# Understanding LCA results variability: developing global sensitivity analysis with Sobol indices. A first application to photovoltaic systems

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# UNDERSTANDING LCA RESULTS VARIABILITY: DEVELOPING GLOBAL SENSITIVITY ANALYSIS WITH SOBOL INDICES. A FIRST APPLICATION TO PHOTOVOLTAIC SYSTEMS.

**Pierryves Padey (1),(2), Didier Beloin-Saint-Pierre (2), Robin Girard (2), Denis Le-Boulch (1), Isabelle Blanc (2)**

(1) EDF R&D, Les Renardières 77818 Moret sur Loing Cedex, France
pierryves.padey@mines-paristech.fr

(2) MINES ParisTech, 1, rue Claude Daunesse, F-06904 Sophia Antipolis Cedex, France

**Abstract**

LCA has been extensively used in the last few years and a large number of studies have been published in the literature. These studies show a great variability in results of comparable systems. It somehow leads policy-makers to consider the LCA approach as an inconclusive method. Some attempts have been developed to assess LCA results variability; however, they remain mostly qualitative.

In this paper, a method based on Global Sensitivity Analysis (GSA) is presented in order to understand the origin of results variability. A general variance decomposition based on the Sobol indices is applied to quantify the influence of input parameters on the environmental answer.

A preliminary study is done by using this GSA on a large set of integrated photovoltaic systems greenhouse gas (GHG) performances. We identify that the irradiation parameter has the biggest influence on those GHG performances. The other parameters such as lifetime or performance ratio have been identified as having a smaller but significant influence on the GHG results variability. The GHG performances range from 24 to 230 g $CO_{2eq}$/kWh with 75% of the performance ranging from 23.8 to 93.5g $CO_{2eq}$/kWh.

**Keywords:**

Sobol indices, variability, GHG performance, photovoltaic, GSA.

# 1. INTRODUCTION

Life Cycle Assessment (LCA) is nowadays considered as one of the main relevant tool to study a product or system environmental impacts. Therefore, LCA has been widely used in order to assess the environmental impacts for a panorama of systems. The result is a large quantity of LCA studies presenting a high variability in impacts results for comparable systems. An IPCC report [1] clearly shows this situation for different sources of electricity production over a large set of publications. In this report, the $CO_2$ equivalent emissions for photovoltaic (PV) electricity generation range between 5 and 217 g $CO_{2eq}$/kWh. This high variability tends to complicate the work of decision makers. We propose a method which aims at explaining such variability in response to this situation.

Recently, the LCA research community initiated new methods; defined as *meta-analysis,* to get a comprehensive panorama of systems environmental impacts [2],[3],[4]. These meta-analyses aim at synthesizing and identifying the main sources of results' variability [3].

Understanding LCA variability requires the definition of its types and sources. Different studies [5], [6] underline that defining that kind of information will improve the LCA method reliability. Moreover, a selection of studies [7] has identified the possibility of explaining a large proportion of environmental impacts variability with a limited number of parameters. Sensitivity analyses have been identified as a necessary tool to improve the LCA results representativeness [6] by quantifying the influence of input parameters on a system's environmental performances. However, when dealing with environmental impact assessment, most sensitivity analyses remain at a local level as they evaluate the variation of the input parameters one factor at a time [8]. This approach only partially reflects the LCA results variability, because it does not consider the full range of input parameters interval, as well as the combined variability and their probability distribution [8]. A statistical tool named Global Sensitivity analyses (GSA), by opposition to the traditional local sensitivity analyses, exists but only few studies [9][10] have proposed this systematic and generic method to identify the most environmentally influential parameters for LCAs.

This paper aims at presenting a generic methodology that can explain part of the LCA's results variability through input parameter variability assessment. The methodology we propose relies on the study of different variability sources for electricity generation systems through GSA. The GSA is performed through the computation of Sobol indices that are built upon general variance decomposition [11]. This methodology is applied to a large sample of building integrated PV electricity LCAs as a first example.

