International Energy Agency
Programme on
Energy in Buildings and Communities

Energy performance analysis

Separate Document Volume VI

Total energy use in buildings

analysis and evaluation methods

Final Report Annex 53

November 14, 2013

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Volume VI
Energy performance analysis

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1. General overview

1.1 Key points

What is covered
Subtask D is concerned with Energy Performance Evaluation, which includes the use of simulation models in order to provide assistance to the correct evaluation of energy flows in buildings. Simulation models are available for a while to calculate the energy and thermal comfort performance of buildings. More and more sophisticated tools are used by building practitioners and provide the estimation of the energy demand (or consumption) of buildings as well as a prediction of the thermal comfort status in a given building.

Why is it important
It is frequently observed that the predictions calculated by these tools, although obtained from “detailed” calculations using models submitted to various “validation” exercises, can be quite far from the results of observations realized in running buildings. A number of reasons may explain this; an important factor being the fact that fixed values are usually entered to represent the human factors related variables. The models embedded in simulation tools are not perfect; they always provide a simplification of the reality ignoring certain processes: parameters are fixed according to arbitrary or approximate procedures. Within these parameters, those related to the description of the user behavior were not, until recently, the object of a detailed consideration. Simulations most of the time use arbitrary and standard user profiles concerning a number of behavioral aspects: selection of setpoints, control of shading devices, opening of windows,…

Key points learned
When using a simulation model, it is important to keep in mind that the results of the calculation are very much depending upon the hypotheses which were selected; the consumption which is output by the calculation is the one which is the result of the assumed behavior. Consequently, the use of simulation models is still today a work which offers a number of traps.

Different users of simulation programs can be identified:

- the *designer* (architect, HVAC engineer, installer) who tries to optimize the solution he is developing. Therefore, a number of design alternatives are compared, for instance in a renovation process
- the *building manager* who is searching the correct behavior (sufficient comfort, limited consumptions, minimal claims rate); the objective there is to identify and apply the best management strategies and to understand why the building does not follow the optimal trajectory
- the *policy maker* who is interested by the macroscopic impact of a number of Energy Conservation Opportunities or Measures (ECOs or ECMs) in order the options that show the highest efficiency (cost/benefit analysis for instance)

The presentation of the results is very much depending upon the addressed user.

Conclusions

In order to get the maximum benefit from the use of simulation models in order to analyze energy consumption in buildings, specific methodologies have to be developed and applied. These methodologies use specific concepts like sensitivity analysis, uncertainty analysis and highlight the importance of model calibration when analyzing an existing building. The combination of these approaches allows to take into account in a more realistic way the influence of the user of the building.

1.2 Objectives and contents of Subtask D

In order to analyze energy flows in buildings and to be able predict them with enough reliability, simulation models can provide an important added value. Such models are developed for a while to compute different aspects of building energy performance: thermal losses through the envelope, HVAC system operation and efficiency, thermal bridges, control features.

In Annex 53, the objective of using simulation models is to improve the knowledge and understanding of energy flows in buildings. Models increase the possibility of disaggregating the flows and improve the understanding and the identification of the causal link with the influence factors that are supposed to have an impact on those flows.

In that perspective, the first step is, by running simulation models on different building cases, to identify the cause-effects relations between the influence factors and the energy performance of buildings. Typical building cases are defined in each country, corresponding to national standard buildings, the main parameters affecting energy use are identified and quantified and a large number of simulation runs are carried out in order to estimate the sensitivity of some performance indicators to those factors.

In the second step, new indicators are proposed to better catch, in a standardized way allowing comparison between two different cases, the building performance.

In the third step, models are applied to real cases (the case studies of the Annex) in order to characterize the energy flows in those cases and to provide a quantified method to assess the efficiency (in terms of energy savings) of different Energy Conservation Measures, applied either on the building envelope or on the HVAC system; including its control. This requires an important step to be performed, which consists in calibrating the simulation models to the cases, by comparing with measured performance and adapting some of the sensible model parameters. With a calibrated simulation models, the energy savings can be predicted with a better accuracy and reliability. This prediction considers all factors showing an influence on the performance, including human factors and occupant’s behavior. In order to deliberately point out this influence, the results may be presented as performance range around an average value (corresponding to the “average user”).

When applied to the typical cases in each national context, this methodology allows to perform an extrapolation of the impact of some Energy Conservation Measures to a country or a region and from there to provide a quantified and objective basis to the energy policies in that country. In that respect, the approach developed in this part of the project relies on the databases developed or considered in Subtask C.

To achieve these goals, Subtask D was divided in 3 work items:

1) Work Item D1: Analysis of the effects of six factors on building energy use
2) Work Item D2: Evaluation of existing and new performance indicators of the total energy use considering the influence factors
3) Work Item D3: Demonstration of knowledge and methods developed in this ANNEX to predict the effect of energy saving technologies and occupant behaviors & lifestyle on building energy use

2. Building Life-Cycle and identification of applications of simulation

The practical use of simulation in different steps of the building life-cycle has been identified for a while. For instance, IEA Annex 30 focused on the objective of “Bringing Simulation to Application” and the concept of building life-cycle was recognized as central in this issue. This cycle is usually, whatever the building culture, divided into a number of steps (Figure 2-1):

- Building design with usually 3 successive phases:
  - Conceptual design
  - Preliminary design
  - Detailed design
- Call for tenders and Building construction
- Commissioning
- Building Operation, including Fault Detection, Diagnostics, and Re-commissioning
- Renovation

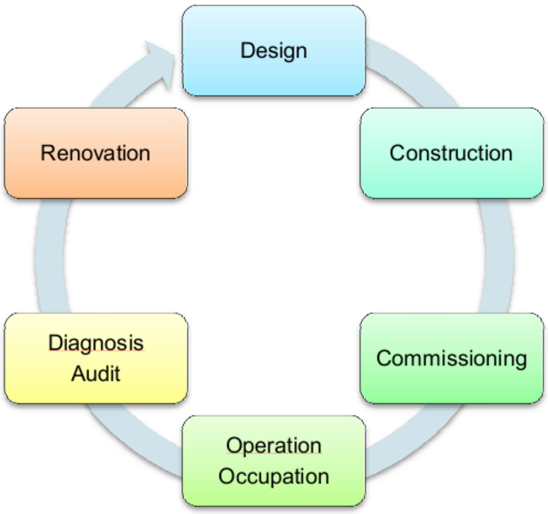


Figure 2-1: Building Life-Cycle

Simulation may be used at each of these steps, asking different levels of data and producing different results. This helps to classify the possible use of simulation according to the Table 2-1, where the simulation applications are classified according to the following criteria:

- Number of building objects considered by the evaluation
- Knowledge of the users profile
- Time scale: short or long

Table 2-1: Classification of simulation applications according to 3 criteria.

# of buildings	User profile # of users	Time scale: Short (s, h)	Time scale: Long (season, year)
Single object	Known user	Commissioning and Re-commissioning	Audit

	Unknown users	Design	Policy making
Multiple objects	Known user		Standardization
	Unknown users	Demand	Economical

Here follows a more detailed definition of the criteria to distinguish between the possible uses:

- Number of buildings: usually analysis is carried out on one building for which the optimization of the design or the operation is looked for; however, some applications like standardization or macroscopic assessment of Energy Conservation Opportunities (or Measures) may require the extrapolation of simulation results to a large building stock
- Level of knowledge of the user of the building: the behavior of the user may be totally or partially unknown (i.e., because the project concerns a new building where the user is not yet identified) or may be approached when the occupied building is submitted to an audit procedure.
- Time frame of the analysis: the analysis of the performance of the building may be targeted on a relatively short time frame (i.e., to identify the instantaneous impact of the building on the energy system) or on a longer time scale (to extrapolate through a detailed audit procedure the seasonal performance for instance).

Combination of the different criteria leads to the simulation applications as shown by table 1.

In IEA Annex 53, it was not possible to cover all the applications listed in this table. The cases which were analyzed allowed illustrating the following applications: design, audit, maintenance.

3. Progress in modeling (link with the task force)

Annex 53 work was more a question of defining and improving possible applications of simulation than producing and developing new models. Indeed, models to assist engineers at different stages of the building life-cycle are available from numerous softwares or research projects. The only segment of building and systems modeling which was specifically addressed by Annex 53 was the modeling of the user behavior. An extensive state-of-the-art of the currently available modeling approaches to represent user behavior was performed by the "Task Force" established within the project and is fully reported in Appendix Volume II. As a summary, modeling of user behavior in buildings may be tackled by the following approaches:

- Theory of the planned behavior
- MODE model of attitude-behavior process
- Modified norm-activation model
- Knowledge-desire-ability-action model

A more detailed description of the characteristics of these modeling issues is given in the Task force final report.

An analysis was carried out to identify the level of detail required for the occupant behavior modeling and the result is shown by Table, in which 3 types of models are considered: scheduled profiles, stochastic models, agent-)based models.

Table 3-1: Level of detail required for occupant behavior modeling

Annex 53 - overview occupant behavior models

Building occupant behavior models (from low to high resolution/complexity):
A. Schedules/diversity profiles
B. Stochastic models
C. Agent based models

Single building

	Design			Commisioning		Operation
	Conceptual	Preliminary	Final	Initial	On-going	Control
Aim:	design concept comparison	design optimization	system sizing building code compliance	initial commissioning	fault detection	model predictive control
Typical time scale:	season, year	season, year	season, year	?	continuous	1 or 2 days ahead
Typical timestep:	1 hour	1 hour	1 hour	1 min, 1 hour	1 min, 1 hour	1 min, 1 hour
Preferred behavior model:	A	A, B or C*	A (B or C*)	A, B or C*	A, B or C*	A, B or C*

* The required model depends on the sensitivity of the investigated building performance indicator to occupant behavior. This sensitivity depends on the performance indicator itself (e.g. compare comfort indicators to energy load indicators) and on various building related aspects, among others, building function and user type (e.g. compare schools to offices), building/system concept (e.g. slow responding to fast responding systems) and the degree of which the occupants are able to interact with the building (e.g. operable windows or no operable windows). See: *P. Hoes, J.L.M. Hensen, M.G.L.C. Loomans, B. de Vries, D. Bourgeois (2009) - User behavior in whole building simulation - Vol. 41, Issue 3, Pages 295–302*

Group of buildings

	Design			Commisioning		Operation
	Conceptual	Preliminary	Final	Initial	On-going	Control
Aim:	policy making solar/shading analysis	solar/shading analysis	design of electricity grid design of district storage	?	fault detection of district storage	district energy storage
Typical time scale:	season, year, 30-years	week, season, year	week, season, year		continuous	1 day ahead, 1 season ahead
Typical timestep:	1 hour	1 min, 1 hour	1 min, 1 hour		1 hour	1 hour
Preferred behavior model:	A	A	A		A	A

4. Building typology

To develop simulation applications, it is first necessary to define the simulated objects. Therefore, building typologies were developed in different countries participating to the Annex standard, addressing both residential and office buildings. In Japan, Hasegawa et al developed a building typology which is used to generate inputs for a simulation program and to analyze the impact of 13 factors related to the performance of the building envelope (sunshine conditions, envelope performance, overhang performance) and occupant behavior (set point for room heating and cooling, domestic hot water use).Each factor is graduated in 3 levels (good, standard, bad) and the sensitivities are calculated. It is shown that 65% savings can be achieved by a combination of energy savings behavior.

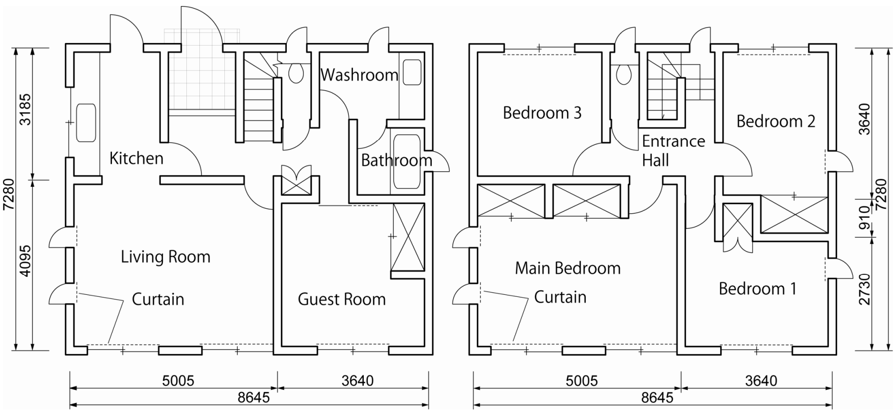


Figure 4-1: Typical residential building geometry used in Japan (Udagawa, 1985)

A more systematic study of the residential building typologies was also conducted in Japan (Nonaka, 2011) to feed simulation programs. The typology addresses the six families of influence factors as considered by Annex 53. The analysis considers 3 generations (new buildings + old ones) of buildings are defined for detached houses and 4 (+2) shaped (ground floors) are considered. Different floor plans are also selected: Strip type, 2-Strip type, Central living type, Hall type, Middle corridor type, Farmhouse type. 5 conditions are defined for the internal environment: luxury, comfort, quality, mezzo, thrifty.

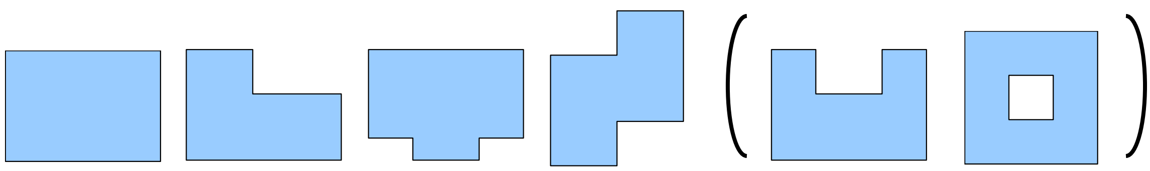


Figure 4-2: Residential building typologies used in Japan

This approach is also followed in Belgium (Ruiz et al, 2011) for the tertiary sector. The analysis considers both the building and the HVAC system. A lot of parameters are varied, starting with the building shape.

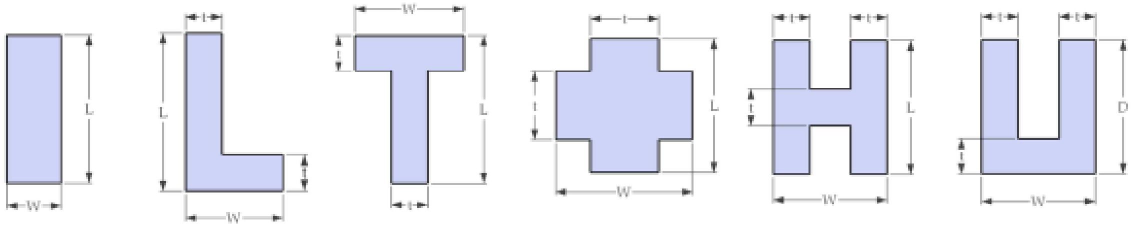


Figure 4-3: Office buildings typology used in Belgium

Another approach is to base calculations on simplified building designs (like “shoe-box” designs. Work carried out in the Netherlands (Hoes, 2011) to optimize building designs using a robustness indicator based on user behavior.

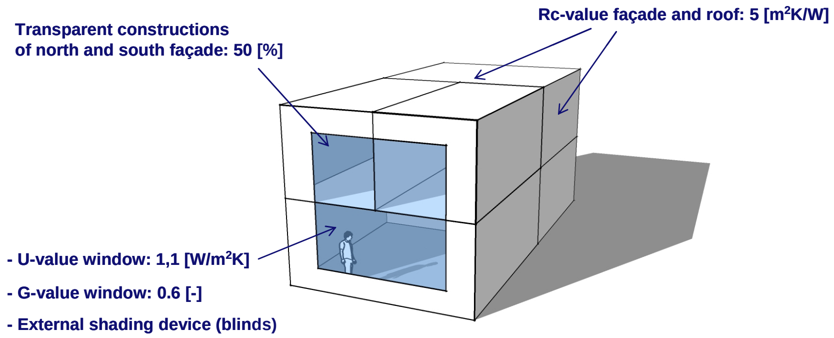
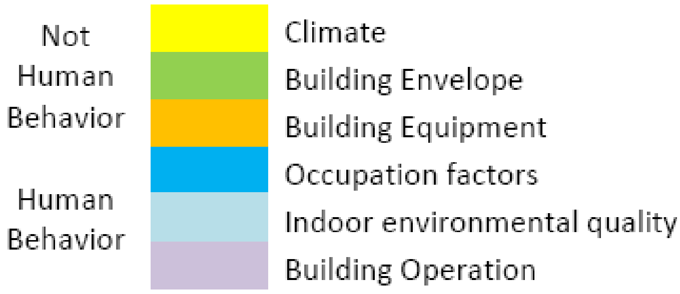


Figure 4-4: Shoe-box design used in the Netherlands

5. Sensitivity analysis

A simple shoe-box building configuration was used in Belgium (Pignon et al, 2011) to generate a sensitivity analysis. A total of 26 parameters were defined and varied according a Design Of Experiments generated by a Monte-Carlo approach. The sensitivity of building performance indicators (energy performance, comfort criteria) is calculated using the TRNSYS simulation program.

The parameters are ranged in the different categories as follows:



The detailed list of considered parameters is given below (paragraph 7.1.3.):

An example of results obtained by the application of the statistical Morris Method is shown by Figure 5-1.

