AN INTEGRATED APPROACH TO UNCERTAINTY ASSESSMENT IN LCA

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ABSTRACT: The use of stochastic models and the presentation of ranges and confidence intervals enhances the decision support capabilities of an LCA study. However, an uncertainty analysis should not merely quantify the uncertainty in the output, but provide a mechanism to direct effort back into the LCA models to manage those uncertainties. This paper demonstrates the valuable assistance an uncertainty assessment can provide to an LCA study, including the selection of meaningful criteria against which to evaluate systems, directing further data collection and modeling effort, and systematically generating scenarios for comparison. The uncertainty assessment takes place according to a 3-layered framework, which is based on the recognition that different sources of uncertainty require different methods for their analysis and reduction.

Keywords: quantitative uncertainty analysis, framework, uncertainty importance

1 INTRODUCTION

A number of studies have demonstrated that the use of stochastic models and the presentation of results in ranges or as confidence intervals enhances the decision support capabilities of an LCA study (e.g. [1; 2; 3]). Quantitative uncertainty analysis is therefore an increasingly accepted component of an LCA study. However, the relative ease with which probabilistic uncertainty simulations (Monte Carlo and others) can be carried out raises the danger of over simplifying the problem and creating a false sense of credibility in the results. It is not well recognized that randomly varying dependent parameters (as happens in a probabilistic simulation of a "black box" LCA model) can lead to meaningless results, nor that a probabilistic treatment of uncertainty is not meaningful for all parameters input into an LCA model. In addition, the ranges or uncertainty intervals (e.g. ±50%) applied to completed inventory items are usually considerable underestimates [4].

This paper argues that for an uncertainty assessment to be meaningful it needs to be an integral part of the LCA process, and begun at the lowest level of the analysis. Furthermore, it contends that the end goal of an uncertainty assessment should not merely be to quantify the uncertainty in the results, but to provide a mechanism to direct effort back into the model to manage those uncertainties.

2 ASSESSMENT OF UNCERTAINTY

The need for a framework to guide uncertainty assessments is evident from the diversity of tools used to address the uncertainty of LCA results [5]. The framework presented here is based on the recognition that different sources of uncertainty require different methods for their assessment. The discussion thus starts with an overview of the sources of uncertainty encountered in LCA models. The brief description of the framework given here is intended only to provide a basis for the following section on the management of uncertainty. A thorough exposition, including a case study applying the framework, can be found in [6].

2.1 Sources of uncertainty

A listing of the general sources of uncertainty relevant to LCA models is given in Table 1. The classification in Table 1 is similar to that of Huijbregts, and incorporates the emphasis he and Weidema place on variability [7; 8]. However, a notable difference is that the classification in Table 1 is according to the appropriate method for analyzing the particular uncertainty. In Table 1, quantities input into LCA models are broken down into two broad classes: empirical parameters and model parameters.

Empirical parameters comprise the majority of data inputs into LCA models. These represent properties of the world, and as they are the only quantities that are, at least, in principle, measurable either now or sometime in the past or future, they are the only type of quantity that may appropriately be represented in probabilistic terms [9]. Decision variables and model domain parameters, on the other hand, define the operating state of the system, and do not have true values, as it is up to the decision maker to select their value. Although there is likely to be uncertainty about the "best" value to choose, it is not meaningful to represent this uncertainty probabilistically, as these parameters have appropriate or good rather than true values. Value parameters are grouped under model parameters, as these quantities are also best suited to assessment via a parametric sensitivity analysis. This is because value parameters tend to be among those quantities decision-makers are most unsure about, and representing them probabilistically may hide the full impact of their uncertainty [9].