## 2. PROBLEMATIC

The LCA modeling process can be summarized as in Figure 1:

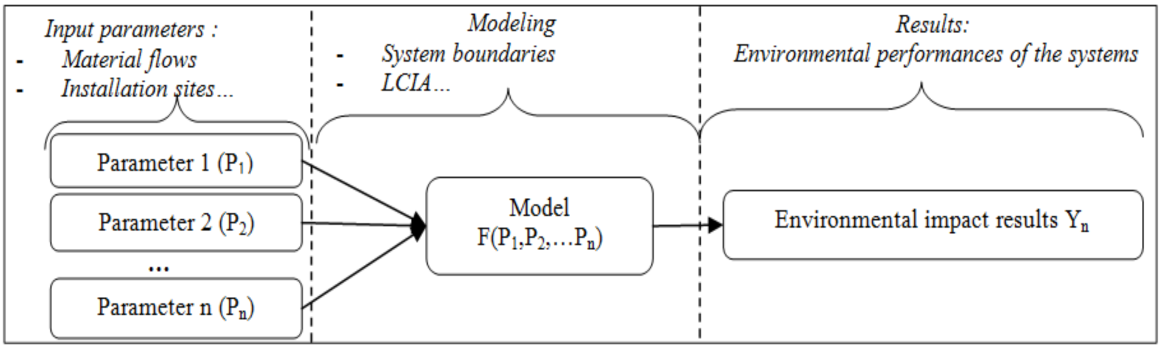


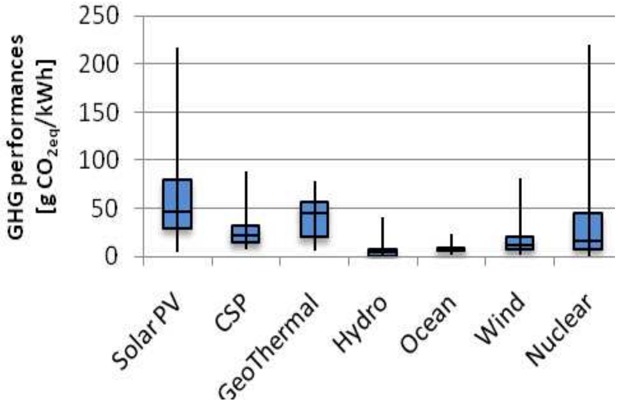

**Figure 1 : Representation of the LCA model**

Each stage of a LCA implies variability and uncertainty. Björklund [5] proposed to classify these different sources; we will focus on the data inaccuracy (the quantifications of all input parameters are dependant of measurements or data given by experts), the model uncertainty (the model of the studied system for the LCA calculations is a simplified representation of the reality), the uncertainty due to choice (the LCA practitioners need to make choices during the modeling phase such as allocation rules, system boundaries, choice of average data…), the spatial variability (a renewable energy system, for example photovoltaic performance is strongly dependant of its geo-localization) and the epistemological uncertainty (due to lack of knowledge on system's behavior, such as the system's lifetime estimation).

These aspects and limitations are known and accepted by LCA practitioners. However, their transparent descriptions are limited in the literature.

This issue is a sensitive debated subject when modeling electricity generation systems. The fast developments of renewable energy technologies and incentives policies require a clear vision of renewable energies environmental impacts panorama. The IPCC [1] has made a literature review of the GHG emissions for electricity generation systems which clearly shows this problematic (see figure 2). This literature review has been based on different criterions such as assumption transparency and temporal representativeness (the LCAs selected in the IPCC review had to correspond to an up-to-date technology or to be representative of a near future).

