# Dealing with sensitivity and uncertainty analysis in integrated building LCA model

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## Abstract

Building design, realization, operation and refurbishment have to take into account the resulting environmental impacts as well as the costs over a long period of time. This can be realized by combining life cycle analysis (LCA), life cycle costing (LCC) and building product models in integrated LCA models. Two difficulties appear:

- The general data uncertainty in LCA/LCI models,
- The lack of experience of practitioners who are not LCA specialists.

As answers to these shortcomings there are the improvement of integrated LCA models by managing uncertainty and, the development of robust, simplified models for building design, construction and operation.
The contribution discusses the available methods to assess the different uncertainty sources in building LCA models (mainly Monte Carlo simulation and experiment plans). Possibilities to use the results for the design of simplified tools are presented.

## 1. Uncertainty sources in building LCA models

In building LCA models [KOH 2002], uncertainty is due to:

- Data quality (incomplete, inaccurate, not appropriate, obsolete etc.)
- Building description (incomplete, inaccurate)
- Building life span and building components lifecycle (assumptions on life span, end of life span, degree of refurbishment)
- Building operation (user influence, performance of HVAC equipment, long term evolution of costs etc.)

Furthermore, additional data uncertainty comes from the upstream process analysis. The inventories of material and energy flows are highly dependent on geographical localisation and technology. Finally calculation methods of impact indicators are not yet all well defined for some categories (for example: toxicity).
Uncertainty analysis is the study for the uncertain aspects of a model and their influence on the model's results. However, a single data or value can have a great uncertainty even if its contribution to the uncertainty of the overall result could be insignificant. It is possible to deal with this problem by performing an uncertainty importance analysis using e.g. Monte Carlo simulation or experiment design techniques.

## 2. Necessity to have relevant results at the planning phase

The desired quality level of the results depends of course very much on the problem which has to be solved, and on the risks (e.g. damage, death). This distinguishes approaches in the field of the reliability of civil engineering structures [DFG 2001 and 2002] from the design of new buildings even if they might use similar methods. The data quality will vary from exact empirical measures to highly speculative assumptions on replacement cycles in 30 years. In the domain of design and refurbishment of buildings, it is crucial to know, at an early stage, the potentials for environmental impacts reduction, cost cuttings and human toxic risks. It is therefore necessary to determine which are the input parameters that have the largest influence on the output results and within which margins. This could be achieved with the help of a sensitivity analysis.

## 3. Methodology of uncertainty and sensitivity analysis

[BJÖ] introduces the different tools available to handle sensitivity and uncertainty analysis. General definitions of sensitivity, uncertainty importance analysis and uncertainty analysis are given in the following table (Figure 1), together with a brief list and description of available tools.

| | **Sensitivity and Uncertainty importance analysis** | | **Uncertainty analysis** |
|---|---|---|---|
| | Sensitivity analysis | Uncertainty importance analysis | |
| **Definition** | Influence of one parameter on the value of an other | Contribution of the uncertainty of different parameters to the total uncertainty of results | Identify and quantify the uncertainty introduced into the results due to the cumulative effects of input uncertainty and data variability |
| **Tools** | One way sensitivity analysis: How much an input has to vary to have x % output change (all others inputs constant)<br>Scenario analysis: Weighting the input parameters to create a scenario for the future, and analyse its influence<br>Factorial design and multivariate analysis: low and high levels for inputs<br>Ratio sensitivity analysis<br>Critical error factor<br>Tornado diagrams | Monte Carlo simulation: calculate the correlation between model input and total model output. This is done by calculating the total model uncertainty with Monte Carlo simulation<br><br>Relative sensitivity = $\sigma_X/\Delta_X$<br><br>Tornado diagrams using known uncertainty ranges of input | (1)Uncertainty of each parameter<br>(2)Uncertainty distribution<br>(3)Uncertainty propagation through models to the final output<br>Means for (3):<br>Classical statistical analysis<br>Bayesian statistical analysis<br>Interval arithmetic<br>Vague error interval (fuzzy)<br>Probabilistic simulation (Monte Carlo)<br>Scenario analysis<br>Rules of thumb<br>Expert judgements |

Figure 1: Tools to deal with sensitivity and uncertainty analysis

In the following the focus will be on the use of experiment design (also called factorial design) and probabilistic simulation (later called Monte Carlo simulation).