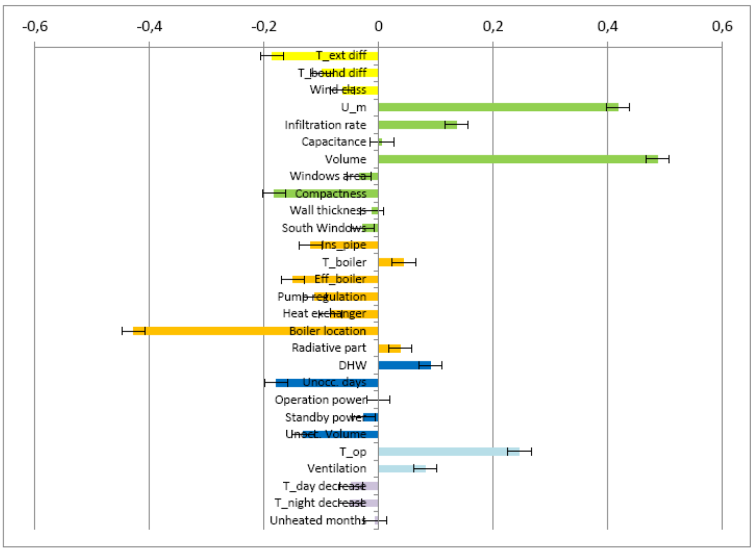


Figure 5-1: Example of results obtained with the Morris statistical method and showing sensitivity of different parameters

Figure 5-2 shows an example of a simulation study of the influence of envelope insulation and occupants' energy saving actions on residential energy use: A two-storey 153 m2 detached house with four occupants in Sendai, Japan, was selected as the simulation subject. The simulation results show that lifestyle greatly influence energy use. Changes in lifestyle are then seen to have a large energy saving potential, while the energy saving effect of envelope insulation is not so distinct.

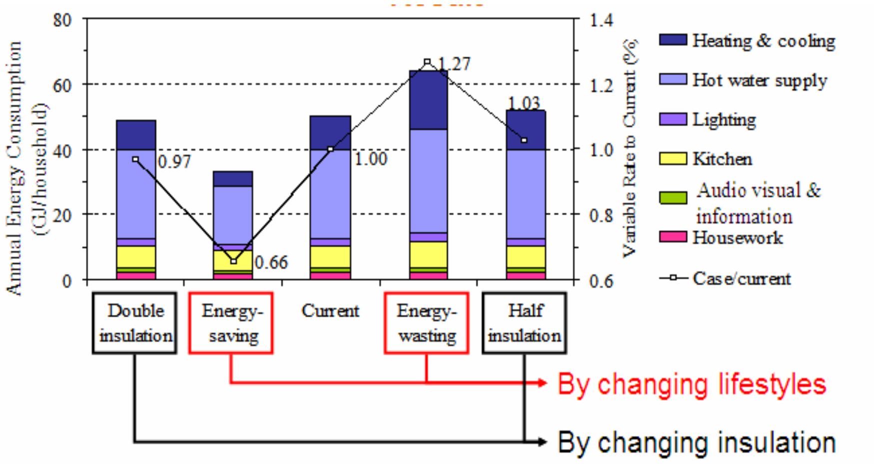


Figure 5-2: Analysis of the effect of lifestyle change on residential energy use in ST_D (Murakami et al., 2006)

An in-depth look at energy performance of office buildings was conducted by (Hong and Lin, 2011).

Their analysis had the following goals:

- Identify and quantify impact of key building design and operation parameters on energy performance of office buildings
- Compare simulated and measured energy performance of buildings to better understand the discrepancies between them
- How building operation practice and occupant behavior influence energy use of buildings

Their approach is based upon:

- Parametric Analysis
  - ➢ Start with the large office from the USDOE commercial reference buildings
  - ➢ Vary potential key design and operation parameters
  - ➢ Look at source energy of the whole building
  - ➢ Select five cities in typical climates
  - ➢ Use EnergyPlus Version 6 and TMY3 weather data

- Compare Simulation Results with “Measured Data” from the following sources:
  - ➢ CBECS, Commercial building energy consumption survey
  - ➢ CEUS, California commercial energy use survey
  - ➢ HPB, USDOE high performance buildings

An example of sensitivity analysis result is shown by figure 8.

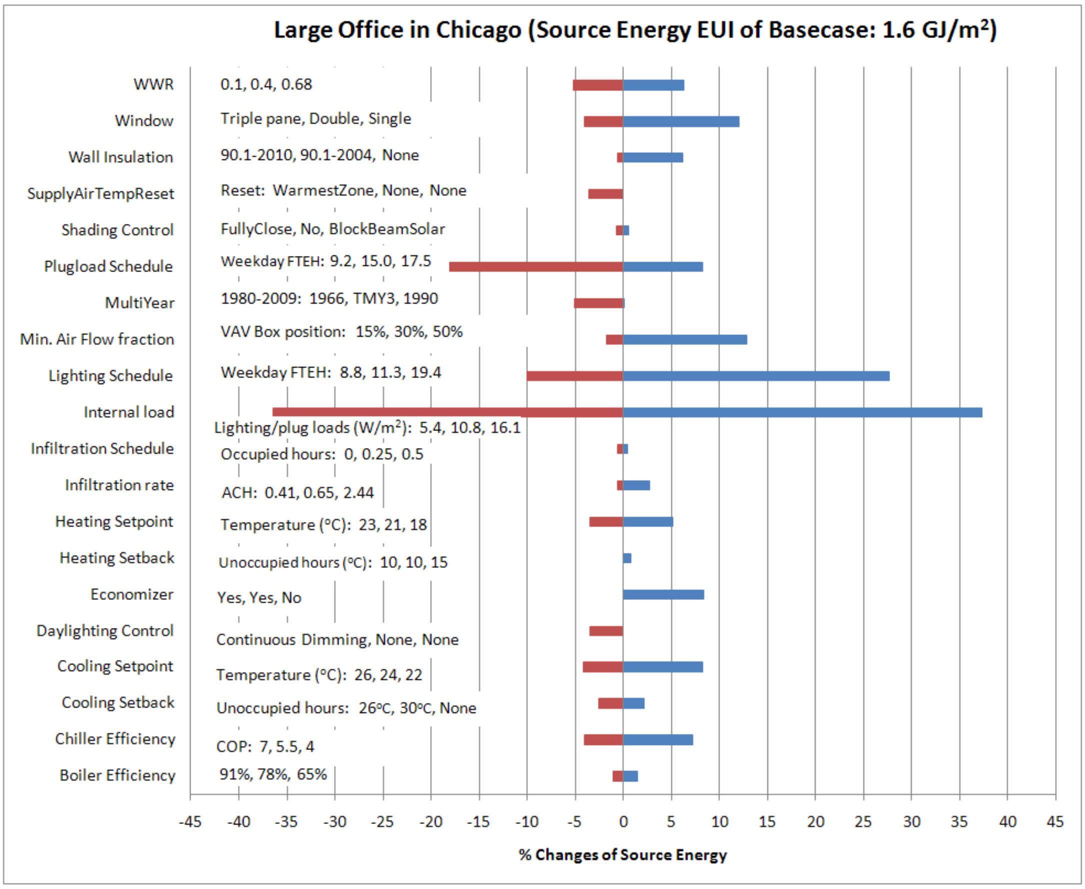


Figure 5-3: Example of sensitivity analysis applied to an office building in the US

Conclusions of this analysis yield:

- Simulated source energy use varies in a wide range from -55% to + 150% depending on key building design and operation parameters
- Most influential parameters are internal loads (rates and schedules)
- Other influential parameters depend on climates, but generally include:
  - VAV box minimum position setting
  - Window (construction and area)
  - Economizer (hot climates)
  - Cooling setpoint temperature (hot climates)
  - Chiller efficiency (hot climates)
  - Cooling setback (hot climates)
  - Infiltration rate and schedule (cold climates)
- Simulated source energy use varies from -5% to +5% when using weather data from historical years
- Building operation and occupants behavior related factors have significant impacts
- The range of simulation results between the Best and Worst cases overlap with most measured energy use of actual buildings

6. Performance indicators

Energy performance indicators usually used in the building sector include: consumption/m², consumption/occupant,…Subtask A revised the indicators currently available. The main goal of indicators is to allow normalization of energy performance for instance according to the climate. The concept of degree-days is useful to do this.

In Annex 53, the role of the building occupant has been recognized as a major one. Consequently, a relevant performance indicator should offer a possibility of normalization according to the user behavior. An example of performance presentation that would consider this occupant performance is a one where the performance would be given for a number (say 3) types of users: an energy-conscious user, an average user, an energy waster user. Each type of users is characterized by a coherent behavior regarding actions like setpoints selection, window opening, heating and cooling system programming,…On the other hand, a normalized energy performance would consider a “typical” or “standard” user behavior.

7. Simulation Applications

A number of simulation applications were developed in order to support different phases of the building life-cycle: design of buildings (residential and office), performance verification of residential and office buildings, simulation-aided maintenance.

7.1 Design of residential buildings

7.1.1 Summary

A simulation methodology targeting the design of residential buildings was developed. This methodology is based upon the a priori realization of a large number of simulations of typical cases (generic buildings) followed by the identification of a simplified regression model expressing the performance in function of the dominating parameters. An uncertainty can be a priori attributed to each parameter and the final performance is consequently given as a range around a central value, depending on the parameters uncertainty.

The objective of this method is to be able to predict a **range** of heating consumption in function of the uncertainty or the variability of several parameters in place of a unique heating consumption for a fixed building, climate and human behavior. This kind of results presentation appears as more realistic and consequently more robust.

The linear regression model is created by a Matlab program. This **linear model** is based on results of TRNSYS simulations, generated from a Monte-Carlo method. **Interaction and curvature effects** (2nd order)are taken into account in this model.

	Colour	Category	# parameters	# Choices
Not Human Behavior		Climate	3	3
		Building Envelope	7	15
		Building Equipment	7	3
Human Behavior		Occupation factors	6	3
		Indoor environmental quality	3	3
		Building Operation	3	3

For each category, there are several **pre-encoded choices** that are proposed (table 2 identifies the number of possible choices per parameter). This helps to give a value to each parameter of the category. Of course these parameters can be manually changed one by one.

As previously mentioned, this method can help a designer to **estimate the heating consumption** of a unique building with **different climates and human behaviors**.

But this approach can also be used in the context of an audit where all the parameters are fixed. Indeed, it is impossible to know perfectly every parameter and it is useful to estimate the consequence of an **uncertainty on the input on the output**. This way, the auditor can detect which are the parameters that really need to be tuned or measured more precisely (or not).

When the parameters are precise enough, the auditor can estimate the **evolution** of the heating consumption with any parameter and this way choose what to do to decrease it. Changes can be made on human behavior parameters or on the building or even the heating system, one by one or all together.

This method is also able to **auto-tune the parameters** if the annual heating consumption is known. It finds the solution that matches **the annual consumption** and which **minimises the standard deviation** between estimated value of the parameters and the ones of the solution, for a number of parameters left "free". Figure 7-1 shows the view of the main interface developed for his calculation method.

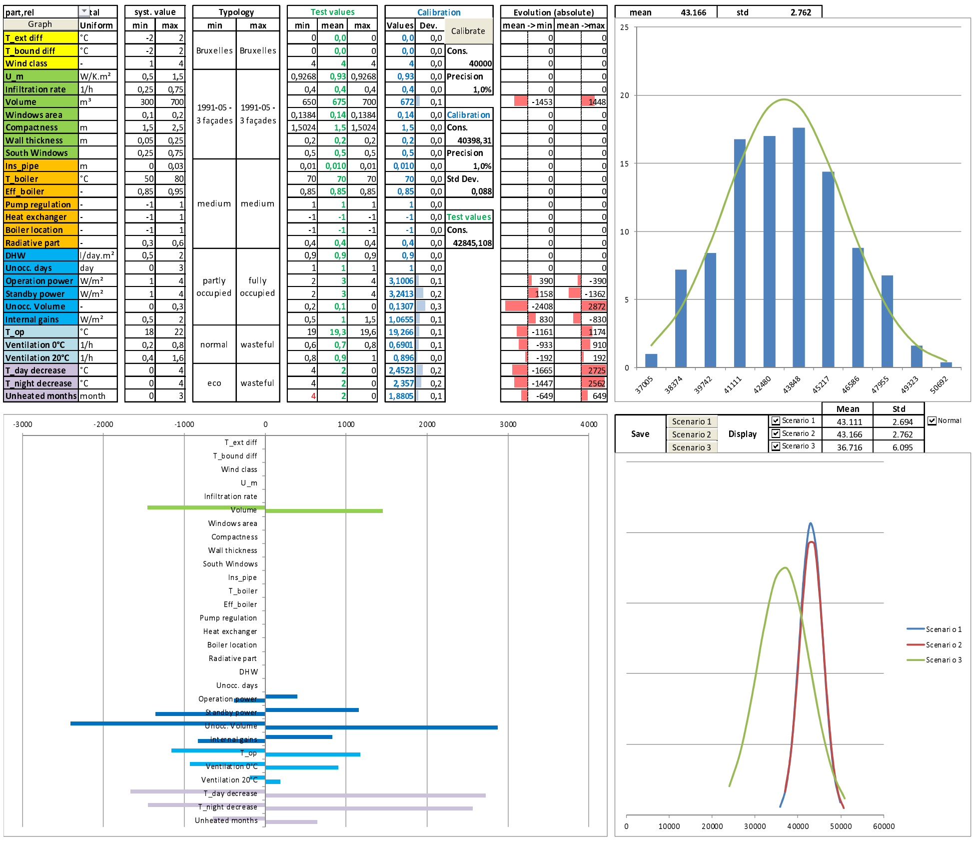


Figure 7-1: General view of the simulation-based evaluation tool developed to analyze residential building design:

Top left: list of parameters and input of values

Top right: statistical distribution of energy consumption for one parameters set

Bottom left: sensitivity of the performance to each parameter variation

Bottom right: comparison of 3 scenarios, corresponding to 3 parameters sets

7.1.2 Introduction

The aim of this paragraph is to briefly explain the necessary steps to represent the results of simulations (results as heating consumption or anything else) in function of different parameters (parameters as Volume, heat transfer coefficient, etc.).

To obtain reliable results it is important to respect a least two points:

- A great number of simulations with a good representation of the domain of the possible parameters
- A model which takes into account no only the linear effects, but also the interaction and curvature effects

Here is a summary of the methodology:

- Creation a simulation file (with TRNSYS) and choice of the analyzed parameters and results
- Matlab routine to allow changing automatically the values of the parameters, running the simulations and reading the results.
- Morris method is used to detect if some parameters have no effects at all on some results
- A great number of simulations are run with different random values for the analyzed parameters at each simulation (Monte-Carlo method). All the results are recorded
- For each result, a matrix of parameters is created. These parameters are of course the ones used in the simulations, but interaction and curvature (multiplication and division of the parameters between themselves) have to be added. The parameters with no effects (detected with Morris method) have to be removed.
- A linear model is created to estimate the results in function of these parameters (ordinary least squares solution). No all parameters are used, only the most influent ones. The evolution of the RMSE (root mean square error) of the model can help to choose the number of parameters to keep.
- This way, it is possible to estimate the results (taking into account the curvature and interaction effects) in function of the parameters without running a simulation.
- The interval of confidence on the results can be calculated and depends of the number of simulations, the precision of the model and the quality and quantity of the parameters used in this model.

7.1.3 List of the parameters and their limits

- Climate:
  - Ambient temperature difference vs a reference year
  - Temperature difference with adjacent house
  - Wind class
- Envelope:
  - Average U-value of the house
  - Infiltration rate
  - Capacitance
  - Volume of the house
  - Windows area
  - Compactness
  - Wall thickness
  - South window relative area
- Building equipment
  - Pipes insulation
  - Boiler temperature
  - Presence of heat exchanger

- Boiler location
- Radiative part of heat emission device

- Occupation factors
  - Domestic hot water daily consumption
  - Number of unoccupied days during the week
  - Electric power in operation mode
  - Standby power
  - Unoccupied volume in the house
- Indoor climate
  - Set Operative temperature
  - Ventilation rate at 0°C and 20°C
- Building operation
  - Daytime temperature decrease
  - Night setback
  - Number of unheated months

7.1.4 **Parametric typology**

A virtual dwelling was created with dimensions and properties defined thanks to several parameters. This way every kind of house can be represented; it is the most complete typology possible.

The external dimensions are determined by:

- Volume [m^3]
- Compactness [m^3/m^2]
- Area Ratio of windows / occupied surface [-]
- Area Ratio of south windows / surface of north and south windows [-]

The thickness of insulation for the walls, roof, floor and the type of windows are determined from:

- Global heat transfer coefficient [$W/K.m^2$]
- Thickness of the brick layer [m]

A virtual building respecting the values of all these parameters is created in a TRNBUILD file (.b17) with the help of MATLAB. The file contains the geometrical and physical characteristics of this building.

7.1.5 **Choice of the results**

Not only the total heating consumption can be retrieved as result, but it is more interesting to split the results that form this total heating consumption. Here is the list of the selected results:

- Q_{heat} : Net heating demand
- Q_{inf} : Infiltrations losses
- Q_{vent} : Ventilation losses
- Q_{trans} : Transmission losses
- Q_{gint} : Internal gains
- Q_{sol} : Solar gains
- Q_{pipes} : Heating pipes losses

- Q_{dhw} : Domestic hot water demand
- Q_{boiler} : Boiler losses
- Q_{total} : Total brut consumption

These powers (kJ/h) are integrated during the simulation time (one year) to give yearly energy values (kJ). Some first principle relations can be identified between these results:

- Wheat + Wgint + Wgsol = Winf + Wvent + Wtrans
- Wtotal = Wheat + Wpipes + Wdhw + Wboiler = (Wheat + Wpipes + Wdhw)/boilerefficiency

7.1.6 Application of Morris method

The Morris methods allow estimating the mean effect of each parameter, but gives also information about the standard deviation of this effect. This way, it's possible to identify important parameters (with a high mean effect), but also if the effects of this parameter are linear or not.

The high-orders effects can be influenced by the value of the parameter itself (curvature effects), but also by the value of the other parameters (interaction effects). It's important to precise that the method is useful to detect high-orders effects, but these effects (the curvatures and the interactions between the parameters) are not detailed.

Here, the method is mainly used to detect if some parameters have no effects at all on the result. A parameter does not have effect if whatever is its value or the values of the others parameters, a change of its own value does not induce a change on the result. These parameters will be removed from the model created with the Monte-Carlo method as they are useless to estimate the result.

7.1.7 Monte-Carlo Method

As for the method of Morris, the mathematical aspect is not detailed here, but only the major steps. Firstly, a great number (here, 2500 for 30 parameters) of simulation are run with a different value for each parameter at each simulation. These random values are chosen uniformly between a minimal and maximal value.

Each value has to be verified before launching the simulations to avoid bugs. The parameters and the results of all the simulations are recorded in matrix in MATLAB.

