Data representativeness in LCA: A framework for the systematic assessment of data quality relative to technology characteristics

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ABSTRACT: A shortcoming in current data quality assessment schemes is that the data quality information is not used systematically to identify the critical data in an LCI model. In addition, existing criteria employed to evaluate representativeness lack relevance to the specific context of a study. A novel framework is proposed herein for the evaluation of the representativeness of LCI data, including an analysis of the importance of the data and a modification of quality criteria based on unit process characteristics. Temporal characteristics are analyzed by identifying the technology shift, because data generated before this time are considered outdated. Geographical and technological characteristics are analyzed by defining a ‘related area’ and a ‘related technology’, which is done by identifying a number of relevant geographical and technical factors, and then comparing the collected data with these factors. The framework was illustrated in a case study on household waste incineration in Denmark. The results demonstrated the applicability of the method in practice, and they provided data quality criteria unique to waste incineration unit processes, e.g. different time intervals to evaluate temporal representativeness. However, the proposed method is time-demanding, and thus sector-level characteristics analyses are feasible instead of the user having to do the analyses.

1 INTRODUCTION

A life cycle assessment (LCA) is an established method for the quantification of the potential environmental impacts from product chains and service systems. In principle, all relevant impacts from upstream, direct, and downstream processes should be included in an LCA, which means that large amounts of life cycle inventory (LCI) data are required (ISO 2006). The main effort in data collection should be prioritized for those data with the largest influence on the final results (in an LCA, the life cycle impact assessment, LCIA, results). Hence, to identify where further data refinement should be prioritized, we need to know the importance of the individual data as well as the quality thereof (Boone et al. 2009; van Der Sluijs et al. 2005). Different sensitivity and uncertainty analysis methods are available that enable the identification of the important parameters in an LCI model, which influence the final results, for example the global sensitivity analysis (GSA) method (Clavreul et al. 2012; Heijungs et al. 2005). Bisinella et al. (2016) suggested a sequential GSA approach starting with a contribution analysis, followed by a perturbation analysis to calculate sensitivity coefficients, an analytical uncertainty calculation, and a calculation of the relative contribution-to- variance (CTV) made by individual parameters. While the GSA approach provides a systematic identification of the *important* parameters (i.e. the parameters with a relatively large CTV), it excludes data quality aspects. The quality of LCI data is typically evaluated with the use of a pedigree matrix. Different pedigree matrices are available, but all contain a number of data quality indicators and a set of qualitative criteria per indicator (e.g. Weidema 1998; Edelen and Ingwersen 2017; Laner et al. 2015; EC-JRC 2010a). These qualitative criteria constitute an ordinal scale ranging from ‘good’ to ‘bad’ data quality, and each level on the scale is translated into a data quality score (Funtowicz and Ravetz 1990). The pedigree matrix contains dynamic and static indicators. Reliability and completeness are static indicators, as they address inherent properties, namely, the acquisition method and the statistical validity of the data (Weidema and Wesnæs 1996). On the other hand, representativeness is a dynamic data quality indicator evaluated relative to the temporal, geographical, and technological scope of a study. Unrepresentativeness can

occur, for example, when selecting a specific technology to represent a mix of technologies, or when applying regionally averaged data to represent a specific site (Henriksen et al. 2017). The criteria used to evaluate representativeness have been fairly constant since the first pedigree matrix was introduced to the LCA field (Weidema & Wesnæs, 1996). The criteria for temporal representativeness are default time intervals for the difference between the target year and the year of data generation, while the criteria for geographical and technological representativeness are linguistic statements, which the user has to relate to his/her specific study. For example, the pedigree in Laner et al. (2015) evaluated the level of similarity with the socioeconomic region of the study, Weidema (1998) evaluated the level of similarity with production conditions at the target location, and Edelen and Ingwersen (2017) evaluated the level of similarity with the geographical specificity of the study *and* whether the data were from a related area of the study. Regarding technological representativeness, Laner et al. (2015) evaluated if the data related to the same or similar product of interest, and Weidema (1998) evaluated the level of similarity with the enterprise, material, process, or technology of the study. These broad criteria are applicable to all sectors (Weidema 1998), but one drawback is the risk of subjectivity and lack of transparency when the user relates them to a specific study (Cooper and Kahn 2012; Maurice et al. 2000). Currently, there is no formal approach on how to define ‘a related area’ or ‘a related technology’ when evaluating the geographical and technological representativeness of the data. For example, lack of geographical accuracy may be acceptable for processes with limited geographical variations but unacceptable for processes with large geographical variations, such as landfill processes (Yang et al. 2015). A limitation of using default time intervals to evaluate temporal representativeness is that technologies develop at different speeds. For example, a lack of temporal accuracy may be acceptable for unit processes representing mature sectors with slow development, such as the pulp and paper sector (Strömberg et al. 1997), but it will be unacceptable for unit processes representing rapidly developing sectors, as previously mentioned by Schwab et al. (2016) and Weidema (1998). Currently, there is no formal approach on how to modify the time intervals to make them more process-relevant.