Figure 2 describes the high variability seen in the literature and confirms the difficulties, for non-expert, to understand such differences. For example the results range from 5 to 217 g $CO_{2eq}$/kWh for PV systems. This complicates the understanding of electricity generation systems GHG performances. Few attempts [12] have presented the main sources of variability of the electricity generation systems; however, these studies remain mostly qualitative. Recent works have been initiated [4],[13] in order to propose an approach to reduce LCA results variability through the definition of a set of normalized values for input parameters. Those approaches enable a reduction of the environmental impact variability but do not quantify the parameters variation influence on environmental performance.




| | PV | CSP | GeoTh. | Hydro | Ocean | Wind | Nuclear |
|---|---|---|---|---|---|---|---|
| | | | | [g $CO_{2\,eq}$/kWh] | | | |
| Min | 5 | 7 | 6 | 0 | 2 | 2 | 1 |
| 1st quartile | 29 | 14 | 20 | 3 | 6 | 8 | 8 |
| 2nd quartile | 46 | 22 | 45 | 4 | 8 | 12 | 16 |
| 3rd quartile | 80 | 32 | 57 | 7 | 9 | 20 | 45 |
| Max | 217 | 89 | 79 | 41 | 23 | 81 | 220 |

**Figure 2 : GHG variability for electricity generation systems from IPCC graph [1]**

Sensitivity analyses (SA) are approaches allowing investigating the results variability from inputs parameters [14]. They are defined as the study of relationships between information flowing in and out of models [9]. Thereby, performing SA enables a better understanding of results variability.

Sensitivity analyses are not always used in LCA and as an alternative only best and worst case scenarios are considered. The commonly used sensitivity analysis (SA) in LCA, named local sensitivity analysis, does not give access to distributions of environmental impact results and does not quantify the full influence of input parameter on the environmental answer. The commonly used SA in LCA is defined as a local study where parameters vary inside an interval around a nominal value. Other particular case of local sensitivity analyses are used in LCA, where one factor is varied and the others are held constant (one-factor-at-a-time approach OAT, [8]) however, this approach does not consider the possible interaction between parameters.

To overcome these limitations (no probability distribution, no consideration of interaction and local analysis only) another type of sensitivity analysis technique called Global Sensitivity Analysis (GSA), by opposition to local SA, is of strong interest. GSA enables the quantification of input parameters influence on the variance of output performance for nonlinear and non monotonic model, by a decomposition of output total variance [15] [16].

To do this, the function *"F"* of the LCA model (see Figure 1) is decomposed over a sum of elementary functions *f*:

$$F(X_1, \dots, X_n) = f_0 + \sum_i^n f_i\,(X_i) + \sum_{i<j}^n f_{ij}\,(X_i, X_j) + \cdots + f_{1,2\dots d}(X_1, \dots, X_n) \quad \textbf{(1)}$$

Where *f* can be integrated on $[0, 1]^d$, $f_0$ is constant and the other functions are orthogonal:

$$\forall u = (i_1, \dots, i_s) \neq v = (j_1, \dots, j_q) \qquad \int_{[0,1]^p} f_u(x_u)\, f_v(x_v)\, dx = 0 \quad \textbf{(2)}$$

This decomposition has been proposed by Sobol [11]. Now, if the parameters $X_i$ are random and independent, from equation (1), we can obtain the variance decomposition of Y:

$$Var[Y] = \sum_{i=1}^n V_i\,(Y) + \sum_{i<j} V_{ij}\,(Y) + \sum_{i<j<k} V_{ijk}\,(Y) + \cdots + V_{1,2\dots d}(Y) \quad \textbf{(3)}$$

Where:

$$V_i(Y) = Var[E(Y|X_i)]\,;\; V_{ij}(Y) = Var\big[E\big(Y\big|X_iX_j\big)\big] - V_i(Y) - V_j(Y) \quad \textbf{(4)}$$

And thus the sensitivity indices also called Sobol indices are expressed as

$$S_i = \frac{Var\,[E(Y|X_i)]}{Var\,(Y)} = \frac{V_i(Y)}{Var\,(Y)} \qquad S_{ij} = \frac{V_{ij}\,(Y)}{Var\,(Y)} \qquad S_{ijk} = \frac{V_{ijk}\,(Y)}{Var\,(Y)} \quad \textbf{(5)}$$

The indices can be interpreted as the percentage of variance of a model answer Y, explained by each variable $X_i$ or their combinations with the other $X_j$.