The aim is to obtain a model that can be written as follows:

$$\bar{Y} = \bar{\bar{X}} \times \bar{b} + \bar{c} + \bar{\varepsilon}$$

With:

$\bar{b} = Linear\ coefficients\ vector$
$\bar{c} = Constant\ terms\ vector$
$\bar{\varepsilon} = Error\ terms\ vector$
$\bar{Y} = Results\ vector$
$\bar{\bar{X}} = Parameters\ matrix$

It is important to understand that the matrix $\bar{\bar{X}}$ contains not only the parameters, but also the interactions and curvature of these parameters.

In general, a change of variable is used to include the constant term in the linear term so that the linear system can be rewritten as follow:

$$\bar{Y} = [\bar{\bar{X}}\ I] \times \begin{bmatrix} \bar{b} \\ \tilde{b} \end{bmatrix} + \bar{\varepsilon}$$
$$\bar{Y} = \bar{\bar{\hat{X}}} \times \bar{\hat{b}} + \bar{\varepsilon}$$

The ordinary least square solution of this system is:

$$\bar{\hat{b}} = \left(\bar{\bar{\hat{X}}}' \times \bar{\bar{\hat{X}}}\right)^{-1} \times \bar{\bar{\hat{X}}}' \times \bar{Y}$$

7.1.8 **Creation of the model**

All the parameters (columns of $\bar{\bar{\hat{X}}}$) are not useful to estimate the vector $\bar{Y}$. First of all, the parameters with no effect at all (detected with Morris method) can be directly removed. Secondly, only the most important parameters have to be kept in the model. The method is to create a routine in MATLAB that will detect the parameters that allow decreasing as fast as possible the RMSE. To choose the first parameter, the RMSE of $\bar{\hat{b}}$ (with $\bar{\bar{\hat{X}}}$ normalized) is calculated with for all the parameters (with only one parameter at time). The one that gives the minimal RMSE is kept. The same routine is run again to choose the second parameter and then the third, etc. The routine is stopped when the RMSE is small enough or when it starts to increase in place of decreasing.

The same technique is used to calculate all the results, considering that:

- Wheat = Winf + Wvent + Wtrans - Wgint – Wgso

The best parameters used to calculate the results on the right part of the equation can be selected to calculate Wheat. This pre-selection helps to find more effectively the best parameters for this result.

Once again, the presences of the curvature and interaction parameters are essential as a simple linear model is not precise enough to create a model. With a linear model, by example, the increasing of the heating consumption of a house with the volume would be the same whatever is the mean heat transfer coefficient what is totally false of course.

7.1.9 **Excel sheet**

Once all the models have been created, it can be useful to introduce them in an excel sheet to realize quick estimation of the results in function of the parameters with a certain level of confidence without running a new simulation with TRNSYS.

For each parameter a minimal and maximal values have to be written. And with the model, it is possible to estimate 1000 results with random values (between the min and the max) and to create a histogram with the repartition of the results (typically the heating consumption). This way it is possible to estimate directly the mean and the standard deviation of the heating consumption with some uncertain parameters. If the value of the parameter is exactly known, the minimal and maximal are simply equals.

A bar plot can be also created to represent the effect of the uncertainty of each parameter on the consumption. This bar plot can help the auditor to know which are the parameters that need to be tuned for precisely or for the owner of the house to know how much it is possible to spare energy by changing the value of each parameter (as the indoor temperature, by example).

The advantage of this method is that possible to take into account the uncertainty on parameters and to analyze what is the effect of this uncertainty on the results.

Another possibility is the auto calibration possibility. Annual heating consumption can be introduced in the calculation and it finds automatically the set of parameters that allows obtaining this heating consumption. Of course, the value of each parameter has to remain between the authorized minimal and maximal values. As there are an infinite number of possible solutions, the selected one is the one which gives the target heating consumption with the set of parameters as close as possible to the mean value of the parameters (mean between the minimal and the maximal value of the parameter).

7.1.10 **Conclusion**

The steps that allow creating a model from the results of thousands of simulations were presented. The objective is to create a user-friendly interface to give an estimation of results (as the heating consumption) in function of a set of parameters.

One of the advantages of using a model rather than really launching simulations is the possibility to estimate the solution of thousand different cases in a few seconds rather than after hours of simulation. In one look, the influence of each parameter can be analyzed with the help of the bar plot. And the result is not consumption for a set of parameters, but a distribution of the possible heating consumption in function of the uncertainty on the parameters. This is not possible without modeling.

Once again, to give certain reliability to the model it is important to take into account all the important interaction and curvature effects. An automatic process is essential to create the best possible model, the one which decreases the RMSE as fast as possible.

7.2 **Design of tertiary buildings**

7.2.1 **Summary**

Historically, building simulation has been integrated into the building design process to give designers a better understanding about how design decisions influence the energy and environmental performance of a building. However, the classical simulation approach consisting on selecting single values for model parameters (usually taken from standards, national regulations, etc.), running dynamic simulation (typically one hour time step) for a typical year and getting only one set of "instantaneous" or integrated results (monthly, yearly, etc.) makes the analysis rigid and limited without allowing the opportunity of evaluating more than one possible situation.

A sensitivity analysis makes it possible by means of identifying the most important design parameters in relation to building performance and to focus design and optimization of energy buildings most important parameters.

Monte Carlo simulation is a method based on performing multiple model evaluations with probabilistically selected model inputs. The results of these evaluations can be used to determine the uncertainty in the model output (prediction) and to perform sensitivity analysis (Ekström, 2005).

The goal of performing sensitivity analysis on a simulation model is to determine which parameter(s) is (are) responsible for most of the output's uncertainty.

For this analysis has been implemented a simplified variance based method proposed by Ruiz et al. 2012. In general terms, variance based methods use the variance (squared value of standard deviation) as a measure of uncertainty. In this method, the total amount of output's variance is considered as an entire which is divided in fractions (or percentages) according to each input parameter contribution. The whole analysis methodology is illustrated by Figure 7-2.

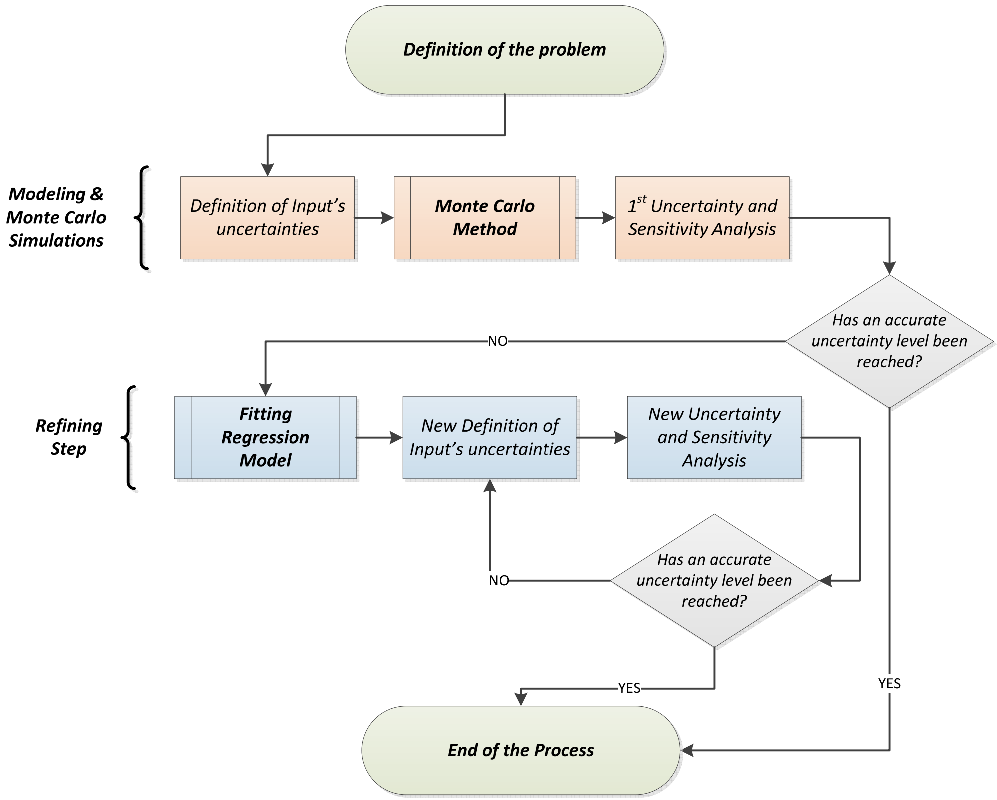


Figure 7-2: Proposed methodology combining sensitivity analysis and disaggregation of output variance

Monte Carlo method is used for generating a set of outputs over which uncertainty and sensitivity analysis is performed. If accuracy level is not reached, the same set of inputs and outputs is used for creating a simplified regression model over which carrying out a “theoretical” uncertainty and sensitivity analysis.

The method includes the following steps:

- Definition of the problem
- Running of Monte Carlo simulations, including first uncertainty and sensitivity analysis
- Refining stage by calculation of a simple regression model which makes further calculations easier and faster
- Exploitation of the regression model to analyze different scenarios

7.2.2 **Introduction**

In the following report presents a novel methodology to be integrated into building energy design process. This methodology proposes the use of uncertainty and sensitivity analysis as well as simplified regression models as tools for decision making. Additionally, it adopts a statistical point of view at the moment of presenting predicted results (in terms of probability distributions).

Historically, building simulation has been integrated into the building design process to give designers a better understanding about how design decisions influence the energy and environmental performance of a building. However, the classical simulation approach consisting on selecting single values for model parameters (usually taken from standards, national regulations, etc.), running dynamic simulation (typically one hour time step) for a typical year and getting only one set of “instantaneous” or integrated results (monthly, yearly, etc.) makes the analysis rigid and limited without allowing the opportunity of evaluating more than one possible situation.
Besides, implementing an approach like that does not permit answering one of the biggest questions made by designers and practitioners which is: *over which parameters should be paid more attention in order to decrease whole building consumption, peak loads, increment occupant’s comfort, etc.?*

A sensitivity analysis makes it possible by means of identifying the most important design parameters in relation to building performance and to focus design and optimization of energy buildings most important parameters.

The purpose of this report is to provide designers, practitioners and people involved the field a set of guidelines and a friendly explanation about how to manage some approaches and what to expect when using sensitivity analysis techniques as a tool for decision making analysis.

In the next chapters is discussed how Monte Carlo method works, the most important steps of a proposed methodology and a case study in order to show how to manage different stages of the process.

7.2.3 **Monte Carlo simulations**

Before proposing any methodology a good exercise would be to introduce and analyze all the techniques and approaches which are intended to integrate.

In this part of the report, it is explained how to manage, analyze and understand results provide by a Monte Carlo simulations.

Monte Carlo simulation is a method based on *performing multiple model evaluations* with probabilistically selected model inputs. The results of these evaluations can be used to determine the *uncertainty* in the model output (prediction) and to perform *sensitivity analysis* (Ekström, 2005). For details about the method, refer to section 3.2.2.

To start the explanation, it is supposed that a design procedure is carried out and several stages have already been completed. Building geometry, thermal zones, BEMS operation, occupant’s behavior approach, etc. have been defined and the model is ready to be evaluated.

Let’s assume the model has k input parameters and is required investigating how much they impact over a desired output (i.e. annual fuel consumption).

For each input parameter has been defined a range of possible values (candidates) and by means of a sampling method (Latin hypercube) has been created a sample matrix containing N combinations (randomly generated) of the k input parameters. Then, it has been decided to evaluate the model N times, in order to obtain a representative sample of model responses which will allow performing uncertainty and sensitivity analysis.

At this point, a situation such as shown in Figure 7-3 is faced.

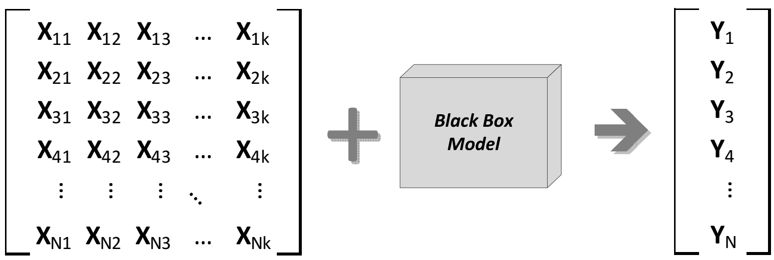


Figure 7-3: Scheme of sampled inputs matrix and model outputs vector.

7.2.4 **Uncertainty Analysis**

Output’s analysis starts evaluating uncertainty over the set of obtained responses. This step helps to determine how accurate results are and how much we can trust on them.
Figure 7-4 shows two graphical representations describing the dispersion range and the relative distribution of the obtained set of responses.

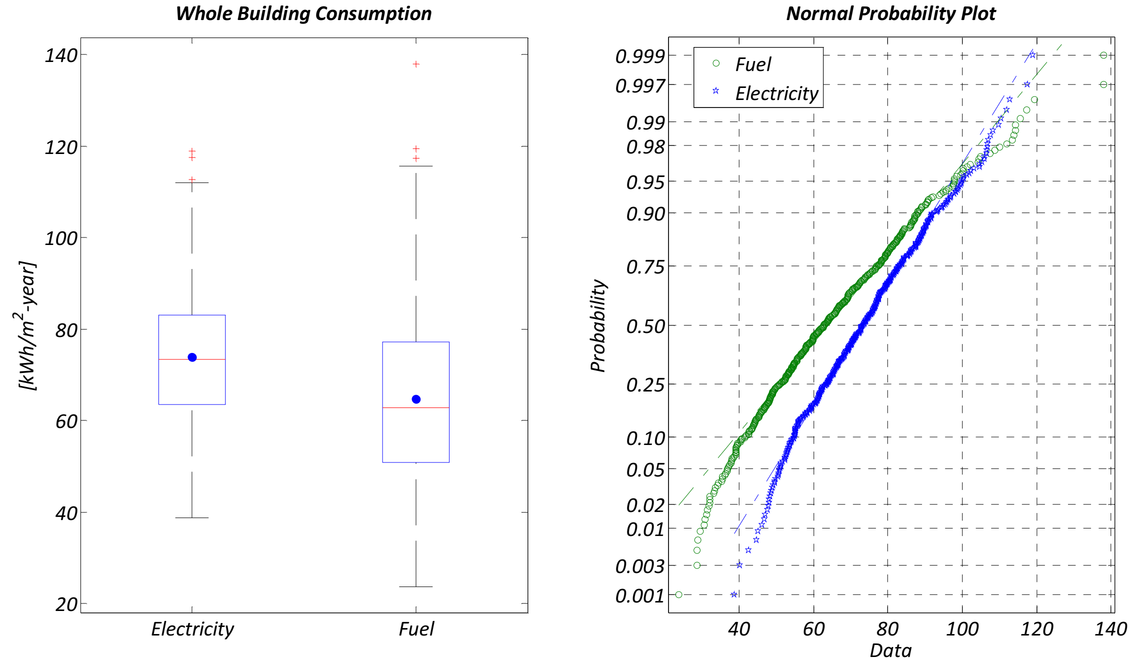


Figure 7-4: Boxplot and normal plot for the set of obtained model responses.

The results obtained by means of Monte Carlo simulations are summarized as boxes and whiskers (left graph). Upper and lower edges of the blue boxes correspond to the 25th and 75th percentiles. The red line corresponds to the median value of the generated sample of values and the blue dots to mean value. The whiskers (dotted lines) extend to the most extreme values without considering outliers. Outliers are plotted separately (red crosses). A data point is considered as an outlier if it is larger than $y^{75th} + 1.5*(y^{75th} – y^{25th})$ or lower than $y^{25th} – 1.5*(y^{75th} – y^{25th})$.

The normal probability plot (right side) is a graphical technique for normality testing: assessing whether or not a data set is approximately normally distributed.

Once is known the uncertainty (characterized by the standard deviation) and the probability density function, it is possible to determine the accuracy of the model response.

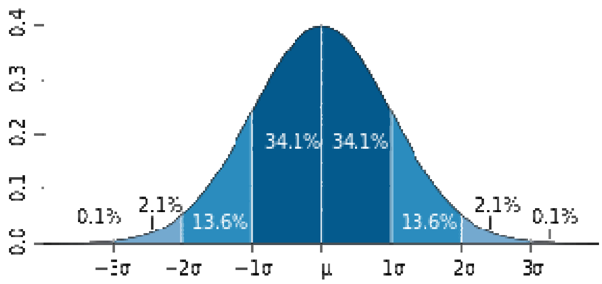


Figure 7-5: Normal distribution representation.

Figure above shows that for a normal distribution the 68.2% of the values are within the range $\mu \pm \sigma$, 95.4% of the values are within the range $\mu \pm 2\sigma$ and the 99.6% of the values within the range $\mu \pm 3\sigma$.

For decision making purposes, instead of using standard deviation as an uncertainty measure, is better to use the coefficient of variation (C_v) because is a normalized measure of dispersion and can be weighted according to the order of magnitude of the mean value.
Defining a maximal value of the coefficient of variation for declaring accuracy is subjective decision and depends on the criterion of the designer.

7.2.5 Sensitivity Analysis

The goal of performing sensitivity analysis on a simulation model is to determine which parameter(s) is (are) responsible for most of the output's uncertainty.

For this analysis has been implemented a simplified variance based method proposed by Ruiz et al. 2012. In general terms, variance based methods use the variance (squared value of standard deviation) as a measure of uncertainty. In this method, the total amount of output's variance is considered as an entire which is divided in fractions (or percentages) according to each input parameter contribution.
Figure 7-6 shows how results are presented when sensitivity analysis is carried out. For instance, for a model containing k input parameters $(k > 4)$, the contribution of each one can be represented by each piece of a pie chart.

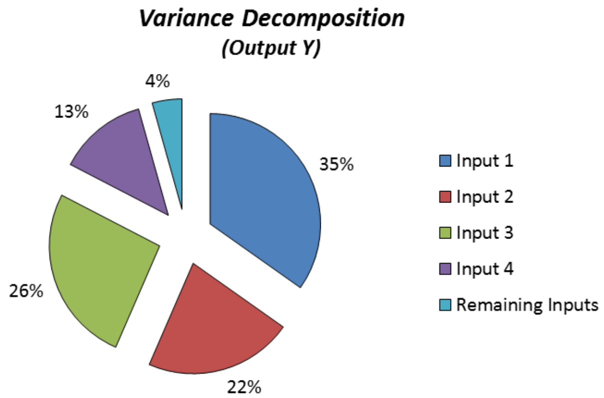


Figure 7-6: Disaggregation of the output variance.

