Environmental Impact Assessment for Manufacturing: Data Requirements for a Simulation-Based Approach

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ABSTRACT

The environmental footprint of products is an increasingly important measure for companies working to improve their sustainability performance, and the same measure has also become popular for marketing purposes. As a result, the demand for environmental product declarations and, thus, life cycle assessment (LCA) projects grows. To reap the full benefit from LCA studies in production systems analysis, LCA has more frequently been complemented with simulation of production flows (i.e. discrete event simulation) during the latest decade. Several examples of the DES-LCA combination in recent literature report substantial potential and successful implementations. However, a common problem is to establish efficient and credible procedures for collecting, analyzing, and representing the extensive amounts of input data required. The aim of this paper is therefore to provide recommendations for the management of environmental data in sustainability simulations. A review of seven previous DES-LCA projects provides a list of common sustainability parameters and experiences on how they should be collected and represented in simulation models. An important result is that deterministic representations appear to be enough for data not directly linked to production time. This finding makes it possible to replace time-consuming data gathering with collection of secondary data from public databases.

Keywords: Data, sustainability, discrete event simulation, EcoProIT, LCA.

1 INTRODUCTION

Environmental footprint of products is naturally a key measure for companies working to improve their sustainability performance and the same measure has also become increasingly important for marketing purposes. As a result, the demand for environmental product declarations (EDP) and, thus, life cycle assessment (LCA) projects rises. Traditional LCA is a popular method but there are numerous inherent drawbacks associated to such analyses. Two drawbacks, specifically apparent in production systems analysis, are the lack of model dynamics and the difficulties related to creation and analysis of "what-if" scenarios [1]. These disadvantages are parts of the motivation for complementing LCA studies with the capabilities and strengths of production flows simulation, i.e. discrete event simulation (DES).

There are several examples of the DES-LCA combination in recent literature and most contributions report substantial potential and successful implementations [1][2][3][4]. However, LCA is associated with problems finding credible and consistent environmental data [5][6] and DES is known for its extensive requirements of detailed production data to mimic the dynamic aspects of production systems [7]. It is therefore easy to understand that the collection and processing of input data is one of the greatest challenges in simulation-based environmental assessment of production systems. High-level analysis, treating the production system as a black-box, is one way to reduce the amount of required data. However, such rough allocation of environmental "costs" to the different products does not add much value for the user. Instead, there is a need to provide better support for managing the data required for detailed modelling including production resources and individual products.

The aim of this paper is therefore to provide recommendations describing the types of data parameters commonly needed in DES-LCA models and how these data should be collected and represented. The recommendations are based on the analysis of seven previously performed and documented DES-LCA projects. This analysis, which is prepared for and presented in this paper, also elaborates on how the level of detail affects the input data management process and relates to the total project process. Efficient and credible management of input data is important to increase performance and decrease cost for sustainability simulations and enable companies to use this powerful tool on a continuous basis. Note that the DES-LCA approach mainly focuses on analysing potential improvement in the production phase of a product's life cycle.

Firstly, the paper introduces related work about data management in sustainability simulations. Thereafter, the seven case studies are described and reviewed successively. Finally, the paper wraps up with a discussion and a conclusion summarizing recommendations and experiences for further success with DES-LCA projects.

2 DATA IN SUSTAINABILITY SIMULATIONS

Input data management is an important and time-consuming step in traditional DES projects contributing around 31% of the project time in simulation studies [7]. The reasons are that many different aspects and parameters of production resources are included in detailed models, and that stochastic representation of simulation parameters requires lots of raw data samples. For example, it is desirable to collect more than 200 real-world measurements when representing machine breakdown patterns, such as Mean Time Between Failures (MTBF) and Mean Time To Repair (MTTR), in dynamic simulations [8]. The problems with finding credible and consistent data for sustainability aspects makes the input data management even more challenging when combining DES and LCA as new parameters are added.

