Exploring the Viability of Probabilistic Underspecification as a Viable Streamlining Method for LCA

by

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Abstract

Life cycle assessment (LCA) has gained much interest in the field of product development and decision making. The resource intensiveness of conducting an LCA has slowed more widespread adoption of the methodology. Although some streamlined LCA methodology exists and are currently be applied, there can be a lot of known and unknown uncertainties in the resulting analysis. These uncertainties could sometimes render the LCA results useless for any decision making activities. Thus this thesis proposes the evaluation of probabilistic underspecification in streamlining LCA and estimating a product's life cycle impact to both reduce LCA efforts and increase certainty in the results.

This thesis focuses the development and application of probabilistic underspecification in estimating the materials impact of a product. In order to account for the uncertain with the degree of underspecificity, we propose structuring of a classification system that will help associate materials specificity, uncertainty in the materials impact, and the degree of effort to retrieve that information. This will serve as the bases for probabilistic methodology to determine what part of product is important to characterize and invest effort in order to reduce uncertainty in the LCA results with less effort than traditional LCA.

Mass can be a key indicator of impact. Therefore, several case studies were conducted comparing the viability of probabilistic underspecification for calculating materials impact value for these products of varied mass compositional characteristics or the degree of mass uniformity. The compositional uniformity was measured by adapting the Herfindahl index used in economics but applied to component-mass share. Despite the difference in the mass uniformity, the methodology significantly and consistently reduced the number of components that needed to be well specified, while retaining a relatively high confidence in the resulting estimates.

Probabilistic underspecification shows promise in both reducing LCA efforts and increasing the significance in the material impact assessment of the case studies in this thesis. This process also allows the leveraging of uncertainty and probability to reduce the effort and may help improve the rate at which life cycle assessment may be conducted. With faster LCA, the move towards a sustainable and environmentally responsible growth economy may be sooner realized.

Thesis Co-Advisors: Randolph E. Kirchain & Joel P. Clark

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1 INTRODUCTION

Life cycle assessment (LCA) is a technique to assess the environmental impact of products, processes, or materials. Recently, its importance as a decision-making tool to help evaluate current product inventories and innovation of environmentally responsible products has grown. The market has become more aware of the value of environmentally conscious materials selection and product development, as is evident in the proliferation of consumer-conscious "green" labels on products ranging from groceries to consumer electronics. As such, there has been an increased interest in standardizing LCA-based carbon footprinting techniques, like the guidelines developed by the International Organization for Standardization (ISO) and the Society of Environmental Toxicology and Chemistry (SETAC), which has helped to further the acceptance of LCA by a broader community (Reap, Roman et al. 2008). However, the cost of conducting a complete LCA continues to inhibit its use, potentially delaying the development of eco-conscious products.

LCA's main cost driver is the large amount of information needed to completely assess a product's impact while conducting its life cycle inventory (LCI). Because a complete LCA considers all inputs and outputs of all phases of a product's life cycle, collecting complete LCI information for even the simplest commodity may require significant time and resources. A survey of LCA practitioners showed that time and resource requirements for data collection hamper a broader application of LCA. For rapidly-evolving industries, such as information technology, the time to complete an extensive LCA may limit its relevance (Cooper and Fava 2006). A quick and conclusive assessment is important for LCA especially in the development of eco-innovative products, especially those where only limited information can be determined about the product's supply chain and life cycle (Chen and Wai-Kit 2003). Given the barriers to obtaining primary information, are there ways to reduce the effort, or streamline, the LCA process?

Since the outset of LCA methodological development, myriad effort-reducing strategies have been considered to accelerate the pace and reduce the cost of LCA. Qualitative and quantitative approaches have reduced the effort required to gather information, thereby allowing for "streamlined" LCA results. Most LCA techniques conducted span the spectrum from purely qualitative to purely quantitative, often varying in their degree of streamlining. Qualitative LCA is a form of streamlined LCA that requires significantly less data gathering than a complete quantitative LCA. Qualitative LCAs are useful because they can provide a quick assessment of products or processes where hard numbers are difficult to obtain. Matrix-type and pattern-based

LCAs are examples of qualitative streamlined LCAs. They have been helpful for rough estimations of impact even during developmental phases of a product (Chen and Wai-Kit 2003).

Meanwhile, due to the increased importance of applications requiring quantitative impact values, such as labeling and benchmarking initiatives, there is an increased interest in quantitative streamlined-LCA. Quantitative LCA is fundamentally more difficult to streamline because it requires more data gathering than qualitative LCA. Therefore, semi-qualitative (using both qualitative and quantitative rules) or quantitative streamlining methods have been developed to ease the data burden for quantitative LCA. For example, one approach uses previously conducted LCAs or experiences as guides to identify the relevant parts of the LCA to quantify. Essentially, past experience is used as high pass filter to identify high-impact life cycle activities that are important to quantify for a meaningful assessment. Tightly defining the goal and scope of a project is another streamlining technique; it confines the analysis to a more narrow area of interest that is relevant specifically to the question the analysis poses (Weitz and Sharma 1998). For example, instead of broadly assessing the impact of an entire product, we may only want to know the manufacturing energy demand. However, this technique does not satisfy situations requiring full quantitative LCA. In those cases, are there ways to reduce the data burden?

One of the most widely applied streamlining approaches is using previously gathered information from LCA databases to build a product's LCI. Instead of gathering first-hand LCI information about the system, standard database values are substituted for primary data. However, in building a quantitative impact model of a product using surrogate or proxy data, the model may not accurately represent the actual impact of the product. Detailed life cycle inventories that constitute the information in databases like ecoinvent 2.0 and United States Life Cycle Inventory (USLCI) contain information on the life cycle activities within select geographic locations at certain points in time. Completely analogous activities may not be available for the product of interest, or the LCA practitioner may not be able to discern the best proxy. Therefore, at best, the models can only be approximations of the real system. Different sources of uncertainties could quickly compound, creating large inaccuracies in an LCA that could spoil its potential use for decision making.

Although these streamlining methodologies reduce the time and effort of conducting LCA by lessening the data gathering burden, they introduce variability and uncertainty into the results. A review by Hunt *et al.* discovered that half of the streamlining methodologies assessed arrived at different results when compared to a full LCA (Hunt, Boguski et al. 1998). Stakeholders cannot confidently make the best decisions if the LCA results are too uncertain. Given that uncertainty exists in streamlined LCA methodology, does it undermine our ability to streamline? This thesis explores the question by systematically evaluating the effectiveness of streamlining approaches at several different levels of data uncertainty. This is done in the context of a number of case studies. These studies specifically evaluate the impact of materials production and use in common consumer products. Materials are frequently the dominant driver of life-cycle impact for products that don't consume significant energy during use.

2 DISCUSSION

Sustainability and environmental responsibility are becoming increasingly important factors in business decisions. Consumers are pushing for more environmentally friendly products, urging companies to explore low impact materials and processes to manufacture their goods (Borland and Wallace 1999; Finster, Eagan et al. 2001; Gaustad, Olivetti et al. 2010). An MIT Sloan School of Management survey of 1,500 global executives and managers and in-depth interviews of over 50 thought leaders revealed that sustainability could affect every short-term and long-term value-creation lever of a company (Berns, Townend et al. 2009). For example, Wal-Mart, the world's largest retailer by revenue in 2010, has responded to market demands by working with The Sustainability Consortium to develop a Sustainability Index for their products. However, lack of information is one of the three top-cited barriers to corporate action to address sustainability. LCA has been developed precisely to produce information crucial in driving more sustainable actions.

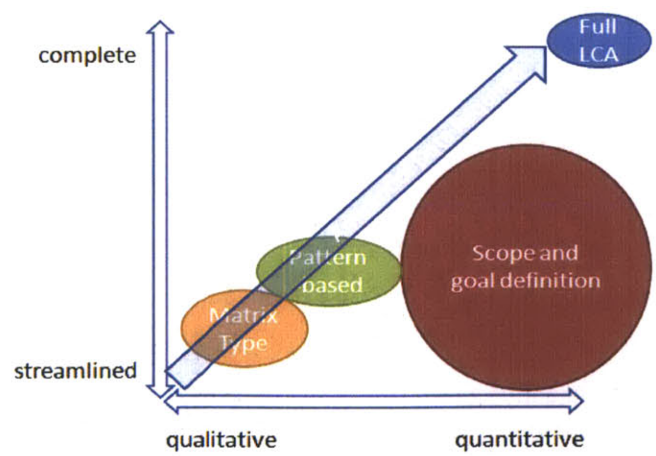

Figure 2-1 Spectrum of LCA methodology with respect to qualitative/quantitative degree and completeness.