Disaggregation of output variance represents a very illustrative way of presenting results. The fact of knowing the position of each parameter on the ranking of most influential ones and the "weight" of each one, allows focusing on them in order to reduce or eliminate their contribution on the output's uncertainty.

However, designers must be aware that sensitivity analysis represents a relative measure (since it is presented in terms of percentages) and must be complemented by uncertainty analysis in order to quantify the amount of variance present on the outputs.

7.2.6 Proposed Methodology

Figure 7-7 shows a proposed methodology.

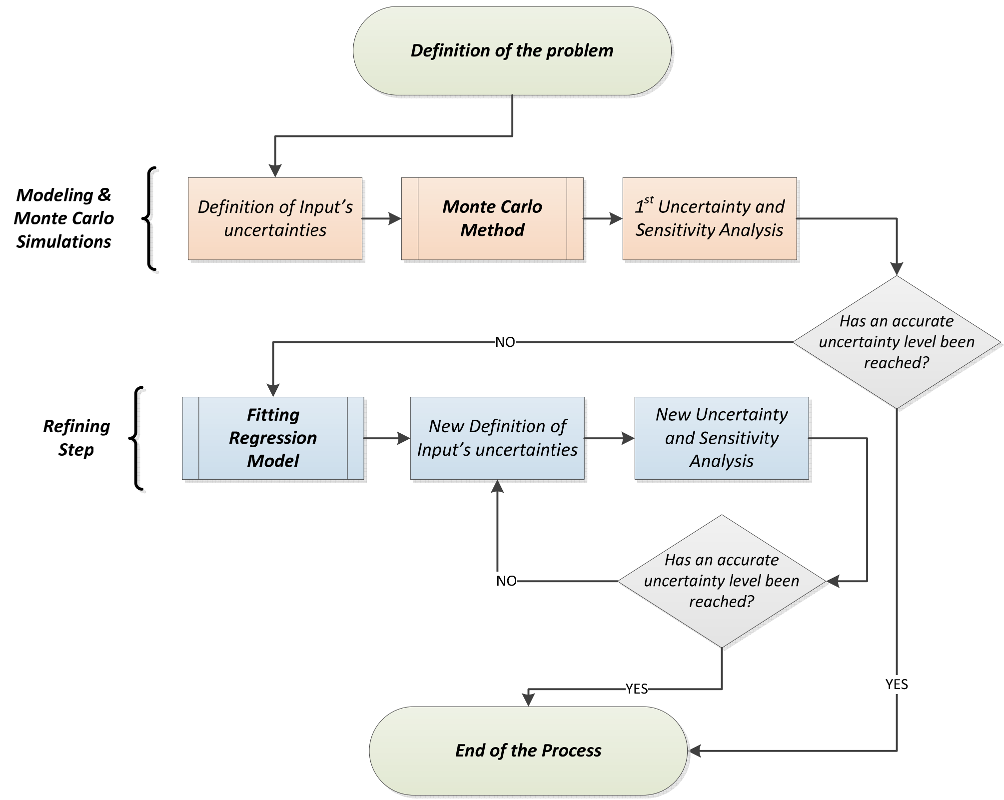


Figure 7-7: Proposed methodology sequence

Methodology comprises all the techniques explained before, placed in sequence according to the requirements of the process at each step.

Monte Carlo method is used for generating a set of outputs over which is performed uncertainty and sensitivity analysis. If accuracy level is not reached, the same set of inputs and outputs is used for creating a simplified regression model over which carrying out a "theoretical" uncertainty and sensitivity analysis.

In this part of the report, each step of the methodology is explained together with the analysis of the results obtained from a case study.

7.2.7 **Definition of the problem**

Definition of the problem is the first step at any analysis. It corresponds to identify the question(s) to be answered (define the output variable of a model to be studied).

Normally, the analyses focus on the building energy performance (e.g. kWh/(m^2-year)) and/or the indoor environmental quality (e.g. average/cumulated PPD, number of hours exceeding a certain predefined temperature etc.).

In this report, results obtained from simulations over a building and HVAC system typology (for details see Ruiz et al., 2011) are analyzed. The analysis is focused on the evaluation of long term data (annual basis) corresponding to *whole building electricity and fuel consumption.*

7.2.8 Monte Carlo Simulations

This phase comprises all the steps corresponding to definition of range variation on the inputs, application of Monte Carlo method and the uncertainty and sensitivity analysis over the obtained results. For a detailed description of the applied method see Ruiz et al., 2012.

7.2.8.1 Definition of input uncertainties

Uncertainty on input parameters must also be defined in terms of a probability distribution. The choice of the type of distribution (normal, uniform, etc.) should be supported by real data (surveys or statistical data available for national regulations). Of course, this information in practice is not available, so when no a priori information is available, and for design purposes the uncertainty range should be defined large enough and following a uniform distribution.

For the analysis presented in this report, a total of 68 parameters corresponding to the 5 family factors defined in Annex 53 were chosen. A generous range of uncertainty and a uniform distribution has been defined for each one.

Since the purpose of this report is to show a methodology, no information is given for defined parameters and ranges assumed for each one.

7.2.8.2 Monte Carlo Method

In simple words, what Monte Carlo method does is propagating input uncertainties trough a specific model by means of a sampling method. Therefore, by means of evaluating the model response according to the variation of input's values, will allow determine the accuracy of a desired output.

The whole procedure can be summarized in 5 steps:

1. Select the model and the questions of interest (section 3.1)
2. Select the uncertain model inputs (k) and set their probability density functions (section 3.2.1)
3. Generate a sample of the model input space size (N)
4. Run the model for each sample point and save the responses
5. Perform uncertainty and sensitivity analysis on the response of interest and interpret the results (section 3.2.3)

One of the main constraints of implementing this approach is the need of coupling different software to perform different parts of the process. Figure 7-8 illustrates all the steps made for carrying out the analysis.

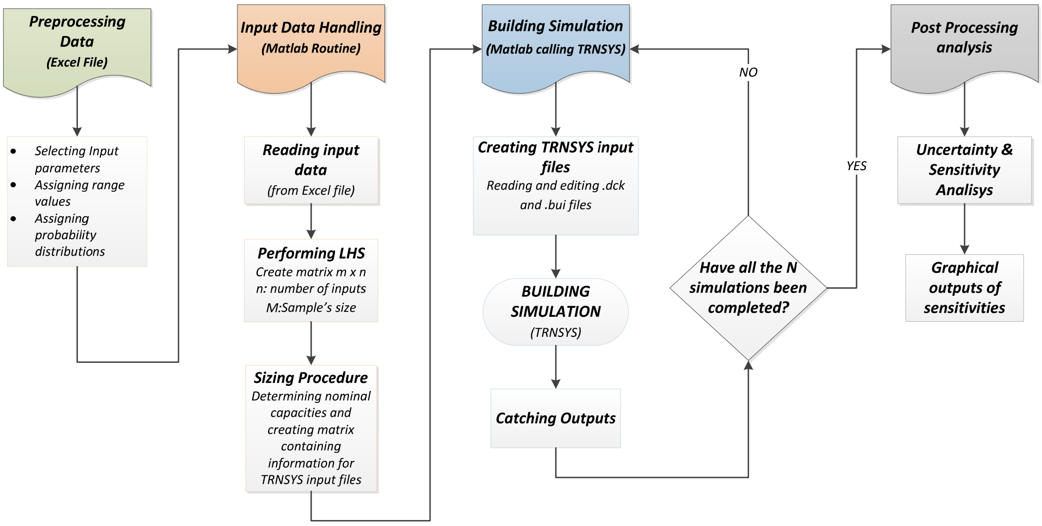


Figure 7-8: Monte Carlo simulation diagram flow

A detailed description of the procedure can be found in Ruiz et al., 2011.

For obtaining modeling assumptions, input parameters and uncertainties defined on them, see the same document.

7.2.8.3 1st Uncertainty and Sensitivity Analysis

Once the results are obtained, it is imperative to know how accurate and how much we can trust on the results. Uncertainty analysis provides information about the possible range of solutions obtained from the uncertainty definition on the inputs.

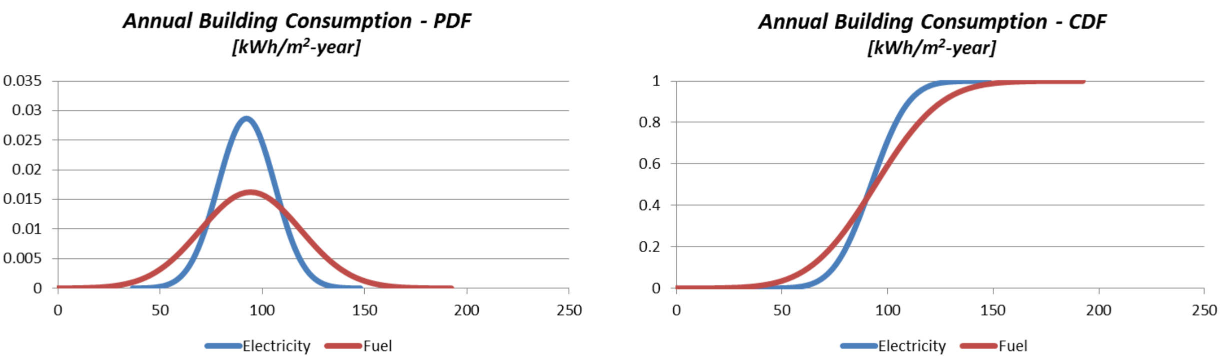
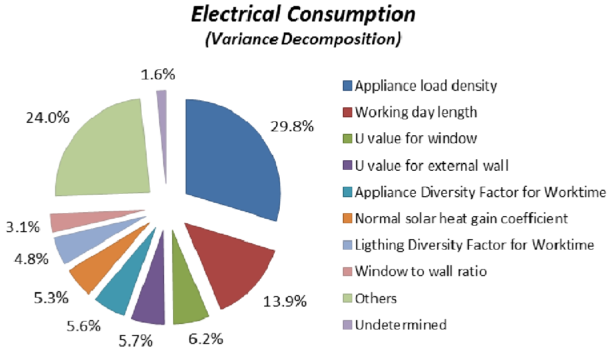


Figure 7-9: Whole building energy consumption outputs (PDF and CDF respectively)

From figure above can be appreciated a big dispersion on both consumptions. Indeed, the coefficient of variation shows values equal to 15% and 26% for electricity and fuel consumption respectively. It means that, following a normal distribution, the 99.6% of the results are within the range $0.55\,\mu - 1.45\,\mu$ for electricity consumption and $0.22\,\mu - 1.78\,\mu$ for fuel consumption.
Next step should considerer identifying the source of this big dispersion.

Figure 7-10 shows the ranking of most influential parameters for both analyzed consumptions.



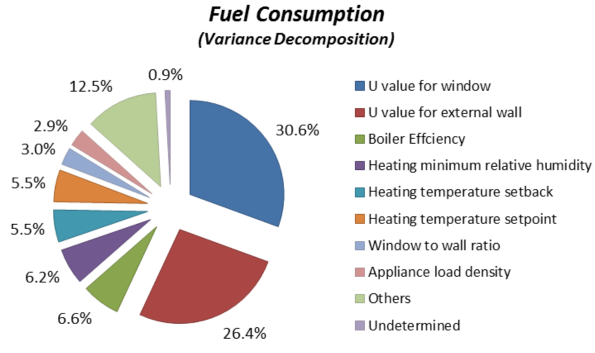


Figure 7-10: Whole building energy consumption – Sensitivity indices

From figure above it is possible to see how only few parameters can be responsible of the biggest amount of variance (it must e remembered that 68 inputs were defined).

Let's assume that the required uncertainty level has not been reached, so the process must continue. To repeat the same analysis, the uncertainty on the parameters shown in figure above should be decreased or eliminated and another set of simulations should be carried out. Of course, repeating this whole step would be very time consuming (even if more of one set of simulation must be run), therefore a simplified procedure is proposed in section 3.3.

7.2.9 **Refining Stage**

7.2.9.1 **Simplified Regression Model**

The use of a simplified regression model is always useful on this type of analysis because can help on:

- Obtaining a considerable decrease of simulation time without losing a significant amount of accuracy
- Identify the nature of the model which helps to understand its behavior.
- Easy obtain of results for a specific situation (i.e. assessing different scenarios such as impact of human behavior).

The proposed model corresponds to a linear one and is obtained from a least square technique. Two models are fitted representing annual whole building consumption of electricity and fuel.

Figure 7-11 presents a comparison between predictions of detailed and regression model.

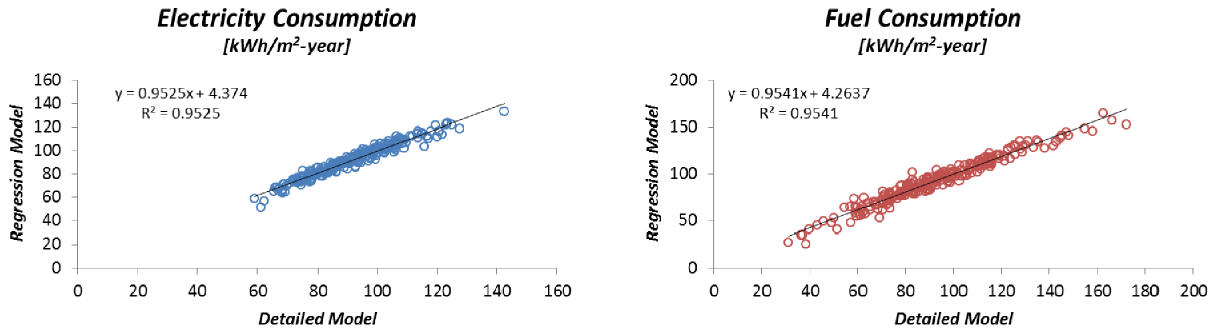


Figure 7-11: Detailed model versus regression model predictions.

As it can be seen the loss of accuracy is negligible in a global point of view and predictions obtained from simplified model can be considered as accurate.

The fact of considering a linear model brings several advantages. They correspond to the facility of computing: model responses, output mean value and output variance (and standard deviation). Equations below show how to obtain these values:

Linear Model	$Y = \sum_{i=1}^{k} a_i \cdot X_i + error_i$	(1)
Expected Value (mean)	$E(Y) = \sum_{i=1}^{k} a_i \cdot E(X_i)$	(2)
Variance	$Var(Y) = \sum_{i=1}^{k} a_i{}^2 \cdot V(X_i) + V(error_i)$	(3)

Note: It must be noted that properties listed above are valid no matter the probability distribution assumed for each input.

Additionally, assuming the same probability distribution of the original data (normal one), the simplified model is able to evaluate as many situations as the designer can imagine.

7.2.9.2 Analysis of Different Scenarios

To show how simplified regression model can provide refined uncertainty and sensitivity analysis results, 2 cases were defined.

Case 1: It was fixed building geometry, envelope properties and occupancy, lighting and appliances densities (for offices, meeting rooms, etc.). Additionally, radiative and space fractions (lighting) were defined. Remaining factors kept the same uncertainty level defined at the beginning.

Case 2: comprise the same parameters listed above (case 1) plus: ventilation rates, indoor set points (temperature and humidity). Additionally were fixed specific fan and pump power and AHU, hot and cold water set points, etc. Parameters related to building operation hours and diversity factors for occupancy, lighting and appliances usage were leave with the same level of uncertainty as the initial model inputs (see Ruiz et al., 2011).

Note: Details about selected fixed values are not specified because the purpose of this report is to show how output variance change when input uncertainties are decreased.

Figure 7-12 shows results for uncertainty analysis for both cases.

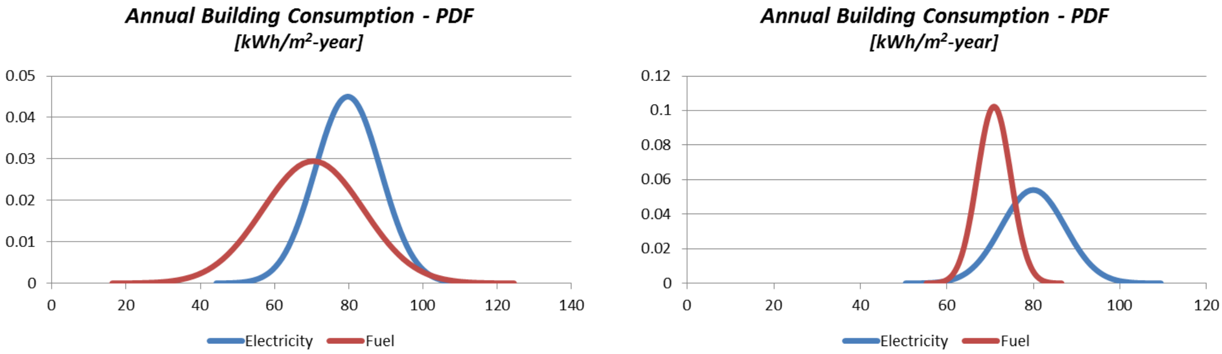


Figure 7-12: Uncertainty analysis results for case 1 and 2 respectively

From figure above can be appreciated how output uncertainty decreases when input parameters are fixed.
Figure 7-13 and Figure 7-14 show ranking of most influential parameters for both cases and both consumptions.