However, this approach presents the drawback of a high computational cost if the number of indices to be assessed is important [8]. Indeed, the number of Sobol indices are a function of the number of the *"d"* input parameters (number of indices = $2^d$-1). Moreover, the Sobol indices are complex to manipulate if they are numerous. One approach to overcome these limitations is to only consider the total Sobol indices of one parameter encountering the total effect of one input parameter on the model output:

$$S_{total\ i} = S_i + \sum_{j \neq i} S_{ij} + \sum_{j \neq i, k \neq j, j<k} S_{ijk} + \cdots \quad \textbf{(6)}$$

For a matter of clarity in the assessment of the variance decomposition results, we will consider these total indices in our approach (note in that case $S_{tot}$ can be greater than 1).

Thereby, using GSA through Sobol indices we ensure the description of a complete panorama for environmental impact variability of a model and their input parameters. This new method can be used to assess the literature variability or the specific variability of a given system or sample and to identify which inputs are responsible for a large proportion of the output variability.

## 3. METHODOLOGY

The methodology we aims at applying Global Sensitivity Analysis and variance decomposition to LCA set of results. It is based on the general pathway of GSA adapted to the specific case of the LCA method through 3 steps:

1. Definition of the studied system
   - Based on the standardized LCA methodology (goal and scope definition, functional unit, system boundaries, general hypothesis).
2. Definition of the system modeling, and parameters characterization for the sample definition
   - List the input parameters and their range of variation based on literature review, expert discussions and goal of the study
   - Define the model which will be use to perform the GSA calculation (how are calculated the environmental performances).
3. Perform the GSA based and variance decomposition (as described in the previous section)
   - Generate inputs randomly from a probability distribution over the domain
   - Plug the random samples into the model to obtain the model output (environmental answer)
   - Assess the model output using variance decomposition (equation 3) in order to enable a hierarchy of the input parameters' influence by computing the total Sobol indices (equations 5 and 6).

The methodology can thereby be summarized as in Figure 3:

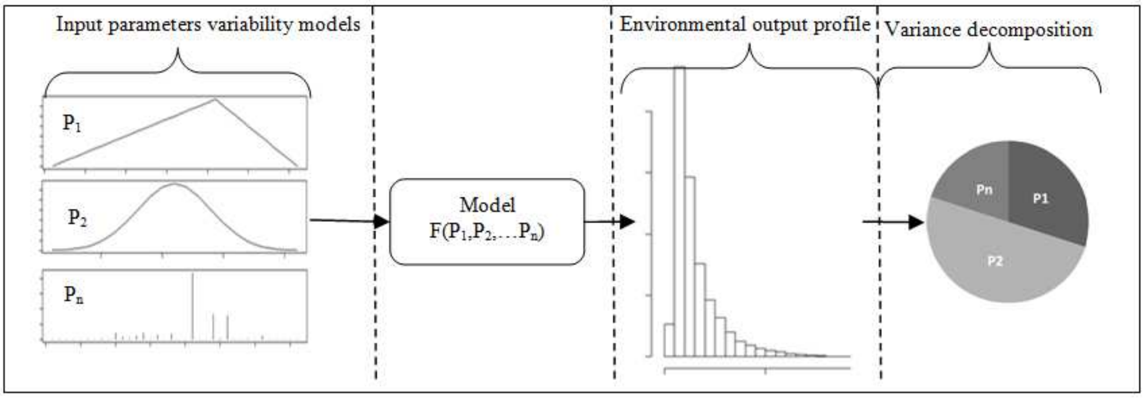



**Figure 3 : GSA Pathways applied to environmental profile**

## 4. FIRST APPLICATION TO PHOTOVOLTAIC ELECTRICITY

### Definition of the studied system

We are aiming at studying the GHG performance variability of building integrated photovoltaic (PV) electricity. The functional unit of studied system is:

**The kWh produced by a 3 kW$_p$ building integrated PV installation**

Our study considers only crystalline silicon technologies (multi and single-crystalline).