Recent developments have taken place to enhance the objectivity of data quality evaluation. New criteria have been defined for technological representativeness, namely, an evaluation of the match between the collected data and the target technology, and they relate to four technology categories: Process design, operating conditions, material quality, and scale (Edelen and Ingwersen 2017). Furthermore, a mathematically-based data quality evaluation has been suggested for data used in material flow analyses, premised on an ‘information defect’ concept and an evaluation structure deviating from the pedigree matrix (Schwab et al. 2016).

Based on this literature review, key shortcomings were identified for data quality assessment in LCA: 1) Lack of a systematic approach for using data quality information to identify the critical data in an LCI model and 2) Need for a formal approach on interpreting the data quality criteria to representativeness in accordance with the scope of specific LCA studies. This article proposes a novel framework for evaluating the representativeness of LCI data, which includes an analysis of the importance of the data as well as modification of the data quality criteria according to the characteristics of the unit processes. The proposed framework is illustrated in a case study on residual household waste incineration in Denmark. The framework is described in the *Methodology* section and illustrated with the waste incineration case study (see the *Case Study* section), followed by a discussion of the feasibilities and limitations of the presented procedure in the *Discussion* section.

2 METHODOLOGY

The proposed framework addresses the evaluation of the temporal, geographical, and technological representativeness of LCI data. For an overall data quality assessment, the proposed framework should be followed in parallel with the evaluation of the static indicators reliability and completeness on basis of existing pedigree criteria. It should also be mentioned that the proposed procedure evaluates data at the process level, which is similar to the approach utilized by EC-JRC (2010) but contrary to other pedigree matrices (Edelen & Ingwersen, 2017; Laner et al., 2015; Weidema, 1998); this difference is discussed in the *Discussion* section. The proposed framework is a procedure running from step 0 to step 3 (Figure 1),

including the identification of important parameters in the LCI model (step 0), analysis of unit process characteristics (step 1), an evaluation of the representativeness of unit processes (step 2), and the identification of critical data defined as having a major importance to the final results and a low data quality (step 3).

Figure 1 Framework for evaluating the representativeness of life cycle inventory data taking into account the importance of the data as well as the temporal, geographical, and technological characteristics of the unit processes.

2.1 Step 0

Step 0 consists of two parts, 0a and 0b, whereby 0a is the goal and scope definition. The target data are equivalent to the data quality goals of the LCA study, namely, the temporal, geographical, and technological coverage of the study (ISO 2006; Edelen and Ingwersen 2016). Step 0b covers the iterative data collection, LCI modeling, and LCIA results analysis, occurring in parallel with the data quality evaluation. This framework does not dictate any specific sensitivity and uncertainty analysis method, but the outcome of the analysis must be an overview of the importance of the LCI data to the final results. For example, the GSA method has been applied to LCA of waste management systems, where the importance was calculated by unifying the input uncertainty and sensitivity of the LCI on the LCIA results (Bisinella et al., 2017; Bisinella et al., 2016).

2.2 Step 1

Step 1 contains two data quality evaluation routes: 1a for data with relatively small importance, and 1b for data with relatively large importance (based on a comparison of the contribution of the data to the final results). In step 1a, a business-as-usual data quality screening is performed with the use of an existing pedigree matrix with pre-defined criteria (such as Weidema 1998; Edelen and Ingwersen 2017; EC-JRC 2010a). A data quality screening is sufficient because the data have a limited influence on the results, e.g. due to a small input uncertainty combined with a small sensitivity in the specific model configuration. Nonetheless, it is essential that a data quality evaluation *is* conducted to detect possibly critical data due to potential bias derived from step 0b, due, for instance, underestimated flow values and input uncertainties. This is in line with (Heijungs 1996) emphasizing that the possibly ‘key issue data’ should not be ignored. For those data with a relatively large importance (i.e. a relatively large contribution to the final results), a technology-adjusted assessment is done, starting with an analysis of the temporal, geographical, and technological unit process characteristics (step 1b).

2.2.1 Temporal unit process characteristics

In the business research field, the technology lifecycle curve is used to understand the process of innovation and how emerging products or innovations replace mature technologies (Sandström 2013). The steepness of the curve indicates the rate of development and the current development phase. An idealized technology lifecycle consists of initial research and development (R&D), followed by a rapid increase in performance at market introduction, and it peaks when it has reached market saturation (Figure 2). The top diagram illustrates the idealized technology lifecycle as well as a technology currently in the market growth phase and a technology currently in the R&D phase. Understanding the development of a unit process over time can inform about data requirements, and, hence, be useful in data quality assessment. For example, the LCI of a rapidly developing (or emerging) technology needs to be updated more frequently than for a mature technology.

The performance over time of unit processes is analyzed. Available information may be quantitative, e.g. measured, estimated, and/or projected data, or qualitative, e.g. legislation, best available technology reference documents, and sector reports. In LCA studies targeting the present or near-future, the performance analysis ends at the current year, while projected data or planned future legislation are useful in the case of long-term future LCAs, to identify likely scenarios (Quinn 1967). The outcomes of the analysis are:

1. Identification of the current development phase
2. Estimation of the year of the latest technology shift

A technology shift is defined as an increase in the performance of a unit process, e.g. efficiency that results in the need for updated LCI data. This means that data generated *before* the latest technology shift are considered outdated. For example, in Figure 2, inventories from the early market growth phase are not representative of the same unit process at market saturation. There is no mathematical correlation between the slope of the curve and the magnitude of a technology shift, hence, the user should not calculate the

slope. Instead, the user must get an overview of the development of the technology performance over time to understand the current development phase, and the needs for updated data.