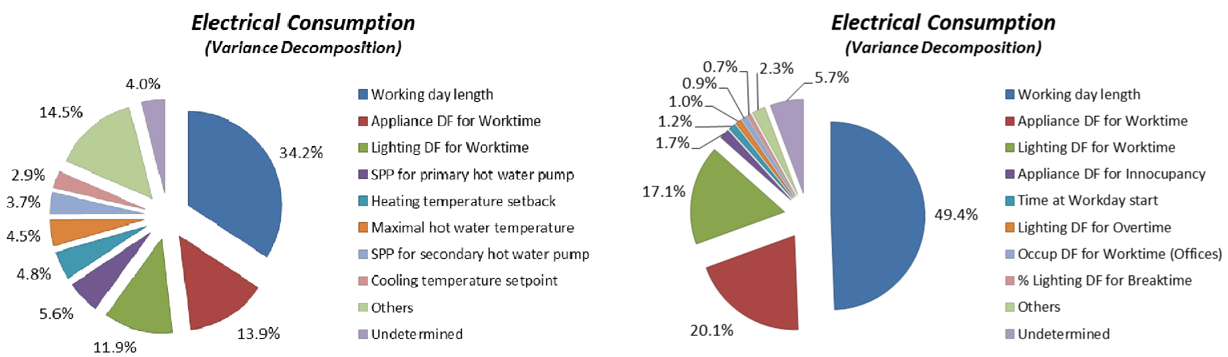


Figure 7-13: Whole building energy electricity consumption – Sensitivity indices for case 1 and 2 respectively

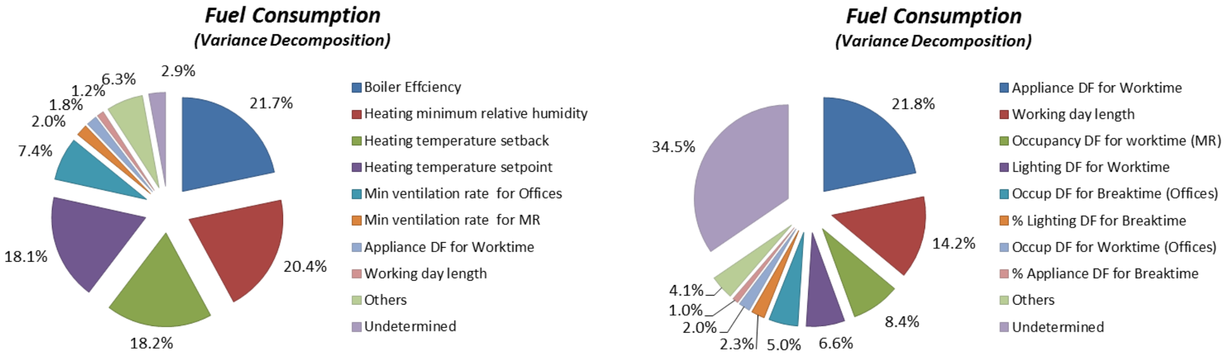


Figure 7-14: Whole building energy fuel consumption – Sensitivity indices for case 1 and 2 respectively

From figures above can also be appreciated how ranking of influential parameters change.

Conclusions

A simple methodology to support decision making has been presented. This methodology integrates uncertainty and sensitivity and a regression model with the aim of making all process as efficient as possible.

In order to obtain valuable information, designer or practitioner must be aware on the degree of uncertainties of the outputs when analyzing the ranking of influential parameters. For high levels of uncertainties, ranking is leaded by fixed parameters such as envelope properties, installed capacities, etc. Only when output variance decrease enough, parameters relates to operation and human behavior take place on the ranking.

7.3 Performance verification of office buildings

7.3.1 Summary

It is commonly admitted that using a building simulation model to assist in analyzing the energy use of an existing building requires the model to be able to closely represent its actual behavior. So, when facing a problem like this, calibration cannot be avoided.

Kaplan et al. (1990) defines calibration as the process of adjusting the parameters of a model through several iterations until it agrees with recorded data within some predefined criteria. The definition of these criteria is a complex issue and, to date, it is impossible to determine how close a tolerance needs to be to fulfill the calibration objective.

A calibration procedure has been proposed in order to get the maximum benefit from the use of a computerized building model:

- Confirm the user's knowledge of the building
- Identify ECOs
- Document the baseline conditions

Focus is given to the development of a calibration procedure dedicated to the steps of the energy efficiency process requiring energy performance diagnosis of the existing situation, i.e.:

- Energy end use breakdown and analysis at inspection and audit stages;
- ECOs evaluation and post-retrofit performance M&V;
- Whole-building level on-going/continuous commissioning.

The main feature of this systematic evidence-based calibration methodology is the integration of a simple sensitivity analysis into the calibration process in order to perform a better measuring and/or estimating of those parameters which are responsible of the biggest consumptions.

The whole calibration methodology is illustrated by Figure 7-15

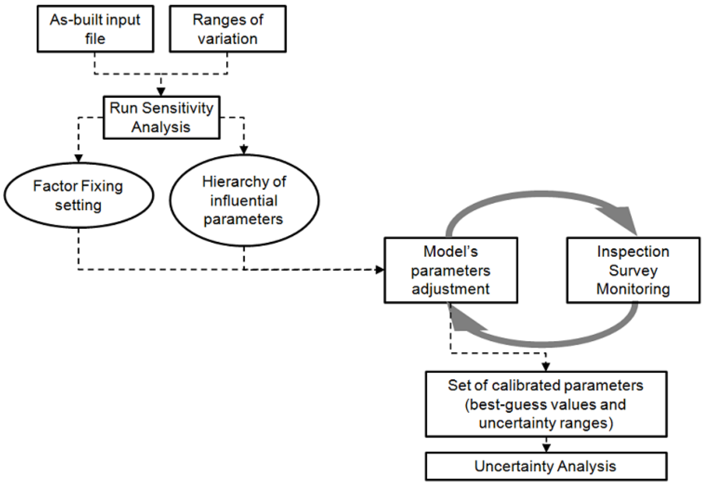


Figure 7-15: Main steps of the evidence-based calibration methodology

At each step of the calibration process, it is proposed to characterize the quality of the calibrated model by means of:

- Classical statistical indexes (Mean Bias Error and Coefficient of Variation of the Root Mean Squared Error) computed on a monthly basis for gas/fuel, peak electricity and offpeak electricity consumptions and,
- Visual comparison of available recorded data (e.g. power measurements) and corresponding predicted values.

7.3.2 **Introduction**

Since the 1960s, building energy simulation was more and more investigated to help in improving energy performance of buildings and HVAC&R systems. Initially, building energy simulation (BES) models were mainly used for design and optimization purposes by means of a forward (predictive) approach.

More recently, the use of these models was extended to other stages of building life cycle (see Figure 2-1), such as energy services activities (including inspection/audit, evaluation of Energy Conservation Opportunities and on-going performance analysis).

It is commonly admitted that using a building simulation model to assist in analyzing the energy use of an existing building requires the model to be able to closely represent its actual behavior. So, when facing a problem like this, calibration cannot be avoided.

Kaplan et al. (1990) defines calibration as the process of adjusting the parameters of a model through several iterations until it agrees with recorded data within some predefined criteria. The definition of these criteria is a complex issue and, to date, it is impossible to determine how close a tolerance needs to be to fulfill the calibration objective.

The process of adjusting the parameters of a BES model according to an existing situation involves using:

- As-built information (geometry, envelope properties, air and water nominal flows, equipment's nominal capacities, etc.)
- survey observations (to characterize building operation and occupant's behavior)
- short and/or long term monitoring (to confront calibrated building model outputs)

In practice, the stage of gathering data is quite cumbersome and difficult to handle for engineers and practitioners. Incomplete and/or outdated as built data, global and limited data (monthly utility bills) and missed consumption's records make the situation quite discouraging.
Of course, each use of a calibrated model involves specific requirements in terms of data gathering as well as modeling capabilities, parameters adjustment process, level of accuracy depending on what the final calibrated model is intended for (stage of building life cycle).

Assuming that a computerized building model is constructed in a good way (i.e. by defining properly the objectives of the calibration, required level of details, type of data to gather, etc.), a considerable number of benefits can also be expected from the use of building simulation (Waltz, 2000):

- *Confirm the user's knowledge of the building*: Constructing the model constrains the modeler to review all the characteristics of the installation (types of equipment, installed power/capacity, performance, operating profiles, etc.)
- *Identifies ECOs*: Frequently, the calibration is made difficult by undiscovered over-consumptions due to some equipment operating out of control. These elements generally correspond to elementary and very cost-efficient energy conservation opportunities. The calibration of the model and the need to represent the whole-building energy use force the modeler to identify such problems.
- *Documents the baseline conditions*: A well-documented calibrated model is generally a complete and detailed statement of the actual conditions. Raftery et al. (2011) applied this principle and provided a very detailed calibrated model of the installation as well as a complete documentation describing all the steps and intermediate runs of the calibration process.

On the other hand, the use of calibrated simulation models has also an important number of limitations.

- *A first limitation relies in the use of a model itself*. Whatever the intended use of the calibrated model, the method employed to build it and the achieved level of accuracy, building energy simulation models remain an abstraction of a certain reality and have numerous limitations.

- *A second limitation relies on the availability of the data used to check the validation and the achieved level of accuracy*. Supposing the model sufficiently (but not too much) detailed is used for evaluating ECOs (the most common application), annual and monthly consumption data are generally used and considered as sufficient to check the validity of the calibration. Kaplan et al. (1990) have shown that, even if the calibration seemed to be successful, the finely calibrated model was not necessarily able to ensure an accurate analysis of ECOs because of lack of data on the pre-retrofit situation and use of an "imaginary" baseline building.
- *The third limitation is related to the accuracy of the available data* and the effort putted in the work which would not be "better" than the accuracy of the available data. As prescribed by Waltz (2000), it is not realistic to try to provide a 1% answer to a10-15% question.
- *A fourth limitation is linked to the building modeler skills*. Whatever the employed modeling technique, very high and very poor quality simulation results can be obtained depending of the modeler.

In addition to the limitations mentioned above, ASHRAE (2002) recommends to avoid the calibration approach when:

- ECOs could be analyzed without building simulation;
- The building cannot be simulated (presence of large atriums, underground buildings, complex shading configurations…);
- The HVAC system cannot be simulated (certain control options cannot be represented…);
- The retrofit cannot be simulated;
- Project resources and financial issues are insufficient to support development and use of calibrated simulation.

Considering all the issues discussed in this section, a calibration methodology is proposed in the next part of this report.

7.3.3 **Proposed Calibration Methodology**

This methodology has been proposed by Bertagnolio (2012). *The objective of this work was developing a simulation-based approach dedicated to whole-building energy use analysis for use in the frame of an energy efficiency service process*. Focus is given to the development of a calibration procedure dedicated to the steps of the energy efficiency process requiring energy performance diagnosis of the existing situation, i.e.:

- Energy end use breakdown and analysis at inspection and audit stages;
- ECOs evaluation and post-retrofit performance M&V;
- Whole-building level on-going/continuous commissioning.

The main feature of this systematic evidence-based calibration methodology is the integration of a simple sensitivity analysis into the calibration process in order to perform a better measuring and/or estimating of those parameters which are responsible of the biggest consumptions.

The basic principle of this new methodology is to give priority to the physical identification of the model's parameters (i.e. to the direct measurement) and relies on the definition of two types of hierarchy:

- A hierarchy of the model's parameters by order of influence built based on the results of a preliminary sensitivity analysis based on the Morris' sampling method and allowing (1) "factor fixing" (i.e. identification of non-influential parameters that could be set to their "best-guess" value) and (2) "parameters screening" (i.e. classification of influential parameters by order of importance).

- A hierarchy among the source of information exploited to identify the value of the parameters based on the reliability of the available data (e.g. direct measurements > observation > default value).

Following these main rules, the user is guided all along the energy use analysis process. The information provided by the preliminary sensitivity analysis is used to orient the data collection work (i.e. the inspection of the building) and the progressive adjustment of the parameters.

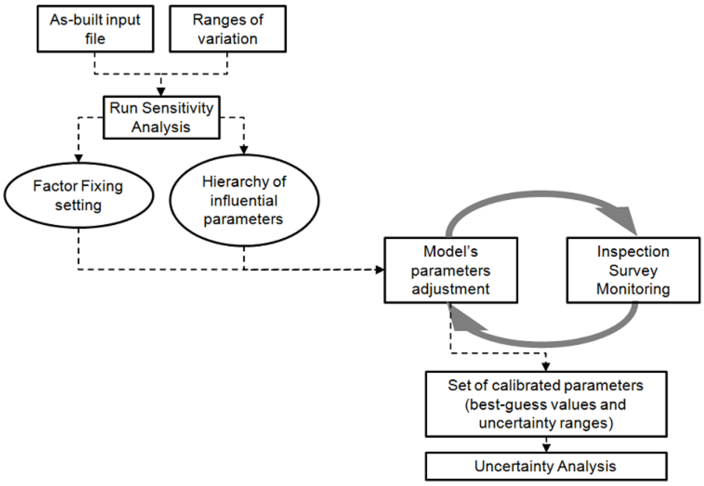


Figure 7-16: Main steps of the evidence-based calibration methodology

All along the calibration process, the values of the parameters are updated, as well as the related probability ranges (reflecting the confidence/uncertainty on the considered value of the parameter). These ranges of variation are used at the end of the calibration process to quantify the uncertainty on the final outputs of the calibrated model by means of the Latin Hypercube Monte Carlo sampling method.

At each step of the calibration process, it is proposed to characterize the quality of the calibrated model by means of:

- Classical statistical indexes (Mean Bias Error and Coefficient of Variation of the Root Mean Squared Error) computed on a monthly basis for gas/fuel, peak electricity and offpeak electricity consumptions and,
- Visual comparison of available recorded data (e.g. power measurements) and corresponding predicted values.

If available, recorded and predicted (quarter-) hourly power demand profiles should be compared to qualify the accuracy of the calibrated model.

In this work, calibration tolerances used correspond to those recommended by ASHRAE (2002):

Table 7-1: Calibration tolerances

	Monthly basis	**Hourly basis**
MBE	± 5%	± 10%
CV(RMSE)	± 15%	± 30%

7.3.4 **Case Study**

The whole calibration methodology presented earlier is applied to a real office building located in the city centre of Brussels, Belgium. The building was built in the 70's and was largely refurbished in 1998. It was recently awarded with an energy performance certificate with a mark of D+ (i.e. just above the average for similar buildings in Brussels area), corresponding to an annual primary energy consumption of about 316 kWh/m²/yr. For technical information of the building see Ruiz et al. (2012).

Figure 7-17: Exterior scene of the studied building (DM 28).

7.3.4.1 **Tasks performed during calibration procedure**

Different tasks were performed in order to organize and provide input data at different levels of the calibration procedure. Table 7-2 shows main task carried out during the whole calibration procedure.

Table 7-2: Tasks performed during calibration procedure

#	Task	Subtask	Description
1	Building description	Geometry	Determination of main surfaces, building footprint, internal volume, etc.
		Building facades	Identification of different types of facades and their corresponding thermal properties, percentage of glazed surfaces…
		Internal layout	Identification of different floor types and zone usages.
2	HVAC system description	Ventilation system	Identification of different AHUs and their corresponding zones to serve.
		Local heating and cooling	Type of terminal units in different zones (main characteristics)
		Heat production	Heating plant, boiler type, nominal capacities, nominal efficiencies, etc.
		Cold production	Cooling plant, chiller type, cooling towers, nominal capacities, nominal EER, etc.
3	Building use and occupancy	Occupancy	Distribution of workers for different zones (nominal values).

		Lighting	Identification of type and installed capacities of luminaries.
		Appliances	Nominal power of existing appliances, differentiation by type of zones (offices, meeting rooms, printshop, etc.).
		Building operation	BEMS control strategy recognition, indoor setpoints, working period for lighting (BEMS controlled), ventilation, etc.
4	Billing data	Fuel & electricity	Analysis of billing data and electrical quarter hour profile.
5	Monitoring campaign	Short-term monitoring	Electrical power demand at different levels, temperature and humidity at different locations, plug electrical demand, lighting and appliances operation time, etc.
		Building energy management system (BEMS)	Identify relevant aspect of the control of HVAC system and the lighting system.
6	Occupant Behavior	Occupancy survey	Identify main trends related to occupant behavior (use of lighting, appliances, terminal units, etc.)
7	Weather Data	Hourly data compilation	Analysis of available weather data. Real data corresponding to Mons (city near Brussels) was used.

7.3.4.2 Calibration levels

Calibration levels correspond to different stages of the data collection process (from data collected during on-site inspection to detailed energy metering and occupancy survey). The process was divided into 5 parts:

1) Level 1 - Initial As-Built Input File

An initial input file is built based on the as-built information (Table 7-2, # 1 and #2) but does not include any information about actual building use or operation (# 3). A preliminary sensitivity analysis is performed in order to orient the data collection work (subsequent steps).

2) Level 2 - Inspection Phase

Information about building and system operation are made available by means of a direct ("on-screen") analysis of the BEMS system. At this stage, no verification of the data provided in the BEMS is done (e.g. no verification about the achievement of the specified setpoints) and no measurement/recording is done but the information collected during the inspection of the building and summarized in # 3 (Table 7-2) is used to adjust the parameters of the model and to define the probability range of each parameter according to the estimated quality of the information.

3) Level 3 - Monitoring Phase

At this level makes an intensive use of BEMS records and of the monitoring data collected on-site by means of the measurement equipment (Table 7-2, #5). At this stage, the probability ranges depend on the accuracy of the sensors, loggers and recorders.

4) Level 4 - Occupancy Survey

his stage includes the information derived from the analysis of the answers to the survey presented #6.

Table 7-3 shows a list of each calibration level.

Table 7-3: Calibration levels

Calibration Levels		Building description and performance data available for calibration					
		Utility bills	WEB demand	As-built data	Inspection	Spot/short-term monitoring	Occupancy survey
Evidence based process	Level 1	x	x	x			
	Preliminary Sensitivity Analysis						
	Level 2	x	x	x	x		
	Level 3	x	x	x	x	x	
	Level 4	x	x	x	x	x	x
	Final simulation results and uncertainty on the predicted energy use						
Final Adjustment	Level 5	Iterative adjustment of uncalibrated parameter					

Final adjust (level 5) was proposed but not performed. This step would consist on carrying out an optimization procedure (taking into account the decrement of uncertain variables) in order to minimize the error between recorded and simulated data.

7.3.5 **Main results**

As a first issue, the accuracy reached at each level of the procedure is shown in Table 7-4.

Table 7-4: Calibration accuracy reached at each level

	Level 1		**Level 2**		**Level 3**		**Level 4**	
	MBE	**CV(RMSE)**	**MBE**	**CV(RMSE)**	**MBE**	**CV(RMSE)**	**MBE**	**CV(RMSE)**
Gas	-3.1	17.9	-14.4	23.9	-1.1	14.8	-2.1	14.9
Electricity	-18.8	20.2	14.7	16.9	2.3	6.8	-2.2	5.6
Peak	11.3	13.5	22.6	24.4	4.6	8.0	-0.9	7.4
Offpeak	-89.3	91.1	-3.7	12.0	-2.6	10.0	-5.1	9.7
Hourly	-18.8	63.4	14.7	47.8	2.3	29.3	-2.2	24.9

At the end of the procedure, calibration tolerances recommended by ASHRAE (2002) were reached. See Table 7-1.