# 4. Different methods available

## 4.1 Monte Carlo simulation

A Monte Carlo analysis consists in performing a large number of successive simulations with the same model, each time with a distinct set of model input parameters.
The procedure can be summarized in 4 steps (Figure 2):

1. Specify uncertainties, width and probability distribution functions for all input data,
2. Select values for variables from the probability distributions,
3. Calculate the results in the conventional way using the selected input values,
4. Iterate until mean and distribution do not change anymore and calculate the probability distributions of the output data.

This technique allows producing a large number of scenarios. For each one the probability distribution of input data is sampled in a manner that reproduces the distribution's shape.
The basic principle is to select a limited number of parameters and then calculate the influence on cumulative results caused by uncertainties on these parameters.
Different sampling strategies of input parameters have been developed:
- Simple random sampling: input parameters are randomly selected from a priori fixed probability density function;
- Stratified sampling procedures, like Latin Hypercube sampling.

Probability distributions may be obtained by a variety of methods, including statistical analysis of data, or the elicitation of expert judgement.
*N.B: It is also possible to run a Bayesian Monte Carlo analysis (BMC). It attributes a posteriori a weight to individual Monte Carlo simulations by comparing them with observations. Simulations, which better fit observations, receive a larger weight.*

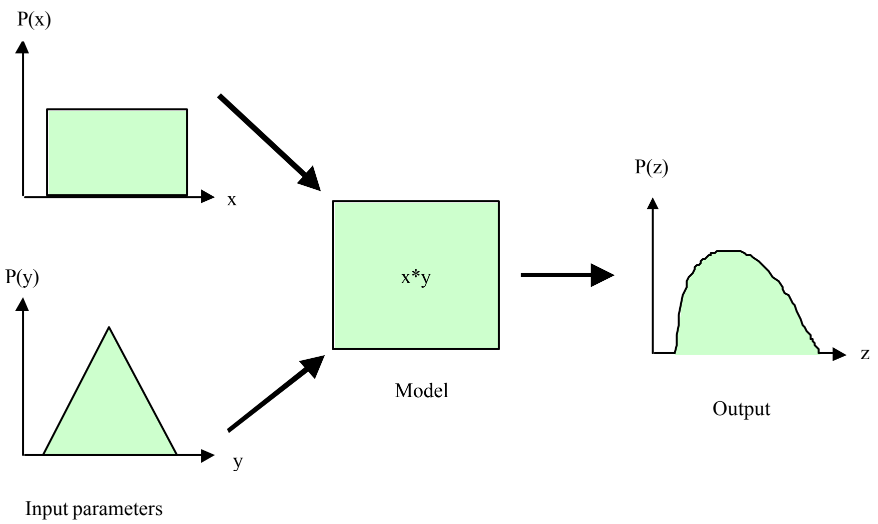



Figure 2: Monte Carlo simulation process

## 4.2 Experiment design

Experiment plans are a succession of carefully planned simulations. They are used in order to determine the different parameters which influence the results more, with a minimum of experiments and for an affordable accuracy. Experimental plans provide answers to the following questions:

1- Between all the inputs parameters:
    a. Which are those having a significant influence?
    b. What is this influence?
    c. Are there any dependencies between parameters?
2- Quantify the parameter's influence by determining an equation
3- Optimise the model for more accurate results.

A simple method consists in fixing all the parameters and vary only one. Applied to all parameters, this will give thousands of results difficult to handle and analyse, and will not provide any information about dependencies between parameters.

Another possibility is to vary some parameters at the same time and repeat the operation with different arrangements. This will provide less results, will be easier to analyse and needs less simulations. Moreover, it will furnish information about dependencies between input parameters. It's called the fractional matrix.

The choice of the matrix has no impact on the description of experimental plans method.

The method can be described in 5 steps:

1- Define objectives to reach and output parameters to be optimised,
2- Determine all the input parameters and their associated levels (minimum and maximum)
3- Choose the experiment matrix (from those available),
4- Run the experiment (in the present case "experiments" are "simulations"),
5- Analyse the results and determine effects of parameters.

The method of experimental plans: does not require any mathematical background (apart from basics statistics knowledge), is easy to operate, gives relevant results (easy to handle and analyse) and allows the deduction of a simplified model.

## 4.3 Comparison between experiment design and Monte-Carlo simulations

Figure 3 provides a short comparison between experiment plan and Monte Carlo simulation. For applying sensitivity and uncertainty analysis to the integrated building LCA model, we have chosen to apply the experimental plan strategy based on the advantages of this method.

