Application of Dempster-Shafer theory to integrate methods to propagate variability and epistemic uncertainty in agricultural LCA

Xiaobo CHEN[1,2,*], Michael CORSON[1,2]

[1] INRA, UMR 1069 Sol, Agro et hydrosystème Spatialisation, F-35042, Rennes, France
[2] Agrocampus Ouest, F-35042, Rennes, France
* Corresponding author. E-mail: *xiaobo.chen@rennes.inra.fr*

ABSTRACT

We represented variability and epistemic uncertainty in LCA with different approaches in the same framework. Probability distributions are commonly used to represent variability in populations, while fuzzy intervals are an alternative approach for representing epistemic uncertainty in parameters when information is incomplete or imprecise. We used Dempster-Shafer theory to combine both approaches for representing variability and epistemic uncertainty and propagated them with Monte-Carlo simulation through the LCA model. We applied approaches to a case study of dairy farms to estimate their potential direct environmental impacts. Results indicated that consideration of incomplete information greatly increases overall uncertainty in impacts, as measured by a "relative interval width", which was useful for comparing the influence of input uncertainty among impact categories. Thus, our method provides conservative estimates of impacts by considering incomplete information, which is ignored by the classic probability method commonly used in LCA.

Keywords: life cycle assessment, Dempster-Shafer theory, variability, epistemic uncertainty

1. Introduction

Life Cycle Assessment (LCA) is a useful tool to estimate potential environmental impacts and resource use of farming systems (van der Werf and Petit 2002; Thomassen et al. 2008). The reliability of LCA results, which depends primarily on the quality of data and their pertinence for the system studied, is affected by uncertainty (Weidema and Wesnaes 1996; Finnveden 2000). Including uncertainty analysis in LCA may yield results that provide more useful information for decision making (ISO 2006; Heijungs 1996). Therefore, there is a need to improve uncertainty analysis in LCA to increase the reliability of its results.

Uncertainty analysis includes a variety of methods that are used to express and propagate uncertainty in many fields, such as risk analysis (Vose 2008) and LCA (Benetto 2005; Bjorklund 2002). Most studies define two main types of uncertainty (variability and epistemic uncertainty), which have fundamental differences (Morgan and Henrion 1992). Variability (also called stochastic uncertainty) represents inherent differences among individuals in a population. It cannot be reduced but can be represented more precisely if more population data are available (De Rocquigny et al. 2008; Vose 2008). Probability distributions have been used widely in LCA (Basset-Mens et al. 2009; Henriksson et al. 2011; IPCC 2006b) to represent the variability due to randomness in the distribution of a given sample (e.g., with a mean, variance, and normal distribution). In contrast, epistemic uncertainty is defined as lack of knowledge (imprecise and incomplete information) about the true value of a variable or about the system mechanism. It can be decreased if more precise information or more accurate measurement becomes available. In LCA, epistemic uncertainty in parameters is often represented with probability distributions (Lloyd and Ries 2007; Huijbregts 1998), and both types of uncertainty are propagated by Monte-Carlo simulation (MCS), especially in complex models. MCS is an effective and robust way to estimate the uncertainty in predicted potential impacts (Payraudeau et al. 2007; Sonnemann et al. 2003). Some authors (Tan 2008; Reza et al. 2013; Andre and Lopes 2012; Mauris et al. 2001; Chevalier and Téno 1996), however, emphasize the difference between variability and epistemic uncertainty and argue that fuzzy-set theory (Zadeh 1978), with subjective degrees of plausibility/possibility, better represents uncertainty due to imprecise and incomplete information.

Since variability and epistemic uncertainty represent distinct states of knowledge, many studies have modeled them separately in the same framework. For example, Ferson et al. (2002) constructed "probability boxes" by combining probability theory and set theory. Baudrit et al. (2006) represented random variability and imprecision with probability and possibility distributions, respectively, and then propagated them for risk assessment. And Baraldi and Zio (2008) combined MCS and the possibilistic approach to propagate uncertainty. These three studies introduced the Dempster-Shafer theory (Dempster 1966; Shafer 1976) to incorporate imprecise information into probabilistic models, making a bridge that combines uncertainties from different sources (Yager 1987).

Although variability and epistemic uncertainty have been defined, and sometimes analyzed, separately in some LCA studies (Heijungs and Huijbregts 2004; Basset-Mens et al. 2009), few studies (Clavreul et al. 2013) have modeled them in the same framework. The aim of this study is to demonstrate how to combine two types of uncertainty, via Dempster-Shafer theory, to estimate potential environmental impacts of dairy farms. We then compare this method to classic probability methods.

2. Methods

We used probability distributions and fuzzy intervals to represent variability and epistemic uncertainty, respectively. These two types of uncertainty were propagated into LCA results by MCS and interval analysis using R software (R Development Core Team 2012). For each impact category, distributions of impact were represented by a Dempster-Shafer structure and mean impacts were represented by fuzzy intervals. In addition, two other methods for analyzing uncertainty were applied for comparison purposes.