The collection, analysis and representation of "traditional" DES parameters are fairly well researched areas, despite the limited number of publications on increasing efficiency throughout the input data management process [7]. However, there are few related studies on how to collect, process, and represent new environmental parameters, such as electrical power, pressurized air, and coolant consumption. This is also necessary when combining DES and LCA. There is currently one contribution (from foundry industry) categorizing manufacturing processes with regard to how power/energy data should be represented [9]:

1. A stochastically represented load when processing, while idling and while off.
2. One stochastic representation during simulation.
3. A parameter that varies over time and/or with the situation.
4. A special logic, due to special or complex use of resources, which does not fit into the first three categories.

The same paper states that category 1 is the most common and it suggests using machine states (working, idling and off) to incorporate the stochastic behaviour in the simulation model. Further, it is mentioned that stochastic distributions <u>can</u> be applied to represent the power levels for each machine state, given that enough data is present.

Another study in Swedish automotive industry further investigates how to represent environmental parameters and power levels more specifically [10]. The study collects and analyses 230 000 samples of power levels in different states (busy, idle, down, and stand-by) of five multi-operational tooling machines performing milling operations. The variations in power levels between different cycles within the same machine state turned out to be limited. For example, the average power consumption varies 1 to 2% between product cycles in the same machine. For idle and down cycles, the same values are 9% and 1% respectively (average standard deviations for all five machines). The general conclusion from the study was that deterministic representations are enough for power levels as input data to DES. This finding saves time in both data collection and analysis but more case studies are requested for validation purposes.

As indicated above, treating environmental parameters deterministically and letting the time-related parameters introduce the stochastic behaviour substantially facilitates the management of new environmental parameters. In other words, manual gathering of data samples can be replaced by finding the necessary data as mean values in various databases. In a first step, such databases can be exemplified by common LCA databases, e.g. the European reference Life Cycle Database (ELCD) [11] or EcoInvent [12].

Another possible source of deterministic data is the Unit Process Life Cycle Inventory (UPLCI). In this work, a new approach to the manufacturing unit process is used as the basis for Life Cycle Inventory (LCI) analyses of production systems. This makes it possible for energy and mass profiles for different production operations to be extracted from a portal [13]. As an addition to the use in Life-cycle inventory (LCI) analyses, this type of data can, for example, be used as inputs to the individual entities of a DES model.

3 METHODOLOGY

In an attempt to concretise the amassed experiences in this rather new field, a number of previously performed studies have been analysed. The experiences are collected and summarized from archived information in the reports and own experiences for some of the cases. The analysis of the material is performed through structured reviews that are focusing on categorizing experiences, problems, and results against the type and level of detail in the data that were used to perform the specific case. The cases A, B, C, F, G are chosen based on that they are executed in projects where the authors have been involved. D and E are two other cases executed during the same time period in Swedish industry.

The selected case studies were all performed at facilities located in Sweden and utilized a combination of DES and LCA techniques. The participating companies represent different industrial sectors such as; food processing, component manufacturing, and metal casting. The studies were all between six months and one year in length and were carried out from 2006 to 2012. All cases are executed by different practitioners. The studies used are all analysing the environmental impact in a specific production phase of the product's life cycle. However, in all but one of the cases, the upstream emissions for the consumables used in the production phase are included in the analysis and accounted for in the final result.

Here follows a brief introduction to each of the cases, describing the industrial setting, the goal and scope, and the level of detail that was modelled.

3.1 Case study A

The study was carried out at a sausage producing company with about fifty employees [14]. Like many other companies in the food industry they are required to meet short lead times, especially when the products cannot be cooled or frozen. The case study analysed the material flow from cradle to gate and DES-modelling was done for the production line with regards to production efficiency and environmental impact. The study presents recommendations that cover mostly economical improvements, but it also highlights which processes and materials that drive the creation of waste and emissions. The model incorporates LCI data for the creation of raw materials, energy, and wastes as consumed and generated by the internal processes.