LCA can also be a useful decision-making tool in analyzing and developing environmental policies (Ross, Evans et al. 2003). Some governments are already using LCA to help set environmental policy and to make decisions (Hofstetter, Baumgartner et al. 2000; Troge and Schmitz 2000; Blengini and Di Carlo 2010). Regulatory pressures have contributed to increased demand for LCA results. For example, after the European Commission passed the Energy-using Product, or EuP, Directives on efficient home lighting, a comprehensive LCA helped confirm the policy's environmental benefits (Welz, Hischier et al. 2010). Although LCA results are becoming more important, they remain costly to obtain due to the effort required to gather the LCI data needed for a complete analysis. In some cases, LCI data may be unobtainable due to proprietary information that companies cannot afford to divulge (Todd and Curran 1999).

To lessen the information gathering burden in conducting LCA, numerous streamlining methods have been proposed over the years. Streamlining methodologies tend to fall along a spectrum between qualitative and quantitative approaches. Examples of methodologies on the qualitative end of the spectrum are the matrix-type LCA formalized by Graedel and Allenby (Graedel 1998) and pattern-based LCA (Chen and Wai-Kit 2003). In a matrix-type assessment, a predefined impact scoring list combines with estimated LCI information to reach a rough conclusion about the product. This streamlined process is generally used for the development phase of a product (Weinberg 1998; Chen and Wai-Kit 2003). The pattern-based qualitative LCA is useful in product development as well (Chen and Wai-Kit 2003). The pattern-based approach uses previously conducted LCA to map out a product's characteristics and environmental impact. This method assumes that a product being developed with similar characteristics as a previously studied product would have a similar environmental impact. This methodology is also used to help make product-development decisions (Chen and Wai-Kit 2003; Myeon-Gyu, Hyo-Won et al. 2010). Although useful, most purely qualitative streamlined LCA lack the quantitative impact outputs necessary for certain applications. Therefore, qualitative streamlining has also been used to help derive quantitative outputs as well. For example, a methodology developed by Sousa (Sousa, Wallace et al. 2000; Sousa and Wallace 2006) uses the inference-based LCA to arrive at a quantitative result. Furthermore, due to an increase in information and computational power, rather than relying on human judgment, Sousa applied neural network classification systems to take advantage of previous product LCA experiences in helping assess a product's impact (Sousa, Wallace et al. 2000; Sousa and Wallace 2006).

SETAC's 1999 streamlined LCA report describes the advantages and disadvantages of a number of other quantitative streamlining LCA methods. These methods and their application procedures are summarized in the Table 2-1. Goal and scope definition was cited as one of the main ways in which an LCA practitioner can reduce the data burden. Identifying goals will determine the specific types of analysis needed and how to present the data, and defining the scope will allow the practitioner to limit the details and information quality of the LCI (Weitz and Sharma 1998).

Table 2-1 Streamlining approaches as recognized by the SETAC North America Streamlined LCA workgroup in 1999.

	Streamlining approach	Application procedure
Scope Limiting	Removing upstream components	All processes prior to final material manufacture are excluded. Includes fabrication into finished product, consumer use, and post-consumer waste management.
	Partially removing upstream components	All processes prior to final material manufacture are excluded, with the exception of the step just preceding final material manufacture. Includes raw materials extraction and precombustion processes for fuels used to extract raw materials.
	Removing downstream components	All processes after final material manufacture are excluded.
	Removing up- and downstream components	Only primary material manufacture is included, as well as any precombustion processes for fuels used in manufacturing. Sometimes referred to as a "gate-to-gate" analysis.
	Using "showstoppers" or "knockout criteria"	Criteria are established that, if encountered during the study, can result in an immediate decision.
	Limiting raw materials	Raw materials comprising less than 10% by mass of the LCI totals are excluded. This approach was repeated using a 30% limit.
Surrogate Data	Using surrogate process data	Selected processes are replaced with apparently similar processes based on physical, chemical, or functional similarity to the datasets being replaced.
	Using qualitative or less accurate data	Only dominant values within each of 6 process groups (raw materials acquisition, intermediate material manufacture, primary material and product manufacture, consumer use, waste management, and ancillary materials) are used; other values are excluded, as are areas where data can be qualitative, or otherwise of high uncertainty.
	Using specific entries to respresent impact	Selected entries are used to approximate results in each of 24 impact categories, based on mass and subjective decisions; other entries within each category are excluded.

Another semi-qualitative and quantitative LCA approach is to complete a qualitative overview of the life cycle of the product in order to identify the life cycle activities that comprise of a set of interest (SOI). Then, a more in-depth quantitative LCA is conducted on the SOI (Ong, Koh et al. 1999). However, the qualitative LCA overview still requires a significant amount of expertise to judge the importance of activities to refine with quantitative data gathering. This barrier prevents widespread application. An alternate method requiring less expertise is to use publically available data as a surrogate for primary data, which also serves to reduce the cost of data collection (Todd and Curran 1999; Weckenmann and Schwan 2001; Hochschorner and Finnveden 2003). The acceptance of this methodology is demonstrated by the wide use of commercial software suites such as SimaPro and Gabi, which rely on secondary data sources like the U.S. LCI Database and ecoinvent for LCA calculations. The advantage of this method is that the resulting output may provide quantitative impact values similar to a full LCA.

Although streamlining techniques could significantly reduce the effort required to conduct an LCA, the results from streamlined LCA studies are not as accurate as full LCA results. A study comparing streamlining methods, such as removing upstream/downstream life cycle components, revealed that over half of the streamlined LCA results arrived at a different conclusion than the complete LCA study (Hunt, Boguski et al. 1998). Although surrogate data is widely used, any use of proxy data increases the uncertainty in the LCA results because the previously collected data is regionally and/or temporally specific. The use of surrogate data requires the practitioner to use his or her expertise to select the best proxy. A 2011 survey conducted by Vee Subramanian of Arizona State University revealed that LCA experts may not be significantly better than non-experts at choosing surrogate data from databases that reflected a reasonable approximation of the real system (Subramanian, Williams et al. 2011). Furthermore, by using proxy data as point

Table 2-2 Classification of uncertainties according to several authors reproduced from Heijungs and Huijbregts 2004.

Bevington & Robinson (1992)	Morgan & Henrion (1990) Hofstetter (1998)	Huijbregts (2001)
systematic errors random errors	statistical variation subjective judgment linguistic imprecision variability inherent randomness disagreement approximation	parameter uncertainty model uncertainty uncertainty due to choices spatial variability temporal variability variability between sources and objects
Funtowicz & Ravetz (1990)	Bedford & Cooke (2001)	US-EPA (1989)
data uncertainty model uncertainty completeness uncertainty	aleatory uncertainty epistemic uncertainty parameter uncertainty data uncertainty model uncertainty ambiguity volitional uncertainty	scenario uncertainty parameter uncertainty model uncertainty

estimates of actual LCI data, one may have false confidence in the resulting LCA report. Therefore, uncertainty in streamlined LCA, especially with the use of surrogate data, must be understood for the streamlined LCA results to be useful for decision making (Heijungs and Huijbregts 2004).

Academics have acknowledged and extensively discussed uncertainty in LCA. In Table 2-2, Heijungs and Huijbregts review various ways in which authors in the field have classified and discussed uncertainty in LCA studies (Heijungs and Huijbregts 2004). These sources of uncertainties are not limited to streamlined LCA but are pervasive in "complete" LCAs as well. Although acknowledged in literature, LCA practitioners often fail to address properly the issue of uncertainty in their reports. In a 2002 report by Ross *et al.* (Ross, Evans et al. 2002), of 30 LCA studies surveyed, fourteen mentioned uncertainty, three conducted qualitative uncertainty analysis, and only one quantified the uncertainty in the LCA results (Ross, Evans et al. 2002). The reason many fail to address uncertainty may be due to the additional data required and the complicated calculations necessary to report statistical values like confidence intervals and significance levels (Bedford and Cooke 2001; Heijungs and Huijbregts 2004). Moreover, reporting uncertainties associated with the LCA report might overshadow the report's results (Heijungs 1996; Ross, Evans et al. 2002). However, despite the lack of implementation, it is very important to quantify the uncertainty in LCA results because uncertainties can be significantly large (de Koning, Schowanek et al. 2010). Not knowing about the uncertainty does not shield the LCA report user from the uncertainty in the product's impact and non-optimal decision-making that could result.