The third class of uncertainty in Table 1 is uncertainty about the form or structure of the model itself. Any model is a simplification of reality, so even if a model provides a good approximation of a particular system, it can never be exact. A competing model may be said to give better predictions, but it cannot be called a more probable model. A sensitivity analysis is thus the most appropriate tool to examine the effect of model uncertainty [9]. Although likely to have the most substantial effect on the uncertainty of the results, few opportunities exist through which uncertainty in model form can be investigated. As they are currently conceived LCA models incorporate a fair degree of irreducible model uncertainty, particularly due to the spatial and temporal limitations intrinsic to the LCA method [10; 11; 12]. However, for certain aspects of the LCA model, various degrees of model sophistication have been developed (e.g. characterization models), which provide some scope to investigate model uncertainty using sensitivity analyses.

Table 1. Summary and description of sources of uncertainty relevant to LCA models (based on [9]).

Sources of uncertainty	**Breakdown according to parameter type / source**		**Description / Examples**
Empirical Parameters *(Probabilistic assessment)*	Parameter uncertainty	Measurement errors Inherent randomness Subjective judgement Approximation	Random errors, e.g. in monitoring data Unpredictability, e.g. ore quality Systematic errors, e.g. measuring proxy quantity, biases in measurement etc. “Best guess” values
	Variability	Geographic variability Temporal variability Technological variability	Variation across regions, countries etc. Variations with age, season etc. Variations not accounted for by regional or temporal variability.
Model Parameters *(Parametric sensitivity analysis / multivariate analysis)*	Uncertainty arising from choice of variables to specify system	Decision variables Model domain parameters	Quantities over which decision maker exerts direct control, e.g. plant capacity Quantities specifying spatial and temporal domain of system model.
	Disagreement	Value parameters	Preferences of decision makers, e.g. panel weights in valuation.
Model structure / form *(Sensitivity analysis)*	Limitations on form of model	Choice of LCA method	Degree of sophistication of model, e.g. allocation method.
	Limitations of LCA model structure.	Spatial limitations Temporal limitations Inherent model uncertainties	Aggregation over plants, regions etc. Aggregation over time. Epistemological and paradigmatic uncertainty (particular “world view” forced by LCA model).

2.2 A framework for the assessment of uncertainty

The framework presented here builds on those presented in the literature [2; 13], but places a particular emphasis on providing a structure to evaluate the way in which the three major sources of uncertainty interact. The analysis takes place according to a three tier process, in which the three major sources of uncertainty are analyzed in a series of nested loops.

Empirical parameter uncertainty is analyzed in an iterative probabilistic assessment. The LCA model is initially defined with a single model form, and the most likely model parameter values. Probability distributions are assigned to each empirical parameter, and a simulation using Latin Hypercube sampling is used to propagate the input uncertainty through the inventory models to the output sample. The analysis is iterative in that each empirical parameter is initially assigned a “quick and dirty” probability distribution (an over-estimate of uncertainty incorporating the range encountered in data collection and subjective estimates to cover any suspected sources of uncertainty not covered by the data sample). The rough estimates for those parameters found to contribute significantly to the output uncertainty in an uncertainty importance analysis, are then refined in subsequent iterations. The iterations are continued until the variance is reduced to a level compatible with the goal and scope of the study (see section 3.1).

The second tier of the analysis is an assessment of model parameter uncertainty, in which the effect the choice of each model parameter value has on the output is analyzed in a parametric sensitivity analysis (i.e. a sensitivity analysis in which the variables are systematically “stepped” through their operating ranges in combination with the other model parameters). In a study with a manageable number of decision variables the analysis is formalized in a multivariate analysis (or factorial design), whilst in those studies with a large number of decision variables, a pre-screening sensitivity analysis is applied. The significance of the range in output the choice of model parameter introduces is assessed with respect to the empirical uncertainty, and operating “states” (appropriate combinations of model parameters) are chosen to reflect the range in results (see section 3.3).

The top tier of the analysis is a assessment of uncertainty in model form, where possible model forms are analyzed in a sensitivity analysis (e.g. allocation method). To fully span all possible outcomes of the study, the alternative model forms should be calculated for each scenario selected in the previous layer of the analysis.

