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Global sensitivity analysis in LCA of emerging technologies: Accounting for inputs' variability

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1. Introduction

Life Cycle Assessment (LCA) has been widely applied over the last three decades as a standardized tool for the comprehensive environmental impact assessment of products and processes. While LCAs have traditionally been based on available data from existing processes at pilot or large scale, it is estimated that 80% of environmental impacts of a process are linked to decisions at the design phase [1]. It is therefore worth to develop tools that allow adapting the current LCA framework for the application to early-stage schemes and emerging technologies. Several difficulties hinder LCA practitioners from conducting such studies. In particular, emerging technologies tend to differ significantly from the existing processes they aim to substitute and may have unknown future applications. They present a wider data gap linked to the lack of information on the life cycle phases [1,2]. Moreover, many of these systems are still at the laboratory stage, which involves substantial differences compared to industrial scale procedures [1]. As a result, LCAs of emerging technologies are subject to an increased level of uncertainty that needs to be estimated to contribute to the reliability and credibility of the results [1,2]. Global sensitivity analysis (GSA) has been proposed by several authors as a tool to evaluate the global uncertainty of LCA results and the influence of each variable input on the total variability of the model output [2,3]. However, the GSA results and their corresponding parameter ranking depend on the description of each input's variability, namely the corresponding probability distribution used by the practitioner to model the range of values that an input may assume. In this study, we propose a protocol to evaluate the effect of the choices in the selection of inputs' distribution functions on GSA results and provide recommendations for LCA practitioners.

2. Materials and methods

The proposed methodology consists in an extension of the protocol presented by Cucurachi *et al.* [3]. After the identification of the LCA model and associated inputs (Step 1) and the allocation of probability distribution functions, referred to as inputs descriptions (Step 2), a single GSA is conducted for a baseline set of distributions (Step 3a) to obtain the ranking of key parameters according to the available methods based on the decomposition of the variance (*i.e.* Sobol' indices).

We introduce an additional step (Step 3b) to analyze the influence of the inputs' description by performing GSA calculations for different sets of input distribution functions [2]. Step 3b relies on the definition of the criteria to determine whether the inputs' descriptions have an influence on the identification of the set of key parameters or not. Alternative descriptions of the inputs with respect to the baseline set are identified in terms of different ranges, different types of probability distribution functions or different descriptive parameters for a given parametric distribution function. Then, GSA is conducted reiteratively by applying in each reiteration one of the k possible alternative descriptions for a given input parameter, while keeping the baseline distribution functions (defined in Step 2) for the other inputs. Bootstrapping can be used to obtain the parameter ranking several times for each set of distribution functions by randomly resampling the data. Based on the results of these GSAs, the practitioner analyzes the influence of the inputs' description according to the defined criteria. First, the number of key parameters needed to achieve a targeted threshold is determined. Then, the descriptions having an influence on the obtained sets of key parameters are identified. Finally, the confidence in the influencing descriptions is evaluated: thus, if the description of a particular input influences the GSA output but the modeler has a high confidence on it, the description does not need to be refined. Otherwise, if the influencing description has a low level of confidence, further data should be collected to refine the corresponding distribution function. When this is not possible (especially when evaluating emerging technologies), GSA results must be carefully interpreted and a larger number of key parameters may be selected to ensure including all those that are "potentially" key parameters. Step 4 consists of the overall consistency check (partially developed in previous steps) to verify whether the results

are in accordance with intuition and confidence or not. Key input parameters are finally identified (Step 5) and GSA results can be further used for the targeted applications (e.g. obtaining simplified LCA models based on key parameters).

3. Results and discussion

The protocol was applied for the identification of key parameters and the development of a parameterized equation modelling the life cycle greenhouse gas emissions (GHG) for an emerging renewable energy technology: the enhanced geothermal systems (EGS). The LCA model consisted of 9 parameters that allow determining the environmental performance by obtaining the ratio of the total impact of the plant to the total electricity production (Step 1). Continuous distribution functions (uniform, normal or lognormal) were used to describe 8 of the parameters (borehole depth z , enhancing factor SFe , flow rate f , fuel for drilling d , lifetime LT , load factor LF , pumps power P_p and installed capacity of the organic Rankine cycle P_{ORC}) while a discrete distribution function was used for the number of wells, Nw (possible values of 2 or 3) (Step 2). After the baseline GSA (Step 3a), the identification of each set of key parameters was based on a 66% threshold for the aggregated variance contribution to the total variance (Step 3b). Four alternative descriptions were proposed for each of the 8 abovementioned continuous parameters and two additional descriptions were considered for Nw , resulting in 35 combinations of input distributions. Table 1 shows the aggregated results of 3500 GSA calculations, corresponding to 100 bootstraps per set of distribution functions. According to the results, a minimum number of 3 key parameters was required to cover at least 66% of the variability of the quantified GHG emissions. The variations in the ranking induced by the change of inputs' distributions showed that the descriptions of z and LT were the most influencing ones. Since EGS are an emerging technology with few operating plants, both distributions had a low level of confidence, since no additional data were available to refine the description. Two possible approaches are recommended: 1) a conservative approach considering a final set of 5 parameters instead of the initial 3 identified with the baseline GSA or 2) maintaining these 3 key parameters while including an alert regarding the influencing critical descriptions. The first approach was selected here. After a consistency check (Step 4), the 5 key parameters were identified (Step 5) and a simplified LCA model was obtained as a function of P_{ORC} , z , Nw , f and LT .

	P_{ORC}	z	Nw	f	LT	d	P_p	LF	Sfe
1 st	3400	100							
2 nd	100	3300	100						
3 rd		68	3362	32	38				
4 th		32	38	2968	449	13			
5 th				400	2907	193			
6 th				100	106	3150	144		
7 th						144	3356		
8 th								3500	
9 th									3500

Table 1: Sensitivity of the ranking with respect to the inputs' description: number of GSAs with each position in the ranking

4. Conclusions

The application of GSA to LCA of emerging technologies requires the development of specific approaches to evaluate the effect of potential high uncertainty of inputs' variability on GSA results. The addition of an intermediate sensitivity analysis step within conventional GSA protocols allows the identification of inputs' descriptions for which uncertainty has high influence on GSA outcomes. The approach helps avoiding inaccurate interpretations and increases robustness of GSA results for its application at early stages of process design.

5. References

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