The GHG performances are calculated as the ratio of the environmental impacts over the electricity produced for the life time considered:

$$PV\ GHG\ performances = \frac{PV\ system\ \ Impact}{\eta.OR.PR.S.Irr.LT.loss} \quad \textbf{(7)}$$

The PV system impact refers to the carbon footprint of manufacturing a 3kWp system (including modules, installation structure, cables, inverters…). The system efficiency is defined by $\eta$, *OR* is the orientation factor which shows the difference in energy production between possible orientations and optimal orientation; *PR* is the performance ratio (it takes into account: shadowing losses, connection losses, inverters losses); *S* is the system surface, *Irr* is the irradiation, *LT* is the lifetime and loss is a factor considering the loss of system efficiency during the lifetime compared to initial efficiency.

The set of defined assumptions are the following:

- End of life is not considered
- Two types of technologies are considered (multi-crystalline and single-crystalline)
- Two types of installations are considered (mounted and integrated)
- The system impacts are extracted from the ecoinvent 2.2 inventories [17](PV modules, installation structure, cables, inverters…). The details about the system boundaries can be found in [18]
- Characterization factors (corresponding to the Global Warming Potentials) are from the IPCC [19] with a 100 years' time horizon

### Characterization of the inputs parameters

The input parameter definitions, characterizations and distributions of our model are:

| Parameters | Distribution Characterization |
|---|---|
| **Peak Power [kW]** | Since the study is on residential, we fixed the value at 3kWp |
| **System selection** | As described above, there are 2 types of technologies (single or multi-silicon) as well as 2 types of installations structure (mounted or integrated). The system selection is made with equiprobability distribution over these 4 technical choices. |
| **System Impacts [kg $CO_2$ eq]** | Module impacts (for both technologies and installation structures) are issued from ecoinvent V2.2 [17]. In addition, we defined an uncertainty impact distribution following a normal law centered on the ecoinvent values with a 15% relative standard deviation This has been proposed in order to assess the influence of the possible inventory uncertainty on the GHG performances |
| **Irradiation [kWh/m$^2$]** | Annual irradiation between 900 to 2200 kWh/m² with equiprobability distribution |
| **Lifetime [years]** | In the literature, we observed lifetimes ranging between 20 and 30 years. We decided to define the lifetime distribution as a normal law centered on 25 years with SD=2 |
| **Efficiency [%]** | The efficiency range and distribution for each studied technologies (multi and single Si) have been estimated according to IEA PVPS work [20]. Therefore, the variability due to the system selection as well as the efficiency variability for a same technology are addressed. The range is between 0.10 to 0.16. |
| **Orientation factor [-]** | The orientation factor has been defined as ranging between 0, 75 to 1. This represents installation ranging from optimized to fully perpendicular to fully horizontal but it can also represent installation directed in the western or eastern direction |
| **Performance ratio [-]** | The efficiency range and distribution have been estimated according to IEA PVPS work [20] ranging from 0.65 to 0.90 |
| **Surface [m$^2$]** | The systems' surfaces have been calculated as a function of system efficiency in order to keep the system peak power constant |
| **Loss [%]** | Loss factor of 1% each year in production compared to year n-1 (estimation) |

**Table 1 Input parameters characterization for a GSA on residential PV electricity**

### Results from the GSA

The Monte Carlo simulations are performed applying randomly the inputs as defined in Table 1 to calculate the GHG performances distribution of the residential PV electricity (Figure 4).

