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Quantifying uncertainty in LCA-modelling of waste management systems

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26 **Abstract**

27

28 Uncertainty analysis in LCA studies has been subject to major progress over the last years. In the context of waste
29 management, various methods have been implemented but a systematic method for uncertainty analysis of waste-
30 LCA studies is lacking. The objective of this paper is (1) to present the sources of uncertainty specifically inherent to
31 waste-LCA studies, (2) to select and apply several methods for uncertainty analysis and (3) to develop a general
32 framework for quantitative uncertainty assessment of LCA of waste management systems. The suggested method is a
33 sequence of four steps combining the selected methods: (Step 1) a sensitivity analysis evaluating the sensitivities of
34 the results with respect to the input uncertainties, (Step 2) an uncertainty propagation providing appropriate tools for
35 representing uncertainties and calculating the overall uncertainty of the model results, (Step 3) an uncertainty
36 contribution analysis quantifying the contribution of each parameter uncertainty to the final uncertainty and (Step 4)
37 as a new approach, a combined sensitivity analysis providing a visualization of the shift in the ranking of different
38 options due to variations of selected key parameters. This tiered approach optimizes the resources available to LCA
39 practitioners by only propagating the most influential uncertainties.

40

41 **Keywords**

42

43 LCA-modelling; waste management; uncertainty; sensitivity

44

45

46 **1. Introduction**

47

48 Waste management has during the last decade been subject to a range of life cycle assessment (LCA; described in
49 ISO, 2006) studies e.g. Damgaard et al. (2011), Finnveden et al. (2005), Lazarevic et al. (2010) and Pires et al.
50 (2011). The purposes of these studies have been to help quantifying, for example, where in the waste management
51 system the environmental loads and savings are taking place, which technologies are preferable under specific
52 conditions, or the balance between material and energy recovery. LCA-models specifically focusing on waste
53 management systems are available; see Gentil et al. (2010) for a review of the models.

54 As for any LCA study, results are subject to uncertainty due to the combined effects of data variability,
55 erroneous measurements, wrong estimations, unrepresentative or missing data and modelling assumptions.

56 Uncertainty is of two different natures: while epistemic uncertainty relates to an incomplete state of knowledge
57 (Hoffman and Hammonds, 1994), stochastic uncertainty originates from the inherent variability of the natural world.
58 Such uncertainty can be spatial (e.g. when the farming practice of land receiving compost varies spatially) or
59 temporal (e.g. when the performance of a process varies with time). These two different natures of the uncertainty are
60 usually treated together and referred to by the term “uncertainty”.

61 Several authors have suggested typologies to describe the different types of uncertainties in LCAs. A well
62 established one was introduced by Huijbregts (1998) and divides uncertainties into three groups (Lloyd & Ries,
63 2007): (1) parameter uncertainties refer to the uncertainty in values due to e.g. inherent variability, measurement
64 imprecision or paucity of data; (2) scenario uncertainties are due to the necessary choices made to build scenarios;
65 and (3) model uncertainties are due to the mathematical models underlying LCA calculations. A first objective for
66 this paper is to identify uncertainties in the particular context of waste-LCA studies.

67 Numerous methods have been developed to assess uncertainties and gathered under the term “uncertainty
68 analysis”. Their common goal is to assess the robustness of results, but they employ different mathematical
69 techniques to reach this goal. Sensitivity analysis evaluates the influence of input changes on a model’s results. The
70 most common example is scenario analysis where assumptions are changed one-at-a-time. The procedure of
71 calculating the uncertainty of a result due to all input uncertainties is referred to as “uncertainty propagation”. In
72 LCA, uncertainty assessments are increasingly included in the interpretation phase, and life cycle inventory (LCI)
73 databases include increasing amounts of information concerning uncertainty (Finnveden et al., 2009). Lloyd and Ries
74 (2007) reviewed quantitative uncertainty analysis in 24 LCA studies performed on various products and services.
75 They found that stochastic modelling was the most frequently-used method to propagate uncertainties in LCA. This
76 method propagates probability distributions using random sampling like the Monte Carlo analysis. However, they
77 noted that many of the studies using such modelling seemed to select uncertainty distributions somewhat arbitrarily.

78 Other methods have been proposed to more faithfully depict epistemic uncertainties in LCA modelling e.g. by
79 Benetto et al. (2008) and Heijungs and Tan (2010) using possibility theory (Dubois and Prade, 1988), or Chevalier
80 and Le Téo (1996) using intervals.

81 In LCA-modelling of waste management the amount of data available is still limited for establishing the
82 inventories of the waste management systems under study (including data on waste composition, collection systems,
83 source separation systems, recovery and conversion technologies, landfilling, and technologies for utilizing
84 recovered materials). Few waste management LCAs have employed quantitative uncertainty assessment and these
85 studies have often been limited to scenario analyses. Uncertainty propagation has been applied to specific waste
86 management issues: for example Sonnemann et al. (2003) used stochastic modelling to evaluate emissions from an
87 incinerator followed by a sensitivity analysis by means of correlation coefficients. Kaplan et al. (2009) used the same
88 approach to evaluate and compare different waste management planning options, while Hung and Ma (2009)
89 evaluated the relative contributions of the inventory, impact assessment, normalisation and weighting steps. Lo et al.
90 (2004) applied a Bayesian Monte Carlo method to compare various waste treatment options. Each uncertainty
91 analysis method has a specific goal and applicability depending on the nature of the model. Therefore the choice of
92 the right tool may be difficult for LCA practitioners not familiar with uncertainty analysis.

93 Consequently we propose to select appropriate methods for waste-LCA models and show their benefits,
94 complementarities and levels of complexity. The purpose of this paper is (1) to review the uncertainties commonly
95 encountered in waste LCA-modelling, (2) to select and apply a range of methods for uncertainty analysis to waste
96 LCA-modelling, (3) to develop a framework for the uncertainty analysis of waste management systems that
97 combines various methods. The methods in this paper are applied to a case study that compares anaerobic digestion
98 and incineration of organic kitchen waste in Denmark.

99

100 **2. Uncertainties in LCA of waste management systems**

101

102 This first section presents and discusses the sources of uncertainty typically encountered in LCA-modelling of waste
103 management systems, based on the literature and experience acquired over the last decade. The characteristics and
104 importance of an uncertainty analysis depend on the scope of the study and on the quality of the data available. The
105 presentation and discussion below may provide valuable input for identifying sources of uncertainty in waste-LCAs,
106 but each study should be associated with a specific identification. These uncertainties are presented in Table 1 using
107 the framework introduced by Huijbregts (1998) that divides them into model, scenario and parameter uncertainties.
108 Other frameworks have been developed that provide different insights into uncertainties in LCA such as by Reap et
109 al. (2008) and Williams et al. (2009). Concerning the choice between attributional and consequential approaches or

110 the choice of the impact categories included in the assessment, we realise they are issues but they were considered
111 methodological choices rather than uncertainties.

112

113 **2.1. Model uncertainties**

114 Model uncertainties arise from the mathematical equations used to model reality. Generic problems in LCA are
115 presented first, followed by model uncertainties more specifically found in waste management (See Table 1 for an
116 overview of processes).

117

118 **Intrinsic limitations of LCA:** In most of the current models, emissions are aggregated over time and space before
119 impact assessment is performed. This loss of spatial information generates uncertainty regarding the potential
120 damage to the environment. Therefore several site-dependent impact assessment models are being developed, e.g. by
121 Finnveden and Nilsson (2005) and Mutel and Hellweg (2009), but they are not yet implemented in commonly used
122 methods. Furthermore, most of the LCA models assume linear processes, both for inventory and impact assessment,
123 which may not reflect reality. For example, the effect of an emission on the environment and human health is
124 modelled as linear while it often depends on the concentration in the environment and the period of exposure rather
125 than on the total amount released over years (Ekvall et al., 2007). These simplifications are recognized by LCA-
126 practitioners and sometimes incorporated in the discussion section.

127

128 **Impact assessment method:** Life-cycle impact assessment (LCIA) methods hold large uncertainties because they
129 attempt to model the impacts of each substance on humans and the environment by quantifying substance fate,
130 pathways through the environment and potential effects. Several studies have illustrated the large discrepancies in
131 results obtained with different LCIA methods e.g. Pizzol et al. (2011a, 2011b).

132

133 **Models of waste treatment facilities in general:** There are different approaches to model emissions from a waste
134 treatment, as presented by Gentil et al. (2010). Emissions are usually modelled as process-specific (e.g. the emission
135 of nitrous oxides from combustion does not depend on waste composition and thus can be modelled as a function of
136 the quantity of entering waste) or waste-specific (e.g. the emission of mercury from an incinerator is a function of the
137 quantity of entering mercury).