2.3 Characterizing input parameter uncertainty

By far the most challenging aspect of a quantitative uncertainty analysis lies in determining relevant ranges and probability distributions for the input parameters. The framework presented here is developed specifically for process LCA (i.e. where the basic building blocks of the LCA model are process models). Specifying the model domain parameters (with the exclusion of value parameters) poses less of a problem than the empirical parameters as their range is most often restricted by operability requirements (i.e. a decision maker generally only considers technically operating, profitable processes). The probabilistic analysis, on the other hand, presents some considerable difficulties.

The first of these is the requirement that the input parameters be specified at the lowest level of aggregation possible. This is important for two reasons. In a probabilistic simulation, the independent random sampling of the input distributions of correlated variables leads to infeasible combinations of parameters. The best way to avoid hidden dependencies between the variables is to model the process at a sufficiently detailed level that correlated variables are broken down into the individual variables and the relationships between them. Although a balance obviously has to be reached between increasing the accuracy of the model on the one hand and its complexity on the other, “black box” models should be avoided if at all possible (or at least, restricted to “background” processes only). The second reason requiring the model to be specified at a low level of aggregation is to improve the realism of the uncertainty estimates. This allows a more meaningful and far simpler definition of uncertainty, as the probability distribution is applied to the actual measured quantity (for which statistical data is frequently available), rather than to an aggregated quantity for which uncertainty information can only be estimated. Furthermore, ranges of values are incorporated into the models as they arise in data collection, removing the need to isolate an often unrealistically defined average or "most likely" value.

Another considerable constraint to specifying quantitative probability estimates is that, if these are to be comprehensive, they inherently include a degree of subjectivity. Even when based on large, representative data samples (which is all to often not the case in LCA models), the statistically measurable component of uncertainty only accounts for a small portion of the overall uncertainty [14]. It is therefore necessary to estimate the portion of uncertainty not accounted for in the data sample. This estimation can be most conveniently structured against an independent set of data quality indicators (DQIs) (such as found in the "pedigree matrix" [15]). For quantitative estimates of uncertainty, it is important that the DQIs be independent, or the estimates of uncertainty are not additive, whilst the DQI set chosen also needs to cover all potential sources of uncertainty. A considerable constraint to making quantitative uncertainty estimates is that these rely on knowing something about the quality of the data (e.g. its geographical coverage, the time period over which it was collected etc.).

3 MANAGING UNCERTAINTY

An uncertainty analysis forms an integral role in the LCA process, where the aim of the LCA is to support the decision making process. This is shown in Figure 1, where the uncertainty analysis is placed in the context of the overall decision making process. The key decision making steps to which the uncertainty analysis contributes are choosing the criteria against which options will be compared, generating the options to be put forward for possible implementation in the decision, and aiding with the selection of the best option.

3.1 Uncertainty importance analysis

The iterative procedure for the probabilistic assessment of empirical uncertainty outlined above rests on the ability of the uncertainty importance analysis to direct attention to those parameters contributing the most to the variance in the output. As the procedure starts by defining "quick and dirty" definitions of the probability distributions (simple distribution shapes with overestimates of variance), the first solution to addressing a parameter returned with high uncertainty importance is to make a more considered estimate of its probability distribution (i.e. to use whatever statistical and qualitative information is available on the parameter, or similar parameters, to determine as accurately as possible its distribution shape and variance). If the parameter is still returned with high uncertainty importance in subsequent iterations, it is an indication that the variance in the output cannot be reduced further without reducing the uncertainty of this parameter. For most empirical parameters this requires increased data collection and/or modeling effort, hence the importance of having a mechanism to direct where effort can best be invested.