2.1. Representing variability with probability distributions

In a frequentist approach, a probability distribution assigns a probability of any possible event in a random experiment. It is often used to represent the variability of a variable. A random variable X, which is an element of all real numbers ($\mathcal{R}$), has a probability Pr(x) of having value x. In addition, the probability distribution can be described by its cumulative distribution function (CDF) and explained as the probability that X is less than x:

$$F(x) = Pr(X \leq x), for\ all\ x \in \mathcal{R} \qquad \text{Eq. 1}$$

In general, determining a distribution requires empirical data to identify its shape and basic parameters (e.g., mean and variance). If the amount of empirical data is sufficiently large, it can be considered to represent the entire population. However, since data acquisition is often limited by time and cost in LCA studies, probability distributions are generally determined subjectively based on the literature or expert judgment (Heijungs and Frischknecht 2005).

MCS is the most common method for propagating variability to estimate uncertainty in LCA studies. It consists of sampling input variables from their distributions and then calculating potential impacts through the model. By repeating the MCS many times, a CDF can be constructed to predict a probability range that represents overall uncertainty in impacts due to uncertainty in input variables.

2.2. Representing epistemic uncertainty with fuzzy intervals

Fuzzy-set theory is an alternative approach to express epistemic uncertainty. In this approach, an uncertain variable is modeled by a set of “fuzzy” intervals, each with a level of possibility (α) that ranges from 0 (least possible) to 1 (most possible). Denoting each fuzzy interval as $\pi(\alpha_i)$, there is:

$$\pi(\alpha = 1) \subseteq \pi(\alpha_i \in [0,1]) \subseteq \pi(\alpha = 0) \qquad \text{Eq. 2}$$

An uncertain variable can be mapped by a membership function defined by these “fuzzy” intervals and their corresponding levels of possibility. Commonly-used membership functions are shaped as triangles or trapezoids having minimum, maximum and mode values (mode intervals for the latter) (Fig. 1). For example, the minimum-maximum range of variable x, called the “support” (α=0), indicates all possible values of x. The mode (or mode interval), called the “core”, indicates the most likely value(s) (α=1). At any given α level, there is a corresponding interval (called the “α-cut interval”). To propagate uncertainty, the fuzzy intervals of input variables are decomposed at each α level, and interval arithmetic is applied to generate a set of fuzzy intervals of the final result.

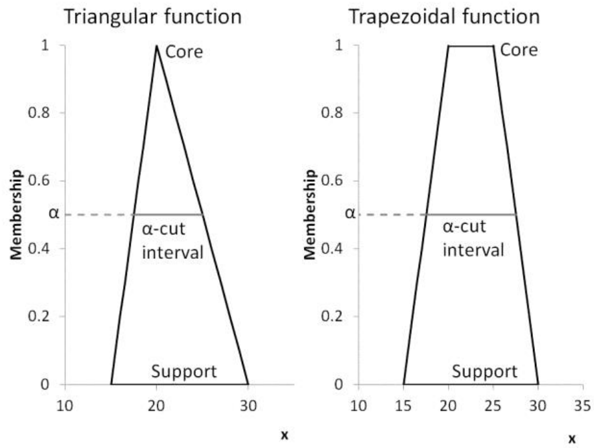

Figure 1. Triangular (left) and trapezoidal (right) fuzzy-interval membership functions for an uncertain variable x defined by core, support and α-cut intervals.

2.3. Dempster-Shafer theory

Dempster-Shafer theory (DST) is a "mathematical theory of evidence" introduced by Dempster (1966) and further developed by Shafer (1976). It is a generalization of discrete probability theory in which probabilities are assigned to sets of values rather than a single value. One important feature of DST is that imprecise information can be used to represent the state of knowledge quantitatively. It includes three basic functions: the basic probability assignment (bpa) function (or "mass function"), the belief function (Bel) and the plausibility function (Pl).

The bpa for a given set *A* (denoted *m(A)*) indicates the proportion of all available evidence that supports the supposition that a particular element of *x* belongs to set *A*. It has axioms such as:

$$m: 2^{\Omega} \rightarrow [0, 1] \quad \text{Eq. 3}$$

$$m(\emptyset) = 0 \quad \text{Eq. 4}$$

$$\sum_{A \in 2^{\Omega}} m(A) = 1 \quad \text{Eq. 5}$$

where 2^{Ω} is the power set that comprises all possible subsets, including the empty set $\emptyset$. *A* is any subset (called a "focal element") of power set. The belief and plausibility functions are defined from the bpa. The belief function of *A* is the sum of the bpa of all of the subsets (*B*) of *A* ($B \subseteq A$):

$$Bel(A) = \sum_{B \subseteq A} m(B), B \textit{ is all of the subsets of } A, \textit{and } B \neq \emptyset \quad \text{Eq. 6}$$