Numerous reports discuss ways in which LCA practitioners are addressing the issue of uncertainty (Heijungs 1996; Björklund 2002; Finnveden, Hauschild et al. 2009). A recent review of current trends in LCA recognizes three major ways LCA uncertainty is being dealt with: scientifically, socially, and statistically (Finnveden, Hauschild et al. 2009). Techniques for dealing with uncertainty scientifically include finding more accurate data or building better models to reduce uncertainties (Heijungs 1996). Although this approach can lead to more accurate LCA results, it is also more costly than other streamlining methods due to the increased research and model refinement needed to conduct LCI, efforts that may not be feasible due to time or cost restrictions. Addressing uncertainty through social means involves reconciling the issue of data and choices with stakeholders. Under this approach, the LCA community must agree on specific rules on how to conduct LCA and deal with certain situations. This may also include relying on authoritative bodies like the ISO and United States Environmental Protection Agency (USEPA) to regulate standard or guidelines to make LCA more consistent. An approach that falls along this vein is the LCIA method Used for a Canadian-Specific context (LUCAS) model (Bulle, Godin et al. 2007). The LUCAS authors propose a standard method to deal with data gaps by transforming them using normalization factors to make the values more relevant to Canada. Tools for Reduction and Assessment of Chemical and other environmental Impact (TRACI) is an analogous methodology for the United States (Bare 2002).

In contrast to these methods, the statistical approach to dealing with uncertainty focuses on incorporating uncertainties into the analytical procedures of LCA and quantifying the uncertainties in the analysis instead of mitigating them. Statistical approaches include methods like sensitivity analysis by parameter variation, scenario analysis (Björklund 2002; Tan, Culaba et al. 2004), Monte Carlo simulation (Hung and Ma 2009), stochastic processes, and other sampling methods (Kennedy, Montgomery et al. 1996; Hertwich, McKone et al. 2000; Huijbregts 2002; Lo, Ma et al. 2005; Bojacá and Schrevens 2010), first order error propagation, Bayesian analysis (Lo, Ma et al. 2005) and fuzzy set theory (Weckenmann and Schwan 2001; Tan, Briones et al. 2007).

The statistical approach to dealing with uncertainty acknowledges that a range of values that can attribute to the impact of a product exists. This range of values could stem from the sources of uncertainties described in Table 2. The size of this range will vary according to the amount of information known about the system or its degree of underspecificity. Here, a component is underspecified if further specific information could be obtained about the product for a more accurate impact assessment. For example, in the case of surrogate data, the range of values would be quite different if we only knew that a component is made out of a generic metal as opposed to a specific nickel-titanium alloy. The ability to conduct a conclusive LCA with only the information that a component is made out of metal rather than a specific nickel-titanium alloy, for example, can lead to considerable streamlining.

Although many studies describe ways to incorporate uncertainty, they do not explore the effect of the amount of knowledge or level of underspecification on the resulting LCA's uncertainty. This information can prove crucial to the ability to mitigate uncertainty and streamline LCA. For example, Heijungs 1996 proposes an iterative statistical screening method that identifies SOI contributing the most uncertainty to the LCA results to be resolved at higher resolution (Heijungs 1996). The author, however, reveals that the problem with this approach is the lack of knowledge of the uncertainty to begin the analysis. In the study, a margin of error of 5% was assumed on all the figures used in the analysis. A more recent article by the same author suggests using the widest reasonable range based on expert judgments or measurable data (Huijbregts, Gilijamse et al. 2003).

In the end, while there has been considerable work both proposing streamlining methods and on characterizing the role and impact of uncertainty in life-cycle assessment, there appears to be little to no work exploring how these two issues affect one another. The next chapter details a set of specific research questions that this thesis will explore in order to gain insights into this interaction.

3 THESIS QUESTION

To address this issue systematically, we propose to carefully characterize uncertainty in the information within a life-cycle assessment through structured underspecification of the parameters of the life cycle activities. This exercise will be carried out across a range of different levels or degrees of underspecification. Higher degrees of underspecification will correspond to a larger range of possible parameter values (higher uncertainty). Lower degrees of underspecification will correspond to a smaller range of possible parameter values (lower uncertainty). For the purposes of this thesis, this exercise will be limited to the impacts associated with materials. For example, say that one wanted to know the life-cycle impact associated with a given component X. For the purpose of discussion, let's assume that X is made of aluminum produced in a specific location using a specific process, but that the life-cycle analyst does not have access to that information or, even if he or she does, the available databases do not contain process inventory data that matches the specific provenance of X. In such a case, the analyst must either utilize expensive resources to collect more information about X and its processing or carry out the analysis using proxy data. Using the analytical approach that will be described later, X could be (under)specified simply as a metal, further specified (albeit still clearly underspecified) as a non-ferrous metal, or even (if sufficient information were available) as a generic aluminum alloy. Each of these options would have clear impact on the uncertainty in the impact of component X. Examining each of these alternative ways of specifying the materials within a life-cycle allows us to determine objectively and systematically the possible range and distribution of values for the projected impact of a product based on how much we know about that product-system.

To help advance the field of streamlined LCA, we propose a methodology that incorporates structured underspecification of life cycle activities to leverage the fact that, in many cases, only some activities must be well specified. Where uncertainty comes from underspecifying a product life cycle, it should be possible to reduce result uncertainty through better information. Such information gathering is expensive and is the very activity that streamlining aims to avoid. Fortunately, some evidence suggests that it should be possible to prioritize targets of that data collection. This prioritization concept was explored by Huijbregts and others by qualitatively and quantitatively identifying the SOI. We propose identifying the SOI with a statistical ranking system based on the probability that the life cycle activity contributes to the impact and uncertainty of the product. Then, the SOI would be further specified to a greater resolution to obtain an LCA result with minimal effort to resolve the LCI and with minimal uncertainty. By probabilistically underspecifying parts of the life cycle activity we hope to reduce the effort of conducting the LCA.

This thesis explores the viability of probabilistic underspecification in streamlined LCA and mitigating uncertainty in the LCA results. As the proof of concept, this thesis focuses on streamlining the materials impact assessment portion of the life cycle. This thesis will address the following questions:

1. How does structured underspecification of raw materials affect the precision of the estimate of product environmental performance?
2. How efficient and effective is structured underspecification analysis for identifying the SOI and reducing residual uncertainty in the results given:
   - The degree of confidence
   - The degree of streamlining
   - A specific ranking criteria
3. How much residual variation remains in an evaluation based on a partially specified, partially underspecified analysis?

4 METHODOLOGY

Although the practice often goes unremarked, effectively all life cycle assessment today relies upon the use of secondary data or proxy data. That is data that the facilities, processes, users, or other operators within the life-cycle under study did not collect. This practice is necessary to make life-cycle assessment feasible because primary data for complete LCA, as diagramed in Figure 4-1, may not be readily available.

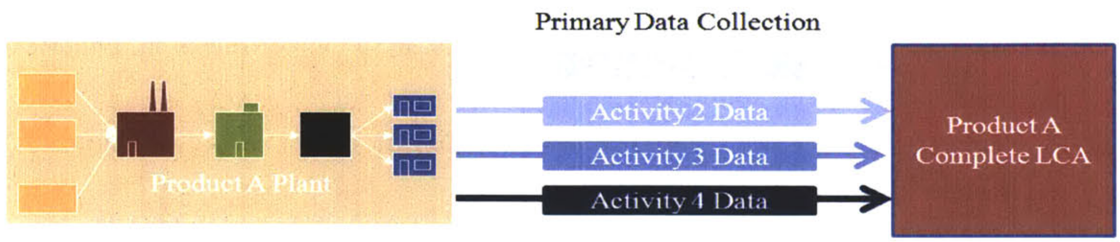

Figure 4-1 Diagram of primary data gathering for a complete LCA of a product. This is not often conducted because it is very resource intensive to investigate and obtain primary data for all necessary impact factors.