The uncertainty importance analysis uses a rank-order correlation analysis to obtain a relative ranking of each parameter's contribution to the overall uncertainty. This simple method, compatible with the simulation approach to probabilistic uncertainty analysis, estimates the effect of the uncertainty of a particular input on the uncertainty of the output, averaged over all possible combinations of values of the other inputs weighted by their probabilities. In many instances, the overall uncertainty in a particular impact category or environmental intervention is found to be dominated by only a few key input parameters. It may not always be possible to reduce the uncertainty in these parameters (see following section), but identifying the limiting parameters is important, as it prevents unnecessary effort addressing the uncertainty of those input parameters with lower uncertainty importance (where this yields no significant reduction in the overall uncertainty).

3.2 Managing empirical uncertainty

The management of uncertainty in models tends to focus on empirical uncertainty, partly because empirical parameters constitute the majority of quantities input into models, but also because the uncertainty of these parameters can be reduced within the current model form. Generally speaking, uncertainty in empirical parameters arise because of shortcuts and simplifications made during data collection and the modeling process. The necessity of better data collection or additional modeling effort is therefore common to reducing the uncertainty of all empirical parameters. The way in which the uncertainty can best be reduced is dependent on the source of uncertainty.

Measurement errors and inherent randomness are usually the easiest of the sources of parameter uncertainty to reduce, as often all that is required is that more measurements be taken. This allows the error due to the measuring process to be better defined, or for a more accurate characterization of the random quantity. For measurement errors, if taking additional measurements still does not allow a sufficiently precise determination of the parameter, a more accurate measuring procedure would have to be developed. Whilst for truly random quantities, this is the most than can be done to reduce the uncertainty. However, for many apparently random quantities, closer examination yields some underlying cause of the variability. For such pseudo-random quantities, the uncertainty can be reduced by modeling the processes responsible for the variability. A similar strategy can be employed to reduce the uncertainty due to approximations. However, the fact that these quantities are initially characterized as random or by approximations generally means that modeling their causal mechanisms is too complex, introduces too many additional variables into the analysis, or that data is not available. Uncertainty associated with subjective judgement is probably the least straightforward to reduce. It may be possible to refine the measurement to better relate the measured quantity to the quantity of interest, or to find a more appropriate quantity on which to base the measurement. However, the uncertainty associated with subjective judgement is generally vastly underestimated, so a better understanding of the mechanisms involved is probably more likely to increase rather than reduce the estimate of uncertainty [9].