2.2.2 Geographical and technological unit process characteristics

Current data quality assessment schemes require that the user relates the pedigree criteria for geographical and technological representativeness to the context of the LCA study, yet, no formal procedure for this is available (e.g. Edelen and Ingwersen 2017). To enhance the level of transparency and documentation, we suggest an approach to define and evaluate a ‘related area’ and a ‘related technology’. The principles are similar to those used when evaluating the number of matches with four technology categories (Edelen and Ingwersen 2017). Hereby, four geographical and technological categories are defined (Figure 2). The geographical categories are novel and cover socioeconomic, climatic, and regulatory aspects, whilst the technological categories are similar to Edelen and Ingwersen (2017), i.e. input material, process design, capacity, and operating conditions. The categories are broad, thereby making them applicable to all sectors. However, in order to be relevant to a specific LCA study, a number of subcategories (‘factors’) must be defined, which are relevant to the unit processes in question. The user can define zero, one, or multiple factors per category. For example, the accuracy of climatic factors such as precipitation and temperature is relevant for agricultural processes (Yoshida, H., Nielsen, M.P., Scheutz, C., Jensen, L.S., Bruun, S., Christensen et al. 2016). The outcomes of the analysis are:

1. A list of relevant geographical factors per geographical category in Figure 2.
2. A list of relevant technical factors per technological category in Figure 2.

The representativeness of the data is then assessed by evaluating how well the collected data match the target data. This is done by comparing the specified factors per geographical and technological category in Figure 2 with the metadata of the collected data. The metadata is relevant because it informs about the production process of the data.

Figure 2 Conceptual approach of the analysis of the temporal, geographical, and technological unit process characteristics to be used for the evaluation of LCI data representativeness: (a) Idealized technology lifecycle providing inputs to analyze the temporal characteristics of a unit process. A brief outline of the steps are given to the right of the subfigure; (b) Four geographical and technical categories providing inputs to the evaluation of geographical and technological representativeness. A brief outline of the steps are given to the right of the subfigure.

2.3 Step 2

The outcomes from step 1b feed into the data quality evaluation in step 2. First, the user must decide if quantitative data quality scores are needed (i.e. a pedigree matrix), or if a simpler, qualitative evaluation is sufficient. If the evaluation of representativeness is to be combined with the evaluation of the static indicators, then a pedigree matrix is needed. If the purpose is simply to gain a rough overview of the representativeness of the data, the qualitative evaluation is sufficient. Table 1 contains the templates of the qualitative evaluation ('Non-pedigree format') and quantitative evaluation ('Pedigree format'). The user must modify the template that is relevant to his/her needs based on the analysis of the unit process

characteristics from step 1b. The following text describes the ‘Non-pedigree format’ and ‘Pedigree format’ including the procedure for modification of the tables.

Table 1 Data quality criteria templates used to evaluate the representativeness of life cycle inventory data with the consideration of unit process characteristics: Non-pedigree format and pedigree format.

Non-pedigree format					
Temporal			Geographical and technological		
Are data generated after the technology shift?			Are relevant factors represented by the collected data?		
- Yes indicates an acceptable age of data			- Yes indicates representativeness		
- No indicates outdated data			- No indicates lack of representativeness		
Pedigree format					
Score	1	2	3	4	5
Temporal	0-MTI	>MTI to 2×MTI	>2×MTI to 3×MTI	>4×MTI to TD _{shift}	> TD _{shift}
Geographical	Specific location	76-100% related area	51-75% related area	26-50% related area	0-25% related area
Technological	Specific technology	76-100% related technology	51-75% related technology	26-50% related technology	0-25% related technology

NOTE: MTI [yr] = modified time interval. TD_{shift} [yr] = target year of study minus year of technology shift.

The format of the non-pedigree template is binominal, i.e. a ‘yes’ or ‘no’ answer to whether the collected data are equivalent to the relevant factors, and a ‘yes’ or ‘no’ answer to whether the collected data were generated after the occurrence of the technology shift. The ‘yes’/‘no’ answers are noted down in tabular form for an overview of data quality information.

The format of the pedigree template is a matrix with minimum two scores (see five-score matrix in Table 1). For temporal representativeness, a modified time interval (MTI) must be calculated as the time difference between the target year and the year of the technology shift (TD_{shift}) and a division:

$$TD_{\text{shift}} [\text{yr}] = \text{Target year of study} - \text{Year of technology shift} \quad (\text{Eq. 1})$$

$$MTI [\text{yr}] = \frac{TD_{\text{shift}}}{i - 1} \quad (\text{Eq. 2})$$

With $i = 2, \dots, n$ number of scores in the pedigree matrix.