7.3.6 **Electrical consumption disaggregation**

The final electricity consumption disaggregation is presented in Table 7-18. About 33% of the total electricity consumption is due to artificial lighting.

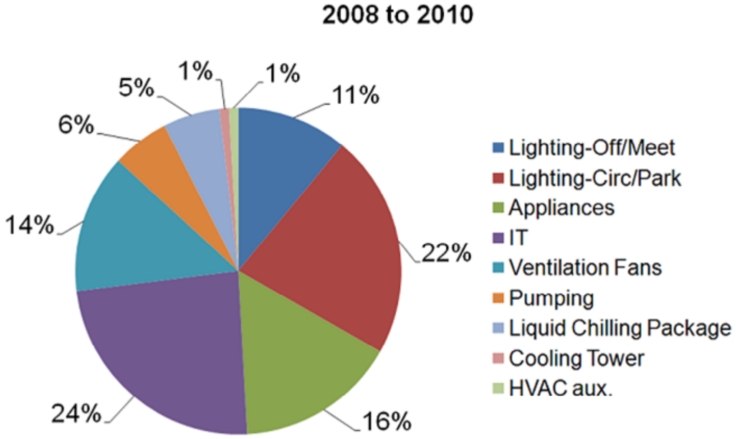


Figure 7-18: Whole-building electricity consumption disaggregation (at Level 4)

Only one third of this part of the consumption is due to lighting in occupancy zones. Offices appliances (computers, printers, etc) represent about 16% of the total consumption while almost one quarter of the total consumption is due to IT rooms. Ventilation fans are responsible of about 14% of the consumption. The hot and chilled water production and distribution equipments represent about 13% of the total consumption.

7.3.7 Heating and cooling demands

The calibrated model can only be used to generate some annual energy balances. Figure 7-19 shows the disaggregation of the annual heating and cooling demands. On the heating side, it appears that the heating of the parking level (-2) is responsible of about 16% of the total hot water demand (and so, about 16% of the natural gas consumption). About 33% of the hot water demand is due to local zone heating by the fan coil units. Only a limited part (14%) of the total hot water demand is due to humidification of the supply ventilation air by adiabatic humidifiers. The relatively high supply air temperature set points (between 20°c and 25°C) explain why supply air reheat is the most important hot water consumer.

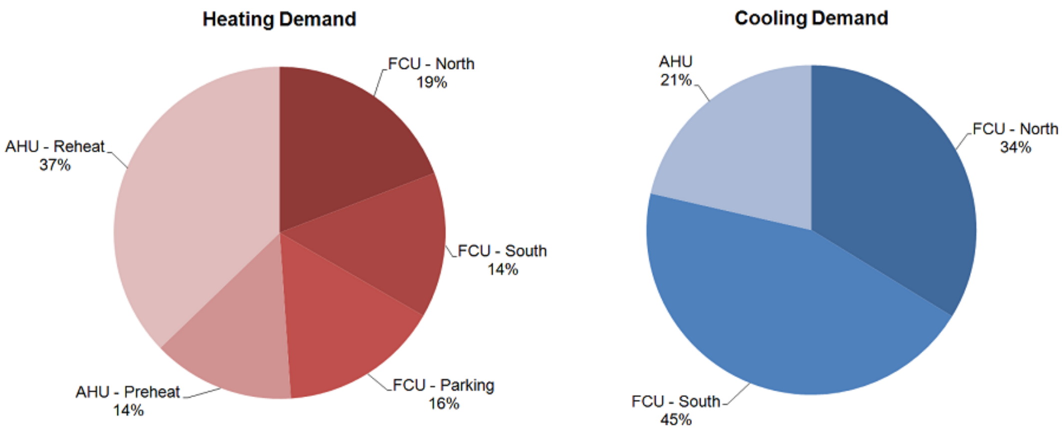


Figure 7-19: Heating and Cooling Demands Disaggregation

7.3.8 **Conclusions**

In the present study, a model calibration procedure was shown and used to disaggregate the final energy use and to identify the intermediate energy flows in the buildings (specific heating and cooling demands per zone and/or HVAC component).

This case study confirmed that it is possible to calibrate a simplified hourly simulation model by means of a relatively little amount of physical measurements if focus is given to critical issues and a systematic and efficient approach is followed.

Sensitivity analysis showed to be of great help when identifying those “critical issues” mentioned above was required, allowing improving significantly the quality of the model.

7.4 **Development of a smart counting method**

7.4.1 **Summary**

A new smart counting method has been developed in order to better understand, by means of simulation model, the impact of the user on the total energy consumption and also to have an impact on this behavior to make it more efficient.

The first idea proposed hereafter is to support the energy recording currently available by a dynamic simulation of the building (and of its HVAC system) in such a way to allow some “smart counting” of the energy consumption.
A new approach consists in using indoor temperatures recorded inside different building zones and integrated energy demands as simulation input and output variables, respectively. This is the contrary of what is usually done: in most current simulations, control laws and set points are imposed, in such a way to reproduce as well as possible (but with questionable accuracy) the real behavior of the (building and HVAC) system.
With the new approach, one can be sure that the indoor temperatures are fully realistic, because being imposed as recorded; focus can then be given on the most important result: the energy consumption.
A second idea is briefly suggested hereafter: correlating integrated energy and water consumptions among themselves.
Water consumption seems indeed reflecting rather well the occupancy rate of the building and therefore also the heating demand “intensity”, for a given set of weather conditions (i.e. a given seasonal period).
The method includes the following steps:

- Development of a simulation model for the case to study
- Recording of data (energy and water consumption, indoor temperatures, weather data) on a few days
- Simulation of this short time period using measured temperatures as inputs in order to eliminate control uncertainty
- Comparison between measurements and simulations which shows a smart counting on such a short period may be applied to warn the occupant about any abnormal energy consumption
- Analysis on a longer period (typically one month) which confirm the feasibility of the counting method (see Figure 7-20)

- Calculation of correlations between energy and water consumption which shows water consumption may be used as a good tracer of occupancy.

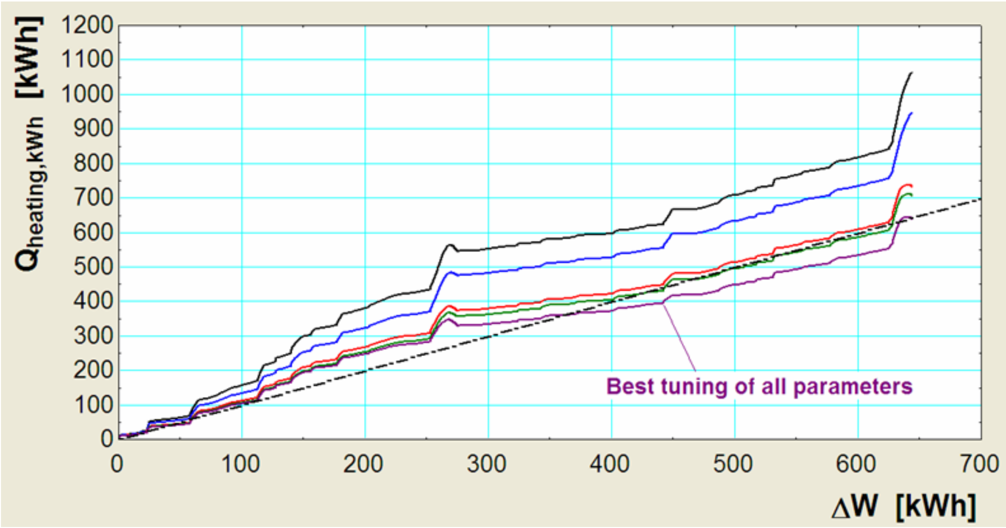


Figure 7-20: Simulated heating demand as function of the electricity consumption

As a conclusion, a more significant building signature could be established by correlating its energy consumption with two independent variables: the water consumption and the outdoor temperature. In order to make this signature easy to read, the three variables considered would have to be integrated on time.

7.4.2 **Introduction**

Annex 53 is concerned by the main factors influencing the building energy consumption. One of these factors is the human behavior, which includes the occupancy schedules, the activities and the possible actions of the occupants on the building- HVAC system. In view of reducing the building energy consumption, it seems necessary, not only to identify and to take into account the actual behavior of the occupants, but also to encourage them to behave more efficiently, thanks to a quick and accurate feedback on their actions. In short, the occupants, as well as the managers and all concerned people, need to be informed as soon as possible about the consequences of their actions and about any “abnormal” consumption.

This may help a lot at different phases of the building life cycle: commissioning, audit, retrofit and current life. Such feedback must be as quick as possible, reliable and easy to understand. Any mistake might have a contrary effect: distract, or even discourage, the occupants and other people concerned.
This task is made difficult by many lacks of information about the building and system characteristics, about the actual indoor and outdoor climates, about the actual control and management of the system…and about the actual behavior of the occupants!

The first idea proposed hereafter is to support the energy recording currently available by a dynamic simulation of the building (and of its HVAC system) in such a way to allow some “smart counting” of the energy consumption. A new approach consists in using indoor temperatures recorded inside different building zones and integrated energy demands as simulation input and output variables, respectively. This is the contrary of what is usually done: in most current simulations, control laws and set points are imposed, in such a way to reproduce as well as possible (but with questionable accuracy) the real behavior of the (building and HVAC) system. With the new approach, one can be sure that the indoor temperatures are fully realistic, because being imposed as recorded; focus can then be given on the most important result: the energy consumption.

A second idea is briefly suggested hereafter: correlating integrated energy and water consumptions among themselves. Water consumption seems indeed reflecting rather well the occupancy rate of the building and therefore also the heating demand "intensity", for a given set of weather conditions (i.e. a given seasonal period).

In the frame of annex 53, both ideas were tested on the simple case of a dwelling with direct electric heating. The main results of this case study are summarized hereafter; more details are given in a companion report [1] and in two conference papers [2], [3].

7.4.3 The dwelling

The dwelling selected for this study is located on the Belgian coast and presents a total floor area of 95 m^2. Direct electric heaters are available in all rooms, except the kitchen, the corridor, the toilet and the boiler room. The dwelling considered and the four other ones surrounding it are submitted to very intermittent (and not simultaneous) occupancies. The living room only is heated all along each occupancy periods. According to occupancy rates, the other rooms are heated during limited morning and evening periods. The dwelling is equipped with (peak and off-peak) electrical and water counters. These counters are read at different times when the dwelling is occupied. Indoor air temperatures are continuously and automatically recorded in four zones of the dwelling: the living room, two sleeping rooms and the bath room. Weather data are taken from the nearest meteorological station.

7.4.4 The simulation model

The simulation model of this dwelling is subdivided into 8 "internal" zones, connected to 7 "external" zones, as indicated in Figure 7-21. All heavy walls are represented by first order R-C-R elements as in other studies [4]. The model is built and run with the help of the EES software [5].

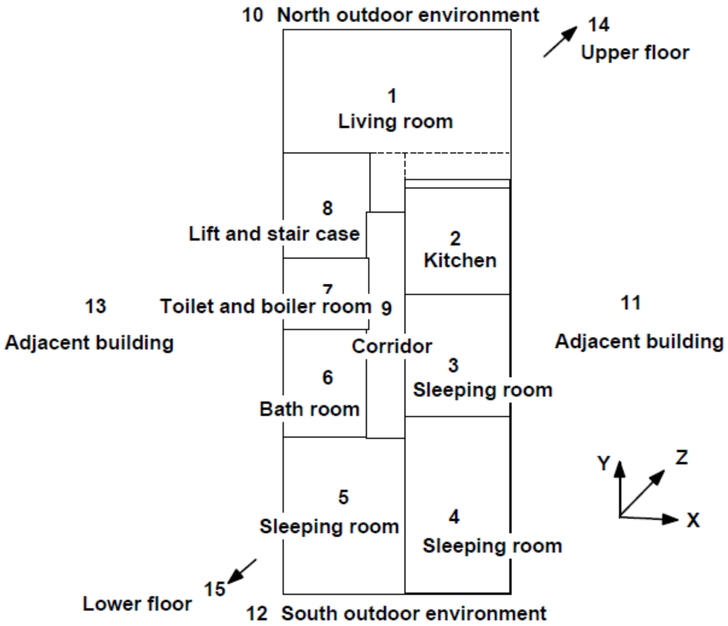


Figure 7-21: the dwelling subdivided in 9 zones

The simulation model is built in three steps.

The *first step* consists in subdividing the building and its surroundings into different zones and in identifying all internal and external walls. The internal zones are distinguished among themselves according to occupancy schedules and to indoor environmental requirements. A matrix of zones interconnections is easy to build on basis of building pictures and geometrical data. Each interconnection corresponds to one or to several walls, doors and windows, whose characteristics are defined in the next step.

The *second step* consists in identifying the R and C components to be used to represent the internal and external zone "partitions". The solution obtained from the first step is here used (by "copy and paste") as input data.

The *third step* consists in interconnecting all the R-C-R circuits and establishing the energy balances of all nodes. This doesn't require any graphic tool: the matrix established in the first step allows the user knowing which (internal or external) zones are interconnected through each wall. Again here, the solution of the previous step is used (by "copy and paste") as input data. In the example considered, the whole building model corresponds to a set of 822 (769 algebraic and 53 integral) equations. These equations are repeated and adapted, step by step, with the help of the classical "copy", "past", "find" and "replace" functions for all walls and all zones.

7.4.5 **Recording of indoor climate and electrical consumption on a few days**

Examples of recordings are presented in Figures 7-22 to 7-24.
Indoor and outdoor temperatures recorded on a period of one week are presented in Figure 7-22.
The dwelling stays unoccupied during the first six days of that week. The occupancy period starts on the evening of the sixth day. A zoom on that last 25 hours period is presented in Figure 7-23.

The shapes of the curves correspond to the following events:

- Arrival of the occupants on December 3rd around 19h (the 8083rd hour of the year), starting of the heating in three zones of the dwelling (living, sleeping and bath rooms);
- Shutting down of the heating in the evening (first in the living room and a little later in the two other zones) around the 8087th hour;
- Re-starting of the heating on the next morning (first in the bath room and two hours later in the living room) for a while;
- Shutting down again a few hours later (first in the bath and sleeping rooms and then in the living room).

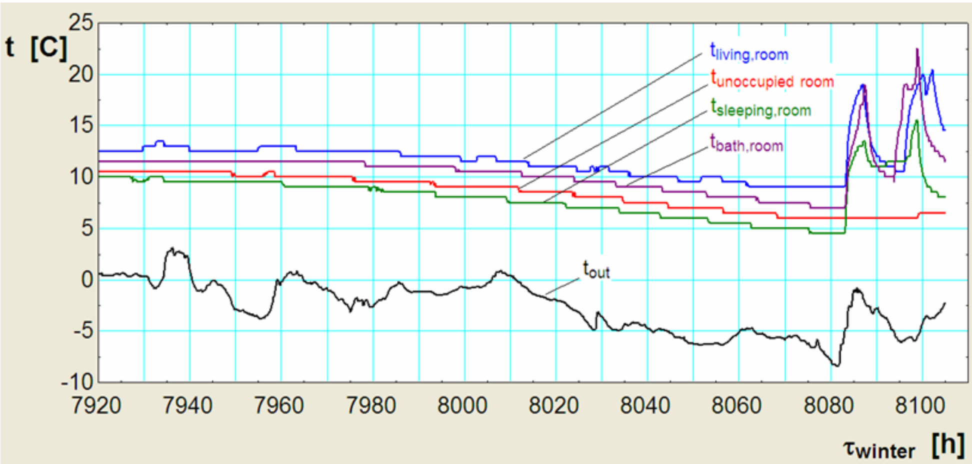


Figure 7-22: Indoor and outdoor temperatures recorded on one week

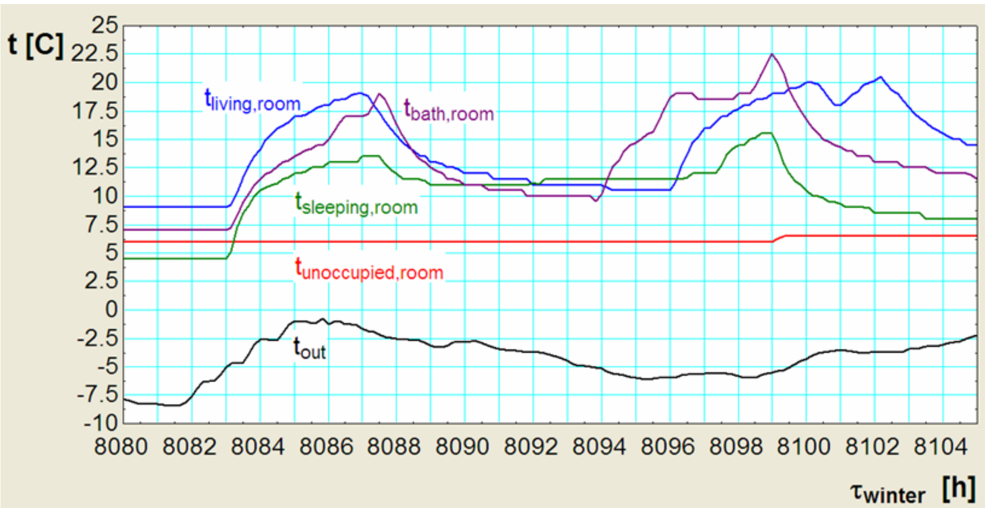


Figure 7-23: zoom on the left side of Figure 7-22 (last 25 h time period)

Cumulated peak, off-peak and total electricity consumptions are manually recorded.
The points of the diagram of Figure 7-24 correspond to occasional readings of the counters.
Off-peak periods are from 10 pm to 7 am and weekends.

The smooth slopes of the three curves on the left side of the diagram correspond to the non-heating period. On the right side of the diagram, the sharper slope increases correspond to occupancy periods with (growing) heating needs.
The curves of Figure 7-24 correspond to the same 25 hours period as in Figure 7-24. The peak counter is here only working during the very first period (on Friday evening).
The apparent superposition of peak and off-peak demands occurring between the hour 8085 and 8086 is due to the fact that the counters were not read at change-over time.