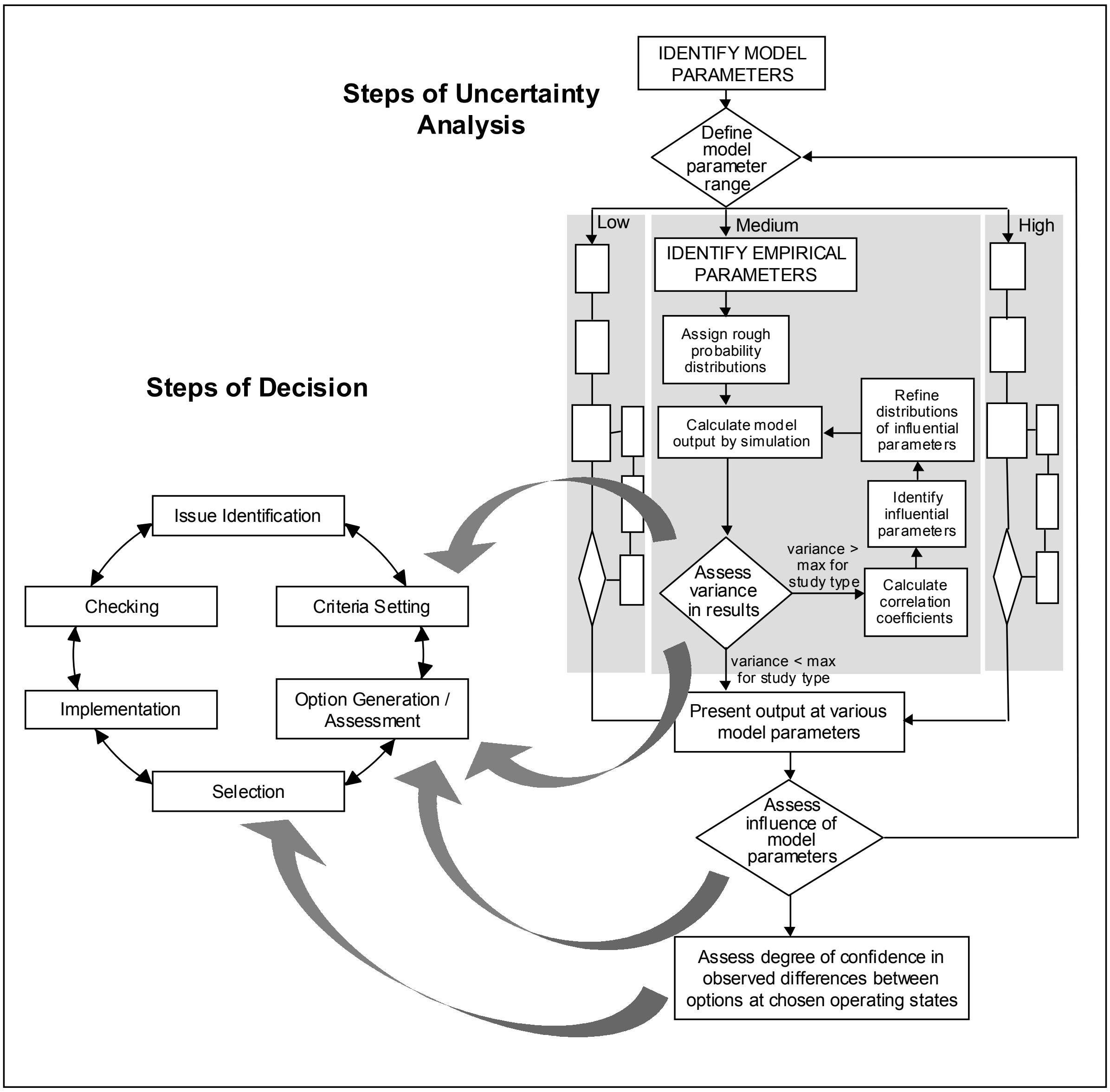

Figure 1. Schematic of the bottom two tiers of the uncertainty framework described in section 2.2, placed in the context of the overall decision making process.

Variable quantities have two distinct components to their uncertainty. The uncertainty associated with selecting a value for the parameter from the range of possible values the quantity may have (i.e. sampling its frequency distribution), as well as uncertainty associated with measuring or estimating this value. The latter is a result of the measurement errors and/or subjective judgement discussed above, so it is the first component of uncertainty that is of note here. A distinction between uncertainty due to variability and parameter uncertainty is made in Table 1 because the uncertainty in variable parameters can uniquely be reduced by a better definition of the temporal, spatial and technological placing of the quantity of interest. Focussing on the particular region, time-span or technology of interest results a narrow span of variation over the actual zone of interest, and consequently less uncertainty associated with sampling the frequency distribution.

Breaking down highly variable parameters into narrower and more manageable bands of variability offers an important opportunity for managing empirical uncertainty in LCA models. This is especially significant in processes where highly variable parameters dominate the empirical uncertainty (e.g. resource-based industries [16]). For example, in a case study evaluating the fluidized bed combustion (FBC) of discard coal the sulfur content of the waste coals identified as possible fuel sources for the FBC boiler is highly variable. Good data, available from a number of collieries over a number of years, is available, allowing for a good characterization of the probability distribution of sulfur in discard coal. However, because of the high variability of this parameter, it is not possible to discern any clear differences between the options under consideration in those impact categories for which this variable has high uncertainty importance. A solution is found by breaking up the parameter into a number of scenarios to be incorporated into the model parameter analysis (see Figure 2). As the new parameter has a narrower range of variability, this essentially shifts a portion of the empirical uncertainty to the model parameter uncertainty. The potential range in results is therefore not lost, but it is now possible to discern differences between the options with greater clarity.