Data quality is evaluated by comparing the MTI with the actual time difference between the target year of the study and the year the unit process data was generated (TD_{actual}). Calculation of TD_{actual}:

$$TD_{\text{actual}} [\text{yr}] = \text{Target year of study} - \text{Year of data generation} \quad (\text{Eq. 3})$$

The worst score of 5 is given if $TD_{\text{actual}} > TD_{\text{shift}}$, i.e. if the data were generated before the technology shift. In its current form, the temporal criteria do not apply to long-term future LCAs, because the MTI is based on the *last* technology shift and not on the *next* technology shift.

For geographical and technological representativeness, the best score of 1 is given if data stem from the specific location and specific technology, respectively. Scores 2 to 5 are given according to how well the data covers the ‘related area’ and ‘related technology’, which is evaluated as the ratio of matching factors (Eq. 4). The numbers of factors are summed across the geographical and technological categories given in Figure 2, following which the total match is the number of factors equivalent to the target data divided by the sum of relevant factors:

$$\text{Total match } [\%] = \frac{\text{Number of equivalent factors}}{\text{Sum of relevant factors}} \quad (\text{Eq. 4})$$

An evaluation of the equivalence of the individual factors is done by assigning a factor equivalence value, e_f , between 0 (no equivalence) and 1 (full equivalence). When evaluating the equivalence of compositional data, it might be relevant to assign a fraction; for example, if 90% of a product portfolio is represented, then the $e_f = 0.9$. Thus, equivalence evaluation method:

$$e_f = \begin{cases} e_f = 1 & \text{if full match} \\ e_f = 0 & \text{if no match} \\ 0 < e_f < 1 & \text{if partial match} \end{cases} \quad (\text{Eq. 5})$$

2.4 Step 3

Critical data are those unit processes that contain the important parameters (defined as having a relatively large contribution to the final results) identified in step 0b *and* which have low data quality. The combination of quantitative uncertainty and data quality provides for a robust identification of critical LCI data in a study and thereby highlights data-related limitations. When applying the GSA method to

calculate the CTV, the input uncertainty and sensitivity of the data are unified. Hereby, the axes of uncertainty and contribution in Heijungs (1996) are being collapsed into one axis. For a graphical overview, the average data quality score can be plotted with the parameters' CTV to evaluate the criticality of the data (please see conceptual diagram in Figure S1-5 in the supporting information S1). The unit processes containing the critical parameters should be improved by modifying single values and datasets, or by replacing the entire process. If such improvements are not possible, an uncertainty interval can be added to the data that reflects the un-representativeness. Default uncertainty factors are available (Muller et al. 2014; Citroth et al. 2016), but due to their potential inaccuracy, we recommend to estimate the interval based on sector understanding and/or literature (see also Henriksen et al. 2017; Cooper and Kahn 2012).

3 CASE STUDY

3.1 Goal and scope definition (step 0a)

A simplified case study was defined to illustrate the application of the framework in practice, and it included a scenario for the management of residual household waste in Denmark, which is traditionally incinerated. Modeling of incineration involves a number of possible technical configurations, such as energy recovery and the design of air pollution control (APC) operations (Beylot et al., 2018).

The functional unit was the collection and incineration of 1000 kg of residual household waste at a dedicated waste incineration facility. Residual household waste is what is left after source-separation of recyclable materials (paper, glass, metals, etc.). To consider the entire lifecycle, the upstream production of fuels and auxiliary materials consumed at the incineration facility were included, as well as the downstream substitution of marginal electricity and heat due to energy recovery at the facility. Modeling was done with the EASETECH model (Clavreul et al. 2014). Please see the supporting information S1 for further details on the model and applied data.

The incineration process was further divided into the flue gas cleaning and energy recovery unit processes. The flue gas cleaning unit process consisted of APC operations, which required the collection

of two datasets: Applied chemicals and pollutants emitted via the treated flue gas through the stack. The energy recovery unit process consisted of electricity and heat generation, whereby electricity was added to the electricity grid mix, and the heat added to the local district heating network. The required data were electricity and heat efficiency, aligned with background datasets for avoided marginal energy production. The case study was intended to represent average waste incineration in Denmark. The average waste incineration technology was estimated based on a country-level summary (ISWA, 2012), which is plotted in the supporting information S1. Summary of the case study target data:

- Target year = 2020
- Target location = Denmark [average household = 1/3 multi-family and 2/3 single-family (Statistics Denmark 2019)]
- Target technology = mass-burn/moving grate furnace with medium capacity (80 MW feed); combined heat and power generation with flue gas condensation; four APC operations, i.e. a mix of wet, semi-dry, and dry scrubbers (acid gases), electrostatic precipitators (particles), selective non-catalytic reduction (nitrogen oxides), and activated carbon (dioxins and mercury).

Environmental burdens from waste incineration stem from flue gas emissions, and potential environmental savings stem from the energy recovery, *if* more polluting sources of electricity and heat are substituted. Fly ash and bottom ash disposal are also the responsibilities of waste incineration facilities, but they were excluded here because their impacts tend to be minor (Astrup et al., 2009; Beylot et al., 2018) and for the sake of simplifying the case study. Characterized LCIA results were calculated with characterization methods selected among those recommended by the European Commission (2010).