138

139 **Model for waste collection:** Driving, idling and compaction during collection of waste can be modelled in different
140 ways: some models are very detailed and take into account the number of stops and the truck capacities, while others

141 have generic emissions per tonne and/or per kilometre related to the diesel consumption for serving a certain urban
142 area.

143

144 **Model for biodegradation:** Models for degradation in biological treatments take different approaches: some assume
145 generic emissions and quantities of biogas and products while others calculate them based on waste composition and
146 technical parameters as described for example by Boldrin et al. (2011). The same applies to landfill gas generation: it
147 can be based for example on a first-order decay of degradable organic carbon as suggested by IPCC (2006), with
148 varying numbers of waste fractions and properties. In addition, some models include site-specific gas collection,
149 utilization and oxidation rates, while others assume default values. These modelling choices influence significantly
150 the way emissions are quantified and consequently the environmental profile of the biological treatment or the
151 landfill.

152

153 **Model for leaching:** Leaching models are needed when applying materials on soil: in landfills (e.g. Damgaard et al.,
154 2011), when using residues from thermal treatment (e.g. Toller et al., 2009) or residues from biological treatment
155 (e.g. Boldrin et al., 2010). They estimate the amounts of pollutants transferred to soil and groundwater, or generic
156 emissions per tonne of waste. They are usually based on experimental leaching tests but the behaviour of each
157 pollutant depends highly on the geochemistry of the solid which is much more complex, with variations as a function
158 of pH, Eh, mineral phase solubility, etc. Therefore simplification of these processes generates model uncertainty.

159

160 **Model for use of waste on land:** Several models have been developed to quantify direct and avoided impacts of
161 application of treated organic waste on agricultural land. Even if they have the same general approach, they use
162 slightly different assumptions and calculation methods, e.g. with respect to plant uptake and the substitution of
163 fertilizer production. Furthermore, agricultural practice and climate conditions affect nutrient cycling. This leads to
164 variations in the results obtained when the same scenario is simulated in different models as shown in the comparison
165 presented by Hansen et al. (2006).

166

167 **2.2. Scenario uncertainties**

168 Scenario uncertainties arise from the construction of scenarios when choices have to be made to model the different
169 options under study.

170

171 **System boundaries:** The decision as to which processes to include in the assessment and which not to include is a
172 key aspect in LCA and the reliability of its results. According to the ISO 14040 (ISO, 2006) all significant processes

173 should be included and the decision of leaving out processes, called a cut-off, should be justified. The most-frequent
174 way of aggregating inventories is the process-LCA technique: a bottom-up approach which uses process-specific
175 data gathered at the plant's scale and chains of processes (the top-down approach, called input-output-LCA, IO-LCA,
176 is explained further). In process-LCA the practical difficulty is to evaluate a priori if a process will be significant and
177 should be included in the assessment (Finnveden et al., 2009). This decision should be based on a scientific
178 justification of the small environmental relevance of an input or output stream in comparison with the environmental
179 relevance of the main streams: however this is often poorly justified (Suh et al., 2004). In waste management, the
180 treatment of ashes or gypsum produced in incineration plants is often disregarded, but when making this choice,
181 modellers must be certain of the absence of high-value metals in these ashes. Another common cut-off is the
182 exclusion of capital goods from inventories. Frischknecht et al. (2007) have investigated the contribution of capital
183 goods to several environmental impacts for a range of products and services of the database ecoinvent v1.2. In their
184 study, capital goods contributed 6.6% of the acidification potential for incineration and 45% for sanitary landfills.

185 The underestimation of impacts induced by cut-offs is often called a truncation error and several studies
186 have tried to quantify it by using IO-LCA (Lenzen and Treloar, 2003). The IO-LCA originates from the input-output
187 analysis and is a top-down technique: it uses sectorial monetary transactions to model exchanges between industries
188 in a national economy (Suh et al., 2004). Thus where process-LCA has finite boundaries, IO-LCA includes all
189 interconnections between industries. This means that capital goods are systematically included in IO-LCA, e.g. the
190 impacts of the construction of an incineration plant, but also higher orders of service like the impacts of the transport
191 sector for bringing materials to the construction site. In this way, IO-LCA gives a more complete impact assessment
192 than process-LCA. However it suffers from other uncertainties in particular the high level of aggregation of data and
193 the conversion between monetary and physical flows (Reap et al., 2008). A hybrid LCA technique has been
194 introduced to take advantages of process-LCA and IO-LCA, see Suh et al. (2004) and Finnveden et al. (2009) for
195 further details.

196 Another system boundary issue in consequential LCA is to consider all consequences of a decision. In the
197 example of paper recycling, waste management systems can be expanded to take into account the effects of saved
198 biomass: the newly available quantities of wood produced by forestry can be sent to energy production which will
199 substitute for energy production from fossil fuels. Merrild et al. (2008) have shown that this change in system
200 boundaries had a determining effect on assessing the environmental performances of paper recycling over
201 incineration.

202

203 **Representativity of technologies:** Technology data are usually available only for a specific process or plant. This
204 may limit the value of the data with respect to geographical and temporal representativity (e.g. ten year-old data from

205 a single composting plant may not represent the composting plants operating in a large region for the next 20 years).
206 Furthermore, recovered materials may be traded on a market, maybe a world market, and since the plant receiving
207 the recovered materials cannot be known, a world average technology should be used. However, such data are
208 usually not available. For example, with respect to paper recycling, Merrild et al. (2008) compared global warming
209 impacts when combining low- and high-performing recycling plants to low- and high-performing incineration
210 technologies with energy recovery. This led to a large range of results, favouring in some cases recycling and in
211 others incineration.

212 Moreover, LCA generally tries to assess future situations, typically for periods of 20 to 30 years in the case
213 of waste management systems, while LCIs are normally based on former measurements. Spatial representativity is
214 also questionable, especially when the study intends to evaluate a technology for an entire region or country. This
215 applies to waste technologies but also to every process of material and energy productions included in available
216 databases. They all have spatial, temporal and technological variabilities. Williams et al. (2009) suggested ways to
217 improve the analysis of them by using IO-LCA, while Bovea et al. (2010) performed a sensitivity analysis where two
218 different databases were tested: the ecoinvent database and the integrated waste management (IWM) model.

219 When performing a consequential study, the practitioner must decide on the marginal technology, meaning
220 the technology affected by the change. This marginal technology is most often difficult to select and depends largely
221 on the extent of the change. Testing different alternatives is usually recommended, as done for example by Gentil et
222 al. (2009) who implemented two different marginal electricity productions in their waste management systems.

223

224 **Waste composition:** Waste composition data are expensive to produce and only few data sets are available. As for
225 technology data, this limits the geographical and temporal representativity of the data available and adds significant
226 uncertainty if waste composition data are used outside their geographical and temporal window.

227

228 **Time horizon of inventories:** In LCA, all inputs should be traced back to raw materials and all outputs should be
229 emissions to nature. In many cases, the definition of this second type of system boundaries is relatively simple.
230 However in systems implying a time perspective like landfilling, forestry and agriculture, the definition of these
231 boundaries is more complex (Finnveden et al., 2009). In these processes, emissions occur over long periods of time,
232 e.g. carbon emissions to air from landfill or nitrogen leaching from application of compost on land. The choice of
233 this time horizon will directly affect the inventories of these processes.

234 In particular, landfill emissions of pollutants to water, air and soil occur over hundreds of years (Manfredi
235 and Christensen, 2009). On the one hand, if a time horizon of 100 years is chosen, the toxic impacts from landfilling
236 will appear very low. On the other hand, the impacts from emissions of pollutants leaching over hundreds of years

237 cannot be put at the same level as the impacts from emissions occurring during the first 100 years. As a temporary
238 solution, Hauschild et al. (2008) suggests to sum these impacts in separate toxicity categories and let the LCA
239 practitioner discuss this issue in the weighting and interpretation phases.

240 The inclusion of carbon sequestration is directly related to the selection of a time boundary. When waste is
241 landfilled or applied on land, a fraction of its biogenic carbon will not be degraded and emitted to the atmosphere.
242 Depending on the study, this carbon sequestration is either accounted as an avoided emission of CO₂ or else not
243 considered (Christensen et al., 2009).

244

245 **Time horizon of impact characterisation:** This is the time period during which the fate, exposure and effects of
246 each emission are modelled to calculate characterisation factors. A hundred years is a common choice but if other
247 time horizons were selected, characterisation factors of emissions could vary significantly. For example the
248 characterisation factors of methane for global warming rises from 7.6 (kg CO₂-eq / kg CH₄) for 500 years, to 25 for
249 100 years and up to 72 for 20 years (Ramaswamy et al., 2001). This has a particularly large influence on results from
250 waste-LCAs because of the methane emissions from anaerobic decomposition of organic materials common in waste
251 management systems.