The plausibility function of *A* is the sum of the bpa of any subset (*C*) of power set with the condition that the intersection of *C* and *A is a non-empty set* ($C \cap A \neq \emptyset$):

$$Pl(A) = \sum_{C \cap A \neq \emptyset} m(C), C \in 2^{\Omega}, \textit{and } C \neq \emptyset \quad \text{Eq. 7}$$

The three concepts can also be used in continuous probability distributions where any element of the uncertain parameter *x* is expressed as an interval ($[a_i, b_i]$) with bpa_i (where $a_i \leqslant b_i$ for all *i*). Thus, the power set *A* is the collection of these intervals with their corresponding bpa_i, and the sum of bpa_i equals 1. So, Eq. 6 and 7 can be transformed as:

$$Bel(x \in]-\infty, x]) = \sum_{b_i \leq x} m([a_i, b_i]) \quad \text{Eq. 8}$$

$$Pl(x \in]-\infty, x]) = \sum_{a_i \leq x} m([a_i, b_i]) \quad \text{Eq. 9}$$

The belief and plausibility functions can be considered the lower and upper probabilities of a given value of x (Ferson et al. 2002), respectively, and the true probability distribution of x ($Pr(x)$) lies inside them, interpreted as:

$$Bel(x) \leq Pr(x) \leq Pl(x) \quad \text{Eq. 10}$$

with an interval of the mean of x

$$\sum m_i a_i \leq E(x) \leq \sum m_i b_i \quad \text{Eq. 11}$$

If uncertain parameter x is determined by a single set of values ($a_i = b_i$ for all i) instead of intervals, the belief and plausibility functions converge on the same distribution, as in a classic CDF.

We considered fuzzy intervals of uncertain parameters as focal elements, used DST to combine variability and epistemic uncertainty in input-parameter values, and propagated them with MCS. Thus, assuming that impact category (y) is calculated by the model ($f(x_1, x_2 \ldots x_k, x_{k+1}, x_{k+2} \ldots x_n)$), we:

1. Randomly generate a matrix (B rows (10,000) × k columns) of the first k variables using each one's probability distribution while preserving correlations between them: $M_b(x_1, x_2 \ldots x_k)$.
2. Select a possibility level α_i (e.g., assign values from 0 to 1 with step 0.1) and its corresponding fuzzy interval ($\pi^{k+1}, \pi^{k+2} \ldots \pi^n$) for the last n-k uncertain parameters ($x_{k+1}, x_{k+2} \ldots x_n$).
3. Using the variables in each row of $M_b(x_1, x_2 \ldots x_k)$, calculate minimum and maximum values of y with all possible combinations of the last n-k variables ($= 2^{(n-k)}$) in α_i, with a lower bound of L(y) = max [$f(x_1, x_2 \ldots x_n)$] and an upper bound of U(y) = min [$f(x_1, x_2 \ldots x_n)$]. For a model with only monotone functions, the optimization algorithm can be simplified by interval analysis.
4. Repeat steps 2 and 3 for all α_i to generate the fuzzy intervals of y_b ($[U(y), L(y)]_b$) and find the support of y_b (denoted $\pi (y_b)_{\alpha=0}$). Then attribute a mass ($m_b = 1/B$) to the support.
5. Repeat steps 2-4 B times to obtain a set of supports ($\pi_1, \pi_2, \ldots, \pi_B$) as focal elements, which is used to construct lower (belief function) and upper (plausibility function) bounds of y using Eq. 8 and 9.
6. Calculate the mean of the lower and upper bounds of y using Eq. 11 for each α to generate fuzzy intervals of the mean of y.

For example, assume that indicator Y is modeled by a function with two uncertain parameters (X_1 and X_2), $Y = X_1 \times X_2$, where X_1 is normally distributed ($X_1 \sim N_{prob}(100,20)$) and X_2 is modeled by a triangular membership function ($X_2 \sim T_{fuzzy}(2, 6, 3)$). Thus, we construct the lower and upper bounds of Y and fuzzy intervals of the mean of Y at each α (Fig. 2) by following the above steps. Consequently, this procedure generates a set of intervals (11, in this study) with their corresponding α, and the mean of Y is represented as a membership function of this fuzzy set that is determined by its support, core and other α-cut intervals.

