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UNDERSTANDING UNCERTAINTY PROPAGATION IN LIFE CYCLE ASSESSMENTS OF WASTE MANAGEMENT SYSTEMS

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SUMMARY: Uncertainty analysis in Life Cycle Assessments (LCAs) of waste management systems often results obscure and complex, with key parameters rarely determined on a case-by-case basis. The paper shows an application of a simplified approach to uncertainty coupled with a Global Sensitivity Analysis (GSA) perspective on three alternative waste management systems for Danish single-family household waste. The approach provides a fast and systematic method to select the most important parameters in the LCAs, understand their propagation and contribution to uncertainty.

1. INTRODUCTION

Identifying the key inputs and understanding how their associated uncertainties affect the results is fundamental to master any Life Cycle Assessment (LCA) model. Within the waste sector, LCA is being increasingly used to quantify the environmental performance and the sustainability of alternative management solutions, and uncertainty analysis is becoming increasingly essential for a balanced interpretation and use of LCA in decision making.

LCAs of waste management systems are usually wide and complex models, where results are subject to uncertainty due to combined effects of parameter, scenario, and model uncertainties (Clavreul et al., 2012). Focusing on parameters, common key variables in waste-LCAs are waste chemical composition, material and energy recovery efficiencies, consumption of fuel, etc. Nevertheless, these factors are very case-dependent, e.g., on the size of the system modelled, its boundaries, and on the specific modelling choices. For these reasons, they should never be selected *a priori*, but identified with a systematic and rigorous approach on a case-by-case basis.

Clavreul et al. (2012) and Heijungs et al. (2005) suggest stepwise procedures that assess parameter importance firstly with sensitivity analysis, then with uncertainty propagation. For the latter, different practices are available, involving analytical and sampling methods. The analytical

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approaches exploit the theory of error propagation, but usually result obscure for being explained in the literature in conflicting ways and are thus rarely implemented in LCA applications. Alternatively, sampling methods consist of repeatedly calculating the result scores with inputs randomly sampled from their previously specified probability distributions (Imbeault-Tétreault et al., 2013). Most software applications for LCA nowadays deal with uncertainties by means of Monte Carlo techniques, but often result computationally heavy to conduct and do not automatically assess the sensitivity and contribution to overall uncertainty of individual parameters (Heijungs and Lenzen, 2014; Hong et al., 2010).

Exhaustive and case-specific parametrical uncertainty analyses can thus become confusing and time-demanding. Moreover, traditionally, sensitivity and uncertainty analysis are run independently, and uncertainty is usually propagated only for the most sensitive parameters (Clavreul et al., 2012). This does not allow quantifying the full influence of input parameters that can be characterized by an average or low sensitivity and a high uncertainty. Saltelli et al. (2006) identifies importance measures, which couple of the concepts of sensitivity and uncertainty of parameters, commonly known also as Global Sensitivity Analysis (GSA), as the best practice.

The paper aims to summarize the key messages of a thorough research carried out by Bisinella et al. (2015). A simplified analytical approach based on GSA was applied in order to estimate the most important parameters in a waste-LCA model in a GSA. Three waste management alternatives for municipal solid waste in Denmark were modelled with the waste-LCA software EASETECH (Clavreul et al., 2014). Uncertainties were propagated (i) analytically and (ii) by means of Monte Carlo sampling. The results from the two propagation approaches were compared across all ILCD recommended impact categories to evaluate applicability towards a wide range of impacts.

2. METHODOLOGY

The global sensitivity analysis allows unifying the concepts of sensitivity and uncertainty in the concept of importance. Sensitivity of parameters is calculated as Sensitivity Ratio (SR) and Sensitivity Coefficient (SC) as reported in Bisinella et al., (2015) and Clavreul et al., (2012). Uncertainty is then given as input uncertainty for parameter, with the formulation depends on the kind of distribution chosen.

Schematizing a general LCA with a mathematical relationship as:

$$Y^j = f(X_1, ..., X_n)$$

Where Y is the result score for the impact category j, depending on a number n of input parameters X_i. Then, the analytical uncertainty for the individual parameter will then be simply given by:

$$V(Y)_i^j \approx \left(SC_i^j\right)^2 \cdot V_{input}(X_i) \qquad (1)$$

When considering all the parameters in the scenario, the total parametrical variance corresponds to:

$$V(Y)^j \approx \sum_{i=1}^{n} \left[\left(SC_i^j\right)^2 \cdot V_{input}(X_i)\right] \qquad (2)$$

The variance in the result score in a specific impact category will thus be given by the sum of the single parameter uncertainties. Bisinella et al., (2015) provides a review on analytical methods and the concept of additivity of variances.