252

253 **Allocation:** Allocation is one of the two ways of handling multi-functional processes (Finnveden et al., 2009). Waste
254 management is often dealing with multi-functional processes such as an incineration plant which has the functions of
255 treating waste, producing energy and recovering materials. In most cases, waste-LCAs will use systems expansion to
256 deal with these processes by accounting for the substitution of primary energy and virgin material productions.
257 However, system expansion is a demanding work and it is common to perform allocation for higher-layer processes
258 for example in a combined heat and power plant.

259

260 **Normalisation and weighting:** The impact assessment phase involves many choices, for instance the normalization
261 and weighting methods to use and their reference periods and scales. This will have a substantial influence on the
262 importance given to each impact category and consequently on the final recommendation.

263

264 **2.3. Parameter uncertainties**

265 Each specific parameter in the model has inherent uncertainty and/or variability. The ones particularly relevant in the
266 context of waste management systems are listed in Table 1; some of them will be further discussed in the case study.

267

268

269 **3. Methods for uncertainty analysis of waste-LCA studies**

270

271 **3.1 Selection of methods**

272 Various methods for sensitivity and uncertainty analyses have been developed in scientific and engineering
273 modelling; as presented by Saltelli et al. (2006). No single best method can be applied to all models: the choice
274 depends on different criteria, namely the nature of the model, the requirements of the analysis and the resources
275 available especially in terms of software (Morgan and Henrion, 1990). In this study, methods were selected that are
276 adapted to different levels of available resource and to different waste-LCA models, that are relatively simple in
277 terms of continuity and complexity.

278 It is fundamental to start by defining the requirements of the analysis in terms of expectations. A common pitfall
279 is to perform an analysis without having a clear goal. Morgan and Henrion (1990) identified three key questions,
280 which we address in the following sections:

- 281 - Sensitivity analysis: computing the effect of changes in input on model results,
- 282 - Uncertainty propagation: calculating the uncertainty of the model result due to all input uncertainties,
- 283 - Uncertainty contribution analysis: investigating where the output uncertainty originates.

284

285 **3.2. Sensitivity analysis**

286 Sensitivity analysis aims at identifying sensitive inputs. Local one-at-a-time approaches were selected because
287 calculations are simple to implement and results easy to communicate, which is why these techniques have been the
288 most used among the scientific community for years (Saltelli et al., 2006). Like any method, they have limitations in
289 particular related to non-linearity in waste-LCA models but they provide useful first approximations. Other methods
290 including global sensitivity analysis are presented by Saltelli et al. (2006) and might be more adapted to other types
291 of models.

292

293 **3.2.1 Contribution analysis**

294 Contribution analysis is used very often, although not always identified as a sensitivity analysis. It is a self-evident
295 method presented by Heijungs and Kleijn (2001). Contribution analysis consists in decomposing the LCA result
296 (characterised, normalised or weighted impact) of a system into its individual process contributions, providing a
297 quick overview of the important contributors. Processes that have both positive and negative impacts have to be
298 subdivided into their sub-components, to avoid neglecting important processes. For example an incineration process
299 might have an impact close to zero, but as the net total of high direct impacts (fossil CO₂ emission from burning of

300 plastic) and high avoided ones (produced electricity substituting fossil CO₂ emissions from a coal-burning power
301 plant).

302

303 **3.2.2 Perturbation analysis**

304 Perturbation analysis is used to assess the influence of parameter uncertainties (Heijungs and Kleijn, 2001). The aim
305 is to determine the effect of an arbitrary change of single parameter values on the model's result. Each parameter
306 value is individually varied by a small increment. The variation of the result is calculated and two ratios are
307 particularly interesting to generate:

308 - The sensitivity coefficient (SC), which is the ratio between the two absolute changes.

$$309 \quad SC = \frac{\Delta result}{\Delta parameter} \quad (1)$$

310 - The sensitivity ratio (SR), which is the ratio between the two relative changes. If a parameter has a SR of 2,
311 it implies that when increasing its value by 10%, the final result is increased by 20%.

$$312 \quad SR = \frac{\frac{\Delta result}{initial_result}}{\frac{\Delta parameter}{initial_parameter}} \quad (2)$$

313

314 **3.2.3 Scenario analysis**

315 This sensitivity analysis consists in testing different options individually and observing the effect of these changes on
316 the final result. The new results obtained for each scenario can easily be compared with the baseline results to
317 identify the uncertainties that change some scenario result significantly or the ranking between alternatives.

318

319 **3.2.4 Combined sensitivity analysis**

320 In this analysis two parameters are varied simultaneously and the change in the results is observed, for example the
321 difference between the two scenarios' results. The aim is to find the conditions for which the ranking of scenarios
322 may change. This can be visualized in a two dimensional contour graph with contour lines showing the difference
323 between the two scenarios. Scenario and model uncertainties could be analysed as well by performing separate
324 calculations using different scenarios and models.

325

326

327

328 **3.3 Uncertainty propagation**

329 Uncertainty propagation consists in propagating input uncertainties to calculate the result's uncertainty. Before
330 propagating them, the practitioner has to choose a representation for these input uncertainties. A short introduction to
331 the question of uncertainty representation is given in section 3.3.1. For this case study, the probability theory was
332 adopted and a sampling propagation method selected. An analytical method could as well have been implemented,
333 e.g. the first order approximation from the Taylor series as explained by Morgan and Henrion (1990), but it is
334 impractical in the case of waste-LCA models because it requires lots of resources to express each LCA impact as a
335 function of all input parameters. Hong et al. (2010) performed analytical uncertainty propagation in an LCA study.

336 Among sampling methods, the Monte Carlo analysis was chosen because it is the most common method and
337 the calculation was fast enough. If larger data or more complex modelling was used, a more efficient sampling
338 method could be used such as the Latin Hypercube technique (Morgan and Henrion, 1990).

339

340 **3.3.1 Choice of representation**

341 Two main approaches can be chosen to represent uncertainties: the probability and possibility theories. In the case
342 study presented below, it is assumed that all uncertainties can be represented by single probability distributions, even
343 though there may be little data to substantiate these distributions in a statistical sense. If so-called "subjective"
344 probability distributions (Savage, 1954) are selected for representing each uncertain parameter, then uncertainty
345 propagation can be performed using the Monte Carlo method.

346 It is recognized, however, that this is not necessarily the case, especially considering that in real-world
347 waste LCAs, epistemic uncertainties (reflecting paucity of information) generally dominate and therefore the
348 modeller must rely on information sources such as expert (or personal) judgement, literature data, scarce
349 measurements, etc. Alternative tools have been developed for representing uncertainty with an aim of consistency
350 with available information. Such tools range from simple min-max intervals (as in Chevalier and Le Téo, 1996) to
351 fuzzy sets (Dubois and Prade, 1988) or, more generally, imprecise probabilities (Shafer, 1976; Walley, 1991).
352 Benetto et al. (2006) introduced the question of uncertainty representation in the field of LCA. As shown by many
353 researchers (e.g. Ferson and Ginzburg, 1996), the arbitrary selection of probability distributions in the presence of
354 incomplete information, especially associated with the common hypothesis of parameter independence, leads to
355 severe underestimation of the likelihood of outlier results. Yet in a context of aversion to risk (e.g. of greenhouse gas
356 emissions), outliers are of significant importance for the decision-making process.

357

358

359

360 **3.3.2 Uncertainty propagation for all scenarios**

361 Monte Carlo analysis consists in randomly sampling the probability distribution of each uncertain parameter and then
362 computing the result using the model. By performing this procedure a large number of times, a frequency histogram
363 is constructed from the results and a probability distribution representing model results can be computed. While
364 independence between model parameters is assumed below, dependencies between parameters can be accommodated
365 using rank correlation methods (Conover and Iman, 1982). Adopting the point of view of Morgan and Henrion
366 (1990), scenario and model uncertainties were not modelled in the probabilistic modelling: decision variables and
367 value parameters are better assessed by performing separate uncertainty propagations using several « plausible »
368 scenarios and models in the calculations, to reflect the variability of possible outcomes.

369

370 **3.3.3 Discernibility analysis**

371 While uncertainty propagation yields the probability distribution of the LCA results for each scenario, discernibility
372 analysis provides the distribution of the difference between the scenarios' results (Heijungs and Kleijn, 2001). This
373 can be important because some uncertainties may have the same influence on the scenarios but no influence on the
374 differences between them. For instance, if two scenarios have the same consumption of electricity and the electricity
375 mix is uncertain, both scenario results will have uncertainty but this should not affect the difference between them.
376 Therefore the final decision should not be affected by this uncertainty.