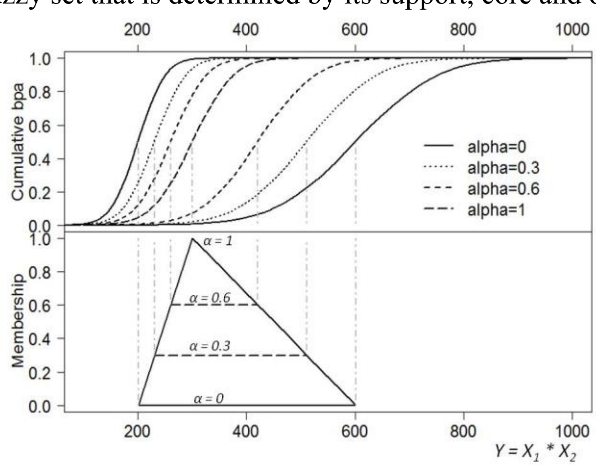

Figure 2. (Top) Lower (belief) and upper (plausibility) bounds of indicator Y at different possibility levels (α) and (bottom) fuzzy intervals of the mean of Y with support (α=0), core (α=1) and two α-cut intervals (at α=0.3 and 0.6).

2.4. Case study

We constructed an LCA model to estimate environmental impacts (climate change, acidification and eutrophication) of on-farm emissions of dairy farms. The functional unit was 1 metric ton of fat-and-protein corrected milk (FPCM). This model was based on the EDEN-E (Evaluation de la Durabilité des ExploitatioNs) tool, developed previously to estimate LCA-based environmental impacts of individual dairy farms (van der Werf et al. 2009). In this study, we focused only on direct impacts of the milk-production subsystem, because they were affected directly by uncertainty in emission factors. We used data from 41 conventional dairy farms from EDEN-E datasets. We obtained input variables such as animal production (e.g., meat, milk), number of animals by age and sex, and usable agricultural area. Other variables such as quantities of nitrogen (N) in farm inputs and outputs (e.g., fertilizers, feed, waste, animals), energy agents (e.g., diesel, gasoline, electricity), lubricants and plastics were also taken from EDEN-E. In addition, emission factors were used to estimate gaseous emissions; their default values and ranges of uncertainty were taken from the literature (IPCC 2006a; EMEP-CORINAIR 2001). These variables were used in the model to estimate direct impacts of conventional dairy farms. We considered two types of uncertainty in input variables: variability in structural characteristics of sampled farms and epistemic uncertainty in emission factors. Impact categories were calculated by multiplying emissions with the characterization factors of the CML-IA database (Guinée et al. 2002).

To compare results with those of the classic probability method, we made three scenarios to analyze uncertainty in the LCA model. For all scenarios, we used truncated normal or uniform distributions to represent variability in each farm characteristic because they provided only non-negative values. Means and standard deviations for each characteristic were determined from the empirical EDEN-E sample. Correlations between these variables were preserved using Spearman rank-order correlation (Helton and Davis, 2003). In the first scenario (S1), uncertainty in emission factors was ignored (default constants used). In the second scenario (S2), we considered uncertainty in emission factors with triangular probability distributions. In S2, default values and ranges of uncertainty were used as the mode and minimum/maximum values in the distribution, respectively. In the third scenario (S3), we used fuzzy intervals with triangular membership functions to represent uncertainty in emission factors. The same default values and ranges of uncertainty were used as the core and support in the membership function, respectively. Indeed, S1 can be considered a special case of S3 that considers only the core interval (α=1). Each emission factor was assumed to be independent. Scenarios S1 and S2 used MCS to propagate uncertainties, while S3 combined MCS and interval arithmetic to generate an interval distribution. Simulations were repeated 10,000 times. In S3, finding minimum and maximum impact values for each of the 10,000 replicates theoretically required calculating all possible combinations of emission factors (2^m combinations, m = number of emission factors), but doing so would have increased calculation time considerably. Therefore, since the LCA model was monotonic (emission factors used only addition and multiplication), calculations were optimized by using the minimum and maximum of each α-cut interval of emission factors.

Statistics (mean, 5th and 95th percentiles) of impact indicators were calculated as single values in S1 and S2 and as intervals in S3. To compare uncertainty in mean impact between categories, we calculated a "relative interval width" (RIW), equal to the maximum of a statistic's interval minus its minimum, divided by its mode. Thus, the RIW of mean impact in S3 was the width of the indicator's mean interval (i.e. its support) divided by its core (i.e. the most likely mean value). Because uncertainty in emission factors was assumed to be zero in S1 and a known distribution in S2, they were considered to have intervals of zero width.

3. Results

Statistics of the three impact categories differed by scenario (Table 1). For all three impact categories, the difference between the 5th and 95th percentiles ($I_{percentile}$) in S1 and S2 was narrower than the difference between the minimum of the 5th-percentile interval and the maximum of the 95th-percentile interval in S3, indicating higher overall uncertainty in S3. The increase in overall uncertainty was due to inclusion and representation of epistemic uncertainty in emission factors. The percentage increase in $I_{percentile}$ from S1 to S2 was 25% for climate change, 80% for acidification, and 0% for eutrophication, while that from S1 to S3 was 212% for climate change, 372% for acidification and 29% for eutrophication. Thus, overall uncertainty in impacts increased greatly when uncertainty in emission factors was considered as imprecise information.