3.2 Case study B

The company studied produces a range of fruit based liquid products; the case study focuses on an apple juice production line [15]. The food industry is under pressure to shorten lead times and increase delivery precision, a combination that demands smaller batches and hence an increasing number of setups. The main purpose of the case study was to identify the most efficient batch size for the production line, both in regards to economic cost and environmental impact. The environmental data used spans from cradle to gate but the simulation model is restricted to the in-house manufacturing processes. The modelling encompassed all product variants in the apple juice production line and the level of detail includes the creation of individual production batches.

3.3 Case study C

The object of this case study was a facility that produces cultured dairy products [16]. The production environment is process oriented and partly made up out of large mixing and heat treatment vats. Cleaning these vats is a large part of the setup work between batches. The goal of the study was to create a simulation decision support tool to help lower both the cost of production and the emissions to the environment. The level of detail varies throughout the model and is increased at bottlenecks and emission generating processes.

3.4 Case study D

The case study looks at a foundry and casting facility with a staff of about forty five [9]. As electricity costs go up, energy intensive sectors such as foundries are under pressure to improve their energy efficiency. The case study tries to identify strategies for improving energy efficiency at the foundry. Energy consumption from the core processes such as melting, mould making and pouring as well as from supporting processes such as HVAC (Heating, Ventilation, and Air Conditioning) equipment is accounted for. This case did, apart from the other cases, only look at electricity use.

3.5 Case study E

Performed at a bearing manufacturer, this study investigates how manufacturing decision parameters affect the energy consumption and CO_2 generation at one of its production lines [17]. The scope of the material flow mapping is cradle to cradle, but the focus of the DES model is the internal manufacturing. Raw materials and components are refined through a number of process steps including hardening, machining and assembly. Aside from the manufacturing unit processes, the simulation model also accounts for material handling and several supporting systems such as HVAC (heating, ventilation, and air conditioning) and waste handling.

3.6 Case study F

This study was conducted at a forklift component manufacturer with about twenty employees [2][18]. The production system is characterized by high product variation, functional grouping of machines and product specific production flows. The main process steps are metal cutting and welding. The aim of the case study was to assess cradle to gate environmental footprint for one of the products that the factory produces. The DES model is restricted to the in-house processes and LCI data is utilized for external processes such as raw materials and electricity production. The level of detail of the study is high and the environmental footprints are calculated on a part by part basis.

3.7 Case study G

This work was carried out at a tin can production facility, producing painted tin cans from metal sheets [19]. The production is characterized by large batches and process steps that are partially decoupled by large material buffers. The study scope was cradle to gate with the objective to calculate the current state CO_2 emissions and identify strategies to reduce it. No priority was given to production efficiency optimization.

4 CASE STUDY REVIEW

In all of the seven cases, production system dynamics are analysed in a DES model. To model the dynamics of the system, stochastic distribution are applied for most of the traditional input parameters, such as cycle times, mean time between failures, mean time to repair, and setup time. Those are collected by manual measurements, database extraction, interviews and other practical methods. This chapter will not consider such traditional DES parameters from now but only focus on the additional inputs required for sustainability analysis. However, some case-specific dependencies between dynamic aspects of the production system and sustainable inputs are highlighted.

All sections in this chapter are identically structured to cover the following aspects:

- Which input parameters are used in the model and how are they represented in the simulation model?
- From which sources are they collected?
- How is the sustainability output from the DES model communicated?
- Experiences and problems related to data management.

4.1 Case study A

This case study in food production is one of the first projects using a DES model for LCA analyses.

Input parameters

The parameters used as input to the model from a sustainable perspective are usage of raw material, the processes power consumption, and waste from the processes per setup. Other consumables such as packaging per batch, product water usage for cleaning, and pallets per send batch are also included. All values are deterministic. All the consumables traced in the model are coupled to deterministic LCI data.

Collection of sustainability data

The power consumption data for all machines are compiled from data sheets provided by the machine vendor together with own measurements. Waste from the processes is estimated by the modeller together with production engineers at the company. LCI data for the consumables were compiled and provided by an external LCA consultant. The data are represented as deterministic numbers for each and every parameter.