Multiple methods to select or characterize this proxy exist. The most common approach appears to be to select data associated with an activity that is similar or analogous to the relevant activity. This selection generally comes from an available activities database. This process is diagrammed in Figure 4-2. Ultimately, evaluating the appropriateness of similarity rests with the analyst. As discussed by Weidema and Wesnæs (Weidema and Wesnæs 1996), the

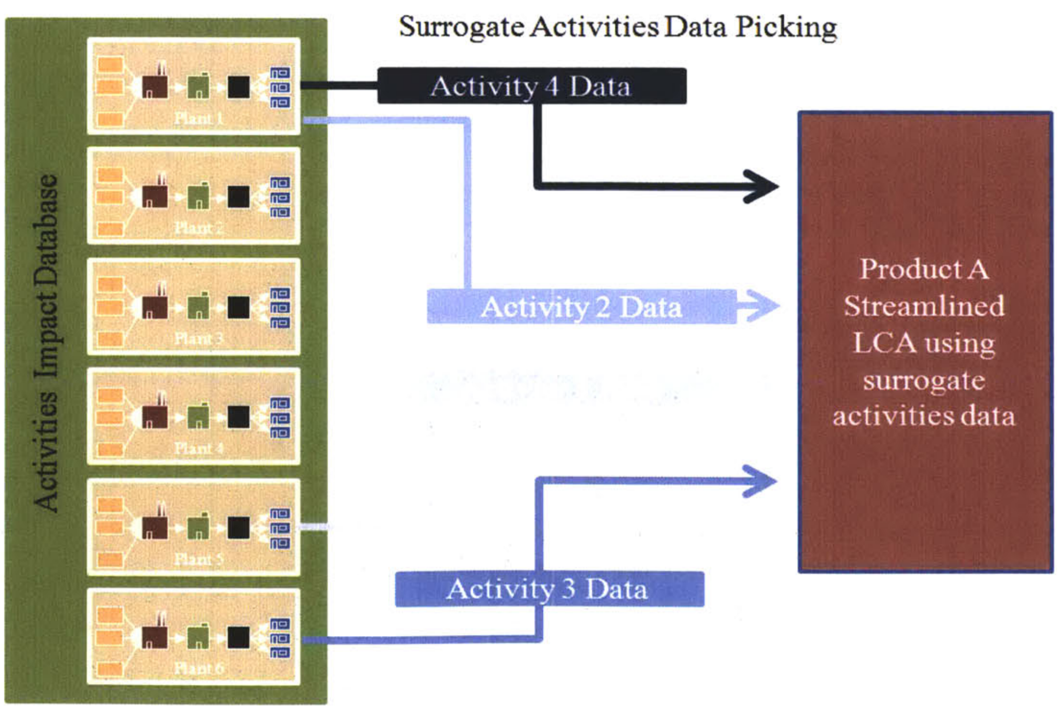

Figure 4-2 Streamlined LCA in which the practitioner uses experience and best judgment as a guide to picking out representative activities in order to estimate the impact of a product.

appropriateness or representativeness of this surrogate introduces another form of uncertainty into the analysis. Also, Weidema and Wesnæs (Weidema and Wesnæs 1996) have suggested that this uncertainty can be estimated by using the pedigree matrix approach. Given that data on a surrogate process probably will not mirror that of the process of interest, using that surrogate data likely introduces bias into an analysis. Hopefully, analyst expertise mitigates this bias or at least constructs a bias whose nature is conservative towards the goals of the analysis.

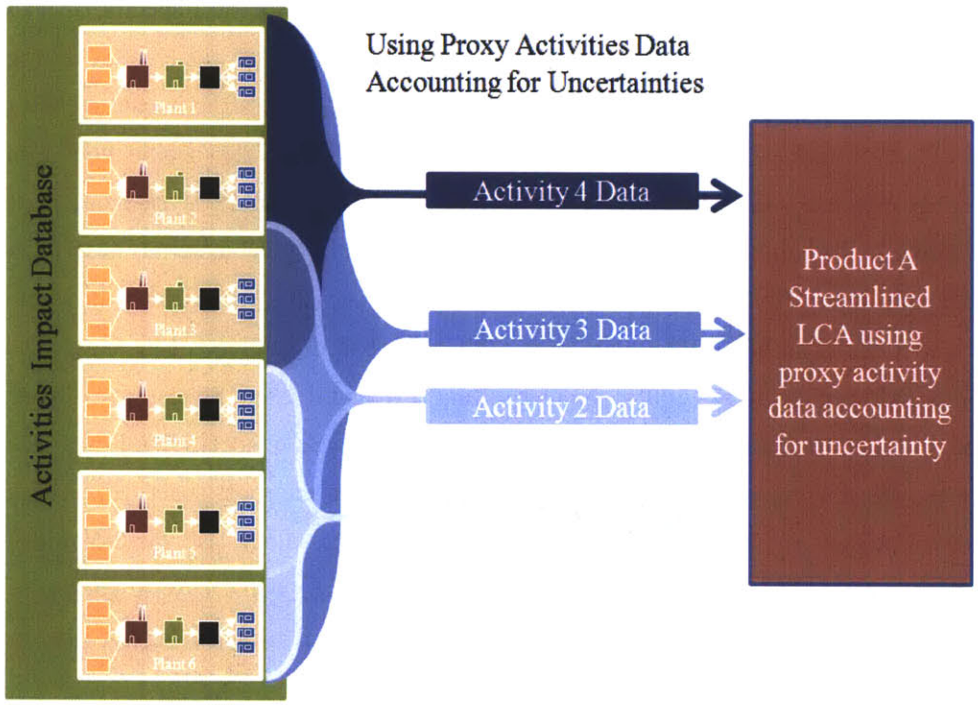

Figure 4-3 Streamlined LCA with the use of proxy data while taking into account the uncertainty in the surrogate data. A more general proxy impact range is taken into account for a range of possible impact values rather than point estimates.

This thesis explores using an alternative to the use of surrogate data as an approach to defining a data proxy. This methodology, referred to as underspecification, defines the proxy based on the distribution of data associated with similar processes or activities. The distribution of associated processes can be referred to as a class. This class should be broad enough to contain several similar processes (i.e. candidate surrogates). The goal of the underspecification approach is to remove the potential of statistical bias due to erroneous surrogate selection and to fully capture, if not overestimate, the uncertainty associated with using proxy data of uncertain representativeness. This final point is of particular relevance to this thesis. If streamlining methods can be developed which are robust to high levels of uncertainty, it may be more appropriate to overestimate rather than underestimate the uncertainty associated with data. The next section describes the approach taken in this thesis to define classes of activities for probabilistic underspecification.

4.1 Structured Underspecification

Structured underspecification is a way to categorize and to index materials information so that LCA practitioners can understand the degree of uncertainty of different materials specificity about a component. For example, assume a component is made of a specific sheet steel alloy. However, the only certain information about the component is that it is a metal component. The LCA model incorporating structured underspecification will assess the impact of that component and of that product with the uncertainty factored in. Structured underspecification is implemented in a database in which the most specific proxy data information is categorized into groups according to different characteristics. For this thesis, the individual materials description and their values for cumulative energy demand (CED) were extracted from the following databases: ecoinvent 2.2 (Frischknecht, Editors et al. 2007), European Reference Life Cycle Data (ELCD) (Wolf, Pennington et al. 2008), Industry Data 2.0 and United States Life Cycle Inventory (USLCI). This information is then categorized into five levels of specificity, Level 1(L1) to Level 5 (L5), with L1 being the most underspecified and L5 as the most specified. The L5 level of information consists of individual entries from the database. In our case, the individual entries are the best estimate for surrogate data that the LCA practitioner would have to choose as the proxy for the relevant component in impact assessment conducted using LCA software like Gabi or SimaPro.