Table 1. Statistics of potential climate change, acidification and eutrophication impacts per t of fat-and-protein-corrected milk (FPCM) in three scenarios that represented uncertainty in emission factors (EFs) differently: S1 - no uncertainty in EFs, S2 - probability distributions for EFs, S3 - fuzzy sets for EFs.

	Climate change ($kg\ CO_2$ eq./t FPCM)			**Acidification ($kg\ SO_2$ eq./t FPCM)**			**Eutrophication ($kg\ PO_4$ eq./t FPCM)**		
Statistics	**S1**	**S2**	**S3**	**S1**	**S2**	**S3**	**S1**	**S2**	**S3**
Lower limit (5th percentile)	775	852	[511, 1383]	8.1	9.5	[3.6, 18.2]	4.3	3.9	[2.7, 5.0]
Mean (support of the mean)	1065	1208	[718, 1874]	10.8	14.3	[4.8, 24.3]	8.6	8.2	[6.6, 9.4]
Upper limit (95th percentile)	1400	1632	[947, 2459]	14.2	20.5	[6.3, 32.4]	13.7	13.3	[11.4, 14.8]
Relative interval width of the mean	0%	0%	89%	0%	0%	134%	0%	0%	35%

When visualized as CDFs (Fig. 3), S1 and S2 were represented by a single CDF each, while S3 was represented by two CDFs (plausibility and belief functions) defining upper and lower bounds of impact in each category (Fig. 3). These bounds were more widely separated for acidification and climate change impact than eutrophication.

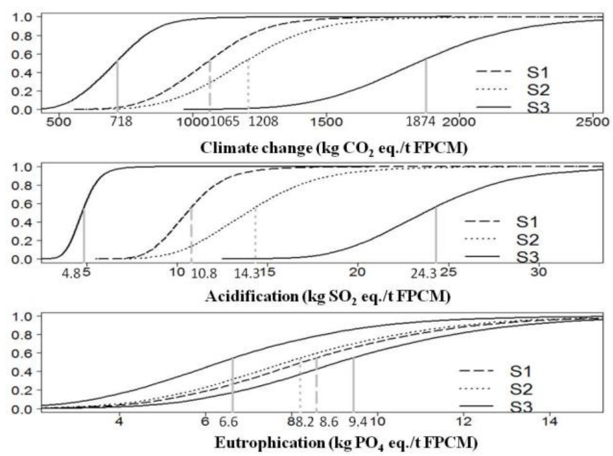

Figure 3. Cumulative density functions of direct (on-farm) climate change, acidification, and eutrophication impacts per t of fat-and-protein corrected milk (FPCM) in three scenarios that represented uncertainty in emission factors (EFs) differently: S1 - no uncertainty in EFs, S2 - probability distributions for EFs, S3 - fuzzy sets for EFs (solid curves bound 90% of possible values). Vertical gray lines indicate the mean impact (support of mean impact in S3) of each scenario.

Membership functions of mean impacts in S3 were nearly triangular, with minor skewness (Fig. 4). For example, the support of climate change ranged from 718-1874 kg CO_2 eq./t FPCM, with a core of 1065 kg CO_2 eq./t FPCM. Note that the core of mean impact in S3 equaled the mean impact in S1, for which default values (considered as the true values) were used for emission factors. RIWs of mean impacts in S3 indicate that uncertainty in mean acidification impact (134%) was larger than that in mean climate change (89%) or eutrophication (35%) impacts (Table 1). However, S1 and S2 each had a single mean (e.g., 1208 and 1065 kg CO_2 eq./t FPCM, respectively) and RIWs of mean impact of 0%.

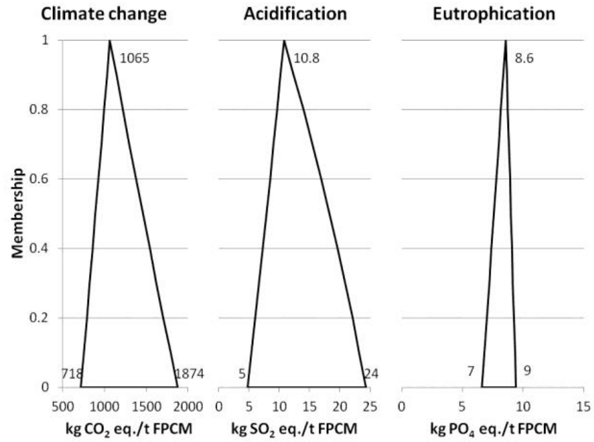

Figure 4. Fuzzy-interval distributions of means of climate change, acidification, and eutrophication impacts per t of fat-and-protein-corrected milk (FPCM) in scenario 3 (based on Dempster-Shafer theory).