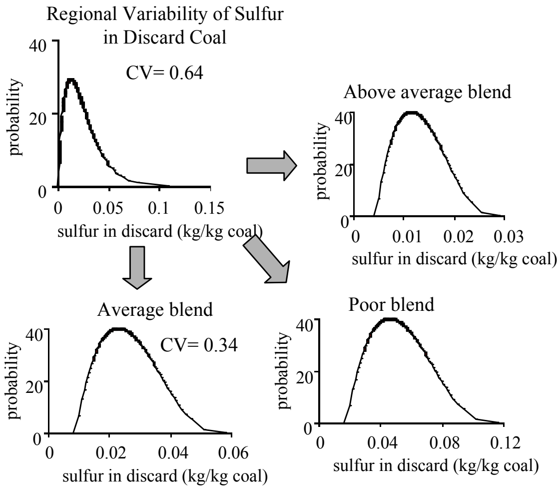

Figure 2. High variability of sulfur in waste coal is broken down into three discard scenarios, each with a more manageable variable range (CV = coefficient of variation, the ratio of the standard deviation to the mean)

Where little is known about a parameter value, an analyst has no recourse but to estimate high uncertainty. This is particularly problematic in LCA studies, where good data quality information is often lacking. In particular, aggregated LCI data (as found in LCA databases) is associated with high uncertainty. This is partly because sufficient information is rarely included in LCI databases for a user to make meaningful estimates of uncertainty, and partly because the nature of LCI data is that it is highly variable (averaging over regions, technologies etc). Better documentation would allow for a more informed estimate of uncertainty, but reducing the uncertainty further would require disaggregating the inventory (e.g. to obtain an LCI for the actual technology affected in the particular region of interest).

3.3 Criteria Selection in Comparative systems

Criteria setting is an iterative process, where an initially comprehensive range of impacts is subsequently refined by removing those criteria not helpful to the analysis. The uncertainty analysis is helpful in this process as it identifies those criteria for which the systems are too uncertain or the differences between them too slight to say with a high degree of confidence that one system always performs better than another.

An analysis of the variance present in the systems and of the magnitude of the differences between them can identify those criteria for which it is not possible to achieve high confidence levels within the constraints of the study. For example, in a case study looking at technology options for coal-fired power generation, it was determined that for comparative systems with coefficients of variance (CVs) of around 20% and less than 20% difference in their mean values, it could not be predicted with more than 80% probability that the one system would always perform better than the other system. Such “rules of thumb” can provide useful guidelines for setting realistic certainty criteria (e.g. in this case study, since data restrictions limited the variance in the output of most impact category results to CVs in excess of 20%, those categories exhibiting differences of less than 20% could not be considered meaningful selection criteria). In fact, the very high uncertainty in certain impact categories in this case study meant that for these impact categories comparisons were not meaningful even where significant differences in the mean values were observed, e.g. an 80% difference in carcinogenic effects was found between certain options, but there was only a 50% probability that this would occur.

3.4 Uncertainty in model parameters and model form

Uncertainty in model parameters and model form can better be said to be managed rather than reduced. The central idea in the management of these sources of uncertainty is ensuring that the potential range covered by the results is made explicit when they are presented. The following discussion centers on decision variables, since these offer greater opportunities for exploring model parameter uncertainty within the restrictions of the LCA model. An assessment of model form is typically restricted to the common choices encountered in LCA studies, whilst guidelines and “common practice” create the apparent sense that the effect of the choice of model domain parameters does not need to be investigated. Those that are able to be identified (e.g. time horizon considered, time interval modeled, degree of spatial breakdown etc.) can be considered in the parametric sensitivity analysis along with the decision variables.

