Application of uncertainty analysis based on Monte Carlo (MC) simulation for life cycle inventory (LCI)

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Abstract. You The use of Monte Carlo (MC) simulation was presented in order to assess uncertainty in life cycle inventory (LCI) studies. The MC method is finded as an important tool in environmental science and can be considered the most effective quantification approach for uncertainties. Uncertainty of data can be expressed through a definition of probability distribution of that data (e.g. through standard deviation or variance). The presented case in this study is based on the example of the emission of SO2, generated during energy production in Integrated Steel Power Plant (ISPP) in Kraków, Poland. MC simulation using software Crystal Ball® (CB), software, associated with Microsoft® Excel, was used for the uncertainties analysis. The MC approach for assessing parameter uncertainty is described. Analysed parameter (SO2,) performed in MC simulation were assigned with log-normal distribution. Finally, the results obtained using MC simulation, after 10,000 runs, more reliable than the deterministic approach, is presented in form of the frequency charts and summary statistics. Thanks to uncertainty analysis, a final result is obtained in the form of value range. The results of this study will encourage other researchers to consider this approach in their projects, and the results of this study will encourage other LCA researchers to consider the uncertainty in their projects and bring closer to industrial application.

1 Introduction

1.1 Uncertainty analysis of LCI

By definition, statistic and uncertainty are inexorably linked [1]. Definition of uncertainty given by Huijbregts [2] is the following: "Uncertainty is defined as incomplete or imprecise knowledge, which can arise from uncertainty in the data regarding the system, the choice of models used to calculate emissions and the choice of scenarions with which to define system boundaries, respectively", and uncertainty defined by Walker et al. [3] as „any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system" was quoted in . According to [4] uncertainty analysis is another important issue in LCA, as average data is usually used without considering the associated variability, and the results can be misleading when comparing systems [4]. Deterministic approaches and the description of processes in the studies of ecological life cycle assessment do not properly reflect the reality [5]. The analysis of uncertainty, a pervasive topic in LCA studies

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[6], has been a subject for more than 10 years, and many LCA software tools (e.g. SimaPro, GaBi) facilitate uncertainty propagation by means of sampling methods, most often used Monte Carlo (MC) simulation [7,8,4]. Following the categorization of the US-EPA, quoted in [9], tree types of uncertainty can be distinguished: parameter uncertainty, model uncertainty, and scenario uncertainty. Also in this work [9] has been presented the main sources of uncertainty (e.g. data inaccuracy and gaps, unrepresentative data, model uncertainty, estimation of uncertainty). Detailed description of the combination of sources of uncertainty (parameter, model and scenario uncertainties) and combination of source of uncertainty and methods to address them (deterministic, probabilistic, possibilistic, and simple methods) is discussed in the [10].

2. Monte Carlo Simulation

2.1 Parametr uncertainty – Data quality

One of the difficulties encountered in constructing a representative LCA is data availability [11]. The quality of the data collected in the inventory is crucial to the outcome of the LCA [12]. McCarthy [13] quoted many excellent texts on probability and probability distributions used for uncertainty modelling. Analysis of this literature [e.g. 7, 8, 14] indicated that majority of the data in environmental as well as ecological estimations and in the description of chemical parameters have most often a log-normal followed by normal or uniform shapes to use.

Parametr uncertainty of an LCA study is discussed in several studies [e.g. 8, 15, 16]. In this study uncertainty analysis at the LCI level is conducted using Oracle Crystal Ball® (CB) associated with Excel spreadsheet models for performing MC simulation. The CB software helps analyse the risks and uncertainties associated with Microsoft Excel spreadsheet models. LCI data were defined as probability distributions instead of deterministic values.

The MC approach for assessing parameter uncertainty involves the following steps [17]:

1/ select a distribution to describe possible values of each parameter;

2/ specify properties of each parameters;

3/ generate data from the distribution;

4/ use the generated data as possible values of the parameter in the model to produce output.

In fact, data uncertainty is often mentioned as a crucial limitation for a clear interpretation of LCA results. However, uncertainty analysis is not commonly performed in LCAs [2, 9, 18], although great efforts have been made on classification, definition, and sources of uncertainty as well as methodological aspects for expressing uncertainty [19].

The knowledge of geometric mean, μ_g, and geometric standard deviation, σ_g, of probability distributions of input data, may prove useful during the process of defining the confidence intervals. Effective formula for the multiplicative confidence interval is provided in the work of other researchers [e.g. 7, 14], and take the following form:

$$[\mu_{g/}\,\sigma_{g,}\,\mu_{g*}\sigma_g] \text{ for confidence interval of 68\%} \qquad (1)$$

where:

μ_g – mean geometric value

σ_g – standard geometric deviation.

