.7	8	0.58	1.3	5	28	0.86
MBE -	1	12	0.68	1.7	8	12	0.9
MBE +	-0.7	6	0.59	1.6	0	49	1.7
RMSE 21	0.54	9	0.65	1.3	4	35	0.9
RMSE 56	0.56	7	0.57	1.3	7	26	1

Evaluation of the confidence interval results

We made new BES calculations with this 4 sets of parameters. Table 7 presents MBE and CVRMSE for BES calculation.

All solutions give good calibration results but with very different parameter values.

Table 7
Error made between BES calculation and re-calculation

	MBE -	MBE +	RMSE 21	RMSE 56
MBE	1.4%	2.8%	2.5%	0.6%
RMSE	4.2%	2.8%	2.5%	0.8%

BES calculation with projected baseline data

The last step is to evaluate the influence of the identification results as regards the goal of the BES use. In our case, the audit could lead to a retrofit project.

Then we imagined 4 retrofit actions that are :

- A1 : 20 cm mineral wood roof insulation,
- A2 : 8 cm mineral wood wall insulation,
- A3 : new windows and improvment of air tighness ,
- A4 : ventilation.

We want to evaluate 3 retrofit solutions :

- R1 = A1 + A2 + A3 + A4,
- R2 = A1 + A3,
- R3 = A1 + A3 + A4.

Then we did BES calculation for these 3 retrofit solutions for the 4 identified solutions. Table 8 presents energy savings estimated using BES calculation.

Table 8
Energy savings estimation as a function of a retrofit solution and a calibration solution

	MBE -	MBE +	RMSE 21	RMSE 56
Retrofit 1	48%	64%	61%	64%
Retrofit 2	5.3%	17%	14%	25%
Retrofit 3	5.7%	14%	-	-

As intended, the two identification solutions at MBE 56 yield a high uncertainty in retrofit energy consumption improvement. What is more surprising is that even with closed identifed solutions (with RMSE), there is still a high uncertainty for retrofit Solution 2.

CONCLUSION

Our study confirms that the calibration problem is under-determined. Experimental design seemed to be a successfull method for calibration. It enables the exploration of the search space of calibration solutions and estimate not only the precision of the callibrated BES model but also the uncertainty of the retrofit solution that was chosen.

It shows that the confidence interval of calibration improves with the number of monitored days, even if the root mean square indicator yields the same results. This indicator provide key to optimize measurement time.

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