3.2 Data collection, modeling, and results analysis (step 0b)

Residual household waste composition is defined by the fractions (share of food, plastics, metals, glass, etc.) and physico-chemical properties, e.g. water content, heating value, fossil carbon, etc. (Edjabou et al. 2014; Götze et al. 2016). The data sources represented Danish household waste generation by single-

296 family households (Petersen, 2011; Petersen et al., 2012; Riber & Christensen, 2006; Riber, Rodushkin,
297 Spliid, & Christensen, 2006; Riber, Petersen, & Christensen, 2009).

298 The flue gas cleaning data were from facility-level reports. The data were operational averages reported
299 by ten Danish incineration facilities in 2016. The ten incineration facilities received 80% of the total
300 amount of waste incinerated in Denmark in 2018 (Danish Energy Agency 2018). More recent data were
301 unavailable because the reporting requirements ended in 2016 and were replaced by the European
302 Pollutant Release and Transfer Register (EPRTR), which includes emissions but excludes materials
303 consumption and energy recovery (Danish EPA 2019a; European Commission 2006; Yoshida et al.
304 2014).

305 Projected electricity and heat recovery data were applied that represented 2020 and assumed the
306 installation of a flue gas condensation mechanism at the facilities, which is augmented by heat pumps and
307 gives a total efficiency of 105% based on a lower heating value of 11.5 MJ/kg waste (Danish Energy
308 Agency 2016).

309 The marginal electricity and heat mixes were based on Schmidt et al. (2016) and Jensen et al. (2013),
310 respectively, and the background datasets were from the ecoinvent database. A process-specific
311 incineration model was built in EASETECH as a sequence of modules corresponding to the three unit
312 processes. The LCI is documented in the supporting information S1.

313 Sensitivity and uncertainty analyses were conducted in accordance with the GSA method following the
314 approach of a former publication (Bisinella et al. 2016). The GSA procedure and quantitative outcomes
315 are documented in the supporting information S1 and the identified important data are summarized as
316 follows: Across a number of impact categories, the important parameters, with relatively large CTV
317 values, were the heat and energy recovery efficiency, process-specific flue gas emissions, and waste
318 composition (e.g. fossil carbon content). The important unit processes were those containing the identified
319 parameters, namely the waste generation, flue gas cleaning, energy recovery, and marginal energy

production processes. A business-as-usual data quality screening should be done for the data of limited importance (i.e. with a relatively small CTV), but this was excluded in the case study for simplification.

3.3 Characteristics of unit processes (step 1a)

The characteristics of the unit processes identified as being important were analyzed. For simplification, the case study only included foreground unit processes data, meaning that the data quality of the background marginal energy and auxiliary production were not included.

3.3.1 Temporal characteristics

In accordance with Figure 2, the performance over time of the energy recovery and flue gas cleaning unit processes were plotted (Figure 3). The legislation timeline shows legislation relevant to waste incineration in a Danish-European context, which was used to verify the trends (but can also be used instead of the quantitative plots). The applied data were reported by ten Danish incineration facilities from 1995 to 2016, after which Danish reporting requirements ended. The projected energy recovery data covered 2020 and 2050 (Danish Energy Agency 2017). The emission plots ('flue gas cleaning process') include the pollutants regulated in the integrated pollution prevention and control (IPPC) directive, nine of which are illustrated in Figure 3 (European Commission 1996). All pollutants regulated in the IPPC directive are illustrated in the supporting information S1. Emissions decrease over time, so the performance of the flue gas cleaning process improves. Relatively large emission reductions occur around 2005, which correlates with the implementation of the waste incineration (WI) directive that required continuous Hg measurement and led to new Hg removal installations and, consequently, the reduction of other emissions (European Commission 2016). The relatively flat curves from 2006 indicate that flue gas cleaning was mature and only experienced incremental improvements, as described by the Danish Energy Agency (2016). The consumption of chemicals increased, especially from 2004 to 2010, thereby overlapping with the implementation of the WI directive. The consumption is relatively constant after 2010. The decreasing emissions and increasing consumption illustrate a trade-off, suggesting that the two datasets are linked and should both be modeled with temporal accuracy.

From the ‘energy recovery process’ plots in Figure 3, there is a minor increase in energy recovery until 2005, followed by a fairly constant development until a shift occurs as a result of projected efficiencies. The relatively constant performance since 2005 suggests that energy recovery was a mature technology over a long period, albeit with significant deviations among the facilities (min-max intervals). The reason for the shift between 2016 and 2020 is the assumption of flue gas condensation in all facilities by 2020 (Danish Energy Agency 2017). Due to the lack of reported data between 2016 and 2020, it was estimated that the technology shift occurred in year 2016. The other estimated technology shifts were in 2005 for the flue gas emissions, and in 2010 for the chemicals.