377

378 **3.4 Uncertainty contribution analysis**

379 The uncertainty contribution analysis, also called key-issue analysis, consists in calculating the contribution of each
380 parameter uncertainty to the calculated uncertainty (Heijungs et al., 2005). This method is different from perturbation
381 analysis (Section 3.3.1) because input uncertainties are included in the calculation. An analytical calculation based on
382 the first order approximation of the Taylor series was chosen because a simplified method (called later the SC
383 method) was identified and applied. Other methods based on sampling uncertainty propagation can also be used, as
384 described by Morgan and Henrion (1990). This method is based on the additive property of variances and uses the
385 first-order terms of a Taylor Series expansion. Considering two variables x and y independent and normally (or at
386 least symmetrically) distributed and z a function of these variables, the variance of z can be approximated by:

$$387 \quad \text{var}(z) \approx \left(\frac{\partial f}{\partial x} \right)^2 * \text{var}(x) + \left(\frac{\partial f}{\partial y} \right)^2 * \text{var}(y) \quad (3)$$

388 Thus, the relative contribution of the uncertainty in x to the uncertainty in z is:

389
$$\frac{\left(\frac{\partial f}{\partial x}\right)^2 * \text{var}(x)}{\text{var}(z)} \quad (4)$$

390 This contribution can be calculated analytically by defining the LCA result as a function of all parameters or by
 391 approximating $\frac{\partial f}{\partial x}$ by $\frac{\Delta f}{\Delta x}$ considering that the variations of x are relatively small. In this case the SC calculated
 392 using Equation 1 can be used:

393
$$\frac{\left(\frac{\partial f}{\partial x}\right)^2 * \text{var}(x)}{\text{var}(z)} = \frac{\left(\frac{\Delta f}{\Delta x}\right)^2 * \text{var}(x)}{\text{var}(z)} = \frac{SC^2 * \text{var}(x)}{\text{var}(z)} \quad (5)$$

394 The results obtained with the analytical method and the SC method are compared in Section 4.4, to validate the SC
 395 method.

396

397 **4. Uncertainty modelling of a case study**

398

399 A hypothetical case study was set up in order to implement the methods, illustrate their features, identify their
 400 complementarities and propose a procedure for uncertainty quantification in waste LCA-modelling. While the focus
 401 was not on intense data collection, processes were taken from the EASEWASTE database (Kirkeby et al., 2006). For
 402 the purpose of clarity, the study only presents results for the impact category global warming. Hence normalisation
 403 and weighting are excluded, although these may be important steps contributing to uncertainty in LCA modelling.
 404 The latest characterisation factors from the IPCC (Forster et al., 2007) were used, on a 100-year time horizon.

405 The two systems were modelled in the waste-LCA tool EASEWASTE (Kirkeby et al., 2006) and global
 406 warming factors (GWF) of all sub-processes were calculated. GWF are defined as the impact on global warming of
 407 the waste management system and expressed in kg CO₂-eq per tonne of waste treated. They were directly used for
 408 one-at-a-time sensitivity analyses, while they served as inputs in a MATLAB (R2010b version) program to perform
 409 the uncertainty propagation and the combined sensitivity analysis.

410

411 **4.1 Case study**

412 The case study aims at evaluating the benefits of sorting organic kitchen waste at the source and sending it to
 413 anaerobic digestion (AD), versus incineration together with residual waste. The functional unit is the collection and
 414 treatment of 1 tonne of organic kitchen waste from households in Denmark in 2011.

415 The waste composition used originates from a sorting analysis of residual household waste in Denmark in
416 2001 by Petersen and Domela (2003). Organic waste was source-sorted from this waste with an assumed efficiency
417 of 60% and, as erroneously-sorted materials, 5% of other combustible and non-combustible fractions. This
418 corresponds to a composition of the sorted waste of 62% of vegetable food waste, 19% of animal food waste and
419 18% of ten other waste fractions. The detailed distribution as well as chemical composition and physical
420 characteristics of each material fraction are presented in Table A.1 of supplementary information (Riber and
421 Christensen, 2006a, 2006b).

422 In the first scenario, the organic waste is routed with the residual waste to an incineration plant, while in the
423 second scenario the organic waste is sorted at the source and brought to an AD plant. Both plants are located 10
424 kilometres from the collection area and the vehicles transporting the waste use diesel and subscribe to the Euro3
425 exhaust standard. Two different collection technologies were used: organic waste collected as part of the residual
426 waste used 3.27 L diesel/t, while separately collected organic waste used 7.2 L diesel/t.

427 The incineration plant used to represent incineration in Denmark is based on data from the plant located in
428 Aarhus. It is a grate incinerator with mixed flue gas cleaning (two lines with wet, one with semidry) and has 20.7%
429 electricity and 74% heat recovery based on the lower heating value (LHV) of the waste. Bottom ashes are transported
430 50 kilometres away to be landfilled, while air pollution control residues and fly ashes are shipped to Norway to be
431 utilized for neutralization of waste acid.

432 The AD plant represents the state of the art in Western Europe (Møller et al., 2010). The gas produced is
433 used in a gas turbine which recovers electricity (39% efficiency) and heat (46%). The digestate, which has 97%
434 water content, is transported 30 km away to be used on agricultural land where it substitutes for the uses of N, P and
435 K fertilizers (Bruun et al., 2006). Carbon sequestration was accounted for. In both scenarios, the energy system is
436 based on marginal electricity and heat productions from hard coal. Concerning the heat production, the substituted
437 technology is a combined heat and power (CHP) plant located in Aarhus and the allocation is made based on exergy
438 (See Cherubini et al., 2011 for a review of allocations methods).

439

440 **4.2 Results of sensitivity analysis**

441 **4.2.1 Contribution analysis**

442 Both scenarios have beneficial GWF: -357 kg CO₂-eq/t waste collected for the incineration scenario and -301 kg
443 CO₂-eq/t for the AD scenario. Figure 1 presents the contributions of all processes to the two scenarios' GWF and the
444 details for the three processes that contribute both to direct and avoided emissions.

445 The two scenarios obtain almost equal benefits. The AD scenario obtains benefits from both the energy
446 recovery (-398 kg CO₂-eq/t waste) and from the land application of digestate because of the substitution of fertilizer

447 production (-60 kg CO₂-eq/t waste) and carbon sequestration (-41 kg CO₂-eq/t waste). Incineration obtains 21% more
448 benefits from energy recovery than AD because the LHV of the collected waste is 4.8 GJ/t while the energy
449 contained in the biogas produced anaerobically is 2.9 GJ/t waste. In addition, the heat recovery is much higher in the
450 incinerator (74%) than in the gas engine (46%). At the same time, the AD scenario has larger loads than the
451 incineration scenario. While the direct loads from the waste treatments are almost equal, the difference between the
452 two scenarios' loads originates from the use on land of the digestate, which generates emissions of nitrous oxides and
453 a consumption of diesel.

454

455 **4.2.2 Perturbation analysis**

456 Sensitivity coefficients (SC) and sensitivity ratios (SR) were calculated for all parameters of the two systems.
457 Variations of +10% and -10% were generated for 55 parameters and only the highest of the two SR values was
458 retained. Figure 2 presents, for each of the two scenarios, SR higher than 0.1 as absolute values. SC results are not
459 presented; they will be used in the uncertainty contribution analysis.

460 This analysis highlights the parameters that have a large influence on each scenario's GWF. For example,
461 the electricity recovery of the incinerator has a SR of 0.81 on the GWF of the incineration scenario. This means that,
462 when increasing this parameter by 10%, the benefits of the incineration scenario in terms of GWF increase by 8.1%.
463 Yet this is only a relative result: it does not show anything about how uncertain the result is, because it does not take
464 into account the actual uncertainty of the input values.

465 The analysis shows that three parameters have SR values greater than 1 (as absolute value) for the
466 incineration scenario, meaning that a variation of their value induces a larger relative variation in the scenario's
467 GWF. These parameters are all related to the waste composition. For the AD scenario four parameters have such
468 high SR: the methane yield and the electricity recovery are parameters of the digester, while the methane potential
469 and water content are properties of the treated waste. It can be noted that the water content has a significant negative
470 influence on both scenario performances as it dictates how much solid is available for energy production, since the
471 amount of waste is depicted as wet weight.

472 The use of SR is particularly useful for evaluating the sensitivity of the model to parameter uncertainties and
473 comparing them in order to select important parameters for the uncertainty propagation. It also helps to identify
474 needs for further data collection. Between the two ratios, SC is quite easy to communicate but is not well suited for
475 comparing the relative influence of parameters. SR enables comparison of the sensitivities of the model to different
476 parameters.