4.1.1 Why Do We Need Structured Underspecification?

Structuring the underspecification allows one to model the effort necessary to gather information about a product and to assign a quantitative value to that effort. Additionally, structuring underspecification provides the ability to estimate the uncertainty associated with each level of specificity. This approach derives from the process in which streamlined LCA practitioners specify what material a component is made from in order to decide which representative proxy data to use in the impact assessment when primary information cannot be readily obtained about the component. However, as the discussion chapter covered, it can be challenging to identify the specific materials composition for a product. This uncertainty translates to difficulty choosing the most representative proxy material from the database. Structured underspecification will allow the LCA practitioner not to specify fully the materials composition of a product and to account for the degree of uncertainty in the impact of whole products and their components parts when modeling and conducting an LCA.

4.1.2 Materials Categorization

In terms of this thesis, structured underspecification begins with materials categorization. As schematically demonstrated in Figure 4-4, each level of specificity is associated with a different amount of information known about a component. The five levels of specificity include material category, material property, material type, material processing and specific database entry. The material category includes broad categorization type like metals, chemicals, minerals, and other very general classifications of materials. In the material property level, the materials that were sorted into their respective categories are then separated along different materials properties. For example the metals category is divided into ferrous metals, non-ferrous metals, and metal alloys, whereas the polymers category is divided into thermoplastics, thermosets, and elastomers. The complete list of categorization scheme is available in APPENDIX A: Table of Database Classification.

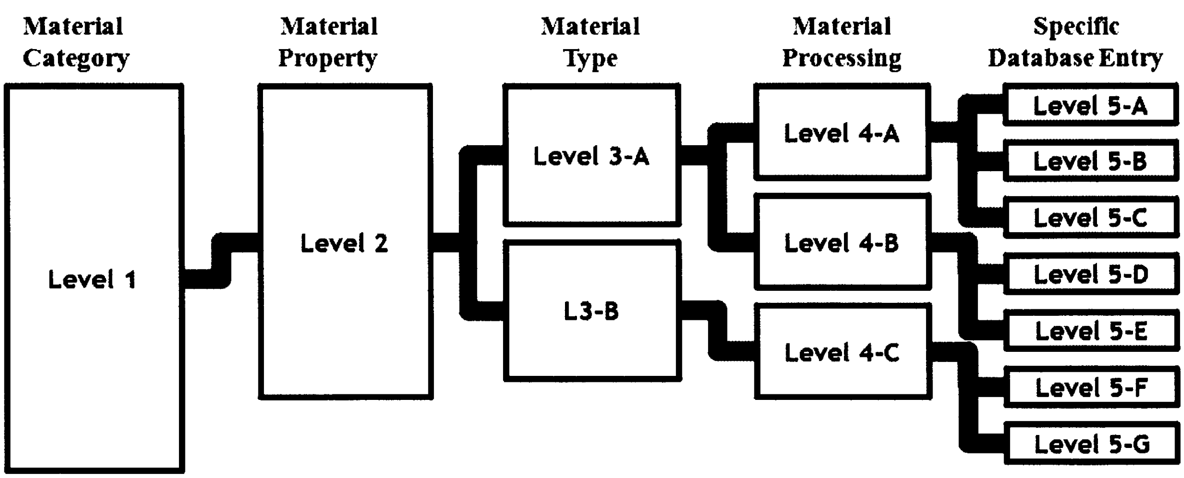

Figure 4-4 Schematic example of the database information hierarchy for structuring underspecification.

When modeling the impact of a component, the number of possible proxy database entries depends on the level of specificity. This fact allows us to account for the uncertainty of the underspecified component. In the schematic example, a component identified at the L2 specificity can be of any material from L5-A to L5-G. However, if the component is further specified to be L3-A, the possible proxy entries from the database will now only consist of materials L5-A to L5E. This will be statistically incorporated when the impact is modeled. The practitioner should expect the degree of uncertainty of which proxy should be used to shrink as the component is less underspecified and subsequently the resulting estimated impact value becomes more certain.

4.1.3 Level 5 Uncertainty Assumption

The most specific level in our analysis is L5, which contains information about the specific material impact and the uncertainty around those values. Individual entries from databases carry a degree of uncertainty because they are used to approximate measured data in first-hand LCA. One has to account for factors such as temporal variation, measurement uncertainties, geographic correlation, and several other factors that could cause the database value to diverge from its proximity to the measured value it is trying to represent. The pedigree matrix discussed in the ecoinvent documentation (Frischknecht, Editors et al. 2007) can be used to estimate the uncertainty in the proxy data by assigning quantitative values to qualitative judgments on how accurately the proxy data reflects the case being studied. Depending on the quality of the data in six categories, the practitioner will assign an indicator score from one to five accordingly. The qualitative observation and indicator score is summarized Table 4-1. For the case of this study we will assume that the indicator score is three for all of the uncertainty factors. This will give the entries a medium level of uncertainty on the quality of the proxy data.

Table 4-1 Pedigree matrix used to assess the quality of the data source. Derived from Pedersen Weidema and Wesnaes 1996, reproduced from ecoinvent documentation.

Indicator score	1	2	3	4	5	Remarks
Reliability	Verified data based on measurements	Verified data partly based on assumptions OR non-verified data based on measurements	Non-verified data partly based on qualified estimates	Qualified estimate (e.g. by industrial expert); data derived from theoretical information (stoichiometry, enthalpy, etc.)	Non-qualified estimate	verified means: published in public environmental reports of companies, official statistics, etc unverified means: personal information by letter, fax or e-mail
Completeness	Representative data from all sites relevant for the market considered over an adequate period to even out normal fluctuations	Representative data from >50% of the sites relevant for the market considered over an adequate period to even out normal fluctuations	Representative data from only some sites (<<50%) relevant for the market considered OR >50% of sites but from shorter periods	Representative data from only one site relevant for the market considered OR some sites but from shorter periods	Representativeness unknown or data from a small number of sites AND from shorter periods	Length of adequate period depends on process/technology
Temporal correlation	Less than 3 years of difference to our reference year (2000)	Less than 6 years of difference to our reference year (2000)	Less than 10 years of difference to our reference year (2000)	Less than 15 years of difference to our reference year (2000)	Age of data unknown or more than 15 years of difference to our reference year (2000)	less than 3 years means: data measured in 1997 or later; score for processes with investment cycles of <10 years; for other cases, scoring adjustments can be made accordingly
Geographical correlation	Data from area under study	Average data from larger area in which the area under study is included	Data from smaller area than area under study, or from similar area		Data from unknown OR distinctly different area (north america instead of middle east, OECD-Europe instead of Russia)	Similarity expressed in terms of enviornmental legislation. Suggestion for grouping: North America, Australia; European Union, Japan, South Africa; South America, North and Central Africa and Middle East; Russia, China, Far East Asia
Further technological correlation	Data from enterprises, processes and materials under study (i.e. identical technology)		Data on related processes or materials but same technology, OR Data from processes and materials under study but from different technology	Data on related processes or materials but different technology, OR data on laboratory scale processes and same technology	Data on related processes or materials but on laboratory scale of different technology	Examples for different technology: - steam turbine instead of motor propulsion in ships - emission factor B(a)P for diesel train based on lorry motor data Examples for related processes or materials: - data for tyles instead of bricks production - data of refinery infrastructure for chemical plants infrastructure
Sample size	>100, continous measurement, balance of purchased products	>20	> 10, aggregated figure in env. report	>=3	unknown	sample size behind a figure reported in the information source

The scores are then translated into a geometric standard deviation value with Equation [4-1]. The geometric standard deviation value is the exponentiated value of the standard deviation of the log transformed impact value.

$$SD_{g95} = {\sigma_g}^2 =$$
$$exp[\sqrt{[ln(U_1)]^2 + [ln(U_2)]^2 + [ln(U_3)]^2 + [ln(U_4)]^2 + [ln(U_5)]^2 + [ln(U_6)]^2 + [ln(U_b)]^2}]$$

with:

[4-1]

$U_1 = uncertainty\,factor\,of\,realiability$

$U_2 = uncertainty\,factor\,ofcompleteness$

$U_3 = uncertainty\,factor\,of\,temporal\,correlation$

$U_4 = uncertainty\,factor\,of\,geographic\,correlation$

$U_5 = uncertainty\,factor\,of\,other\,technological\,correlation$

$U_6 = uncertainty\,factor\,of\,sample\,size$

$U_b = basic\,uncertainty\,factor$

4.2 Monte Carlo Impact Simulation

To estimate the impact value of each component of the product, Monte Carlo (MC) simulations are used to produce possible impact values for each component of the product and, ultimately, derive the impact value of the product itself. When gathering the materials information for the LCI, the practitioner will gather a bill of materials (BOM), which consists of the components weight and materials information. However, we will refer the BOM as the bill of components (BOC) in this study because one of the questions we would like to answer is how specific we need to be when describing the components in order to obtain credible LCA results, especially as a specific material is not always associated with each component. The information hierarchy provided by the structured underspecification will allow for the estimation of the uncertainty in the impact value of the product as seen at different resolution of the BOC.

