Global Sensitivity Analysis: a tool to analyse LCA variability of energy systems

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1. Introduction

Policy makers are nowadays debating about the future electricity mixes that should be deployed. The environmental impacts of electricity generation systems is one of the central issue for this debate. Environmental impacts of electricity systems have been widely assessed over the past decades, in particular with the LCA approach. Several literature reviews have shown the large variability associated with these results [1]. It leads sometimes policy makers to consider LCA as an inconclusive method [2]. Improving the understanding of the LCA results variability origins is a key issue to extend the use of LCA as a decision support tool.

One approach to adress variability in LCA are sensitivity analysis (SA). However, when dealing with environmental impact assessment, most SAs remain at a local level or evaluate the variation of the input parameters one factor at a time [3]. These approaches only partially reflect the LCA results variability, indeed, it does not consider the full range of input parameters interval and their probability distribution [3]. To overcome these limitations, Global Sensitivity Analysis (GSA) approach has been developped in statistics [4]. It enables apportioning the results variability of a model to its different input parameter variability, by varying all of them simultaneously according to their probability distributions. This link between result variability and parameter variability is quantitatively evaluated by the calculation of the so called Sobol indices [5]. While it has been applied in only a few analyses in the field of environmental impact assessment [6], this statistical tool is yet to be embedded in existing LCA methodology. Thereby, this paper aims at proposing a method to implement GSA in the LCA field to adress the results variability issue and more specifically the one related to energy pathways.

2. Materials and methods

2.1. GSA principle and Sobol indices calculation

The GSA principle, as well as the Sobol indices calculation details can be found in [3–5]. Briefly summarized here, the LCA model can be represented as a function *F*, which calculates the environmental impact *Y*, as a function of $P_1, P_2 \dots P_n$ parameters (database, characterization factors, lifetime…). *F* can be decomposed in a sum of elementary functions:

$$F(P_1, \dots, P_n) = f_0 + \sum_i^n f_i\,(P_i) + \sum_{i<j}^n f_{ij}\,(P_i, P_j) + \cdots + f_{1,2\dots d}(P_1, \dots, P_n) \quad \textbf{(1)}$$

This decomposition has been proposed by Sobol [5] and is unique if f_0 is constant and the other functions *f* are orthogonal. The parameters P_i being random and independent, with equation (1), the variance decomposition of *Y* is:

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

Where:

$$V_i(Y) = Var[E(Y|P_i)]\ ;\ V_{ij}(Y) = Var\left[E\left(Y\middle|P_iP_j\right)\right] - V_i(Y) - V_j(Y) \quad \textbf{(4)}$$

This allows the definition of the sensitivity indices also called Sobol indices:

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

The indices S_i represent the percentage of variance of a model answer *Y*, explained by the variable P_i; S_{ij} the variance due to the joint influence of P_i and P_j.

2.2. Methodology for GSA application to LCA systems

The methodology (represented in Figure 1) we propose, aims at enabling calculations of the Sobol indices to LCA environmental impact indicators issued from a set of systems on which we need to understand the variability. It follows 5 steps:

Step 1 – Definition of the goal, scope of the studied systems and identification of the potential variability sources.
Step 2 – System modelling encompassing the identified variability source (inputs P_i) and **characterization** of the probability distribution of each P_i.
Step 3 – Simulations of scenarios, according to the probability distribution specified in step 2.
Step 4 – Computation of the output environmental impacts resulting from the running of the LCA model to the simulation set of possible systems defined instep 3 (Monte Carlo simulations).
Step 5 – Estimation of the Sobol indices and assessment of the variability origin.

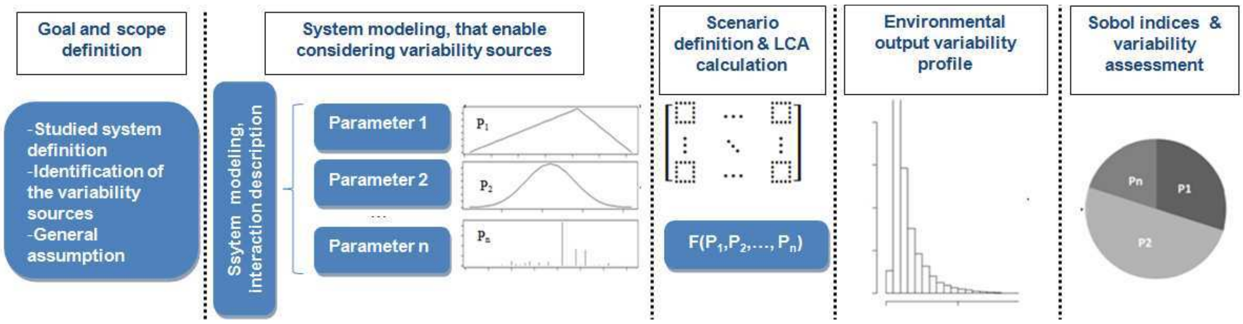

Figure 1: Methodology for GSA application to LCA

3. Results and discussion

Published LCAs performed for renewable energy pathways have shown to cover a wide variability range [7]. Such wide range is difficult to analyze as the source of variability are very diverse : geographical, technical and methodological. We propose for such renewable systems to give an insight on which parameters explain such variability. We therefore applied the proposed methodology for assessing the carbon footprint variability for two renewable systems : the photovoltaic (PV) electricity and the wind turbine electricity production pathway in Europe. Geographical parameters (irradiation and wind profile) are found to be the parameters inducing the highest sensitivity while technical parameters (PV efficiencies for example) and methodological parameters (life time of the system for example) are of the same order of importance. Such ranking is of interest for decision makers to understand the relation between the carbon footprint and its sources of variability.

4. Conclusions

Applying the GSA approach in the LCA field enables a better understanding of the environmental impact variability. Output variability is quantitatively apportionned to the input parameters variabilities and should thus help decision makers into their choices. Indeed, by knowing which parameters are the most influent, criterion to lower environmental impacts could be set. Extension to other environmental impacts could be performed. GSA could also be used to define reduced models, which could enable estimating environmental impacts only knowing the most influent parameters.

5. References

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