Representation of sustainability output

The report declared to have used an excel document to summarise emissions and used consumables for the production. However, they did not present any categorisation or weighted emission results from the sheet. The only sustainability output parameters used in the report are energy consumption and meat consumption aggregated per product and per resource.

Experiences and problems

The modeller states that the restricted project time was not enough for proper data collection. The collected data are not enough to build a trustworthy model that is robust and detailed enough for improved decision making. Data needed for the modelling are not easily available. There were lots of time consuming data collection, and also substantial estimations and assumptions needed to compile all necessary the data.

4.2 Case study B

This case study on juice production is, together with case study C, more impact oriented than the first case study. They are also performed later than case study A when the combination of DES and LCA had reached further in its development.

Input parameters

Used input parameters in the model are, waste represented as deterministic values, power usage per process, and the average water consumption for each production process. For all the consumables in the model deterministic CO_2 equivalents, MJ equivalents, SO_2 equivalents, NO_2 equivalents, and ethane equivalents are used as input.

Collection of sustainability data

Power usage data are estimated and compiled from internal databases, data sheets, and documents describing the total energy consumptions for the company. Recipes are used for the consumption of raw material. For the other consumables the modeller estimated the usage based on best knowledge and interviews. The LCI data for the consumables were provided by an external consultant.

Representation of sustainability output

The output for each product type is the assessments of the impact categories global warming, acidification, eutrophication, and ambient ozone.

Experiences and problems

There were lots of missing LCI data for the products and many assumptions and simplifications were made. This implies a vague final value for the emissions. However, by focusing on waste, energy usage and other consumable usage, the analyses can be done based on values which are easier to collect and validate.

4.3 Case study C

Because raw material is often the main contributor to products from the farming industry, correct LCI data sheets and usage of raw material are keys to get the correct emissions in case study C.

Input parameters

To the model power consumption for process, waste per batch, and the impact of cleaning activities are used as input. Recipes for the products plus wasted materials caused by cleaning declare the used raw materials. All values are deterministic.

All the consumables in the model CO_2 equivalents, MJ equivalents, SO_2 equivalents, NO_2 equivalents and ethane equivalents are parameters to the model.

Collection of sustainability data

The recipes for the products are used to get the raw material usage. The rate of waste due to setup and cleaning are estimated and compiled from data of bought raw material and produced products. Power usage is collected from data sheets for the machines. The information extracted from the data collection is as far as possible validated by internal personal.

The equivalents for the LCI data of consumables are calculated and provided by an external consultant.

Representation of sustainability output

Sustainability output is declared in the five categories used for the input parameters. The output for each product type is the measure for the impact categories global warming, acidification, eutrophication, and ambient ozone.

The output is also declared as summarized consumable consumptions for the processes. The consumptions assessed are water, energy, lye and acid usage. Though raw materials are important, waste is important and declared for each product type.

Experiences and problems

The modeller claims that the project focused more on modelling the production flow and the associated model logic. Therefore, the input data quality was sacrificed given the project time-frame. To fully trust the results from the model, there is a need to revise the collected data of all parameters.

4.4 Case study D

An important remark with this study is that it does not explicitly state environmental sustainability as an objective. The objective is to decrease cost due to reduced energy consumption based on better production planning.

Input parameters

For the processes in the production, three deterministic values were declared; power consumption while processing, while idle, and when turned off. No other sustainability parameters were used.

Collection of sustainability data

Though no power consumption data were available, an external consultant audited and analysed the processes to be able to declare the power usage per process.

Representation of sustainability output:

As output from the model, the modeller used the total used energy separated into different energy sources.

Experiences and problems

The study had complication with the data collection. The current production planning information was carried out by the operators on a day-to-day basis. The day-to-day planning was hard for the modeller to mimic. The model will be hard to use to optimize production for energy level since the production can be modified in too many ways for effective modelling.

