The Influence of Agricultural Data Uncertainty in the Life Cycle Assessment of Biodegradable Hydraulic Lubricants

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Abstract: From a Life Cycle Assessment study of hydraulic lubricants from vegetable and mineral oil, it has been found that the agricultural step in the biodegradable hydraulic lubricant production has the main environmental impact. The aim of this study is to develop an uncertainty analysis of agricultural data used in the biodegradable hydraulic lubricant inventory from this LCA to determine the influence of data uncertainty in the environmental LCA result. Two parameters have been selected for the uncertainty analysis: fertilization practices and machinery operations. A variation parameter analysis has been carried out obtaining that assumptions and simplifications made (pre-treatment soil operations and fertilization rates), which clearly influence on the different impact categories studied. A Monte Carlo analysis has been performed showing Eutrification Potential category is the most affecting by input data uncertainty propagation, which means the fuel consumption and fertilization rates input data need to be selected from a more accuracy source.

Keywords: Uncertainty analysis, Life Cycle Inventory (LCI), data quality, Monte Carlo simulation, agriculture, parameter variation.

1. INTRODUCTION

Thousands of tons of oil are discharged into nature causing important environmental problems and leading to the need of alternative lubricant products with minimal environmental impact. To support the key environmental decision in replacing conventional mineral lubricants with one based on vegetable oil, a cradle-to-grave Life Cycle Assessment (LCA) must be performed following the stages of the both processes, which are shown in the Figure 1.

The process for obtaining mineral lubricants is already clearly defined and well-known. On the other hand, the manufacturing process of vegetable oil based lubricants is not so defined, as the agricultural step has not been so much established.

Thus, the major environmental impact contribution in the biodegradable lubricant process comes from the agricultural step. However, data quality for the agricultural production is one of the main sources of uncertainty, specially regarding the establishment of valid data sets describing crop production in a consistent way, which includes the choice of representative regions as well as adequate scenarios.

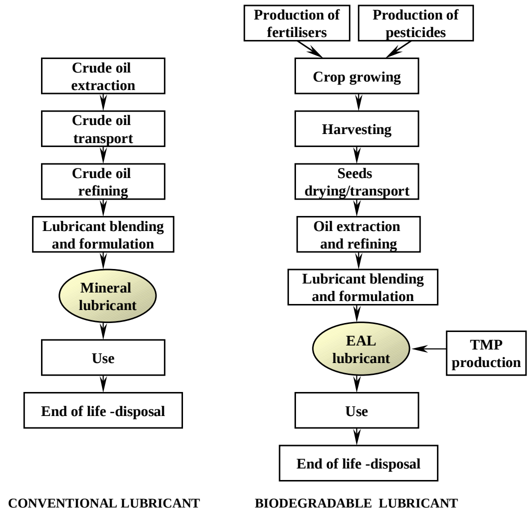

Figure 1. Process stages of two systems compared.

Nowadays, it is well recognized that different sources of uncertainty are present in life cycle inventories and impact assessments, but modelling data uncertainty is not a common practice in life cycle inventories. Validity of results obtained in a Life Cycle Assessment gains by a data quality evaluation.

A LCA study has been carried out on hydraulic lubricants from mineral and vegetable oil in which the functional unit has been defined as 20.000 working hours, taking into account the life expectancy of a lubricant in a typical hydraulic system. From this LCA has been proven that crop production represents the most environmentally unfriendly step in the biodegradable lubricant manufacturing.

The goal of this study, therefore, is to develop an uncertainty analysis of agricultural data used in the biodegradable hydraulic lubricant inventory from this comparative LCA to determine the influence of data uncertainty in the environmental comparative LCA result.

2. MODELLING THE AGRICULTURAL SYSTEM

Concentrating on the crop production step, it is important to consider the influence of agricultural field activities as well as fertilizers and pesticides production or transportation stages [Brentrup, 2000]. Therefore, parameters like yield, fertilization rates, nitrate leaching, ammonia volatilisation or energy consumption do not contribute in the same way in the final environmental impact.

The scheme of the involved steps in a crop production are shown in the Figure 2.