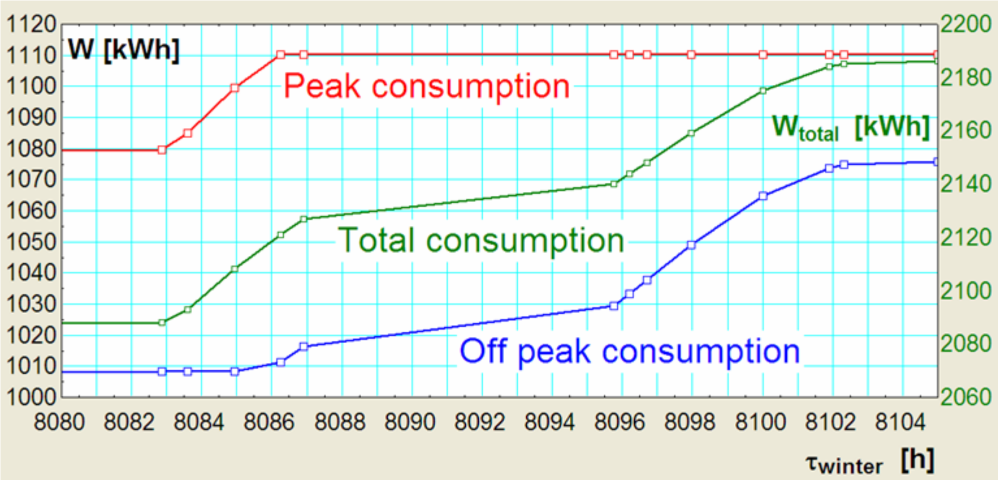


Figure 7-24: Electrical consumptions

7.4.6 Simulation on short time period

A comparative simulation is performed by using the four indoor air temperatures of Figure 7-22 as input data: this eliminates any control uncertainty and should make the measured and simulated consumption directly comparable. The other (unheated) zones are simulated as in “free floating” temperatures.
The heating demands of the four zones whose temperatures are imposed are plotted in Figure 7-25. As to be expected, their shapes are similar to the shapes of the curves of Figure 7-23, except for the time variations which are here a bit sharper. Indeed, in each room, the temperature response to any variation of heating power is damped by the walls thermal mass.
Significant simulation mistakes also appear in Figure 7-24: a non negligible heating demand is calculated before occupant arrival (hours 8080 to 8083); this fictitious heating demand reaches 1000 W in the living room (blue curve), probably due to some erroneous estimate of boundary conditions (mainly the temperatures of the surrounding dwellings).
A slightly negative heating demand is also calculated later in the unoccupied room (red curve), probably also because of erroneous boundary conditions. The simulation model should be tuned on the whole observation periods and mainly when the dwelling is empty.
The heating powers of Figure 7-25 are integrated in Figure 7-26, in order to make them easier to compare with the energy records. It appears that the accumulation of energy in the walls produces a very significant increase of the heating energy demand on the first evening and still on the whole 25 hours period considered…

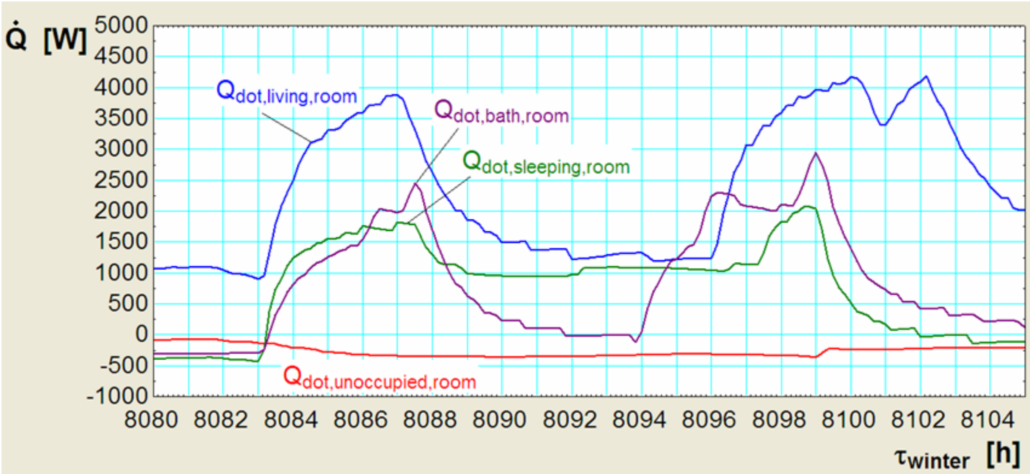


Figure 7-25: Simulated heating demands as functions of the four indoor temperatures of Figure 7-23

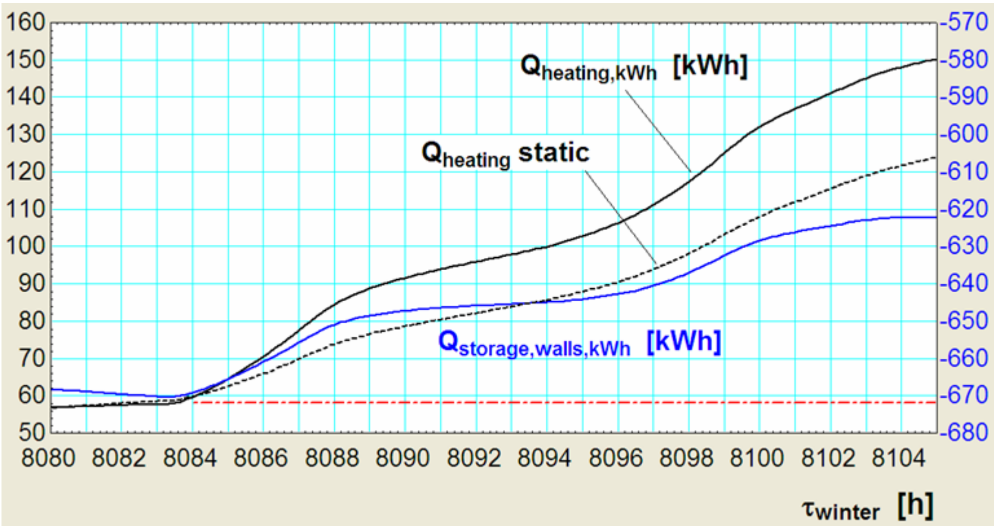


Figure 7-26: Integration of the curves of Figure 7-25

7.4.7 Comparison between simulation and measurements

A fairly satisfactory comparison between the measured electrical consumption and the simulated heating demand is presented in Figure 7-27.
The total consumption of electricity is over-passing the heating demand because of:

- Electrical energy not used to heat the dwelling (of the order of 5 kWh per day, for hot water production);
- Modelling inaccuracies (mainly static and dynamic characteristics and temperatures in surrounding dwellings).

These differences would be easy to reduce thanks to a more detailed analysis of all information available and also by a better tuning of the simulation model.

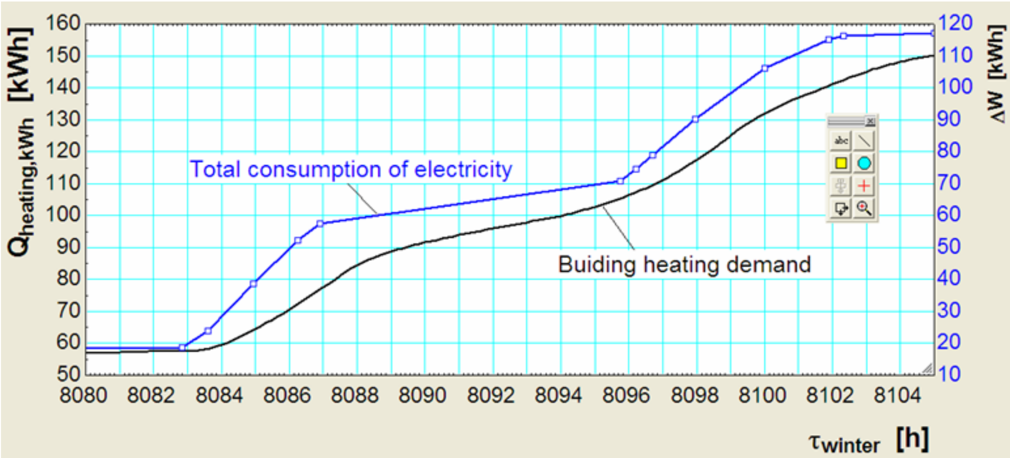


Figure 7-27: Measured electricity consumption and simulated heating demand

This first analysis demonstrates the feasibility of some smart counting on a time period of the order of a few hours only: on such short term basis, it should be possible to warn the building users about any abnormal energy consumption. But this requires a minimum of realism in the building dynamic simulation.

7.4.8 Recordings on one month and comparison with simulation

A detailed analysis on one month (January 2011) is presented hereafter.
Indoor and outdoor air temperatures are shown in Figure 7-28 from the hour 8700 to 9700 (this time is counted from the first hour of 2010).
Occupancy and non occupancy periods are easy to identify in this diagram: during occupancy periods, the indoor temperatures are submitted to sharp increases due to heating (re) starts; during non-occupancy periods, these temperatures are smoothly decreasing until reaching some new equilibrium.
Indoor temperatures are, most of the time, fluctuating between 10 and 20 °C, with maxima reaching 25 °C (t6: bath room) and minima approaching 7 °C at the end of the period considered (dwelling empty and exposed to cold weather) conditions.
One curve (t3 in red) of Figure 7-28 is not issued from measurement, but from simulation: it corresponds to an empty room, which is not in direct contact with the outdoor environment and never heated. This explains its very smooth appearance: no violent perturbation and no digitalization discontinuity.

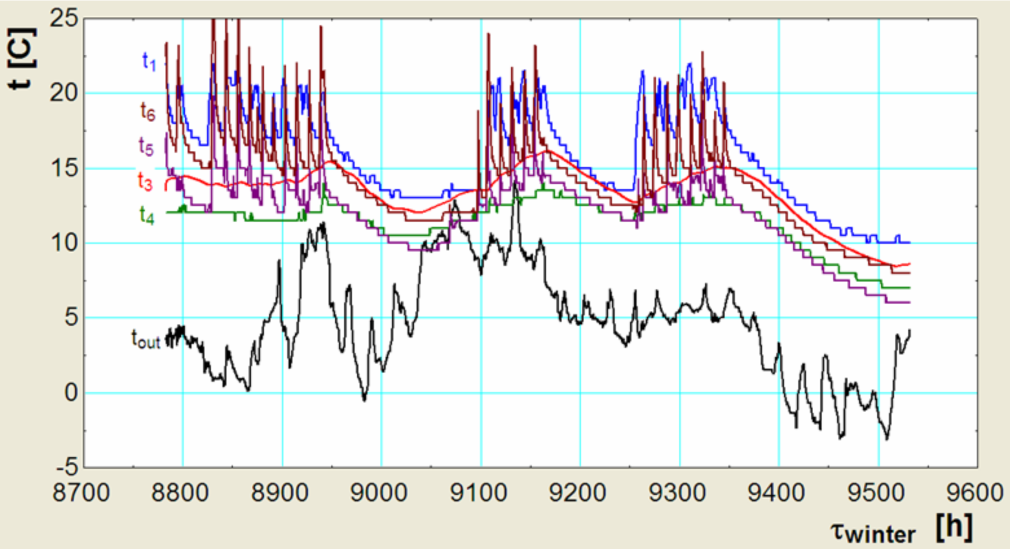


Figure 7-28: Indoor and outdoor temperatures

The global consumption of electricity is plotted in Figure 7-29. The four occupancy and three non-occupancy periods are also easy to distinguish in this diagram, thanks to the two very different associated slopes.

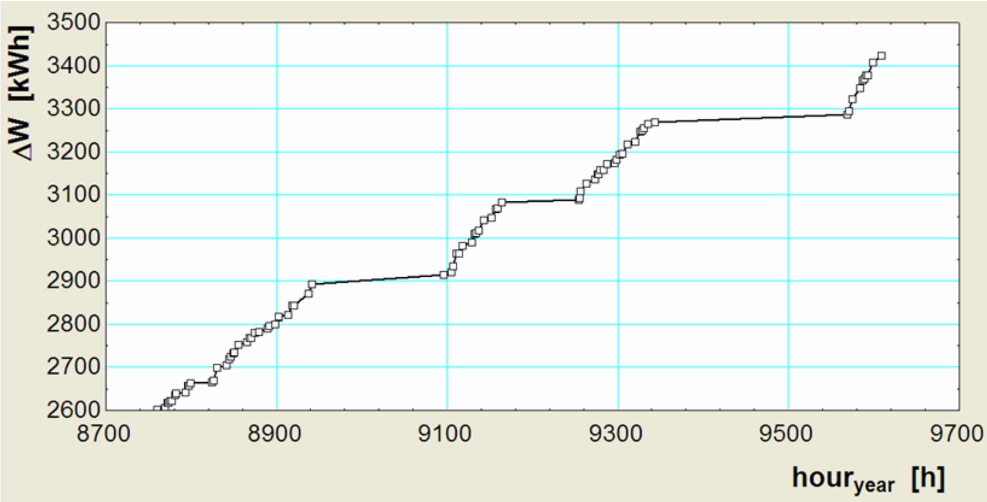


Figure 7-29: Electricity consumption in January 2011

Several parameters and input variables had to be tuned before getting a satisfactory agreement of the simulation with experimental results.

The simulation results presented in Figures 7-30 and 7-31 were obtained with the following combination of (still very hypothetical) assumptions: minimal surroundings temperature of 10°C, significantly reduced heat transfer coefficients and local outdoor temperature staying 0.5 K above its value measured at the weather station (slight microclimate effect).

The fair agreement between simulation and measurements is well demonstrate in Figure 7-30.

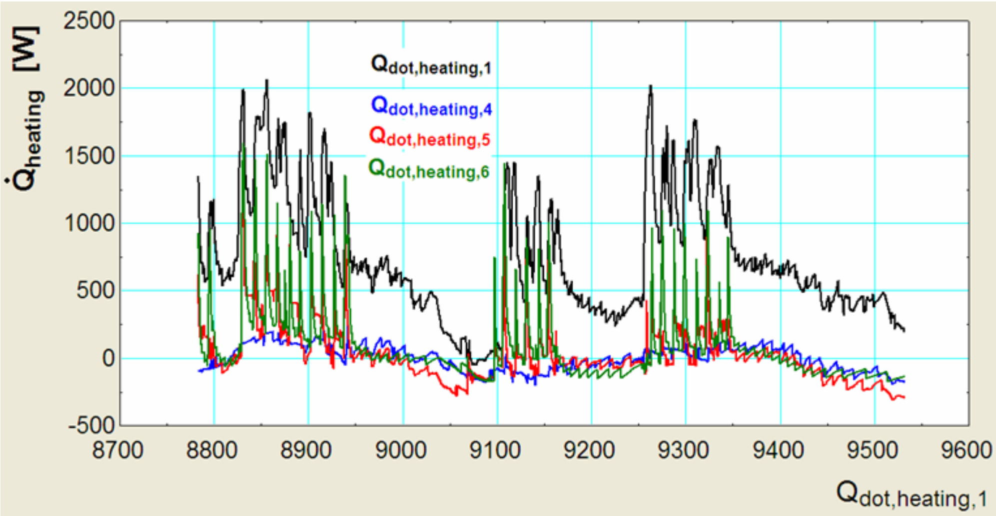


Figure 7-30: Simulated heating demands after best tuning of all parameters

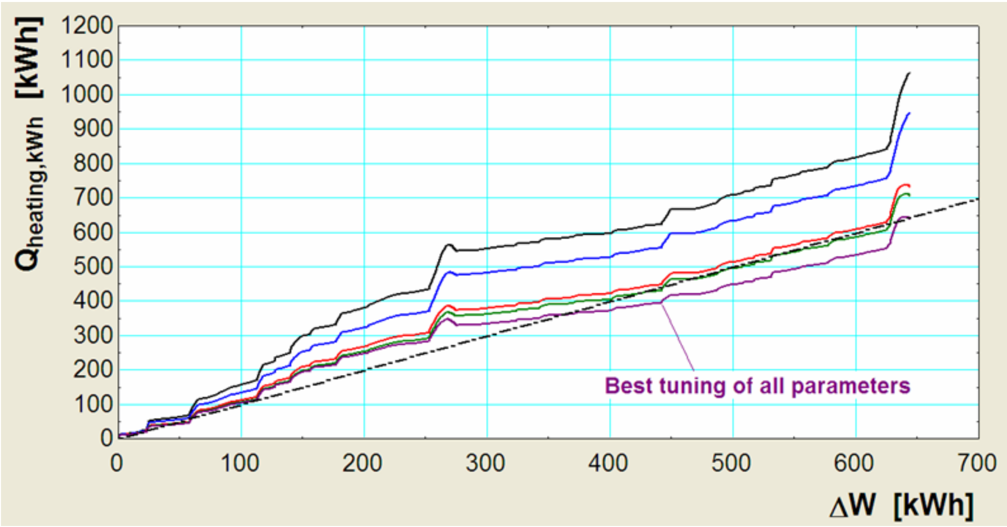


Figure 7-31: Simulated heating demand as function of the electricity consumption

Here also, on longer time period, the smart counting feasibility is well demonstrated: using the measured indoor temperatures as simulation input variables is an expedient way to identify the building heating demand…

7.4.9 **Correlations between energy and water consumptions**

Hand records of electrical energy and water consumptions taken on the whole monitoring period (two years) are presented in Figures 7-32 and 7-33, respectively.
Energy and water integrated consumptions are progressing in a similar way, step by step, according the (intermittent) dwelling occupancy. Both terms are plotted in relationship with each other in Figure 7-34. As to be expected, the slope of this curve is not at all constant all along the year. This slope is reaching roughly the same minimal value at begin and end of the measuring period, i.e. when there is no heating demand. The maximal slope is reached around the middle of the measuring period, i.e. when the heating demand is maximal.

Replacing time by water consumption as “historical” variable gives a much “smoother” (and easier to predict) evolution of the energy consumption, because this consumption is, of course, occurring almost only when the building is actually occupied, i.e. when some water is actually consumed. Uninteresting non-consumption periods are so “eliminated” from the diagram.