The contribution to variance of the single parameters can be decomposed as follows:

$$V(Y)^j \approx \sum_{i=1}^{n} V_i^{\,j} \approx \sum_{i=1}^{r} V_i^{\,j} + \sum_{i=r+1}^{n} V_i^{\,j} \qquad (3)$$

Where *r* represents the number of parameters which, summed progressively according to their importance in the model, is required to reach a desired representativeness level of the total parametrical uncertainty in the scenario. Ranking the most important parameters allows to prioritize research on the pivotal inputs and to fix in their range in a systematic and justifiable way the least influencing ones. This concept unifies sensitivity and uncertainty related to input parameters into importance in a GSA perspective.

3. CASE STUDY

3.1 Scenarios

The case study replicates a real-case modelling size, simulating three scenarios for the management of single-family household waste in Denmark in 2013 (Jensen et al., 2013). The three waste management scenarios focus on increased recycling of paper and glass and test different solutions for managing the residual waste between incineration, anaerobic digestion and landfilling. A full description of the case study can be found in (Bisinella et al., 2015). Figure 1 illustrates a scheme of the scenarios. The study investigates results on the full range of the ILCD recommended impact categories (European Commission, 2010) in order to test the method over a wide range of impacts.

3.2 EASETECH software

The three waste management systems were modelled with EASETECH (Clavreul et al., 2014). This LCA software is specifically tailored for waste management assessments and it allows modelling a reference flow consisting of a mix of materials and tracking substances in the different fractions of the material flows throughout the scenario processes. EASETECH allows the use of parameters in all input fields; for each parameter the user can specify one value, a list of values or a probability distribution between normal, uniform, log-normal or triangular. The uncertainty of the obtained LCA can be propagated with a Monte Carlo simulation tool (Bisinella et al., 2015).

3.3 Tested methodology

For each scenario and impact category, normalized impact scores were calculated and used for contribution analysis and sensitivity analysis; SCs and SRs were calculated for all parameters in the three waste management systems.

Uncertainty analysis was carried out with the proposed analytical method and by means of the Monte Carlo simulation tool in EASETECH, which was carried out with increasing order of magnitude of sampling points (N=1000, 10000, 100000). We used a predefined common uncertainty range of 10% for all parameters, that we assumed to be normally distributed and with a 95% confidence interval. We compared the resulting variances with the coefficient of variation (CV):