477

478

479 **4.2.3 Scenario analysis**

480 The impacts of several scenario and model uncertainties on both scenarios' GWF were investigated individually by
481 the use of scenario analyses. The results are presented in Figure 3.

482

483 **LCIA method:** The use of the IPCC global warming potentials (GWP) from 2001 (Ramaswamy et al., 2001) did not
484 have a significant impact on the two GWF (less than 1% variation).

485

486 **Time horizon of impacts:** The IPCC reports provide global warming potentials for three time horizons: 20, 100 and
487 500 years. The results were tested for the two other time horizons and this choice changed the results significantly.
488 Indeed, as the time horizon increases, the GWP of methane decreases. Consequently emissions of fossil CO₂ become
489 more and more important compared to the other emissions. When changing the time horizon from 100 to 20 years,
490 the GWF of the incineration scenario became 27% more beneficial, while the one of the AD scenario increased by
491 only 9%. This is due to direct emissions of methane from the AD plant. With a time horizon of 500 years, the
492 incineration scenario became 10% less beneficial, while the AD scenario became 1% more beneficial.

493

494 **Carbon sequestration:** The choice of not including carbon sequestration decreased the AD scenario benefits by
495 14%, accentuating the predominance of the incineration scenario.

496

497 **Choice of electricity substitution:** In this consequential LCA, we assumed that the electricity production was
498 marginal electricity produced from coal, emitting 1.042 kg CO₂-eq/kWh. Both scenarios were tested with a marginal
499 electricity production in natural gas CHP plants with steam turbine emitting 0.616 kg CO₂-eq/kWh. Benefits of the
500 two scenarios decreased: -25 % for the incineration scenario and -39 % for the AD scenario.

501

502 **Choice of heat production:** In the two scenarios heat production was modelled as substituting for heat production at
503 a coal-fired CHP plant. The allocation between electricity and heat production at the CHP plant was based on exergy,
504 so the substituted heat production had low carbon emissions: 0.194 kg CO₂-eq/kWh. A high carbon-emitting heat
505 production was modelled to observe the effects on the two scenarios' GWF. A heat production at a hard coal
506 industrial furnace emitting 0.472 kg CO₂-eq/kWh was used. The incineration scenario obtained 77% more benefits
507 and the AD scenario 35% more because the incineration plant recovered more heat than the AD plant. This choice
508 changes the results significantly but does not change the scenario ranking.

509

510 **Choice of material substitution:** Another process of the EASEWASTE database was tested for the substituted
511 production of nitrogen fertilizer. The original fertilizer production process emitted 15.33 kg CO₂-eq/kg N while the
512 second one emitted 16.34. The net benefit of the AD scenario increased by 1.4%, which did not modify the scenario
513 ranking.

514

515 **Choice of incineration process:** The incineration plant used to represent incineration in Denmark was based on data
516 from the plant located in Aarhus. To observe the impacts of this choice, another incineration plant, located in
517 Copenhagen, was used. This plant is a grate incinerator with wet flue gas cleaning and has 17.9% electricity and 78%
518 heat recovery based on the waste LHV. The benefits of the incineration scenario decreased from -357 to -272 kg
519 CO₂-eq/t waste, due to both lower electricity substitution and higher energy and material consumptions in the plant.

520

521 **Choice of AD plant:** The anaerobic digestion could as well be changed to examine the influence of this choice on
522 the results. However this treatment is parameterized to a great extent in the EASEWASTE model, using potential
523 methane yields for each material fraction as well as the content of methane in biogas and the energy recoveries of the
524 gas engine. As all parameters were tested in the perturbation analysis this change of technology was not tested.

525

526 Finally the contribution analysis showed that the treatment of bottom ashes and APC residues did not have a
527 significant impact on the GWF so no other option was studied for these residues. Minor material productions were
528 also discarded for the same reasons. The inclusion of capital goods could not be assessed due to lack of data.

529

530 **4.2.4 Combined sensitivity analysis**

531 The water content and heating value (of dry matter) were chosen to perform the combined sensitivity analysis.
532 Variations of these two parameters within chosen intervals were implemented and the difference between the AD and
533 the incineration scenario computed. The contour lines (50 kg CO₂-eq/t) are presented in Figure 6. The cross shows
534 the initial conditions for which incineration is favourable. If both parameters are varied, the relative benefits s change
535 and a shift of ranking between the two options can be visualized.

536

537 **4.3 Results of uncertainty propagation**

538 **4.3.1 Choice of representation**

539 For the purpose of stochastic modelling, probability distributions were selected for each model parameter. As the
540 purpose of this case study was to illustrate the different methods, these statistical parameters were mainly based on
541 expert judgement. They are presented in Table 2. Section 3.3.1 discusses how other tools that are better suited for

542 representing expert judgement than single probability distributions, can be implemented in the uncertainty
543 propagation.

544 For consumptions of materials and energy as well as for emissions, log-normal distributions were adopted,
545 as they exclude negative value. For these parameters, geometric standard deviations were assumed using a method
546 adapted from Frischknecht et al. (2005). The other parameters are waste properties and technical parameters of the
547 plants, such as methane yields and electricity recoveries, for which normal distributions were selected. Two
548 parameters reflect the uncertainty of the distribution between waste fractions. While all parameter uncertainties were
549 assumed to be independent, it is acknowledged here that the heating value and methane potential could be partially
550 correlated when considering biowaste. Finally, the uncertainties on methane potential and yield were applied only to
551 the two biowaste fractions (vegetable and animal) which contribute to more than 95% of the total methane
552 production of the source-separated organic waste.

553

554 **4.3.2 Uncertainty propagation for all scenarios**

555 The 24 parameters obtaining a SR higher than 0.05 in the perturbation analysis were implemented in a Monte Carlo
556 calculation with 10 000 iterations. Figure 4 presents results as relative frequency histograms as well as cumulative
557 relative frequency plots.

558 The histogram in Figure 4a distributes the calculated GWF relative frequencies between bins of 25 kg CO₂-
559 eq/t. This is useful for visualising the spread of GWF values around their means. The GWF of the incineration
560 scenario obtains a mean of -359 kg CO₂-eq/t with a standard deviation of 104 kg/t, while the AD scenario obtains a
561 mean of -292 kg/t with a standard deviation of 76 kg/t. The cumulative relative frequencies in Figure 4b display the
562 same results in a different form which allows the identification of percentiles. For example, as indicated by the dotted
563 lines, the probability that the incineration scenario should obtain a benefit of at least 400 kg CO₂-eq/t is 34%, while
564 the probability is only 9% for the AD scenario. In a similar fashion, 95% confidence intervals can be determined
565 with this plot: [-570; -166] (kg CO₂-eq/t) for the incineration scenario and [-450; -154] for the AD scenario.

566

567 **4.3.3 Discernibility analysis**

568 The dispersed frequency diagrams obtained for both scenarios do not inform about the relative predominance of one
569 option over the other, because several parameters were used in the two scenarios, e.g. the electricity system and the
570 water content. Therefore a discernibility analysis was performed to compute the difference between the GWF of the
571 AD and the incineration scenarios. The relative frequency histograms and the cumulative relative frequency plots are
572 presented in Figure 5. The difference between the two scenarios is 67 kg CO₂-eq/t with a standard deviation of 74

573 kg/t. Using the cumulative probability distribution, it can be observed that AD obtains more benefits than
574 incineration in 18% of the cases.

575

576 **4.4 Uncertainty contribution analysis**

577 The contributions of the 24 parameter uncertainties to the overall uncertainty were calculated using both the
578 analytical (using Equation 4) and the SC methods (using Equation 5), for the two scenarios and the difference
579 between them. The results obtained by the two methods vary by less than 0.5 percentage points, confirming that the
580 simpler SC method can be used as a good approximation of the contributions. It should be noted that the analysis was
581 performed using Equation 3 even though some of the parameters were not symmetrically distributed and that the first
582 order terms of the Taylor series produce only an approximation. Consequently the sum of all contributions never
583 reaches 100%.

584 The results obtained with the analytical method are presented in Table 3. The water content appears to be
585 predominant as it contributes to more than half of the uncertainty of both scenarios. However, as it has similar
586 negative effects on both scenarios, water content has less influence on the difference between them. The other
587 predominant parameters with respect to uncertainty of the incineration (resp. AD) scenario are the heating value and
588 the electricity recovery (resp. methane content, yield and electricity recovery) because they determine the energy
589 recovery of each treatment.

590 With respect to the final decision, the three most predominant parameters are the heating value and water
591 content of the waste and the electricity recovery from incineration. This analysis makes it possible to consider both
592 data input uncertainties and sensitivities of the model in order to identify the parameter uncertainties of primary
593 importance.