The principal disadvantage of Monte Carlo simulation is the difficulty to assess probability distributions of the input parameters. In addition, experimental plans allow defining a simplified model. Moreover, in the report from 8$^{th}$ SETAC Symposium, it is mentioned, "several participants doubted the general usefulness of Monte Carlo analyses in handling uncertainty in LCA" [WEI 2000].

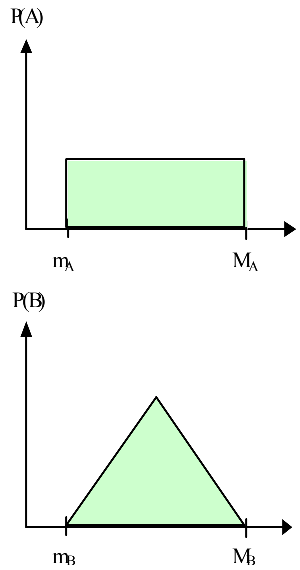
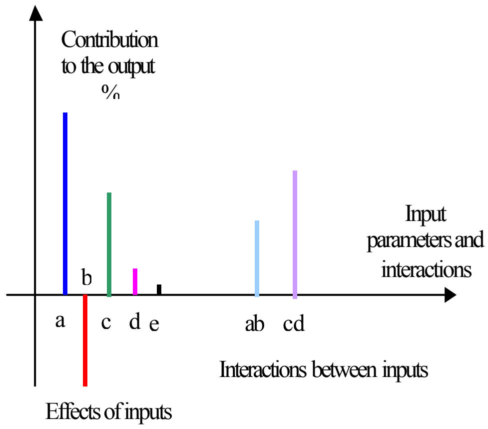
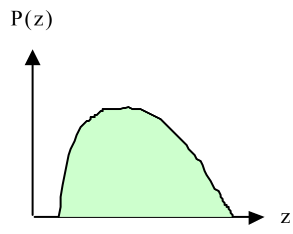
|  <br>Input parameters and their supposed probability function, min. and max values | **Experiment design**<br>1- Use many times the minimum and maximum values of each parameters ($m_A$, $M_A$, $m_B$, $M_B$) as input values.<br>2- Run the model.<br>3- Results are:<br>  | **Monte Carlo simulation**<br>1- Select randomly values of A and B included between minimum values, maximum values and their probability distribution (P(A), P(B)).<br>2- Run the model.<br>3- Results are probability distributions for each output:<br> <br>Output |
|---|---|---|
| **Advantages** | A limited simulation number allows identifying the effect of parameters on results and the possible interactions. Possible to deduce a simplified model from the relevant parameters identified | Simple and efficient |
| **Disadvantages** | | The choice of probability distribution is highly subjective and user dependant ➔thus introduces more uncertainty. |

Figure 3: Comparison between experiment plans and Monte Carlo simulation

## 4.4 The use of experimental plans

The use of experiment design requires the choice of a matrix from four possible ones (cf Figure 4).

*N.B: After running simulations using the selected matrix, the response area can be determined with the help of Doehlert networks.*

| | Matrix names | Possibilities | Disadvantages |
|---|---|---|---|
| More simulations | **Hadamard** | Analyses in depth a range of selected parameters, supposed to be the most relevant ones. | Parameters must not interact. Saturated matrix: no information available on experiment. variance. |
| | **Rechtschaffner** | Analyses parameters influence. Analyses dependencies between two parameters. | Saturated matrix: no information available on experimental variance. Parameters with only 2 levels. |
| | **Fractional** | Analyses parameters influence and their dependencies (no order restriction). Possibility to add more parameters later. Less simulation depending on which dependencies are analysed. | |
| | **Complete** | Analyses parameters influence and their dependencies. | The one, which needs the more simulations. |

Figure 4: Different matrix available for running experiment plans

The undoubted presence of interactions prevents us from choosing the Hadamard matrix.
The large quantity of input parameters doesn't give any chance to the complete matrix, which will be too much time and energy consuming. The non-availability of information about the experimental variance when a Rechtschaffner matrix is used might be an additional difficulty when analysing the results.
The last matrix available is the fractional one. As mentioned above, this matrix leads to a certain number of simulations, depending which dependencies are wanted to be analysed.
The number of simulations with a complete matrix is $2^k$ with k the number of parameters. With a fractional matrix, the number of simulations is $2^{k-r}$, r depends on the choices made concerning the dependencies analysis. These two relations show the advantages of fractional matrix concerning the reduction of simulations number.