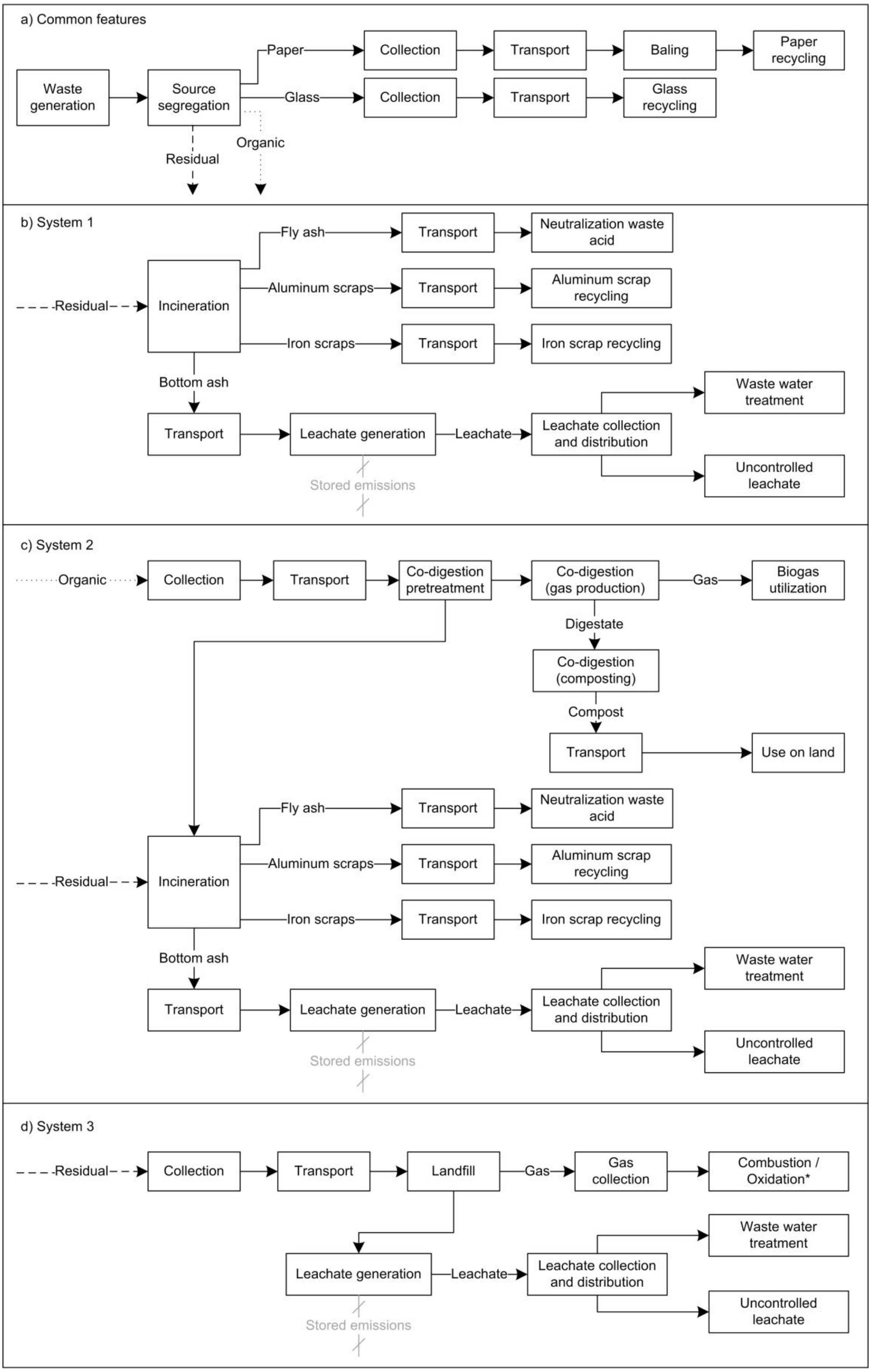

Figure 1. Scenarios implemented for the case study

$$CV^{j} = \frac{\sqrt{V(Y)^{j}}}{Y^{j}} \tag{4}$$

The CV is expressed as a percentage and it is specific for each impact category j. It is given by dividing the standard deviation associated to the impact category to the respective mean result score and provides an indication of how uncertain is the average result.

4. RESULTS AND DISCUSSION

4.1 LCA results

Figure 2 shows the normalized impact scores in persons equivalents (PE) for all scenarios and impact categories. The impact categories with the highest overall scores are climate change (GWP), human toxicity with non-carcinogenic effects (HTnc), marine eutrophication (ME), total ecotoxicity (totET) and depletion of abiotic resources (RDfos).

Regarding GWP, scenario 1 has the largest benefits (-0.09 PE) because a substantial portion of the waste is routed to the incinerator, where electricity and heat are recovered and contribute in displacing electricity production from coal. Scenario 2 shows less overall benefits (-0.08 PE) for the lower efficiency of the energy recovery of the anaerobic digester, and for the reduced waste flow to this treatment scenario. As far as scenario 3 is concerned (-0.02 PE), the savings arise from the recycling aspect, whereas the treatment scenario leads to impacts related to methane emissions from the landfilled waste. For HTnc, impacts are remarkable mainly for scenario 2 (0.21 PE), due to the zinc process specific emissions arising from the use on land of the compost. The major impacts for ME are connected with the landfill management scenario (0.3 PE), where nitrate and ammonium ion leach to surface water. totET shows the highest scores for scenario 1 (-0.05 PE) and 2 (0.17 PE), but with opposite sign. For scenario 1, savings are related to the paper avoided production. In scenario 2, the same recycling of paper occurs, but the burden is shifted by the use on land of the compost. Finally, both in scenario 1 (-0.08 PE) and 2 (-0.06 PE) there is a total overall saving of RDfos thanks for the substitution of fossil fuels by the energy recovery.

4.2 Simplified analytical method

Table 1 provides results of the uncertainty analysis carried out with the two methods for selected impact categories for scenario1. The results of the analytical variance calculated with Eq. (2) are shown in the upper part of the table. The remaining part of the table focuses on the results of the Monte Carlo simulation, obtained selecting all the parameters in the modelled scenario for the uncertainty propagation. The two methods vary on average by 5%, which was also observed for other analytical methods in the literature (Heijungs and Lenzen, 2014; Hong et al., 2010). The CVs calculated with the results from the two uncertainty propagation methods show marginal differences within 1%. However, the speed difference between the two methods is enormous. The analytical method requires summing in a spreadsheet the values calculated with Eq. (1) for all parameters, while the Monte Carlo requires simulation times that range from tens of minutes to hours. The results highlight how the analytical uncertainty can provide a fast approximation of the total scenario parametrical variance, useful for determining immediately a standard deviation for each result score and recognizing the impact categories subjected to the highest uncertainty. This is of great value in case of a comparative LCA, because it would instantly identify which impact categories present potentially overlapping results and thus require a discernibility analysis.