The BOC consists of the product components' mass and the materials specification of the components at each level of specificity. The LCA simulation model then randomly chooses a value using Excel's RANDBETWEEN function to choose an L5 proxy database entry from a list of L5 proxy entries that belong under a materials designation at a given level of specificity. Once a specific proxy is chosen, Oracle Crystal Ball is used to run MC simulation of the L5 proxy. This generates an impact value for the component and then the impact value for the product can be derived from the component impact values. The simulation is repeated 10,000 times to generate 10,000 unique possible impact profile of the BOC. The input into Crystal Ball requires arithmetic mean (μ_{ar}), arithmetic standard deviation (σ_{ar}), and location (L) as input parameters. The arithmetic mean μ_{ar} and standard deviations σ_{ar} were transformed from the geometric standard deviation as presented from the database according to [4-2] and [4-3]. The location parameter is assumed to be zero for all cases.

$$\mu_{ar} = \mu_g * e^{\frac{\log^2(\sigma_g)}{2}}$$

[4-2]

$$\sigma_{ar} = \sqrt{e^{2*\ln(\mu_g) + \ln^2(\sigma_g)} * \left(e^{\ln^2(\sigma_g)} - 1\right)}$$

[4-3]

4.3 Streamlining: Selecting the Set of Interest

The set of interest (SOI) is the subset of components that are determined to be the highest impacting items within the product. The goal of the methodology is to determine which SOI are important to resolve to better characterize the impact, I_A, of the product, A. More formally stated, let SOI be defined as the smallest (in number) set of p components, the impact of which represents at least some threshold fraction d of the total impact of the product A. This fractional contribution d to the product's impact will depend on the LCA practitioner's goal and scope of the study. The fractional contribution of the SOI is expressed mathematically in [4-4].

$$d \leq \sum_{i}^{p} X_i \text{ } such\,that \text{ } X_i = \frac{I_i}{\sum_{j=1}^{N} I_j}$$

[4-4]

4.3.1 Ranking Criteria

As discussed in section 4.2, each MC run produces a possible detailed impact BOC for the product. The SOI in one MC run may not include the same set of components as subsequent runs due to the distribution of possible impact values and uncertainties associated with the underspecified BOC. In order to account for the uncertainty due to underspecification streamlining, we propose determining SOI that probabilistically satisfies the fractional contribution criteria of the fully resolved product; identification of the SOI depends on the probability of components in the SOI to contribute to the majority of the impact and conversely the probability of the small contributors contributing insignificantly to the impact.

In this thesis the SOI is determined by ranking the components based on the percentile, π, of the percent contribution values of a component to the total impact of the product for x number of MC trials with a specified level of confidence α. The percentile value is used because it does not assume any prior knowledge of a probability distribution and is moderated against outlier values. We may not assume that the data distribution in any particular category to be one type of distribution, much less a normal distribution due to the agglomeration of multiple datasets into materials category in the structured underspecification database. Results will be provided as to the ranking scheme that will produce the optimal correct identification of the SOI, which is the SOI as determined at L5.

4.3.2 Streamline Implementation: Two-Level Hybrid

Starting off with the identification or the SOI at L1, the SOI is then fully specified to L5 and the MC simulation is run again to produce an L1/L5 hybrid BOC. This approach will model how well the LCA practitioner can perform by investing all the effort into fully specifying SOI while leaving the rest of the BOC well underspecified at L1, and the ability of the initial L1 resolution of the BOC to offer sufficient information to identify the SOI. This methodology represents a simplified model of reality in which the information about a product can be identified at different levels of specificity. In actuality, the level specificity that can be quickly reached with little resource investment is most likely somewhere between a fully specified BOC and a fully underspecified BOC. The components in the BOC may be specified at L2, L3 or L5 to begin with; however, for the academic analysis, we will look at the worst case scenario as viewed at the L1 underspecified level.

4.4 Assessing Effectiveness: Error Rate & Sensitivity Analysis

The SOI of the product with all its components viewed at L5, represented here as SOI_{L5}, is determined in order to calculate the probabilistic underspecification performance. This set is used to compare the SOI sets as established by different methods of identification of the SOI. The false reject, or Type I, error rate as defined in equation [4-5] and the false accepts or Type II error rate, are determined in equation [4-6]. These values will be established by varying the values of the fractional contribution to the total, *d,* and the level of confidence, α, in order to determine the sensitivity of the results to these parameters.

$$Type\ 1\ Error\colon\ \frac{SOI_{L5} \notin SOI_{LX}}{\text{Total \# Components}}$$

[4-5]

$$Type\ II\ Error\colon \frac{SOI_{LX} \notin SOI_{L5}}{\text{Total \# Components}}$$

[4-6]

4.5 Selecting Case Studies: Herfindahl Index

Selecting representative case studies to test the methodology is important in determining the robustness of the approach; a method may seem to perform much better or much worse depending on the case studies that one chooses. Since a product's impact is roughly related to its mass, one needs to take into account the product's component mass uniformity when choosing case studies. In other words, it is important to know how evenly is the product's mass is distributed among its components. One way in which uniformity is quantified is through the Herfindahl Index, which is traditionally used in economics to measure market uniformity for antimonopoly cases, competition law, and technology management. The Herfindahl Index is the sum of squares of the percentage market share, s_i, of the firms within a particular market [4-7]. In our case, we have defined the percentage as mass percent contribution of each component to the product.

$$H = \sum_{i=1}^{N} s_i^2$$

[4-7]

Due to the wide range of component numbers, we used the normalized Herfindahl, H^* [4-8] index to account for limit of the non-normalized Herfindahl that is 1/N.

$$H^* = \frac{H - {}^{1}/_{N}}{1 - {}^{1}/_{N}}$$

[4-8]

In order to more fully test out the methodology, a portfolio of products with fully specified BOC is gathered from multiple studies that have been conducted at the Materials Systems Laboratory. Their masses, number of components, and normalized Herfindahl indexes are summarized in Table 4-2.

Table 4-2 Summary of the Portfolio of BOC that has been gathered to develop and test probabilistic underspecification streamlining LCA.

Product	Mass [kg]	Number of Components	Normalized Herfindahl
Consumer Product 1	0.04	41	0.555
Consumer Product 2	15	17	0.348
Consumer Product 2 with Scrap and Packaging	20	19	0.213
Consumer Product 3	10	16	0.134
Desktop Computer	14	56	0.130
Consumer Product 3 with Scrap and Packaging	15	18	0.110
GREET Car	1310	90	0.071

The actual identities of some of these products may not be revealed due to confidentiality agreements with the firms who have provided proprietary information about their product. Consumer Product 1 is a disposable consumer product that is mainly composed of one component and hence is reflected in the high normalized-Herfindahl Index. Consumer Product 2 and Consumer Product 3 are two versions of functionally identical products made from different materials. The analysis will also be run on these products to account for their packaging and scrap material expended in the production of the components. The result is a range of Herfindahl indices for very similar products. The desktop computer BOC was obtained using the ecoinvent documentation of a desktop computer composition. The *Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation Model* or GREET 2.7 Model (2006) of a generic vehicle that has been scaled to reflect the components and compositions of a generic US sedan. The scaling is based on the LCA study by Sullivan of US sedans (Sullivan, Williams et al. 1998). In each case, the L5 materials specification of the components is assumed to be representative of the best-known information about the products. Their normalized Herfindahl indexes are graphically summarized below in Figure 4-5.