4. Discussion

We focused on two sources of uncertainty in this case study: variability (in farm characteristics) and epistemic uncertainty (in emission factors). The classic probabilistic approach expresses both epistemic uncertainty and variability with probability distributions; however, subjectively defining probability distributions may underestimate overall uncertainty. Therefore, unknown distributions should be considered as another source of uncertainty due to incomplete information and modeled with fuzzy intervals. If both probability distributions and fuzzy intervals exist in the same analysis, our DST-based method can combine them to estimate overall uncertainty in impact (S3). It provides a more conservative range of uncertainty (i.e. the interval between the minimum of the 5^{th} percentile and maximum of the 95^{th} percentile) than the classic probabilistic approach. Since S1 considered only variability in farm characteristics, the increase in overall uncertainty in impacts in S2 and S3 compared to S1 reflects the contribution of epistemic uncertainty in emission factors alone. Considering emission factors as fuzzy intervals (S3) increased overall uncertainty more than considering them as random values (S2). Unlike variability, epistemic uncertainty in emission factors can be reduced when more precise information becomes available. For example, any distribution inside the bounds of plausibility and belief yields a mean value and a smaller range of uncertainty, because the true values (S1) or distributions (S2) of input variables are known or assumed to be known.

In parallel, the imprecision in emission factors was propagated into mean impacts, which were constructed from membership functions of their fuzzy sets. Those who used a similar propagation procedure in LCA (Clavreul et al. 2013) or risk assessment (Baudrit et al. 2006) studies considered all fuzzy intervals of impact as a set of random intervals with equal probability and then calculated a weighted-mean interval from upper and lower bounds of distributions. In contrast, we separated this process into two steps: (1) estimate the overall range of all possible impact values using the supports of emission factors and (2) model mean impacts with fuzzy intervals. Indeed, showing the membership function of mean impact instead of a weighted-mean interval provides more information to decision makers, such as the levels of possibility corresponding to the most likely mean impact and mean impacts of best- and worse-case scenarios based on the degree of possibility. This information allows a more precautionary approach than a simple interval of mean impact for evaluating the magnitude of and uncertainty in predicted impacts. For fuzzy intervals, the RIW of mean impact is a comparative indicator that reflects the influence of explicitly representing the knowledge of information as incomplete (an unknown distribution), unlike the classic probability method, which ignores this source of uncertainty. It enables the influence of epistemic uncertainty on different impacts to be compared when calculating a coefficient of variation is difficult or complex (e.g., in S3, which comprised multiple probability distributions). Comparing RIWs among impact categories illustrates the relative influence of epistemic uncertainty on overall uncertainty in the impacts of each. If overall uncertainty is hindering decision making, this information could lead decision makers to focus on reducing the sources of epistemic uncertainty that contribute the most to uncertainty in impacts. For example, since epistemic uncertainty in emission factors had a larger influence on acidification than eutrophication impacts in this study, more precise measurement of acidification-related emissions would have a relatively larger influence in reducing overall uncertainty in an impact.

For the sake of simplicity, we illustrated a simple LCA example based on a previous work. It had far fewer variables and parameters than a full LCA study; in addition, the model was monotonic, which simplified the optimization algorithm in the simulation. Increasing the number of uncertain variables (especially imprecise variables) may increase the complexity of computation and even greatly overestimate uncertainty. Therefore, performing an initial sensitivity analysis of the LCA model is recommended (Heijungs 1996; Henriksson et al. 2013) to focus on the input variables that influence potential impacts the most. This decrease in the number of uncertain input variables may accelerate the optimization algorithm, especially in more complex and non-monotonic models.

Correlations between random variables (i.e., inter-farm variability) were preserved in this study, while independence was assumed between random variables and imprecise parameters (emission factors). This assumption allowed a conservative confidence interval of impacts to be generated for all three scenarios, because all possible combinations of input variables were included in the stochastic simulation. However, representing dependence between random variables and imprecise parameters (if known) could improve the precision of predicted impacts. More research is needed on this issue to improve the validity of LCA results.

The DST-based method constructs two boundary distributions using belief and plausibility functions. This structure has been interpreted as “imprecise probability” (Ferson et al. 2002), which covers all possible probability distributions. Although it reflects the true state of knowledge (e.g., incomplete information about emission factors), an extremely wide range of potential impact is likely to be less useful for decision makers. Thus, simplifying interpretation of results by decision makers remains an open question. To address this problem in LCA, Clavreul et al. (2013) calculated a “confidence index” (Dubois and Guyonnet 2011) to generate a weighted probability distribution. Decision makers can choose this confidence index subjectively, depending on whether their decision policies are more optimistic (close to the upper bound) or pessimistic (close to the lower bound). We concur that this kind of confidence index is useful for decision making in LCA studies when uncertainty is modeled with imprecise and incomplete information.