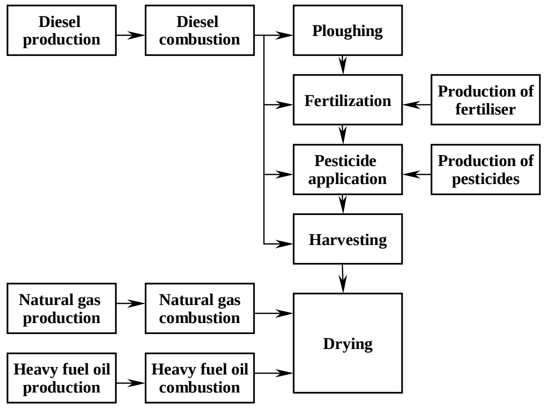

Figure 2. Stages considered in the agriculture step of the study.

Taking into account the preliminary results obtained from the LCA study and in order to carry out the uncertainty analysis, two main parameters has been selected from agricultural step: fertilization rates and energy consumption, which produce the highest environmental impact. In case of energy consumption, the input parameter has been expressed as diesel consumption in the machinery operations.

2.1. Energy consumptions

The machinery operations in the vegetable base hydraulic lubricant production have shown a significant impact on the overall results of LCA. These operations include: pre-treatment, ploughing, harrowing, harvesting, etc. This machinery use is referred to the fuel consumption; which means the fuel combustion is an input variable in the analysis.

The production of machines as such and the effect of use on the life of the machine have been excluded in the study.

The calculation of the use of fuel has been estimated once the farming operations have been established for the crop production which is used in the vegetable oil obtention. This estimation has been based on the average power needed to carry out each operation and on the fuel used to supply this power [Lee, 2000.] Finally, data for emissions associated to fuel combustion in machining operations have been taken from Dalgaard [2003].

In reference to energy consumptions, the energy used to dry grains before storage has to be consider. Seeds are dried by been heated with a natural gas-fired burner which usually operates at moderate temperature to prevent cracking. Therefore, the amount of water to be removed from the crop has been considered as the factor determining fuel consumption [Weidema, 1999].

2.2. Fertilization considerations

LCI average rates estimated from European sources [FAOstat] have been taken due to the data heterogeneity in crops fertilization.

As it has been said before, agriculture is by far the main source of emissions, nearly 90% of the global emissions identified in the comparative LCA analysis [Audsley, 1997] and this impact is directly associated to total NH_3 and NO_x emissions as a consequence of crops fertilization.

N-related emissions have been shown a high influence on many complex interactions between soil type and climatic conditions and, on the other hand, on parameters determined by means the agricultural management practices. That is the reason why it is often difficult to derive exact rates for N release to air and water.

Because of lack of agricultural data to quantify the loss of N fertilizer from ammonia volatilisation and emission of nitric oxide (NO_x) through nitrification after fertilizer is applied to fields, emission prediction models have been considered from Bouwman [1996]. This author proposed an emissions factor for N_2O from mineral and organic fertilizers, simplifying the complex dependencies of the fertilization parameters.

This study has not been taken into account the manure and pesticide application.

3. DATA QUALITY IN AGRICULTURAL LCA STAGE

LCA methodologies were primarily designed for industrial applications, and therefore this tool shows some difficulties when is applied to agricultural systems. Table 1 shows different characteristics assessing industrial and agricultural systems and summarizes the main problems performing an agricultural LCA.

Characteristics (Table 1) determine that the choices made in the agricultural step of a vegetable lubricant life cycle have a major contribution to environmental impacts of the chain.

Table 1. Main characteristics of industrial and agricultural systems[Milà i Canals, 2003].