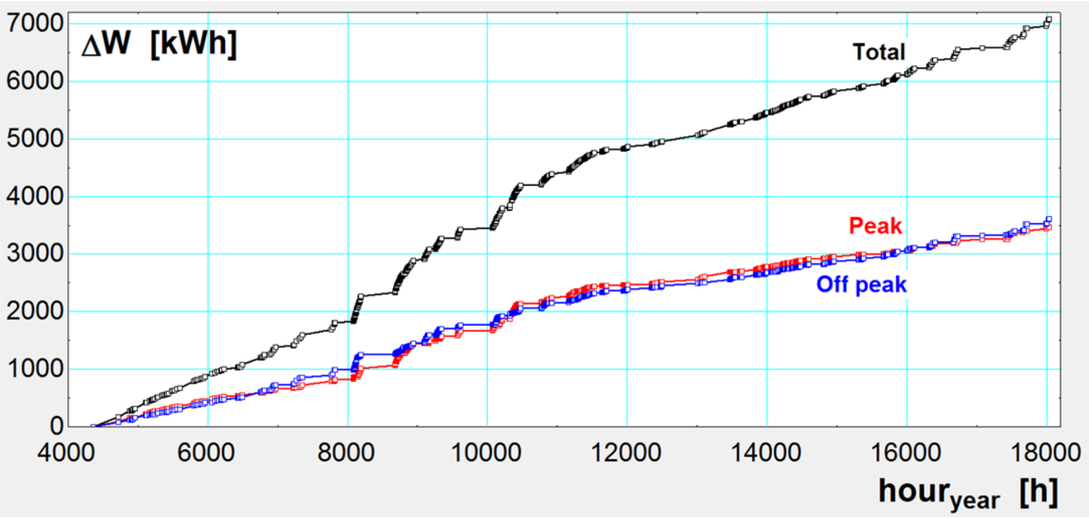


Figure 7-32: Electrical consumption on the whole monitoring period

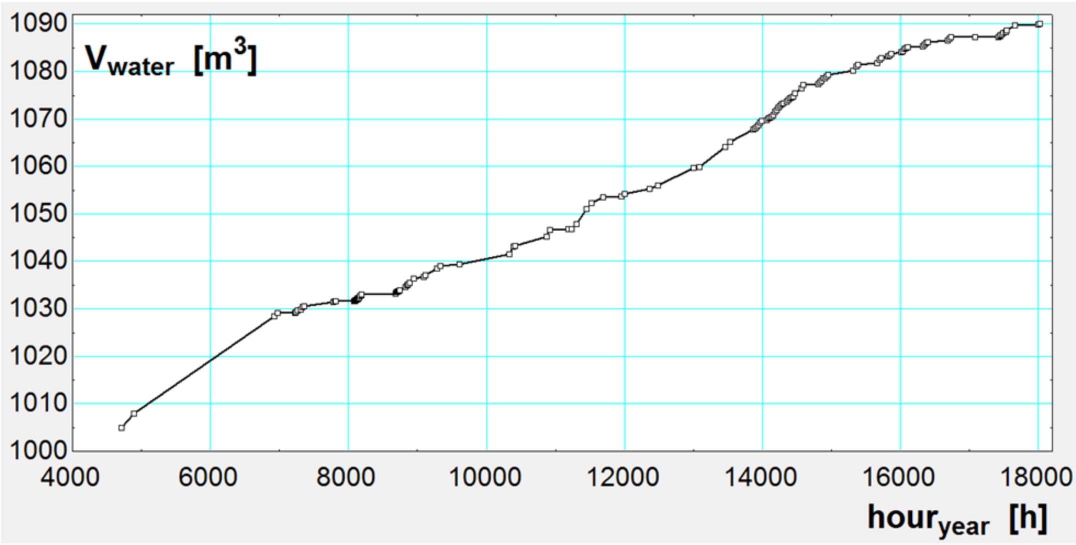


Figure 7-33: Water consumption on the whole monitoring period

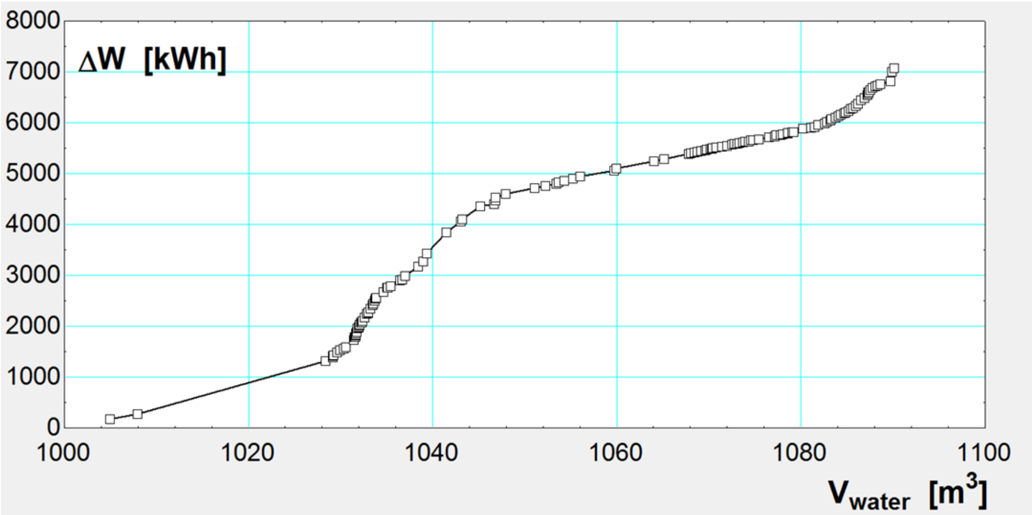


Figure 7-34: Electricity consumption as function of the water consumption

Very significant linear correlations can be identified on shorter time periods, during which the outdoor temperature doesn't vary too much, as shown in Figures 7-35 and 7-36. The slope of each regression line is related to the average outdoor temperature, which determines the heating demand.

When this outdoor temperature is high enough, as for example in August 2011 (Figure 7-35), there is no space heating demand and the electricity consumption is only due to other uses: hot water, cooking, lighting and other appliances. The slope of the regression line is then of the order of 35 kWh per m³ of water consumption.
In colder weather conditions, the regression slope increases, because of the space heating demand. In January 2011, for example (Figure 7-36), it reaches 60 kWh per m3 of water consumption...
Water consumption appears as a reliable occupancy "tracer" and a significant dwelling "signature" could be established by correlating the energy consumption with integrations of two independent variables: the water consumption and the outdoor temperature.

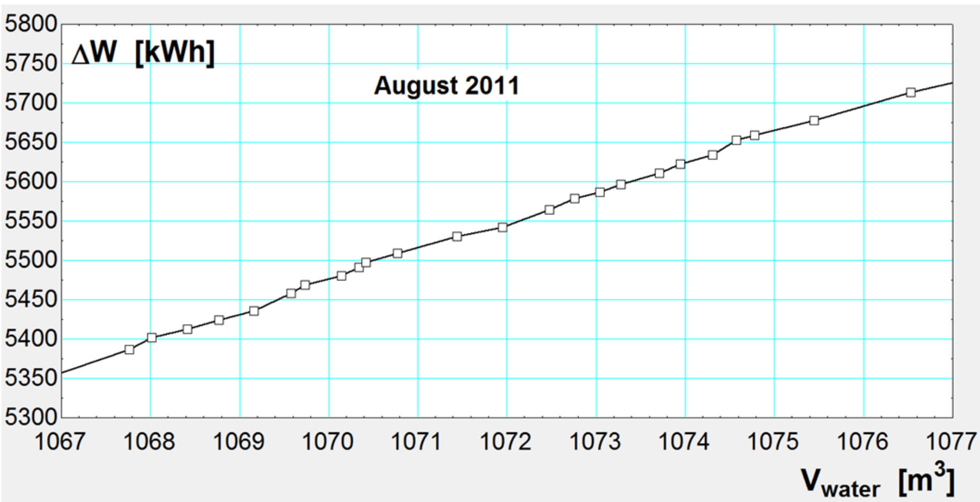


Figure 7-35: Electricity consumption as function of the water consumption in August 2011

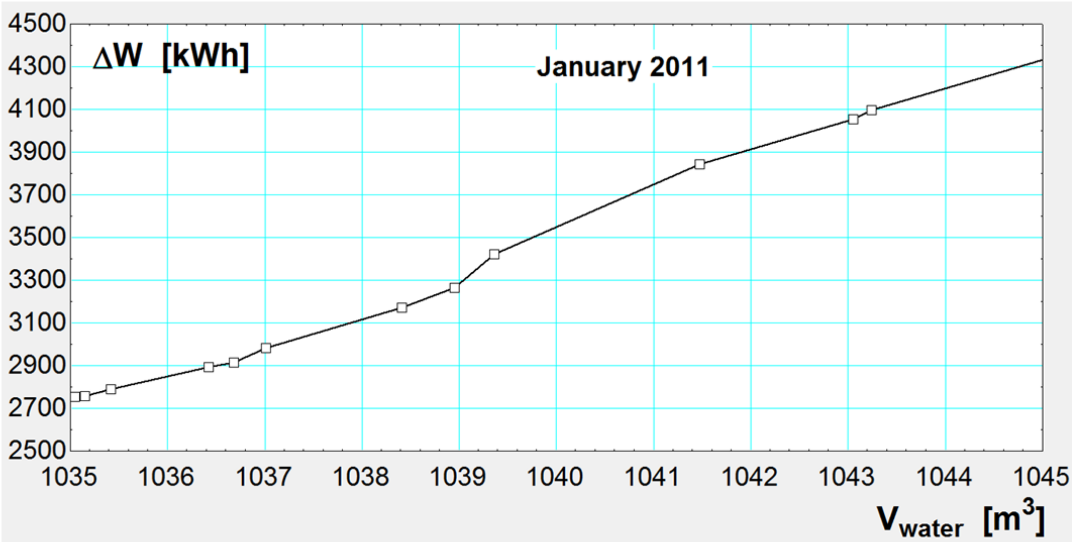


Figure 7-36: Electricity consumption as function of the water consumption in January 2011

7.4.10 **Conclusions**

It seems possible to provide the building occupants with quick and safe information about their energy consumption. This could be done at low cost by using existing counters, a few temperature sensors located in the different zones and a classical dynamic multi-zone simulation model easy to run on any personal computer. The best results could be obtained by tuning the simulation model, among others, on non-occupancy time periods.

Using all measured temperatures as input data in the simulation makes possible a direct calculation of the net space heating (or cooling) demand, without concern about the actual behavior of the control system. Heating (and cooling) demands can also be converted, through system simulation, into corresponding energy consumptions, to be compared with information got (by direct reading or automatically) from the energy counters available.

The new approach appears as very expedient: calculated and measured consumptions can be directly correlated to each other, to assess the simulation accuracy and also to tune the simulation model when required.

In the example considered, the heating demand is strongly affected by both “internal” and “external” (surroundings) occupancy rates. Recorded water consumptions might help a lot in identifying these occupancy rates and also the “non-heating” consumptions. In case of very variable occupancy rate, water consumption might be preferred to time as “historical” variable, in order to get a “smoother” curve of energy consumption.

This last curve can even be approached by a linear regression in each seasonal period. The slope of this regression appears as a “seasonal signature” of the system considered.

A more significant building signature could be established by correlating its energy consumption with two independent variables: the water consumption and the outdoor temperature. In order to make this signature easy to read, the three variables considered would have to be integrated on time.

7.5 Maintenance of buildings

7.5.1 Summary

Maintenance practices for HVAC systems can be categorized into three levels depending on maintenance effort and coverage: 1) proactive, the performance-monitored maintenance representing the good practice; 2) preventive, scheduled maintenance representing the average practice (business as usual); and 3) reactive, unplanned or no maintenance representing the bad practice. Table 7-5 shows the three practices of HVAC maintenance and their implications on equipment operating efficiency and energy use, equipment life, short term maintenance cost, and life cycle cost including maintenance cost, energy cost, and equipment replacement or repair cost.

Table 7-5: Three types of HVAC maintenance practices

Maintenance Practice	Description	Equipment Efficiency	Operating Energy	Equipment Life	Short-Term Costs	Life Cycle Costs
Reactive (Bad)	Deferred or no maintenance, "run to fail".	Low	High	Short	Low	High
Preventive (Average)	Scheduled maintenance, periodic inspection, cleaning, and adjustment.	Medium	Medium	Medium	Medium	Medium
Predictive (Good)	Use periodic measurements to detect evidence that equipment is deteriorating and to avoid failing.	High	Low	Long	High	Low

A few common HVAC maintenance issues are reviewed and selected for the initial modeling and simulations. Table 7-6 lists the issues with their potential impacts and modeling approach according to maintenance types, including sensor calibration, filter replacement, heat exchanger treatment, mechanical repair and refrigerant charge, are investigated using detailed simulation models. Each maintenance issue is modeled and simulated with EnergyPlus, and finally the combination of all issues is simulated.

Table 7-6: Potential impacts and modeling approach for each maintenance type

Maintenance Types	Maintenance Issues	Impacts	Simulated Scenarios	Modeling Approach
Sensor Calibration	Supply air temperature sensor offset	controls, heating and cooling energy	temperature sensors are offset by +2˚C	Direct Model. Adjust supply air temperature setpoint
	Zone temperature sensor offset			Direct Model. Adjust thermostat settings
	Outdoor air temperature sensor offset			New Code. Modify the economizer controls

Filter replacement	Dirty filter	pressure drop, fan energy, airflow	additional 500Pa of air pressure drop	EMS. Adjust fan power for VAV systems
Heat exchanger cleaning/treatment	Fouled cooling tower	Efficiency	overall heat transfer capacity is reduced to 85% of design UA	Direct Model. Adjust tower UA
	Chiller: fouled tubes	Efficiency	chiller COP is reduced by 10%	Direct Model. Adjust chiller efficiency
	Boiler: hard water scale	Efficiency	boiler efficiency is reduced by 10%	Direct Model. Adjust boiler efficiency
	Fouled heating /cooling coil	efficiency, comfort	overall heat transfer capacity is reduced to 50% of design UAs	New Code. Adjust coils UA
Mechanical repair	Outdoor air damper leakage	heating and cooling energy	30% OAD leakage	Direct Model. Adjust minimum OA flow
	Stuck outdoor air damper (OAD)	heating and cooling energy	OAD is stuck at fully open position	EMS. Set constant OA flow
	Blocked OA screen	Outdoor air flow is less than 100% during economizer mode thus increasing cooling energy	maximum percent of intake fresh air is reduced to 70%	Direct Model. Set maximum OA flow
Refrigerant charge	Chiller: over or under 10% refrigerant charge	Efficiency	chiller COP is reduced by 10%	Direct Model. Adjust chiller efficiency

The results shown in Figure 7-37 demonstrated the energy penalty introduced by the reactive maintenance practice for HVAC systems. The percentages are derived by comparing the total source/primary energy use of HVAC systems for the reactive maintenance practice to those of the good practice (Basecase - ASHRAE). The maintenance issues with significant energy impacts for Chicago are OA damper stuck at 100% position, blocked OA screen, supply air temperature offset, boiler/chiller fouling, over/under refrigerant charge for chillers. Although there is no significant energy impact due to heating/cooling coil fouling, the numbers of unmet thermal comfort hours for both heating and cooling are significantly increased due to reduced system cooling and heating capacities. The overall energy penalty by combining the sampled maintenance issues are about 85% of overall HVAC energy consumption for the Chicago climate. The energy penalty introduced by HVAC maintenance issues varies by a few factors including building and HVAC systems types, vintage (design efficiencies), and climates. Our on-going research focuses on identifying a broader list of HVAC maintenance issues for most commercial buildings in various climates, and developing modeling approaches. The research is intended to provide a guideline to help practitioners and building operators to gain the knowledge of maintaining HVAC systems in efficient operations, and prioritize HVAC maintenance work plan.

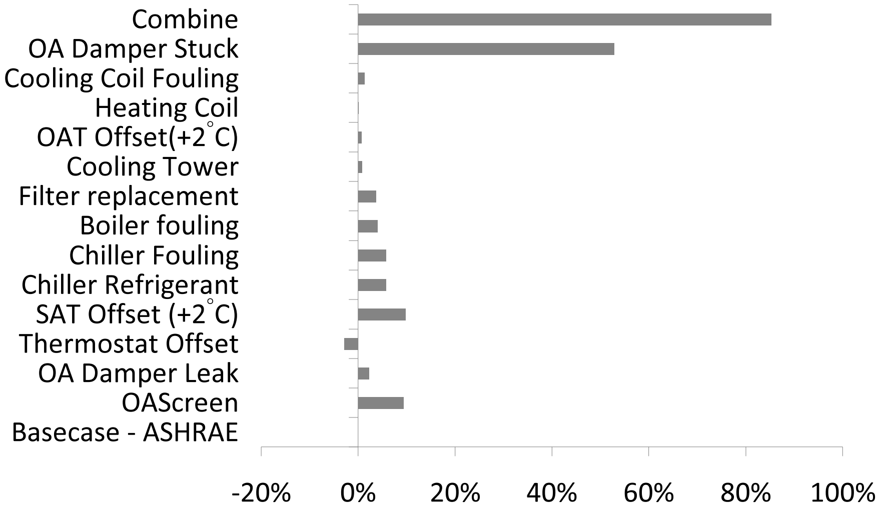


Figure 7-37: The impacts of poor HVAC maintenance on HVAC source energy consumption for a large office building in Chicago, USA

8. Conclusions

In order to get a better benefit from the use of simulation models in order to analyze total energy use in buildings, a number of specific methodologies were developed considering different phases of the building life cycle. These methodologies complement the use of the simulation tools with resources like sensitivity analysis, uncertainty analysis and model calibration in order to get more reliable results and to adapt the presentation of the results to the specific user of the simulation tools. A more realistic consideration of the impact of the user of the building is also pointed out by the methodologies.

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Published by Institute for Building Environment and Energy Conservation, Zenkyoren building Kojimachikan, 3-5-1, Kojimachi Chiyoda-ku, Tokyo 102-0083 Japan

ISBN: 978-4-9907425-7-7

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