Figure 3 Temporal development the flue gas cleaning and energy recovery unit processes of Danish waste incineration facilities: (a) Timeline of relevant legislation on solid waste incineration showing the year of adoption and implementation of three European Union directives. IPPC=Integrated pollution prevention and control directive, WI=Waste incineration directive, IE=industrial emissions directive; (b) Emissions: Averaged direct flue gas emissions for ten Danish waste incineration facilities (y-axis: ‘ton waste’ refers to metric tons waste). The emissions cover the pollutants regulated in the IPPC directive. Note the difference in y-axis scales. Chemicals: Averaged values for the total amount of chemicals

consumed in the flue gas cleaning process, calculated based on ten Danish waste incineration facilities (y-axis: ‘ton waste’ refers to metric tons waste). The chemicals include calcium compounds, activated carbon, ammonia, precipitation chemicals, and acids and bases; (c) Averaged values and min-max values for the net electricity and heat recovery at ten Danish incineration facilities. The shaded area indicates projected energy efficiency data for Denmark for a medium-capacity waste incineration facility (80 MW feed). Underlying data used to create subfigures (b) and (c) can be found in the supporting information S2.

Temporal characteristics of the waste generation process

The fractional composition of residual household waste is influenced by the separation of recyclable materials. In Denmark, there is a political target of increasing the recycling of household waste (Danish Government 2013). The amount of incinerated household waste decreased from 58% to 53% between 2013 and 2017, due to an increase in waste collected for recycling, such as plastic packaging and food waste (Danish EPA 2019b). Ideally, waste composition data should be up to date with this temporal development. In addition, the data should reflect that around 10% of the incinerated waste is imported, mainly from the United Kingdom (DAKOFA 2016; Danish EPA 2019b). This suggests the need for a relatively high frequency of updated waste composition data, and therefore the estimated technology shift is the most recent year of the official waste statistics, i.e. year 2017. The physico-chemical composition of the residual waste is indirectly influenced by source separation, such as decreasing water content when food waste is separated (Edjabou, Boldrin, Scheutz, & Astrup, 2015), but it is excluded in this analysis.

3.3.2 Technological and geographical characteristics

Relevant factors were identified for the technical and geographical categories shown in Figure 2, with the purpose to define a ‘related area’ and a ‘related technology’. The relevant factors were identified based on literature and expert knowledge, in parallel with data collection and modeling. The factors are shown in Table 2 and summarized here.

Geographical factors:

- Precipitation level, because it may cause secondary water addition to waste stored outside, which in turn will lower the calorific value—and thereby energy output—per mass of input.

- Climate region, because it influences the demand for energy by-products. Denmark is in a temperate region with cold winters, thus causing a seasonal demand for increased district-heating.
 - Emission recipient, because it influences local impacts on humans and ecosystems.
 - Income level of households, because it influences the waste amount and composition (United Nations 2014).
- Technical factors:
- Waste type and generators, meaning the category of the waste (households) and the producers thereof (average Danish households).
 - Integral process designs and operating conditions, namely, the type of energy recovered, furnace temperature (for complete combustion), and air emission levels.
 - Capacity of the incineration facility, defined both by mass (metric tons/hour) and energy feed (MW).

Table 2 Relevant geographical and technical factors in the evaluation of representativeness. Identified for unit processes in the waste incineration case study, and for the four geographical and technical categories.

Unit process		Waste generation	Energy recovery	Flue gas cleaning
Considered data		Fractional composition	Electricity and heat efficiency	Air emissions Use of chemicals
		<i>Factors</i>	<i>Factors</i>	<i>Factors</i>
Geographical categories	<i>Climate and environment</i>	Precipitation	Climate region	Air emissions recipient
	<i>Market demand and supply</i>		Electricity demand Heat demand	Supply of chemicals
	<i>Legislation</i>			Limit values
	<i>Income level</i>	Household income		
<i>Sum factors</i>		2	3	3
		<i>Factors</i>	<i>Factors</i>	<i>Factors</i>
Technical categories	<i>Input material</i>	Waste types Waste generators		
	<i>Process design</i>		Combined heat/power Flue gas condensation	APC operations ¹
	<i>Capacity</i>		Mass feed Energy feed	Mass feed Energy feed
	<i>Operating conditions</i>		Furnace temp.	Furnace temp.
<i>Sum factors</i>		2	5	5

¹ Air pollution control (APC) operations include acids removal, particle removal, nitrogen oxides removal, and dioxins and mercury removal (= four main operations).

3.4 Evaluation of representativeness (step 2)

For demonstration purposes, the evaluation of representativeness included both the non-pedigree and pedigree formats. In Table 3, qualitative data quality information is given. The flue gas cleaning and energy recovery unit process data were generated *after* the last technology shift, and therefore they were of an acceptable age. On the contrary, the waste composition dataset was generated *before* the latest technology shift, and therefore it was considered outdated. An evaluation of geographical and technological representativeness indicated good coverage of the target location and technology. Deviations between the collected data and target data are noted in brackets, for example potential technical deviations of the APC operations because information about the specific APC configurations at the ten sampled facilities was unavailable.

Table 3 Evaluation of the representativeness of unit processes in the waste incineration case study: Non-pedigree format. The evaluation was done by comparing the target data of the study with the metadata of the collected datasets.