5. Conclusion

The classic probability method is rigorous in that it requires precise information to express an uncertain variable, but subjective assumption about its distribution may underestimate uncertainty in the predicted result. In addition, it cannot separate epistemic uncertainty from variability, meaning that decision makers will have no information about the relative influence of each on overall uncertainty. Our proposed method overcomes this limit by integrating fuzzy intervals to represent imprecise data (e.g., emission factors) in probability models. As a consequence, a distribution with two bounds and fuzzy intervals of mean impact was generated. Combining the effects of variability and epistemic uncertainty yields a wider range of potential impacts, which may influence decision making. Fuzzy intervals of mean impact model the uncertainty in mean values. The RIW of mean impact, as a comparative indicator, reveals the influence of epistemic uncertainty on uncertainty in impacts, which may help decision makers adopt appropriate strategies if they want to improve the reliability of LCA results.

The paper demonstrated the application of DST in uncertainty analysis in a simple LCA study. Representing the lack of knowledge as fuzzy intervals differs from treating it as randomness. Thus, it provides a conservative but robust way to represent the state of knowledge in LCA studies when information is scarce. Its application in LCA is currently limited, however, due to its greater model complexity and, if epistemic uncertainty is large, greater difficulty in distinguishing potential differences among scenarios. Considering dependence among input variables is also important, since it gives more precise results, but techniques for doing so with fuzzy-interval variables are difficult or complex. Therefore, more research is needed to focus on these issues to improve the feasibility of this method in LCA.

6. References

Andre JCS, Lopes DR (2012) On the use of possibility theory in uncertainty analysis of life cycle inventory. Int J Life Cycle Assess 17 (3):350-361. doi:10.1007/s11367-011-0364-9

Baraldi P, Zio E (2008) A combined Monte Carlo and possibilistic approach to uncertainty propagation in event tree analysis. Risk Anal 28 (5):1309-1326

Basset-Mens C, Kelliher FM, Ledgard S, Cox N (2009) Uncertainty of global warming potential for milk production on a New Zealand farm and implications for decision making. Int J Life Cycle Assess 14 (7):630-638. doi:10.1007/s11367-009-0108-2

Baudrit C, Dubois D, Guyonnet D (2006) Joint propagation of probabilistic and possibilistic information in risk assessment. IEEE transactions on Fuzzy Systems 14 (5):593-608

Benetto E (2005) Analyse du cycle de vie. Incertitudes des évaluations des impacts. Ed. Techniques de l'Ingénieur, Turin, Italy

Bjorklund AE (2002) Survey of approaches to improve reliability in LCA. Int J Life Cycle Assess 7 (2):64-72. doi:10.1065/lca2001.12/071

Chevalier JL, Téno JFÇL (1996) Life cycle analysis with ill-defined data and its application to building products. Int J Life Cycle Assess 1 (2):90-96

Clavreul J, Guyonnet D, Tonini D, Christensen TH (2013) Stochastic and epistemic uncertainty propagation in LCA. Int J Life Cycle Assess 18 (7):1393-1403

De Rocquigny E, Devictor N, Tarantola S (2008) Uncertainty in industrial practice: a guide to quantitative uncertainty management. Wiley, Chichester

Dempster AP (1966) New methods for reasoning towards posterior distributions based on sample data. Ann Math Stat 37 (2):355-374

Dubois D, Guyonnet D (2011) Risk-informed decision-making in the presence of epistemic uncertainty. Int J Gen Syst 40 (2):145-167

EMEP-CORINAIR (2001) Emission Inventory Guidebook - Chapter 10: Agriculture. 3rd edn. European Environment Agency, Copenhagen, Denmark

Ferson S, Kreinovich V, Ginzburg L, Myers DS, Sentz K (2002) Constructing probability boxes and Dempster-Shafer structures. Sandia National Laboratories, Albuquerque, New Mexico

Finnveden G (2000) On the limitations of life cycle assessment and environmental systems analysis tools in general. Int J Life Cycle Assess 5 (4):229-238

Guinée JB, Gorrée M, Heijungs R, Huppes G, Kleijn R, de Koning A, van Oers L, Wegener Sleeswijk A, Suh S, Udo de Haes HA, de Bruijn H, van Duin R, Huijbregts MAJ (2002) Handbook on life cycle assessment operational guide to the ISO standards. Int J Life Cycle Assess 7 (5):311-313

Heijungs R (1996) Identification of key issues for further investigation in improving the reliability of life-cycle assessments. J Clean Prod 4 (3):159-166

Heijungs R, Frischknecht R (2005) Representing statistical distributions for uncertain parameters in LCA. Int J Life Cycle Assess 10 (4):248-254. doi:10.1065/lca2004.09.177

Heijungs R, Huijbregts MAJ A review of approaches to treat uncertainty in LCA. In: IEMSS International Congress: "Complexity and Integrated Resources Management". Osnabrueck, Germany, 2004.