The structure of the input data declared as idle, busy and off gives the modeller an opportunity to analyse the energy consumption in a more extensive way then only using busy or per usage. It also helps to visualize whether there are energy consumption problems with idling processes or if production planning could decrease the idle time.

4.5 Case study E

This case study has two parts used for calculations. One conventional LCA study and one DES model used to calculate energy usage and scrap of manufacturing.

Input parameters

An extensive input data sheet was used in the study, containing 6818 parameters. 1113 of these parameters were related to environmental impact. For the DES model, the processes usage of consumables was declared including compressed air and power consumption. Furthermore, the scrape rate for the processes was used.

Collection of sustainability data

The consumptions of resources were measure or estimated for all the individual processes.

The overall LCA model compiled LCI of raw materials and processes and compiled this with the result form the DES model.

Representation of sustainability output

The study’s approach is generalizable to all LCI linear categorizations used in LCA but this specific study was delimited to CO_2 Equivalents.

Experiences and problems

Starting from an existing LCA study makes it easier to decide where in the DES model to focus and what to actually include in the model. A DES model gives a better and more detailed analysis, but requires a lot of data. The total product lifecycle should therefore not be modelled but only the most critical parts.

4.6 Case study F

This case study modelled a production system with limited in-house manufacturing and assembly. Therefore, major parts of the sustainability impact originate in purchased products and external processes.

Input parameters

The processes in the production were modelled using deterministic scrap rates, electrical power levels for busy, idle and standby machine states. LCI is used for all consumable.

Collection of sustainability data

For the main processes, electrical power consumption were measured and declared for different machine states, i.e. busy, idle, and stand-by. The measurements were carried out with help of external consultants. The LCI data were collected from the EcoInvent database. Scrap rates were estimated based on data provided by the studied company. Overhead energy used in production was calculated and estimated from total energy consumption minus used energy in the measured machines.

Representation of sustainability output

The outputs from the model are greenhouse warming potential (GWP) and acid potential (AP) which were chosen because they are fairly easy to understand and communicate to customers.

Experiences and problems

Some data input decisions make substantial impact on the model. Sensitivity analyses are important in order to understand which data are most important and how they affect the model. The electricity LCI dataset became very important in this study. The modeller presented not only one result but two with totally different results depending on one such decision.

4.7 Case study G

The case study at a tin can factory had three separate processes with big buffers reducing the dynamical effects in the system.

Input parameters

The simulation model includes three major stations. For these stations, the input parameters is deterministic values for waste, and consumable consumption rate. The waste rate was deterministic for each batch and product. Thus, the products in smaller batches have more waste than bigger batches. The consumables for the processes were electricity, compressed air, paint and steel. These inputs are based on LCI data for the cradle to gate representation.

Collection of sustainability data

The data were compiled from data sources inside the company, databases, interviews and own observations. The electricity consumption for busy and idle was measured by internal personal. The LCI data were compiled together with academic experts.

Representation of sustainability output

The study presented the data in the form of GWP per product. In addition, the study presented the information of emissions per resource and type of consumable.

Experiences and problems

Problems to understand the need for input data collection from the processes resulted in less time for the modelling and analyses. The modeller suggests doing a pre-study of available data in the company, while the product is planned. It is important to ask correct and specific questions to the company to get a view of existing data and data that need to be collected.

5 DISCUSSION

The case studies reviewed in this paper include multiple types of consumables, and they have used several types of input parameters. The additional process parameters needed compared to a normal DES analyse for environmental assessment purposes can be identified in the case studies, these are; *spillage rate, waste rate, energy consumption, and/or power consumption for individual machine states, consumption of auxiliary media, additional material flows e.g. glue, consumption during setup activities such as water for cleaning and overhead consumption of energy;* see Table 1. To finally create an emission analysis, LCI data is connected to the consumables and raw material to convert the usages into emissions.