Temporal representativeness				
<i>Unit process</i>	<i>Individual datasets</i>	<i>Technology shift [yr]</i>	<i>Data generation [yr]</i>	<i>Data generated after technology shift?</i>
Waste generation	Fractional composition	2017	2012	No (outdated data)
Flue gas cleaning	Emissions	2005	2016	Yes (acceptable age)
	Chemicals	2010	2016	Yes (acceptable age)
Energy recovery	Electricity and heat efficiency	2016	2020	Yes (acceptable age)
Geographical and technological representativeness				
<i>Unit process</i>	<i>Geographical factors</i>	<i>Match?</i>	<i>Technical factors</i>	<i>Match?</i>
Waste generation	Precipitation	Yes	Waste type	Yes
	Household income level	Yes	Waste generators	No (lack of 10% import and 1/3 multi-family households)
	Climate region	Yes	CHP	Yes
Energy recovery	Electricity demand	Yes	Flue gas cond.	Yes
			Mass feed	Yes
			Energy feed	Yes
	Heat demand	Yes	Furnace temp.	Yes
Flue gas cleaning	Air emissions recipient	Yes	APC operations	Yes (possible deviations)
	Supply of chemicals	Yes	Furnace temp.	Yes

Limit values	Yes	Mass feed Energy feed	Yes Yes
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The obtained pedigree scores are shown in Table 4. The MTIs were calculated based on the TD_{shift} values (Eq. 1), and as a rule-of-thumb, they were calculated at the unit process level. However, in the case where the estimated technology shift differed for the flue gas emissions and the chemical consumption, the MTIs were calculated at the level of the datasets, and, hence, the temporal representativeness was evaluated at the level of the datasets. Next, the MTIs were fitted to the five-score pedigree matrix, which was not always straightforward; for example, for the waste generation process, the time interval was one year between a score of 1 and 2, whilst it was two years between a score of 2 and 3. Similar to the qualitative information (Table 3), the pedigree scores indicated good temporal representativeness of the unit processes, except for waste composition.

To evaluate geographical and technological representativeness, the number of factors were summed across the four geographical and technical categories, respectively. Thereafter, the match ratio and percentage were calculated (Eq. 4). For waste composition, a match percentage of 80% was obtained $[(1+0.9 \times 0.67)/(1+1)]$, because the waste generators were not fully equivalent with the target data, due to the lack of 10% imported waste and 1/3 multi-family households. Overall, the pedigree scores indicated good geographical and technological representativeness.

Table 4 Evaluation of the representativeness of the unit processes in the waste incineration case study: Pedigree format. The evaluation was done by comparing the temporal, geographical and technological target data of the study with the information in the metadata of the collected datasets.

Temporal representativeness							
<i>Unit process</i>	<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>TD_{shift}</i>	<i>MTI</i>
Waste generation	0-2 yr	≤3 yr	≤5 yr	≤6 yr	>7 yr	7	1.75
Flue gas cleaning (air emissions)	0-3 yr	≤6 yr	≤10 yr	≤14 yr	>15 yr	15	3.75
Flue gas cleaning (chemicals)	0-2 yr	≤4 yr	≤7 yr	≤10 yr	>10 yr	10	2.50
Energy recovery	0 yr	1 yr	2 yr	3 yr	≥4 yr	4.00	1.00
Geographical representativeness							
<i>Unit process</i>	<i>Match ratio [-]</i>		<i>Match percentage [%]</i>		<i>Score</i>		
Waste generation	2 factors/2 factors		100		2		
Energy recovery	3 factors/3 factors		100		2		
Flue gas cleaning	3 factors/3 factors		100		2		

Technological representativeness			
<i>Unit process</i>	<i>Match ratio [-]</i>	<i>Match percentage [%]</i>	<i>Score</i>
Waste generation	1.6 factors/2 factors	80	2
Energy recovery	5 factors/5 factors	100	2
Flue gas cleaning	4 factors/4 factors	100	2

NOTE: The cells shown in bold show the assigned data quality scores for temporal representativeness of the waste generation (score 5), flue gas cleaning (score 2) and energy recovery (score 1) unit processes.

3.5 Identification of critical data (step 3)

The average representativeness scores for the processes were 3.3 (waste generation), 1.7 (energy generation), and 2.0 (flue gas cleaning). Adapting the data quality ratings by the EC-JRC (2010b), the overall representativeness was ‘basic’ for all processes except for the waste generation process, which was at a lower level of quality (‘data estimate’). This indicated that the waste generation process was critical due to its importance to the final results and its lack of representativeness. It is resource-demanding to generate new waste composition data, and thus it is considered more feasible to apply literature ranges (Bisinella et al., 2017). If only the qualitative evaluation in Table 3 were conducted, it was not possible to calculate an average score; instead, those data given a ‘No’ would be potentially critical.

4 DISCUSSION

Three major discussion points herein are: the contributions made to representativeness from modifying the criteria, the differences with other data quality evaluation methods, and the approach undertaken to analyze the unit process characteristics.

4.1 Contributions made to representativeness from modifying the criteria

The modified time intervals in Table 4 were one- or two-year intervals for unit processes that had undergone a recent development (waste generation, energy recovery), and three or four years for the unit processes that had been relatively stable for the last 10-15 years (flue gas cleaning). Existing pedigree criteria assign the worst data quality score for temporal deviations above 10 or 15 years (Edelen & Ingwersen, 2017; Laner et al., 2015; Weidema, 1998). Compared with the time intervals in Table 4, existing pedigree criteria correspond to the modified time intervals of the flue gas cleaning process.