Henriksson M, Flysjö A, Cederberg C, Swensson C (2011) Variation in carbon footprint of milk due to management differences between Swedish dairy farms. Anim J 5 (9):1474-1489

Henriksson P, Guinée J, Heijungs R, Koning A, Green D (2013) A protocol for horizontal averaging of unit process data—including estimates for uncertainty. Int J Life Cycle Assess 19 (2):1-8. doi:10.1007/s11367-013-0647-4

Huijbregts MAJ (1998) application of uncertainty and variability in LCA - part II: Dealing with parameter uncertainty and uncertainty due to choices in life cycle assessment. Int J Life Cycle Assess 3 (6):343-351

IPCC (2006a) Emissions from livestock and manure management. In: IPCC Guidelines for National Greenhouse Gas Inventories. Intergovernmental Panel on Climate Change, vol 4: Agriculture, Forestry and Other Land Use.

IPCC (2006b) Uncertainties in: IPCC Guidelines for National Greenhouse Gas Inventories. Intergovernmental Panel on Climate Change, vol 1: General Guidance and Reporting.

ISO (2006) ISO 14040 International Standard. In: Environmental management—life cycle assessment—requirements and guidelines International Organization for Standardization, vol ISO:14044. International Organization for Standardization, Geneva

Lloyd SM, Ries R (2007) Characterizing, propagating, and analyzing uncertainty in life-cycle assessment - A survey of quantitative approaches. J Ind Ecol 11 (1):161-179. doi:10.1162/jiec.2007.1136

Mauris G, Lasserre V, Foulloy L (2001) A fuzzy approach for the expression of uncertainty in measurement. Measurement 29 (3):165-177. doi:10.1016/s0263-2241(00)00036-1
Morgan MG, Henrion M (1992) Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy analysis. Cambridge University Press, New York
Payraudeau S, van der Werf HMG, Vertes F (2007) Analysis of the uncertainty associated with the estimation of nitrogen losses from farming systems. Agric Syst 94 (2):416-430. doi:10.1016/j.agsy.2006.11.014
R Development Core Team (2012) R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing. Retrieved from http://www.R-project.org, Vienna, Austria
Reza B, Sadiq R, Hewage K (2013) A fuzzy-based approach for characterization of uncertainties in emergy synthesis: an example of paved road system. J Clean Prod 59:99-110. doi:10.1016/j.jclepro.2013.06.061
Shafer G (1976) A mathematical theory of evidence, vol 1. Princeton University press, Princeton, NJ
Sonnemann GW, Schuhmacher M, Castells F (2003) Uncertainty assessment by a Monte Carlo simulation in a life cycle inventory of electricity produced by a waste incinerator. J Clean Prod 11 (3):279-292. doi:10.1016/s0959-6526(02)00028-8
Tan RR (2008) Using fuzzy numbers to propagate uncertainty in matrix-based LCI. Int J Life Cycle Assess 13 (7):585-592. doi:10.1007/s11367-008-0032-x
Thomassen MA, van Calker KJ, Smits MCJ, Iepema GL, de Boer IJM (2008) Life cycle assessment of conventional and organic milk production in the Netherlands. Agric Syst 96 (1-3):95-107. doi:10.1016/j.agsy.2007.06.001
van der Werf HMG, Kanyarushoki C, Corson MS (2009) An operational method for the evaluation of resource use and environmental impacts of dairy farms by life cycle assessment. J Environ Manage 90 (11):3643-3652
van der Werf HMG, Petit J (2002) Evaluation of the environmental impact of agriculture at the farm level: a comparison and analysis of 12 indicator-based methods. Agric, Ecosyst Environ 93 (1-3):131-145. doi:10.1016/S0167-8809(01)00354-1
Vose D (2008) Risk analysis: a quantitative guide. 3rd edn. Wiley, Chichester, West Sussex, England
Weidema B, Wesnaes MS (1996) Data quality management for life cycle inventories-an example of using data quality indicators. J Clean Prod 4 (3-4):167-174
Yager RR (1987) On the Dempster-Shafer framework and new combination rules. Inform Sciences 41 (2):93-137
Zadeh LA (1978) Fuzzy sets as a basis for a theory of possibility. Fuzzy Set Syst:3-28

This paper is from:

Proceedings of the 9th International Conference on Life Cycle Assessment in the Agri-Food Sector

LCA Food 2014

8-10 October 2014 - San Francisco

Rita Schenck and Douglas Huizenga, Editors
American Center for Life Cycle Assessment

The full proceedings document can be found here:
http://lcacenter.org/lcafood2014/proceedings/LCA_Food_2014_Proceedings.pdf

It should be cited as:

Schenck, R., Huizenga, D. (Eds.), 2014. Proceedings of the 9th International Conference on Life Cycle Assessment in the Agri-Food Sector (LCA Food 2014), 8-10 October 2014, San Francisco, USA. ACLCA, Vashon, WA, USA.

Questions and comments can be addressed to: staff@lcacenter.org

ISBN: 978-0-9882145-7-6