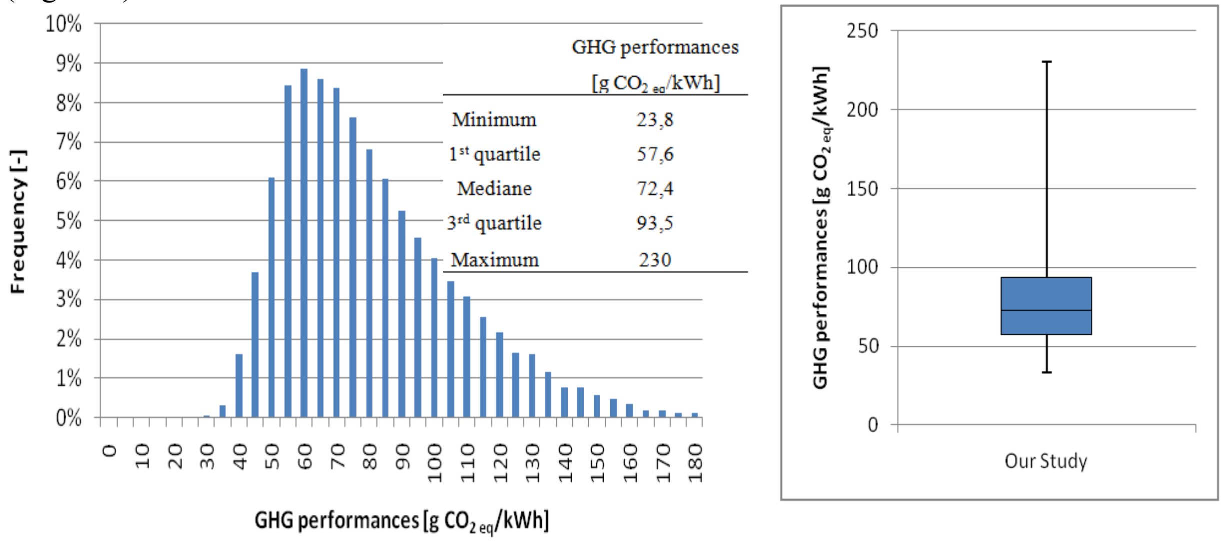



**Figure 4 GHG performances of building integrated PV electricity (20'000 simulations)**

According to our sample definition on which we apply the Monte Carlo simulations, the GHG performances vary from one order of magnitude between the minimum and maximum values. The median, 1st and 3rd quartiles values are below 100 g $CO_2$eq/kWh. Compared to IPCC literature survey [1], the coverage range of GHG performance is slighter higher.

The variance decomposition is then applied to the system described above. The following total Sobol indices are obtained (applying equation 6) on figure 5:

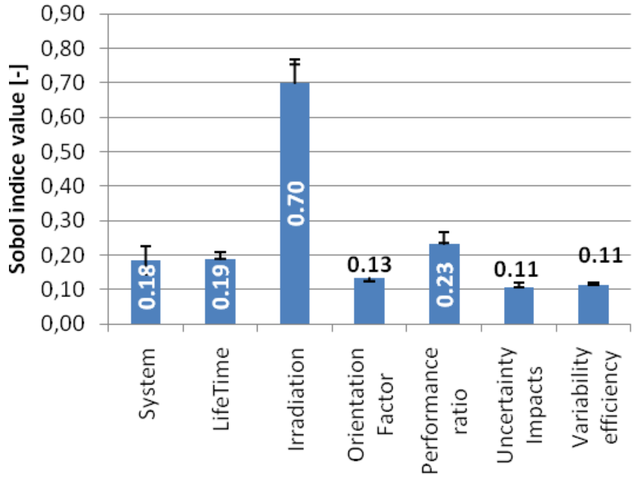



**Figure 5: Sobol indices for the residential PV electricity**

The total Sobol indices show that most of the variability in the PV systems GHG performances is due to the irradiation parameter (and its combination with the other factors since total indices are considered, see equation 6). According to the Sobol indices, the other important parameters are the system choice, the lifetime and the performance ratio which induce a smaller but non negligible variability. The Sobol indices enable a prioritization on parameters which explain the variability.

## 5. CONCLUSION

This approach has proposed a methodology to assess the LCA results variability using the Global Sensitivity Approach based on Sobol indices. This new method applied to a large set of PV LCAs results enables a quantitative assessment of the input parameters influences on the environmental answer of the modeled systems. However, this assessment remains dependant of the system model completeness. In relation with the considered set of systems, a hierarchy between inputs is therefore possible and helpful for decision makers and industries to understand where and how to invest to improve the environmental performances of renewable energies for example.

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