The value of the systematic model parameter analysis outlined in section 2.2 is that it forces a consideration of all decision variables, thereby allowing an exploration of the full solution space of the system. A multivariate analysis of all model parameters found to be significant results in the output for a potentially very large number of scenarios being computed. However, the judicious choice of a few key scenarios covering the full range of results can usually keep the number of scenarios that need to be presented to a manageable number (e.g. best performance, worst performance, mid-range performance etc.). High uncertainty arising from the choice of decision variables can sometimes be reduced by revisiting the goal and scope definition phase of the study, and more tightly defining the problem to be addressed. However, in some studies, especially those of a more strategic nature, the very nature of the problem is a loosely defined option set. In such cases, the model parameter uncertainty analysis is invaluable, as it provides a structure for generating scenarios, and allows an informed selection of the best operating states (appropriate combination of operating parameters) to be taken further in the decision.

The significance of the model parameter uncertainty needs to assessed with respect to empirical uncertainty. If the empirical uncertainty causes a high degree of overlap between the options, it is an indication that model parameter uncertainty might be of lesser importance. However, if the opposite is true, it is an indication that additional effort would best be focussed on a better definition of the system, rather than exhaustively refining empirical parameter uncertainty. For example, Figure 4 shows the range in operating performance found for an FBC power generating plant relative to a conventional PF plant. NO_x emissions are seen to have low model parameter uncertainty (as seen by the range covered by the extreme scenarios in Figure 4), and the empirical uncertainty dominates the analysis (large overlap between the options). SO_2 emissions, on the other hand, show very significant model parameter uncertainty, with the choice of operating scenario determining whether the system performs better or worse than the comparative “base case”.

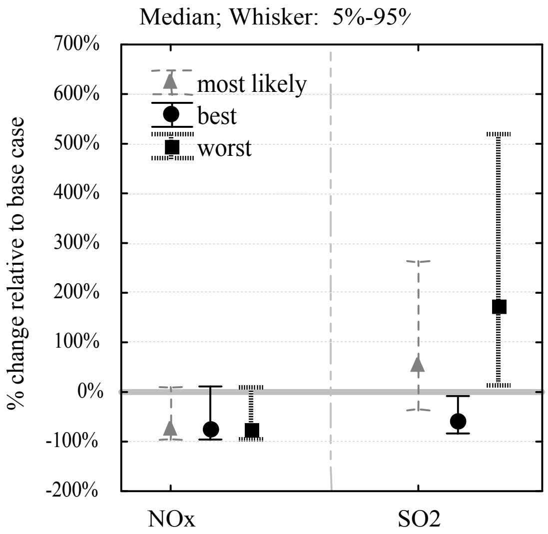

Figure 3. Range in performance of a small FBC power plant relative to a base case PF option. The median value and the interval in which 90% of the data falls is shown for best and worst operating performance, and for the most likely combination of operating parameters..

4 CONCLUSIONS

A quantitative uncertainty analysis adds considerable value to the decision making process, and goes beyond merely providing an indication of the confidence decision makers can have in the results. Where the purpose of the LCA is to support environmental decision making, the uncertainty analysis assists in the selection of meaningful criteria against which to evaluate system performance, directs further data collection and modeling effort, and assists in generating scenarios for comparison. In fact, given the inherent subjectivity in estimating the uncertainty of the input parameters (where these include all sources of potential uncertainty and not merely that reflected in the data sample), rather than expecting the uncertainty analysis to provide objective, realistic estimates of output uncertainty, the value of the analysis in structuring and guiding the decision analysis process should rather be emphasized.

A framework capable of delivering valuable assistance to the decision making process is presented. Although particularly developed for process and decision-oriented LCA applications, the uncertainty analysis framework is compatible with the general framework for LCA set out by ISO [17]. The ISO standards stress the importance of including sensitivity analyses and uncertainty estimates, yet provide no clear procedure for doing so [18]. The ISO standards also provide little guidance on scenario selection, although the choice of scenario to model has the potential to completely change the outcome of an analysis. The framework presented here aims to address these shortfalls, and also to place the uncertainty analysis in the overall context of the decision making process.

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