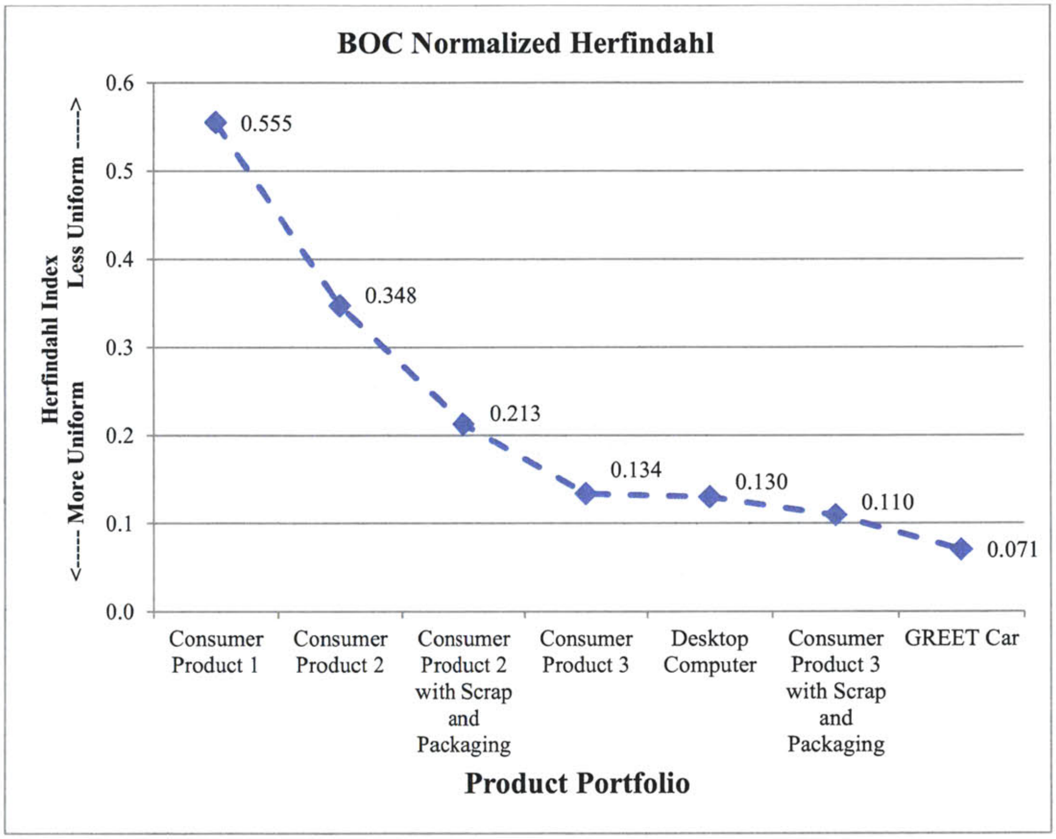

Figure 4-5 Portfolio of products with completely specified bill of components that will be used for testing the methodology.

5 RESULTS AND ANALYSIS

The results of applying the streamlining methodology to a series of case studies are outlined in the following chapter. First, the structured underspecification database is characterized to explore the characteristics of the distribution of the expected impact values of a materials class, as defined by the database developed for this thesis. Then the BOC of all the products is evaluated at each level of underspecification to reveal the expected impact of the product as viewed from differing levels of specificity. The values of the probabilistic streamlining methodology are applied to the BOC of the GREET car with *d (threshold fraction of total impact)* = 75% cumulative percent impact, α = 90% confidence with the ranking percentile criteria of π = 50%. The error rate was determined and evaluated to be promising so the methodology was applied to the rest of the products. The sensitivity of the size of the SOI was evaluated as a function of cumulative percent impact, confidence level, and ranking percentile criteria.

5.1 Structured Underspecification Characterization

The materials specifications entries that are used in LCA simulation of the product case studies were evaluated to determine the characteristic of the distribution of their expected impact values. Monte Carlo outputs of the CED/kg of each of the materials specification entries for Levels

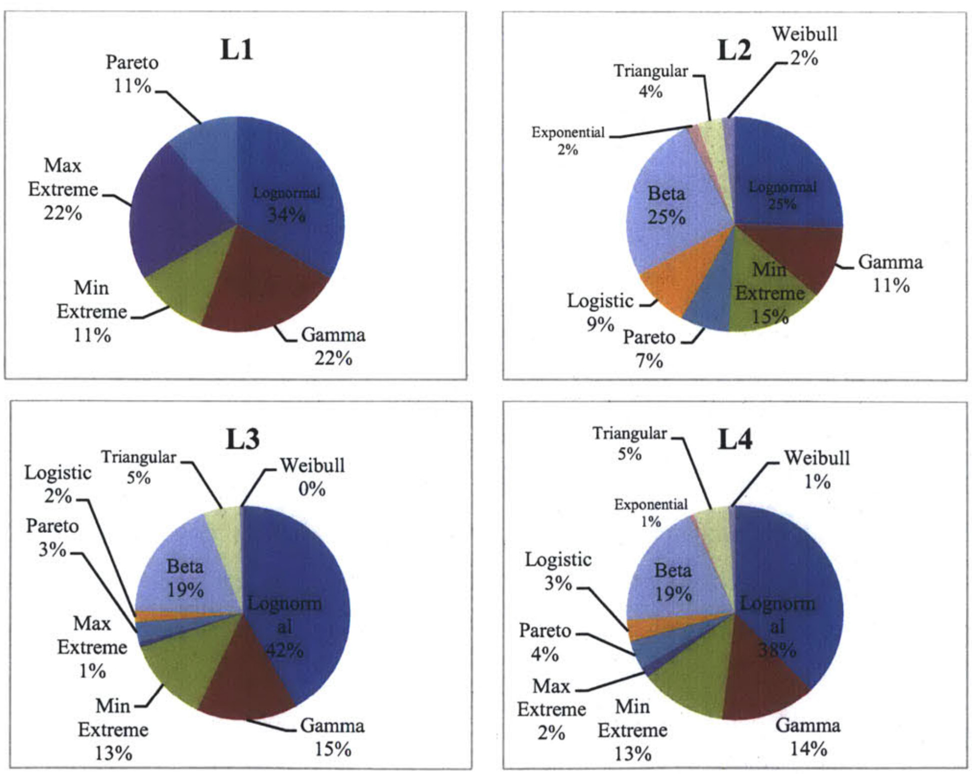

Figure 5-1 Distribution Fits of the impact values of the groups of materials in each level of specificity. L5 is all lognormal according to our model.

1-4 were generated. The results were grouped according to their L1 specification in order to compare how the expected impact distribution changes over the levels of specificity. For example, the "Aluminum" specification at L3 will be grouped with the "Metals" specification at the L1 level of specificity. The statistics of the results were analyzed to determine the characteristics of their distribution. Best-fit analysis was done on the data and it was determined that the majority of the classes were not normally distributed and can be described by a number of skewed distributions as shown in Figure 5-1.

Based on this result, mean and standard deviation values were not used to represent the spread in the data. Instead, the variation in the output is presented using the median absolute deviation (MAD) that is analogous to the standard deviation as it describes the spread in the data while mitigating for outlier values. This value is the median of the absolute value of the residual of the data set as described in the following equation [5-1]:

$$\text{MAD} = median_i\left(\left|X_i - median_j\left(X_j\right)\right|\right)$$

[5-1]

The MAD is used to derive the MAD-coefficient of variation (MAD-COV) value represented in equation [5-2] as the ratio of the MAD over the median value of the dataset. This value describes the median percent variation of the dataset from the median.

$$\text{MAD COV} = \frac{median_i\left(\left|X_i - median_j\left(X_j\right)\right|\right)}{median_j\left(X_j\right)}$$

[5-2]

The MAD-COV plots of eight of the L1 categories are presented in Figure 5-2. The sizes of the circles in the plots represent the number of materials that have that designation at that particular level of specificity. This represents the likelihood that a component composed of a material from that L1 category will exhibit that degree of variability at that particular level of specificity. The materials classes that are in higher level of specificity tend to have smaller variations compared to other materials classes that belong to the same L1 class but are at lower level of specificity. This result was expected because as the materials class gets more specific, the expected impact range should become narrower. The general trend is for a lower MAD-COV for all the L1 categories of materials; however, it is observed that there are cases where materials in more specific levels can turn out to have higher variability than the lower specificity level from which they derive. For example in the Glass category, one of the materials classes in L2 has a higher MAD-COV than the L1 specification. This is most likely due to the elimination of a group of materials that accounts for the mid-values of the distribution as demonstrated in the schematic in Figure 5-3.