## 5. First simulations results

For the first use of experiment plans it was decided to analyse the effects of thermal quality of six envelope elements (windows, lower floor, intermediate floors, upper floor, external walls, internal walls) on the release of $CO_2$ (GWP) and on the ozone depletion (ODP). For the six inputs, two levels of thermal quality are assigned. Each level corresponding to different $CO_2$ and ODP values. For the building dimensions (four parameters), two values are given to each parameter. A certain number of buildings were modelled in detail with a complete integrated LCA tool (LEGOE), which produced the output values for GWP and ODP.
Those considerations are summed up in the experiments matrix (Figure 5).

| Simulation | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | $CO_2$ ($kg_{CO2}$ eq) | ODP ($kg_{CFC11}$eq) | $U_{bât}$ *($W.K^{1}.m$)* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | 254574 | 0,25 | 0,64 |
| **2** | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | 1 | 266399 | 0,26 | 0,87 |
| **3** | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 | 378205 | 0,51 | 0,76 |
| **….** | | | | | | | | | | | | | |
| **1024** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 5239377 | 6,47 | 0,66 |

Figure 5: Simulation matrix

In the current situation, the chosen matrix is complete and can be handled with existing tools such as MATLAB and it allows the analysis of all dependencies. Moreover, doing a fractional plan directly into the integrated building LCA model enables to separate the analysis of dependencies from the principal effects' one.

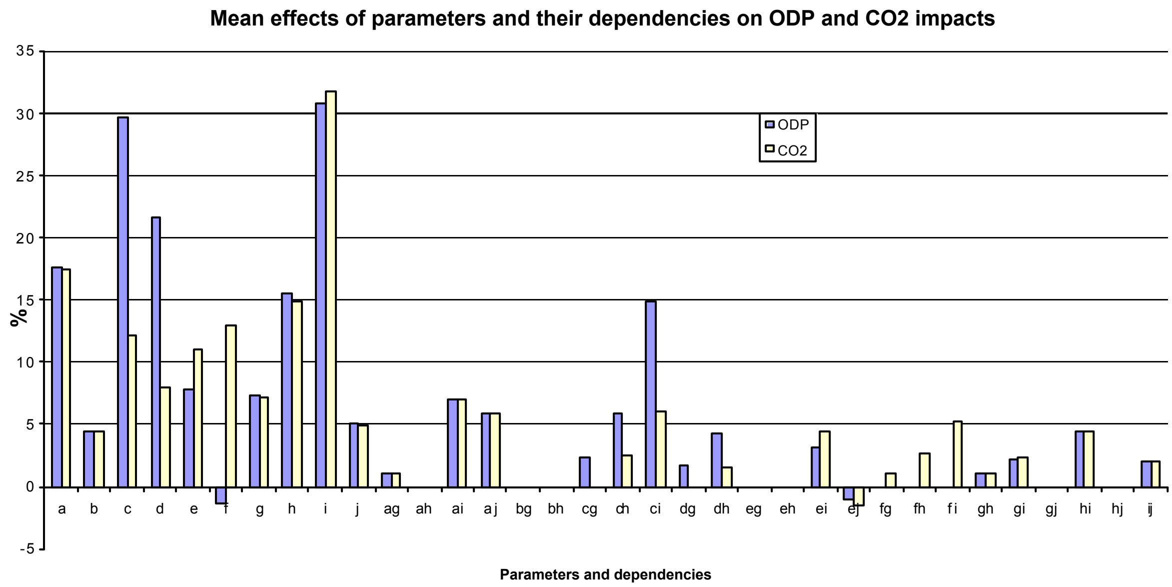



Figure 6: Typical graph of results which can be obtained with the help of experiment plans

The first experiment plans have been chosen for a situation well known in advance. Only the input parameters directly linked to thermal losses will have an influence on the output for GWP but not for ODP. The latter depends much more on the material composition and the masses of some building elements. The results of this first run show how simple known and unknown effects can be reproduced. The next experiments will gradually consider less and less well-known domains.

## 6. Outlook

The aim of this contribution is to show how experiment plans can be used in order to:

- Identify the input parameters which have greater influence on the output results,
- Determine this influence and the dependencies between parameters,
- Developed a simplified model.

The first simulation results given above are encouraging and are a starting point to further investigations. They provide information on relations that may exist between material inputs in the building and their related effects on $CO_2$ and ODP impacts.

The generalization of this analysing process to more inputs and more outputs will lead to:

- Identify specific performance targets for the life cycle behaviour of buildings,
- The possibility to assess a simplified model that can be used at the planning phase of the building.

In short terms, the use of experiment plans in building integrated LCA model is a step towards a simplified model.

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