Table 1. Variance and respective coefficients of variation (CV) obtained with the analytical and sampling method for scenario 1. The Monte Carlo was carried out for an increasing number of runs (N). Results are shown for the selected impact categories: climate change (GWP), human toxicity, carcinogenic (HTc), particulate matter (PM), total acidification (TA), freshwater eutrophication (FE), resource depletion (RD)

		GWP	HTc	PM	TA	FE	RD
Analytical method							
Analytical variance	**[PE^2]**	**2.25E-05**	**2.41E-09**	**1.13E-06**	**3.45E-06**	**1.91E-09**	**1.34E-12**
Coefficient of variation	[%]	-5.20%	4.10%	-5.10%	-5.70%	-6.90%	-6.10%
Monte Carlo simulation							
Sampled variance [PE^2]	N=10^3	**2.38E-05**	**2.53E-09**	**1.08E-06**	**2.97E-06**	**1.87E-09**	**1.32E-12**
	N=10^4	**2.22E-05**	**2.31E-09**	**1.04E-06**	**2.99E-06**	**1.95E-09**	**1.36E-12**
	N=10^5	**2.22E-05**	**2.34E-09**	**1.03E-06**	**3.02E-06**	**1.91E-09**	**1.33E-12**
CV [%]	N=10^3	-5.40%	4.20%	-5.00%	-5.30%	-6.80%	-6.10%
	N=10^4	-5.20%	4.00%	-4.90%	-5.30%	-7.00%	-6.10%
	N=10^5	-5.20%	4.00%	-4.90%	-5.40%	-6.90%	-6.10%

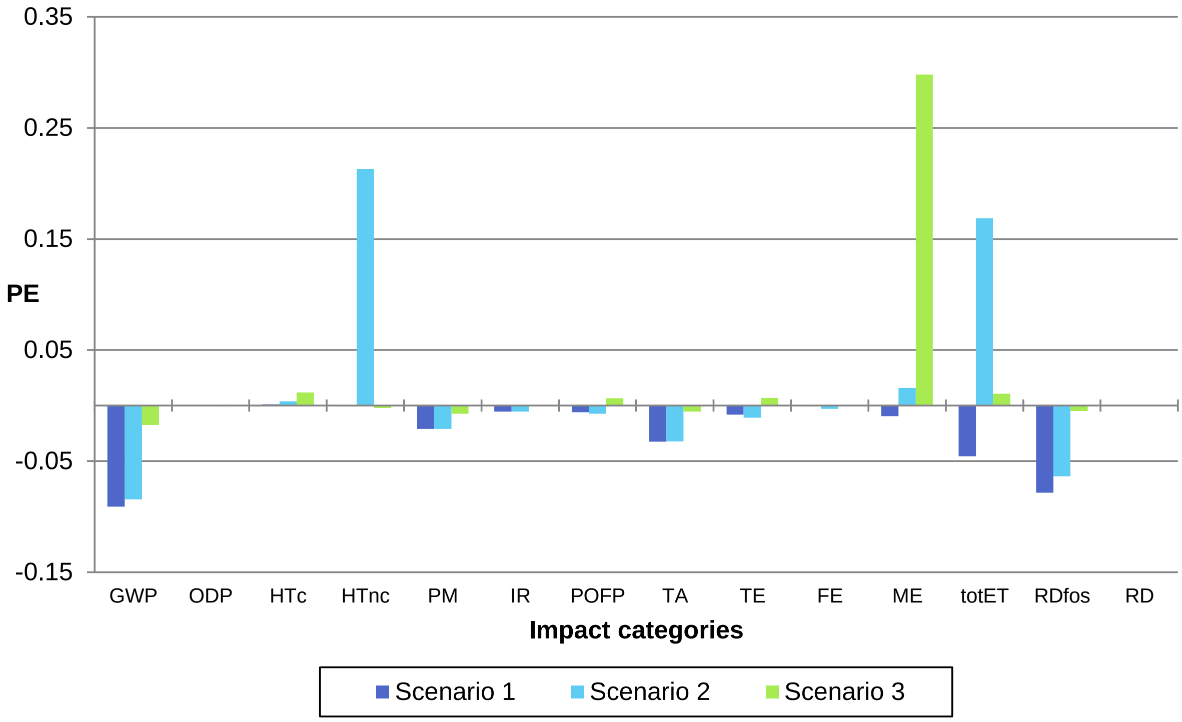

Figure 2. Normalized result scores of the LCA case study. Results are given in Persons Equivalents (PE). The impact categories are: climate change (GWP), stratospheric ozone depletion (ODP), human toxicity, cancer effects (HTc), human toxicity, non-cancer effects (HTnc), particulate matter (PM), ionizing radiation (IR), photochemical ozone formation (POFP), terrestrial acidification (TA), terrestrial eutrophication (TE), freshwater eutrophication (FE), marine eutrophication (ME), total ecotoxicity (totET), fossils depletion (RDfos), metals/minerals depletion (RD)