Characteristics	Industrial Systems	Agricultural Systems
Dependency from location	Highly independent	Highly dependent
System boundaries	Clearly defined	Unclear, both physically and temporally
Main source of impacts	Energy and materials consumption	Land use, energy and materials consumption, and field emissions
Degree of knowledge	High (simple and pre-designed processes)	Relatively low (complex, natural processes)
Functionality	One or few functions	Multifunctional

It is well known the importance of a methodical inventory data collection. However, agriculture process is characterised by a large variation of data sources depending on climate, soil and management systems. That means that agricultural inputs and outputs (yields, emissions to water, soil, and air) must be obtained with precise measurements methods or experts estimations and assumptions to assure their accuracy. Systematic errors leading to wrong issues have to be avoided, for example, the use of unrepresentative farm data, the use of inconsistent values of partial emissions or extrapolation from empirical models.

Consequently, all the assumptions and simplifications, which are made during the data collection, affect in different extend to each impact categories in the evaluation. Thus, it should be accompanied by a appropriately reliability analysis, which is frequently not considered.

Unfortunately, a lack of reliability is frequently observed because LCA performers tend to save time using data from inadequate time periods or sites.

Various methods have been proposed to manage data inaccuracy in LCA, such as analytical uncertainty propagation methods, calculation with intervals and fuzzy logic and stochastic modelling. In particular, stochastic modelling, which can be performed by Monte Carlo simulation, is widely recognized as a valid technique for making data inaccuracy in LCIs operational. The level of mathematics required to perform a Monte Carlo simulation is quite basic [Huijbregts, 1998; Maurice, 2000].

The Monte Carlo simulation basis is to select a value within the distributions assigned for each input variable and to compute the outputs. The process is repeated and the collective outputs from each interaction combine to form a probability distribution function [McCleese, 2002].

The input data are calculated as an average outcome, that is, the medium value of the data collection from different sources. Therefore, every input data has associated a gaussian distribution, with a corresponding confidence interval. Thus, the confidence interval for these input parameters is expressed as the coefficient of variation, in other words, a percentage of the standard deviation.

For this study, the basic scenario of the Monte Carlo simulation analysis is indicated in the Table 2.

Table 2. Basis scenario used in the Monte Carlo simulation analysis.

Operation	Input parameter	Basis scenario	Coef. variation
Machinery operations	*diesel*	109 l/ha	20%
Crop fertilization	*P*	46 kg/ha	39%
	K	60 kg/ha	56%
	N	129 kg/ha	27%

4. RESULTS

The software used in this study is GaBi 4, which applies Eco-Indicator 95 methodology. This software implements parameter variation and sensitivity analysis functions, allowing the modeller to examine how changes in input parameters or different scenarios affect the output results [Spatari, 2001].

Primarily, an analysis of sensitivity using parameter variation has been performed. It has been studied the influence of the following input variables: fuel consumption and fertilizer use in the farming operations.

As an example, Figure 3 shows the influence of variation of fuel consumption parameter on the Global Warming Potential (GWP) impact category. The scenario 1 involves a crop cultivation without pre-treatment soil operations and the scenario 2 includes the pre-treatment soil operations. This reveals an 5% increase in the GWP impact category from the scenario 1 to the scenario 2.

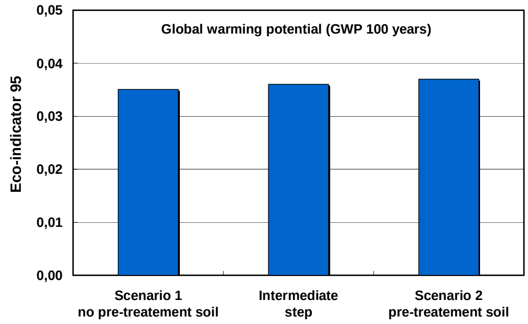

Figure 3. Fuel consumption parameter variation on the GWP impact category.

The parameter variation is more influential when analysing the fertilization practices. The Figure 4 shows how affects the variation of fertilizer parameter on the GWP impact category, where scenario 1 represents a conventional crop (using NPK fertilizers) and scenario 2 implies ecological cultivation (without fertilizers). There is a 15% decrease in the impact category from the first scenario to the second one.

This parameter variation analysis shows the strong repercussion of the considered data inventory assumptions on the study results. It can be deduced the importance to compile the closest field data to the real processes.