594

595 **5. Discussion**

596

597 Seven methods for quantifying the uncertainty of LCA results have been selected and applied in a comparative study
598 of two waste management systems. This study was reduced to two scenarios and one impact category but it led to
599 more general findings presented in this section. The presented study provides valuable insight into the possibilities
600 offered by each method as well as its limitations and the difficulties of implementation. Based on the
601 complementarities of these methods, as illustrated by the case study, we suggest that a tiered approach be used for
602 quantitative uncertainty assessment of waste LCA. The general approach is illustrated in Figure 7. Following an
603 introductory step (Step 0), the sequential approach contains four separate steps: (Step 1) evaluating the sensitivity of
604 the result to each individual source of uncertainty, (Step 2) representing parameter uncertainty based on available

605 information and calculating the uncertainty of the model's results, (Step 3) analysing the origins of this uncertainty,
606 (Step 4) visualising the shift of scenario ranking due to combined variations of key parameters. These steps start
607 from a coarse evaluation and evolve to achieve a more precise analysis of the uncertainty in each step. As the
608 complexity of the calculations and the amount of data required increase, the analysis can be applied on a decreasing
609 number of scenarios, impact categories or input uncertainties, in order to cope with resource limitations. In addition it
610 should be kept in mind that model uncertainties can rarely be assessed quantitatively but should be considered. They
611 can be accommodated by using several plausible alternative models and aggregating the results in a single restitution.

612

613 *Step 0: Contribution analysis*

614 This preliminary analysis should be performed on all scenarios and impact categories. All LCA results are
615 disaggregated to visualize contributions of every process to loads and savings. However, this analysis does not
616 provide any information on the sensitivity or the uncertainty of the results. Figure 1 provided an example of a
617 contribution analysis.

618

619 *Step 1: Sensitivity analysis*

620 A proper sensitivity analysis should always be performed on as many input uncertainties as possible. The method
621 suggests that parameter uncertainties are assessed by perturbation analysis (step 1a) comparing SR. Figure 2
622 provided an example of a perturbation analysis using SR. Model and scenario uncertainties should be analysed by
623 scenario analysis (step 1b) and not propagated in a stochastic modelling. Figure 3 provided an example of a scenario
624 analysis. This should be performed on all scenarios and as many impact categories as possible. It does not require
625 extra data collection and gives valuable information on how the model and the scenarios react to variations in the
626 input. Nevertheless it does not give any information on the uncertainty of the final result because it does not reflect
627 the actual input uncertainties. Sensitivity analysis is very valuable to find where more data collection is needed,
628 estimate the robustness of results and reduce the number of parameters for the uncertainty propagation.

629

630 *Step 2: Uncertainty propagation*

631 The choice of representation is of primary importance since the uncertainty in model results depends largely on the
632 uncertainties assigned to input parameters and scenarios (Step 2a). In this paper, we suggest adopting probabilistic
633 modelling techniques, that are widely used. The shortcomings of these methods in a context of incomplete
634 information have been referred to in section 3.3.1 and are currently being addressed in ongoing research.

635 As shown in the case study, if single probability distributions are assumed for all uncertain parameters, a
636 Monte Carlo analysis can be used to propagate these uncertainties into that of the model results. This analysis

637 provides the modeller with the uncertainty relative to each scenario's results through parameter uncertainty
638 propagation (Step 2b). The uncertainty of the final decision is obtained by considering the difference between two
639 alternative scenarios in the discernibility analysis (Step 2c). Considering the amount of data required in order to
640 inform the uncertainties pertaining to input parameters, it is recommended to use the results of the sensitivity analysis
641 to reduce the number of uncertainties implemented in the uncertainty propagation. The number of scenarios and
642 impact categories investigated can also be reduced to the most critical ones.

643 Results of both steps can be presented as relative frequency histograms and cumulative relative frequencies.
644 Figures 4 and 5 provided an example of an uncertainty propagation using a Monte Carlo analysis. Results of the
645 discernibility analysis (step 2c) might be easier to communicate by presenting only the percentage of cases where
646 one option obtains more favourable results than the other, especially if there are more than two scenarios.

647

648 *Step 3: Uncertainty contribution analysis*

649 This analysis tells us which parameter uncertainties are the most important and can help prioritize further efforts in
650 data collection. The contribution of each parameter's uncertainty to the overall uncertainty can be easily
651 approximated with Equation 5 using results of steps 1a and 2a. Table 3 showed the result of an uncertainty
652 contribution analysis.

653

654 *Step 4: Combined sensitivity analysis*

655 This analysis illustrates the conditions under which one attractive scenario is favoured with respect to another
656 attractive scenario. An example of this result was presented in Figure 6. The result of this analysis is relatively easy
657 to communicate and comparisons between more than two scenarios can be performed by adding more plots in the
658 same figure. However only two parameters can be varied at a time. Finally, implementation of this analysis requires
659 additional resources, either to parameterize the results or to run a large number of simulations.

660

661 The proposed sequential method for quantitative uncertainty assessment should be applied to all waste-LCA studies.
662 However, it can be reduced to steps 0 and 1 if time and available resources are limited, because these steps only
663 require an LCA model and no additional data. To implement waste properties and composition, the use of a
664 dedicated tool for waste management, e.g. the EASEWASTE model, is recommended because parameters can be
665 changed easily. For example, the definition of biogas production potentials of different waste fractions is facilitated
666 in a dedicated waste-LCA model. Step 2 requires the use of additional features to implement a Monte Carlo analysis.
667 This has already been implemented in some LCA models. Then step 3 can easily be implemented by using results
668 from steps 1 and 2. Finally step 4 requires substantial additional resources.

669

670 **6. Conclusions**

671

672 LCA of waste management is subject to significant sources of uncertainty of diverse origins. In order to improve the
673 reliability of the results, uncertainties must be addressed in a systematic and quantitative fashion. We described,
674 based on a decade of experience, where the main uncertainties can be found within LCA –modelling of waste
675 management systems. A systematic sequential method to evaluate uncertainty in LCA studies of waste management
676 systems has been suggested and exemplified. It includes four steps with increasing calculation complexity and data
677 requirement. Modellers can adapt this method to their resources and should first focus on their requirements to
678 choose the right tools.

679 It has been recognized in this paper that in real-world situations of waste LCAs, the modeller is typically
680 confronted with different types of information regarding parameter uncertainties. The information might be “rich”
681 (when a significant number of measurements are available), in which case a statistical analysis of the data can
682 provide probability distributions describing parameter variability, or the information can be “poor” (when expert
683 judgement, literature data, scarce measurements or gross estimates have to be used), in which case alternative
684 uncertainty-representation tools may seem more consistent with available information (e.g. fuzzy sets and probability
685 boxes). As shown previously by e.g. Baudrit et al. (2006) and Dubois and Guyonnet (2011), different modes of
686 uncertainty representation can be propagated jointly in model calculations. Hence forthcoming research will focus on
687 how such methods can be applied to uncertainty representation and propagation in waste LCAs. This will avoid the
688 arbitrary assignment of single probability distributions in presence of incomplete information and hence the common
689 confusion between stochastic and epistemic uncertainties.

690

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903

904 TABLES

905

906 Table 1: Uncertainties in LCA of waste management systems

Process	Model uncertainty	Scenario uncertainty	Parameter uncertainty
General	Linearity of emissions Modelling of waste- and process-specific emissions	System boundaries Database for energy and material productions (e.g. Ecoinvent) Time horizon of inventories Allocation	
Impact assessment	Model for substances' fate and effects to calculate characterisation factors. Linearity of response	Time horizon of impact characterisation Normalization method and reference Weighting method and reference	Characterisation factors
Waste composition		Choice of a specific waste composition	Waste fractions distribution; chemical composition of fractions (e.g. water content; heating value)
Collection	Model for collection	Choice of a collection scheme (e.g. separate or common collection)	Consumption of fuel; emissions from fuel combustion; source-sorting efficiencies
Transport			Distance; consumption of fuel; emissions from fuel combustion
Material recovery facility		Choice of a specific technology	Sorting efficiencies; consumption of materials and energy
Thermal treatment		Choice of a specific technology (e.g. dry/wet flue gas cleaning with SCR/SNCR) Choice of specific technologies for outputs' treatments	Electricity and heat recoveries; consumption of materials and energy; emissions of substances to outputs and environment; water content of produced ashes; consumption of materials and energy for outputs' treatments
Biological treatment	Model for biodegradation (e.g. based on CH ₄ -potential or on hemi-celluloid material) and CH ₄ / CO ₂ ratio in biogas	Choice of a specific technology	Degradation rates of organic matter; nitrogen distribution; gas cleaning removal efficiencies; composition of biogas (CH ₄ /CO ₂); consumption of materials and energy; emissions of CH ₄ and energy recovery in gas engine
Use on land	Model for plant uptakes and fertilizer substitution Model for leaching	Choice of a specific technology (e.g. on sandy or loamy soil)	Substitution rate of compost / fertilizers (%); carbon binding (%); distribution of N; run-off; leaching
Landfill	Model for gas generation Model for leachate generation and leaching to groundwater	Choice of a specific technology (e.g. conventional or bioreactor) Choice of gas utilization Choice of a technology for leachate treatment	Gas composition (elements; CH ₄ , CO ₂); collection, utilization and oxidation rates; leachate composition, collection rate; removal efficiencies at leachate treatment; consumption of materials and energy; emissions and energy recovery of gas engine
Recycling		Choice of specific technologies for the recycling plant and the avoided material production	Substitution rate; consumption of materials and energy of recycling plant and substituted process