Detailed classification of methods for uncertainty characterization, uncertainty analysis, and sensitivity analysis, according to the amount of information they provide, their availability in LCA software, etc. is presented and discussed in [20]. Types of random variables in uncertainty analysis in LCA studies is

2.2 Case study

Thecas study used the MCsimulation approach is illustrated below, based on the example of the emission of SO_2, generated during energy production in in Integrated Steel Power Plant (ISPP) in Kraków, Poland, based on the data obtained in 2005. By approximating the SO_2 emissions with log-normal distribution, with a range of zero to infinity and its parameters set to the levels shown in Fig. 1, where the mean value corresponds to an annual deterministic SO_2 emission level amounting to 916.64 Mg. Simulation, with geometric standard deviation, σ_g =1.5, for the emission of SO_2, is suggested in literature (Sonneman et al., 2004).

The results of the MC simulation, with a 10 000-step randomisation cycle, are shown in Fig. 2, and in the form of statistical reports in Fig. 3 and 4.

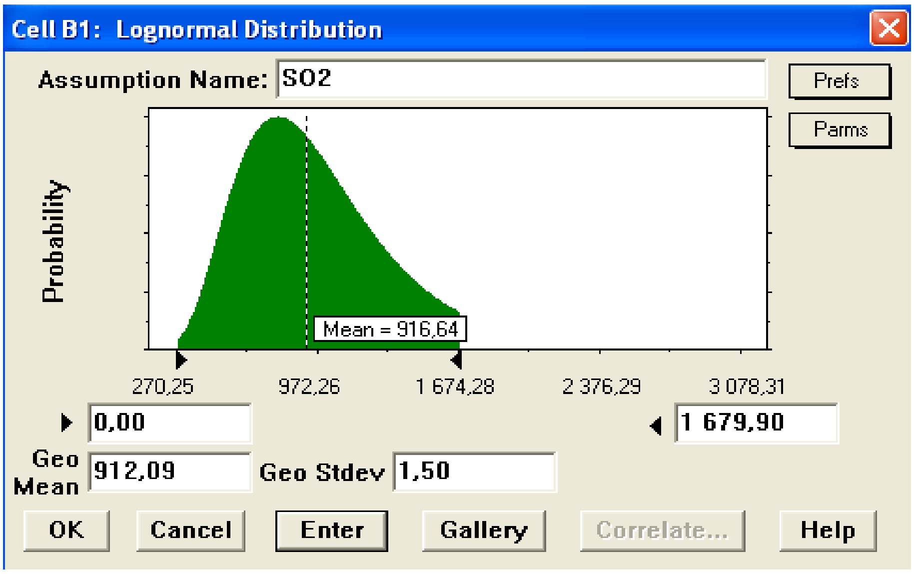


Fig. 1. Parameters of log-normal distribution approximating SO_2 emissions.

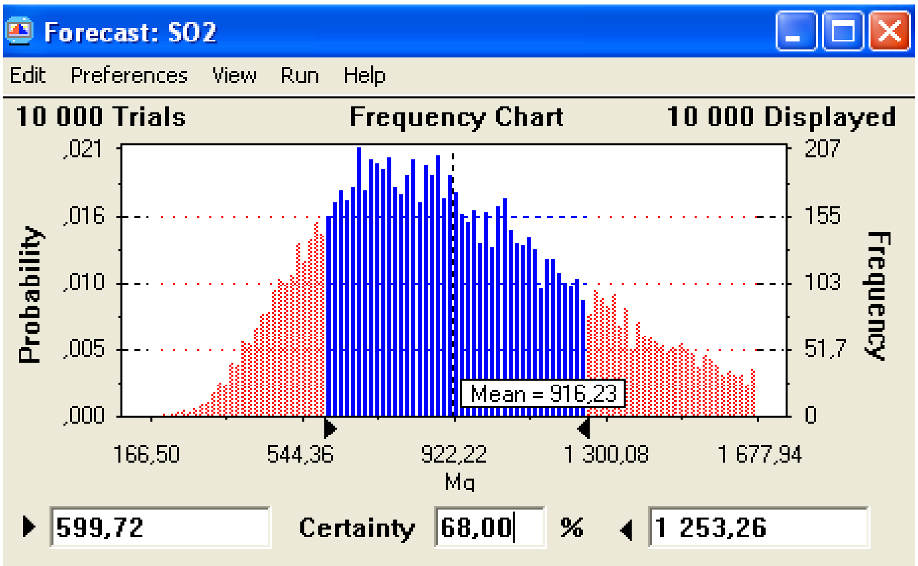
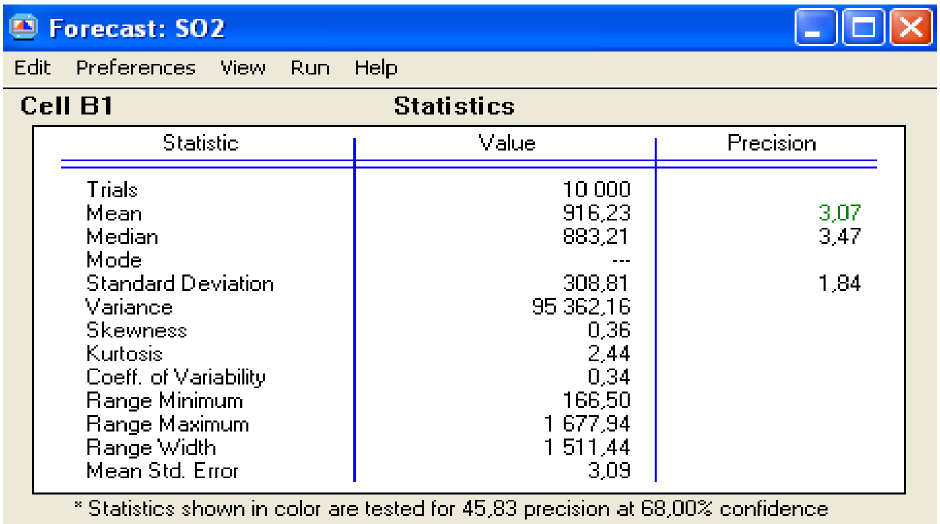