Regarding the waste generation and energy recovery processes, the modified time intervals were stricter than in existing pedigree matrices. This indicates that modifying the temporal criteria makes a difference for rapidly developing processes, where a recent technology shift took place, but it does not contribute with very different time intervals for slowly developing processes. Hence, to reduce workload, the user can start by identifying the latest technology shift, calculate TD_{shift} , and then compare this with the existing pedigree criteria, to determine if it is necessary to apply modified temporal criteria.

The modified criteria for geographical and technological representativeness were the ratio of equivalent factor, which is more quantitative and, possibly, less intuitive than the existing pedigree criteria.

Therefore, to be meaningful, the identified factors and evaluation of equivalence of the factors must be documented. If properly documented, the modified criteria can enhance the transparency of the data quality evaluation process. In addition, with the four geographical categories, it is now clear that geographical representativeness is related to both climatic and socioeconomic aspects, whereas existing pedigree criteria emphasize socioeconomic aspects (e.g. Weidema 1998).

4.2 Differences to other data quality evaluation methods

The proposed procedure evaluates data quality at the unit process level, which deviates from other methods. For example, a US EPA framework and the ecoinvent database defined representativeness as flow level criteria and applied them to each exchange in a unit process (Edelen and Ingwersen 2016; Weidema et al. 2013). . There are examples of pragmatism in the literature, such as applying ecoinvent's flow level criteria for evaluations at the process level (Bassi et al. 2017; Boldrin et al. 2015). We choose to evaluate at the unit process level because it is more feasible in a full-scale LCA with a large number of unit processes and an even larger number of flows. Unit process evaluation requires that data in the unit process are generated under the same conditions, but if this is not the case, a separate evaluation of different datasets is recommended (as in the case study).

The proposed procedure for aggregation is to calculate the average representativeness score or overall data quality, which involves aggregation across data quality indicators, similar to former publications

(e.g. van der Sluijs et al. 2003). Other authors state that the data quality indicators are independent and therefore cannot be aggregated (Edelen and Ingwersen 2017), while others again argue that they all indicate data quality and thereby the indicators share the same ‘unit’ (May and Brennan 2003). When considering the data quality of background processes, from e.g. the ecoinvent database, the data quality has probably been evaluated ‘upstream’ to the actual use of the data in an LCI model (Weidema et al. 2013). We do not think it is feasible to re-evaluate all background processes, but we recommended to re-evaluate those that are important in terms of linked foreground parameters, e.g. heat and electricity efficiencies of waste incineration (Bisinella et al., 2017). The data quality of the background processes is evaluated based on available information, starting at step 1 in Figure 1. The data quality scores for reliability and completeness are static and do not need to be updated.

4.3 Applicability of the unit process characteristics analysis

There are other ways to analyze technologies. For example, the Danish Energy Agency (2016) employed four categories, linked to the level of technological maturity, to estimate the potential for improving technologies; they placed waste incineration in category 4 corresponding to a commercial technology, which is in alignment with the findings of this study. Other authors showed that the same mature technology may have different characteristics in an emerging market and a mature market. This is relevant to waste incineration, which has a mature market in Denmark and the rest of Northern Europe (as indicated in this case study) while, at the same time, it sees emerging markets in other continents and even in other parts of Europe (Danish Energy Agency 2016). This highlights that the outcomes from the technology analysis are not automatically applicable to other geographical contexts. At the same time, the technology analysis is time-demanding. Thus, for potential users with relatively low resources available there is a large potential in sector-level analyses performed across the economy and in specific geographical regions, instead of the individual users having to do the analyses.

5 CONCLUSIONS

A novel data quality assessment framework was proposed for evaluating the representativeness of LCI data, including an analysis of the relative importance of the data and modifications of quality criteria, via an analysis of unit process characteristics. Temporal characteristics were analyzed by identifying the year of the latest technology shift, as data generated before this time were considered outdated. Geographical and technological characteristics were analyzed by identifying a number of relevant factors within four geographical and technological categories, against which the collected data were compared. The user must decide if a qualitative or a pedigree-based evaluation is needed. The qualitative approach is a binominal ‘yes’/‘no’ evaluation, whereas the latter includes the formulation of criteria in a pedigree matrix. Regardless of the choice, it is imperative that an analysis of unit process characteristics, and any evaluation, is documented to ensure transparency. The framework was illustrated in a case study on residual household waste incineration in Denmark. The results demonstrated the applicability and importance of the method in practice, and data quality criteria were formulated for individual waste incineration unit processes, e.g. time intervals calculated based on the technology shift. A limitation of the method is that it is more time-demanding than the business-as-usual data quality evaluation. Therefore, there is significant potential in performing an analysis of sectors across the economy and in different geographical locations, which can be reused by users within the same contexts, instead of individual users having to do this for all processes in an LCA study.

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711 SUPPORTING INFORMATION

712 The Supporting Information (SI) contains a Word file (S1) and an Excel spreadsheet (S2). The word file
 713 provides the background details of the case study analysis. The Excel spreadsheet contains the underlying
 714 raw data of the illustrations in Figure 3.