907

908 Table 2: Assumed probability distributions of parameters used in the case study (AD: anaerobic digestion, UOL: use
 909 on land, TS: total solid, ww: wet weight, VS: volatile solids, LHV: lower heating value, GHG: greenhouse gas)

Parameter	Mean ^a	Unit	Distribution	St. dev. or GSD ² or half-width ^b
Ratio of vegetable out of food waste	76.1	%	Normal	6
Part of plastic fraction in waste	1.12	%	Normal	0.25
Water content of waste	67.1	% ww	Normal	4
Heating value of dry waste	19.21	MJ / kg TS	Normal	1
Methane potential of waste	450	m ³ CH ₄ / t VS	Normal	30
Diesel consumption for collection of organic waste	7.2	L/ t	Log-normal	1.16
Distance from digester to use on land	30	km	Log-normal	2.33
GHG emissions of diesel production	3.108	kg CO ₂ -eq / L	Log-normal	1.14
Electricity consumption of incineration	65.7	kWh / t	Log-normal	1.10
Electricity recovery of incineration	20.7	% of LHV	Normal	2
Heat recovery of incineration	74	% of LHV	Normal	5
CH ₄ content of biogas in digester	63	%	Normal	3
Electricity consumption of digester	48.9	kWh / t	Log-normal	1.10
Electricity recovery from gas in digester	39	%	Normal	2
Heat recovery from gas in digester	46	%	Normal	4
Methane potential yield in digester	80	%	Normal	5
Unburnt methane in digester	2	%	Log-normal	1.10
Water content of digestate	3	% of ww	Uniform	2
Carbon binding in soil	13	% of C	Normal	2
N fertilizer substitution	40	% of N	Uniform	10
GHG emissions from N fertilizer production	15.33	kg CO ₂ -eq / kg	Log-normal	1.23
N ₂ O emissions from use on land	1.4	% of N in digestate	Log-normal	1.43
GHG emissions of electricity system	1.042	kg CO ₂ -eq / kWh	Log-normal	1.07
GHG emissions of heat system	0.194	kg CO ₂ -eq / kWh	Log-normal	1.12

910 ^a: Geometrical mean for lognormal distributions

911 ^b: Standard deviation for normal distributions, square of geometric standard deviation for lognormal distributions,

912 half of the width of the interval for uniform distributions

913

914 Table 3: Contribution of each parameter uncertainty to the uncertainties of each scenario and to the difference
 915 between them, obtained with the analytical method

Parameter	Incineration scenario	Anaerobic digestion scenario	Difference between scenarios
Ratio of vegetable out of food waste	9.9 %	4.6 %	4.9 %
Part of plastic fraction in waste	0.0 %	0.0 %	0.0 %
Water content of waste	66.5 %	56.4 %	14.0 %
Heating value of dry waste	10.4 %	-	20.5 %
Methane potential of waste	-	9 %	9.5 %
Diesel consumption for collection of organic waste	-	0.0 %	0.1 %
Distance from digester to use on land	-	1.4 %	1.5 %
GHG emissions of diesel production	-	0.3 %	0.2 %
Electricity consumption of incineration	0.1 %	-	0.2 %
Electricity recovery of incineration	7.2 %	-	14.2 %
Heat recovery of incineration	1.6 %	-	3.1 %
CH ₄ content of biogas in digester	-	0.0 %	0.0 %
Electricity consumption of digester	-	0.1 %	0.1 %
Electricity recovery from gas in digester	-	4.8 %	5.1 %
Heat recovery from gas in digester	-	0.7 %	0.7 %
Methane potential yield in digester	-	7.9 %	8.4 %
Unburnt methane in digester	-	0.1 %	0.1 %
Water content of digestate	-	2.4 %	2.5 %
Carbon binding in soil	-	0.7 %	0.7 %
N fertilizer substitution	-	1.3 %	1.4 %
GHG emissions from N fertilizer production	-	0.7 %	0.7 %
N ₂ O emissions from use on land	-	2.4 %	2.5 %
GHG emissions of electricity system	0.5 %	1.5 %	0.1 %
GHG emissions from heat system	1.1 %	0.3 %	0.9 %

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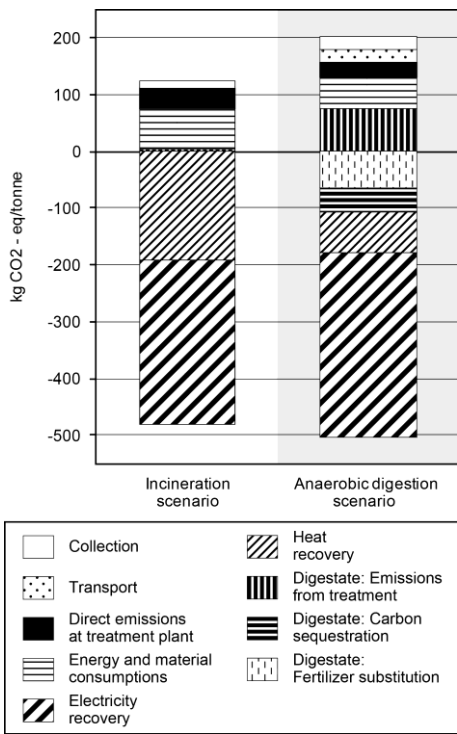
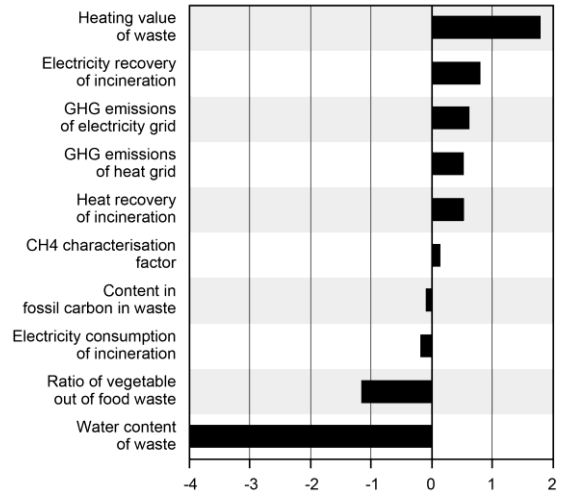


Figure 1: Contribution analysis of the global warming factors of the two scenarios. Rejects refers to ashes for the incineration scenario and to digestate for the anaerobic digestion scenario.