Based on case studies B, C, F and G analysed in this paper: the following consumables are commonly considered as most critical for model credibility:

1. Raw material
2. Waste and spillage
3. Direct energy
4. Overhead energy

Most of the studies seemingly arrive at correct conclusions based on the input information they have included. The problem is to ensure that the input information is complete. In some of the projects, LCI emissions have been applied to uncertain or non-validated model outputs such as resource consumption. This leads one to believe that analyses are being made and conclusions drawn based on non-verifiable data.

This paper suggests that future studies add data to the model in incremental steps.

- Firstly, collect, model, verify and validate a simulation model of the production part to analyse.
- Secondly, add consumption rates for the most used consumables of the modelled processes, e.g. energy consumption and material usage.
- Thirdly, add more consumables until all are covered.
- Fourth, compile LCI data for the consumables, starting with the most significant from a good guess which consumable that is most important.

The methodology enables a project that is running out of time to still be able to make a valid analysis. The more bullet points the project is able to complete the more extensive analysis could be made. However, correct but less extensive conclusion can still be made on a lower level. The methodology supports calculation implementation in multiple levels. Implementation in multiple levels helps validation and verification. In the first level you can validate production output and other process parameters, in the second and third levels, the total consumption can be validated against consumptions in the real production system.

Table 1 Findings Summarized

	Input Parameters	Collections of Sustainable Data	Sustainable output format	Experiences
A	Deterministic LCI data and consumptions of raw material, power consumption for processing, waste.	Non-measured energy data, LCI from external consultants.	Consumption of important consumables	Lot of time for data collection
B	Pre-calculated equivalents of four characterizations for the material (CO_2, SO_2, NO_2 ethane) waste, power consumption for processing, water consumption.	Non measured energy data, LCI from external consultants, estimated waste.	Impact categories for each product type (global warming, acidification, eutrophication, and ambient ozone).	Hard to find correct and available LCI data
C	Power consumption waste per batch, environmental impact for cleaning, raw material consumption, and LCI for all consumables.	Datasheets with recipes, and power consumption. Estimations for wastes, and LCI from external sources.	Impact categories for each product type (global warming, acidification, eutrophication, and ambient ozone).	Sustainable input data for lacks quality due to modelling time
D	Power consumption in idle processing and while turned off	External consultant, audited and assessed the power consumption.	Total used energy.	Analysing idle, processing and turned off states rather than only processing gives lot more information.
E	Usage of consumables in processes, compressed air usage, power consumption, scrap rates.	Measurements and estimations, LCI from external databases and premade LCA.	CO_2 equivalents	Starting from LCA makes it easier to focus a DES on relevant spots.
F	Power levels for busy idle and standby process states, LCI for raw materials, scrap rates.	Measurements for power usage, EcoInvent database for LCI, and estimated scrap rates.	Green house warming potential and acid potential.	Sensitivity analyses vital to find important input data.
G	Scrap rates, raw material consumption including compressed air, paint steel, and electricity.	Used internal documents, interviews, estimations based on observation.	Green house warming potential.	A small pre-study of available data could severely benefit the analyse process.

In the tin can case study [19] the modeller recommended to do a small pre-study. The study would scan availability of collectable data. Such a study could help plan the model design to avoid big changes later in the project. The approach could potentially save time in later stages of the project by avoiding data availability problem.

According to Solding [9] there are four levels at which energy data can be represented while modelling the energy consumption of machines. Skoogh et al. [10] added a representation level to complement those four, suggesting that for manufacturing processes, a trade-off between data granularity and resulting detail level is desired. This recently proposed representation uses deterministic values for machine-state specific electrical power levels but incorporates the inherent stochastic representations of cycle times and idle times that DES provides. Most of the case studies analysed in this paper used simplified and deterministic power data models and current research indicates that it is a sufficient representation [10]. The poor availability and difficulty to get detailed data are the most limiting factors to using more advanced energy models such as Solding's level 1 [9]. However, for the most significant processes in terms of energy consumption it could sometimes be advisable to evaluate the need for more detailed energy models.