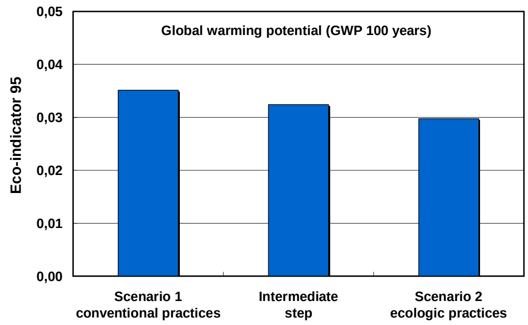

Figure 4. Fertilizer parameter variation on the GWP impact category.

On the other hand, a Monte Carlo simulation has been carried out to promote reliability to the output in the biodegradable hydraulic lubricant LCA.

The Monte Carlo analysis evaluates how the propagation of inputs variation is reflected in output values. The resulting output value corresponding to the impact category presents a mean value with a corresponding standard deviation. As a example, the shows graphically the Monte Carlo simulation outcomes for the GWP impact category.

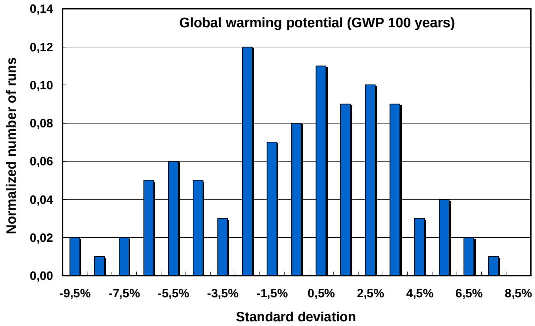

Figure 5. Results of a Monte Carlo Simulation for GWP impact category.

Numerically, Table 3 shows the coefficient of variation (CV) obtained for each impact category analyzed.

The Aquatic Ecotoxicity Potential impact category has not been considered because its contribution is not relevant for this process uncertainty analysis. The variation of the standard deviation is quite different, depending on the impact category studied.

Table 3. Result s for a Montecarlo Simulation in the different impact categories.

Impact Category	Unit/ Normalization	Mean Value	CV
Global Warming Potential, (GWP 100 years)	Eco-indicator 95	0,04	4%
Acidification Potential (AP)	Eco-indicator 95	0,04	4%
Eutrification Potential (EP)	Eco-indicator 95	0,04	14%

For example, Eutrification Potential category is the most influenced for the input parameters variation. It is a consequence of the fertilization step assumptions and considerations through applied fertilization rates. Consequently, it could be convenient a new estimation of the input parameters corresponding to fertilization stage.

5. DISCUSSION AND CONCLUSIONS

To sum up, uncertainty analysis techniques have been used to identify the important weak points in the biodegradable hydraulic lubricants Life Cycle Assessment study. The Monte Carlo simulation based screening methods are beneficial to the LCA results which give added value to environmental impacts obtained.

In other words, this kind of analysis allows to know which environmental impact categories support the major uncertainty. By means of the knowledge of input data which affects each environmental impact category, a revision of data inventory quality could be made improving the uncertainty in the final result.

The assumptions and simplifications made in the LCA study for biodegradable lubricant inventory (pre-treatment soil operations and fertilization rates) clearly influence the Eutrification Potential impact category in more than 10%, as obtained from Monte Carlo analysis.

The set-up of consistent models based on realistic input-output relations using detailed farm data from case studies, surveys, or detailed accounts statistics, makes the LCA to improve the results feasibility, as well as to gain a better knowledge of emission processes together with a check and adjustment of partial emissions of nutrients with balances at farm and enterprise level.

Suitable format databases with verified information concerning production on typical and representative farms and using a combination of detailed farm data, models and comprehensive accounts statistics, could be recommended.

6. ACKNOWLEDGEMENTS

This work has been partly funded by the EC (project contract G5RD-CT-2000-00410). We would like to thank all other partners involved in the project: Vito (Belgium), Volvo (Sweden), ICMM-CSIC (Spain), Doimak (Spain), CTD (Slovenia), Petrol (Slovenia) and Bekaert-Dymonics (Belgium).

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