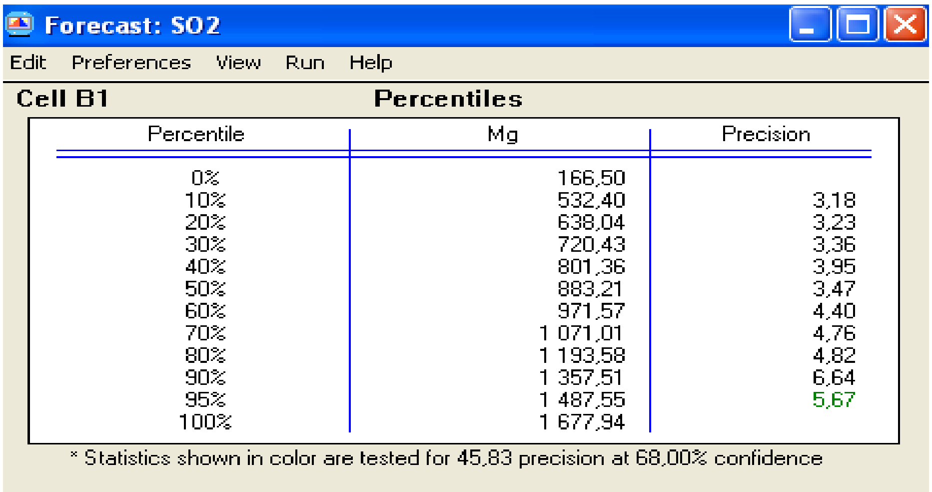
Fig. 2. Frequency chart of the SO_2 emissions forecast, with 68% confidence interval



Statistic	Value	Precision
Trials	10 000	
Mean	916,23	3,07
Median	883,21	3,47
Mode	---	
Standard Deviation	308,81	1,84
Variance	95 362,16	
Skewness	0,36	
Kurtosis	2,44	
Coeff. of Variability	0,34	
Range Minimum	166,50	
Range Maximum	1 677,94	
Range Width	1 511,44	
Mean Std. Error	3,09	

* Statistics shown in color are tested for 45,83 precision at 68,00% confidence

Fig. 3. SO_2 emissions report – Statistics



Forecast: SO2

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Cell B1 Percentiles

Percentile	Mg	Precision
0%	166,50	
10%	532,40	3,18
20%	638,04	3,23
30%	720,43	3,36
40%	801,36	3,95
50%	883,21	3,47
60%	971,57	4,40
70%	1 071,01	4,76
80%	1 193,58	4,82
90%	1 357,51	6,64
95%	1 487,55	5,67
100%	1 677,94	

* Statistics shown in color are tested for 45,83 precision at 68,00% confidence

Fig. 4.. SO_2 emissions report – Percentiles

The intervals corresponding to the 68% confidence level, calculated with the help of suggested geometric standard deviation, σ_g =1.5, for the emission of SO_2 is equal to: [599.72; 1253.26]

Conclusion

Thanks to uncertainty analysis, a final result is obtained in the form of value range. As a result, the results in this study based on the real data and obtained using MC simulation are more reliable than the deterministic approach and has the advantage that no normality is presumed**.**

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References

Online references will be linked to their original source, only if possible. To enable this linking extra care should be taken when preparing reference lists.

References should be cited in the text by placing sequential numbers in brackets (for example, [1], [2, 5, 7], [8-10]).

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