For the cases reviewed in this paper, multiple approaches to model the consumption of resources have been identified:

- Deterministic values for each time the machine is used.
- Stochastic values for each time the machine is used.
- Deterministic values multiplied by stochastic process times.
- Deterministic values multiplied with total simulation time and then allocated to the produced products.
- A set of deterministic values multiplied with the time the machine is in the related machine state i.e.: process time, idle time, and machine down time.

The different representations exemplify different ways to model drivers for the consumption of resources. A rule of thumb is to choose the consumption driver that best mimics the real cause of increase or decrease in consumption. However, time and data availability limits the use of the more data intensive methods, i.e. methods with stochastic values and multiple states. As the input data management accounts for 31 % of the total time spent on a DES study [7], adding more data requirements to the project will definitely add a significant portion of time too. This highlights the increasing need of efficient data collection and pre-emptive screening and ranking of data importance to prioritize collection of the most significant consumables.

When LCI data are collected, the analysis can be based on values that more accurately represent the environmental impact. LCI data could sometimes be hard to collect in a credible way, and project time could often better be used to make the model logic more accurate. A general recommendation is to use LCI data if they are collectable in available databases or available documents. If it is too hard to collect the data, the analysis should be based on consumptions of consumables. Case studies B, C, E, and G performed analyses based both on the consumptions of resources and the environmental impact. Comparison of the analyses show that it is possible to make accurate decisions from both types of results.

Depending on the goal and focus on the environmental analysis, different amounts of time have been put into data collection. For the projects with a high environmental focus (cases E, F, G), more effort has been spent on measuring the sustainability parameters, while system dynamic parameters has not been collected in as much detail. It is important to focus the project time on the most important parameters and allow for estimates on less important parameters. If the focus is to analyse the production flow, more efforts should be spent on production system input data and likewise for sustainability.

In the cases A, B, C, D, F and G the knowledge of the modeller is rather on production flow simulation than environmental assessment. For those cases, LCI and some other sustainability parameters are collected by external experts. The modellers do not need to learn how to find LCI data but can draw on the skill of experiences people, which lowers the need for expert skills in the environmental assessment area.

The results in this paper are based on reviews of publically available documentation from the case studies. Only a few of the authors have actively been contacted to gain further insights. It is therefore possible that certain aspects and details that were not explicitly stated in the articles and reports are omitted in this work. It should also be noted that the case studies are restricted to Swedish industry and consideration should therefore be taken before the findings are applied elsewhere.

Finally, this review of previous DES-LCA studies resulted in a set of important experiences regarding the handling of sustainability data. Many projects report problems with foreseeing the extensive time-consumption related to input data management, difficulties in finding and collecting sustainability parameters, as well as inconsistency and incompleteness of data in LCI databases. These experiences highlight the need for further research within the area, for example on:

- Instructions on which LCI data to use and how to prioritize between the databases.
- Methodologies for identifying the most critical sustainability parameters with regard to model credibility.
- Studies extending the data sets available in LCI databases.

- Recommendations on the selection of abstraction level with regard study objectives and data availability.
- Automated connections between DES models and sources of sustainability data.

6 CONCLUSIONS

The purpose of this paper is to increase efficiency and quality in input data management for sustainability simulations, and more specifically the combination between DES and LCA. Guidelines and recommendations are requested due to the importance of input data and the vast amount of data and information handled in such studies. Therefore, this paper investigates seven previous DES-LCA studies and maps the data parameters included, how these data were collected, and the type of representation chosen for supplying the data to the simulation models. The findings can be used as guides for future similar projects. The findings can also provide important input to a general methodology to standardize future projects.

The major findings include a list of common input parameters, where the usage of raw materials, waste and spillage, direct energy, and overhead energy are identified as the most important for model credibility. It also strengthens the previous assessment that most input parameters related to the sustainability part of the DES-LCA models can be represented using deterministic values. The reason is that the dynamics of these parameters are often connected to processing times, which in turn are stochastically represented using traditional DES parameters. The bottom line is that many sustainability parameters can be collected from public databases or similar sources, which saves time compared to manual measurements on the modelled process.

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