4.2 GSA perspective

We ordered hierarchically the variance associated to the single parameters and calculated progressively a partial variance for increasing r with Eq. (4). Figure 3 illustrates the behaviour of the global warming impact categories within the scenarios. The y axis shows the percentage of the total analytical variance reached with the number of parameters included in the propagation (r) at the corresponding point of the x axis.

The proposed simplified analytical method and a GSA perspective provide a systematic approach to identify the number of parameters that are actually needed to reach a good representativeness of the uncertainty in each impact category. This should be determined on a case-by-case basis, but with considerably shorter times compared to propagations with sampling methods. Uncertainty concentrated in few parameters also highlights the fragility of the decisional process between datasets, since even one external process can completely define the order of magnitude of the uncertainty for an impact category.

5. CONCLUSIONS

Uncertainty propagates in waste LCAs as a combination of sensitivity of parameters and their associated input uncertainty. Adding an importance analysis step to the traditional step-wise approaches would allow understanding how input uncertainties propagate in the model and representing uncertainty sparsely by contextually selecting key parameters in a fast and systematic way.

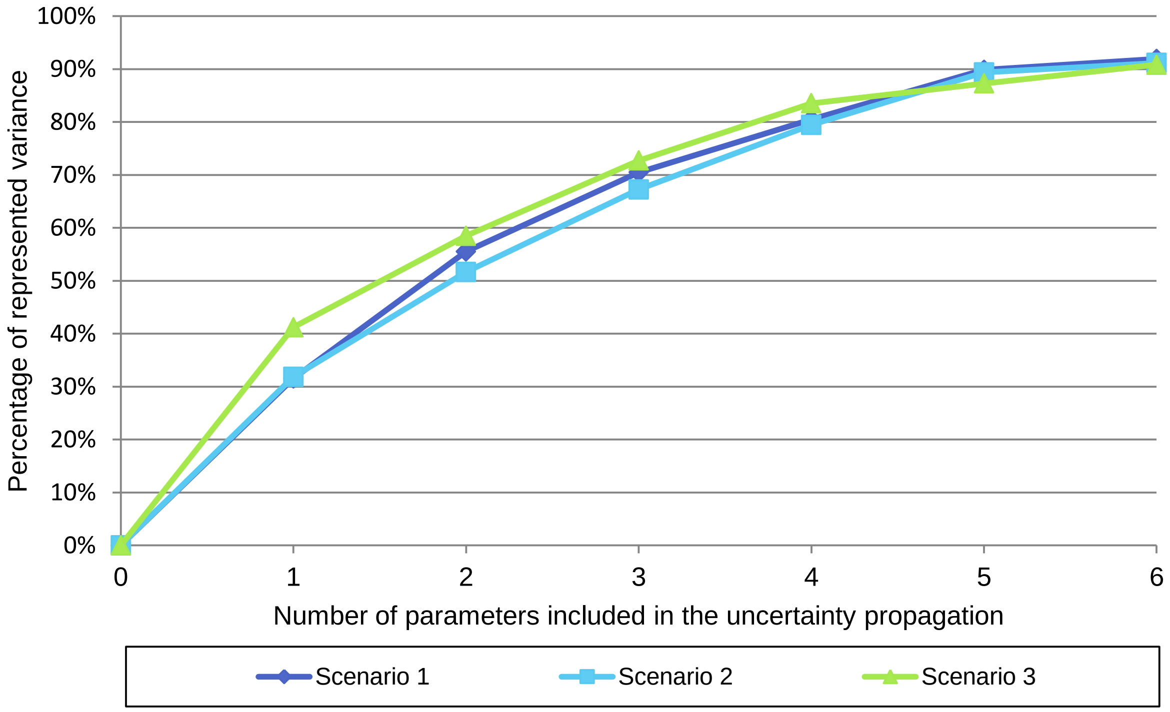

Figure 3. Percentage of the total uncertainty in the global warming impact categories obtained grouping hierarchically the parameters according to their importance in the model.

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