a. Sensitivity ratios for the incineration scenario



b. Sensitivity ratios for the anaerobic digestion scenario

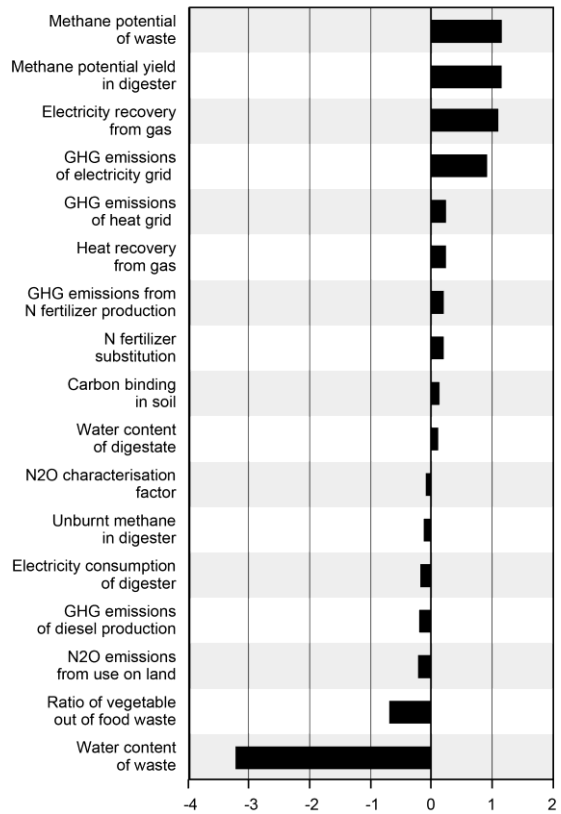
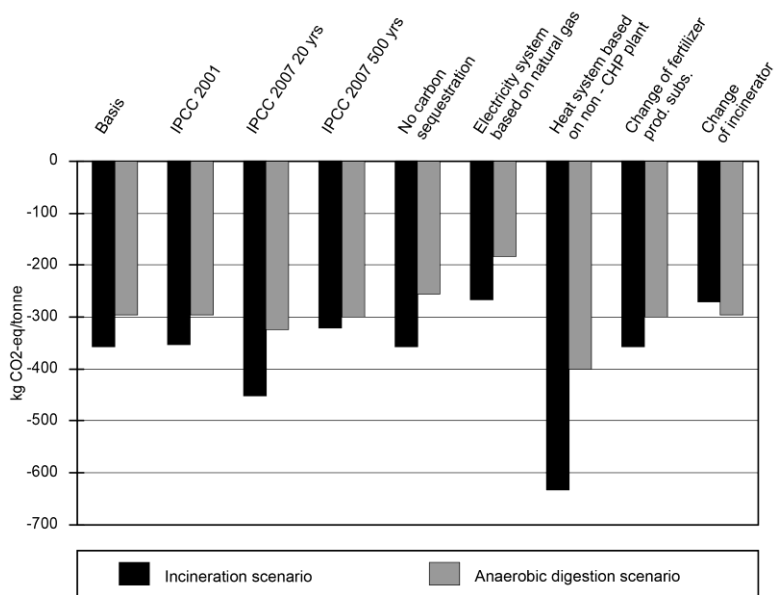


Figure 2: Parameter sensitivity ratios with respect to global warming factors of the incineration and the anaerobic digestion scenarios. Only sensitivity ratios greater than 0.1 as absolute value are presented (GHG: greenhouse gases).



921

922 Figure 3: Global warming factors obtained for the two scenarios when implementing different choices in the

923 scenario analysis.

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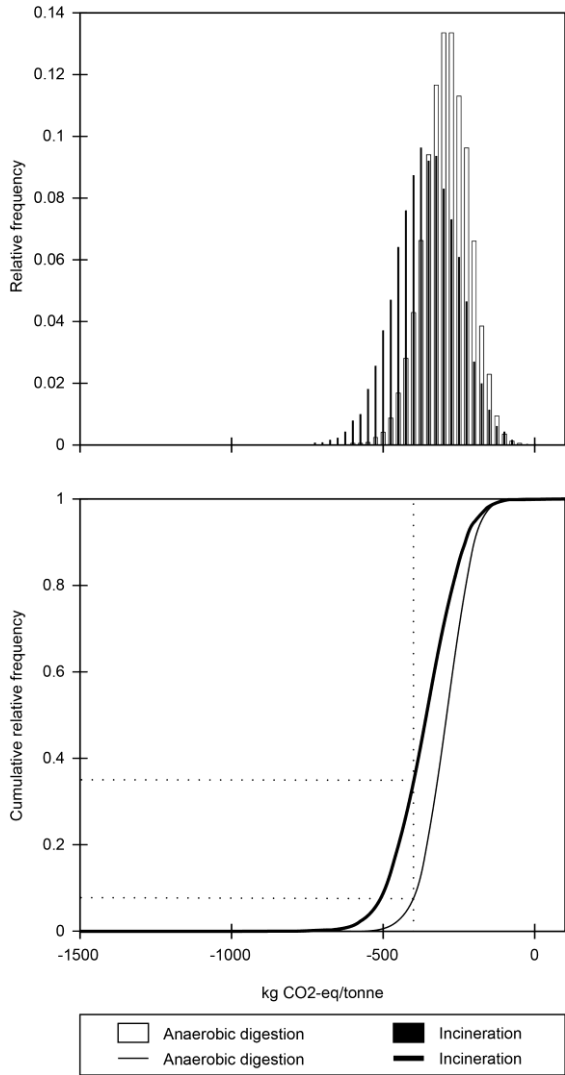


Figure 4: Relative frequency histograms and cumulative relative frequency distributions for the global warming factors of the two scenarios. The dotted lines indicate the percentiles of cases achieving a benefit of more than 400 kg CO₂-eq /t in both cases, i.e. a global warming factor lower than -400 kg/t.

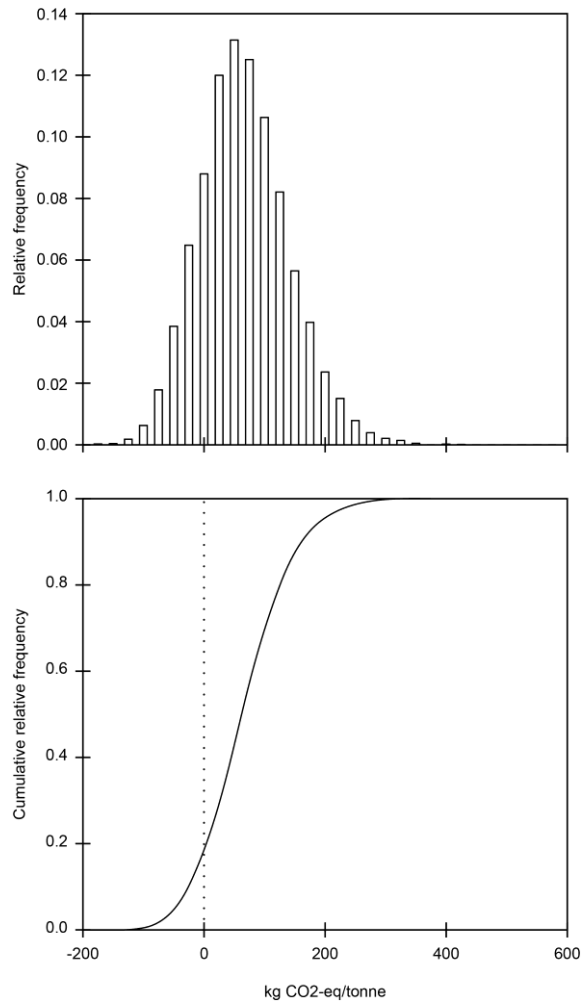
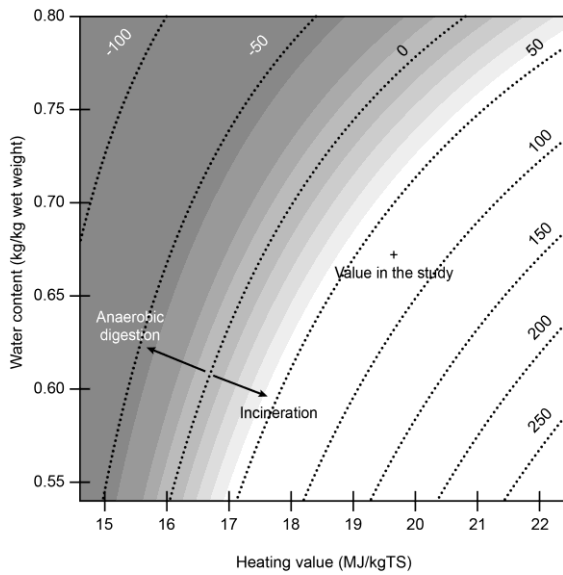


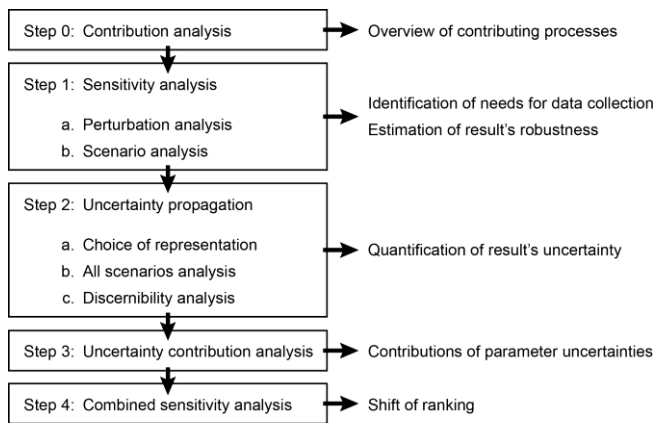
Figure 5: Relative frequency histograms and cumulative relative frequencies for the difference between global warming factors of the anaerobic digestion and the incineration scenarios. A positive difference implies that incineration is preferable to anaerobic digestion.



927

928 Figure 6: Contour lines of the difference between the global warming factors of the two scenarios (in kg CO₂-eq /
 929 tonne) with two parameters variations. The bottom right area shows the conditions where incineration should be
 930 preferred while in the top left anaerobic digestion should be favoured.

931



932

933 Figure 7: A sequential approach for qualitative uncertainty analysis.

934