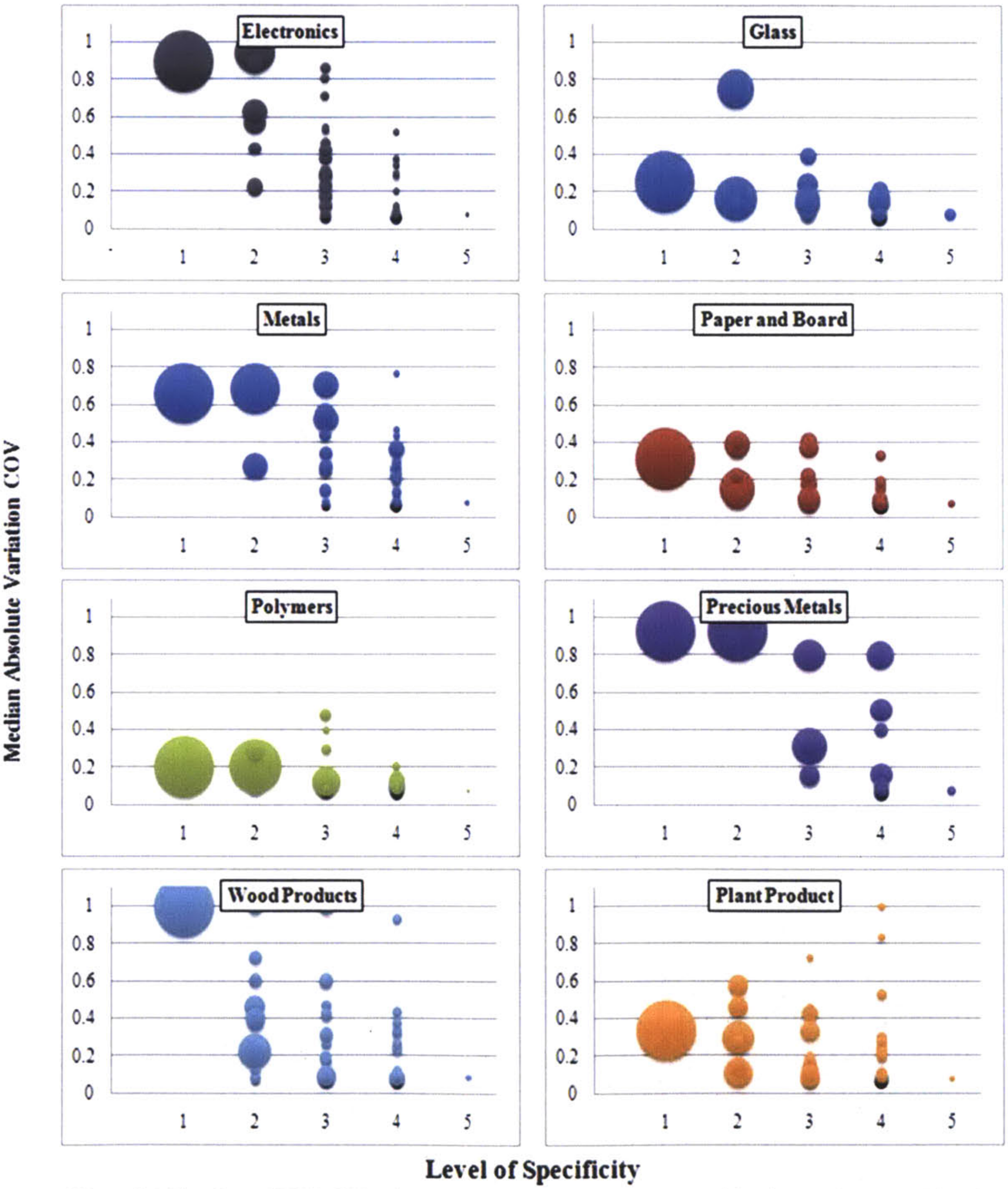

Figure 5-2 The plots of MAD-COV of materials classes grouped by L1 specifications and separated into levels of specificity. The size of the circles represents the number of individual L5 entries that belong in that particular class.

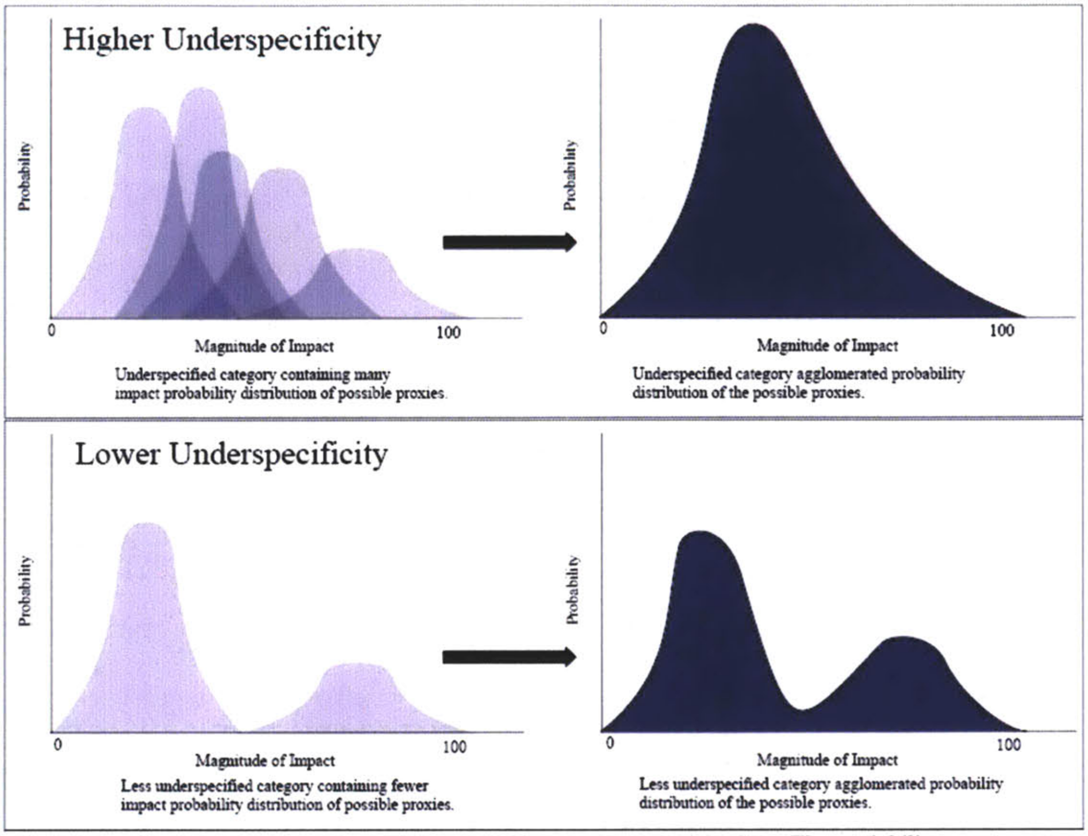

Figure 5-3 Schematic of the probability distributions of a materials class. The variability could widen or narrow depending on the impact values of the materials that are included in the set.

As stated in Chapter 4, a goal of this thesis is understand whether it is feasible to identify the SOI for a given life cycle when the activities within that life cycle have been structurally underspecified. A further goal has been to understand what level of activity specification is required for the approach to be effective and efficient. Implicit in the use of the "levels of specificity" were that the levels serve well as a proxy for overall uncertainty in the underlying data about a materials class; as specificity increases (i.e., moving from Level 1 to 5), data variability would decline. While there is some trend towards lower variability with higher specificity, the number of irregular cases within most of the materials classes suggests that, given the current configuration of the database, this trend may not hold for any given case analysis. Nevertheless, it is interesting to explore how well the method works and if the anticipated trend holds despite these irregularities.

5.2 Impact Assessment of Portfolio

The total materials CED values at each level of specificity are generated for the case study products' BOCs using the stochastic methods as described in the methodology section. The data is analyzed in ten, one-thousand simulation groups taken from the ten thousand simulations run for each product. The standard deviation, mean, median, ninetieth percentile, and tenth percentile values for the ten sets of data are then averaged to generate the box and whisker plots shown below in Figure 5-4 and Figure 5-5. The bottom-most edge of the box represents the 1st quartile or

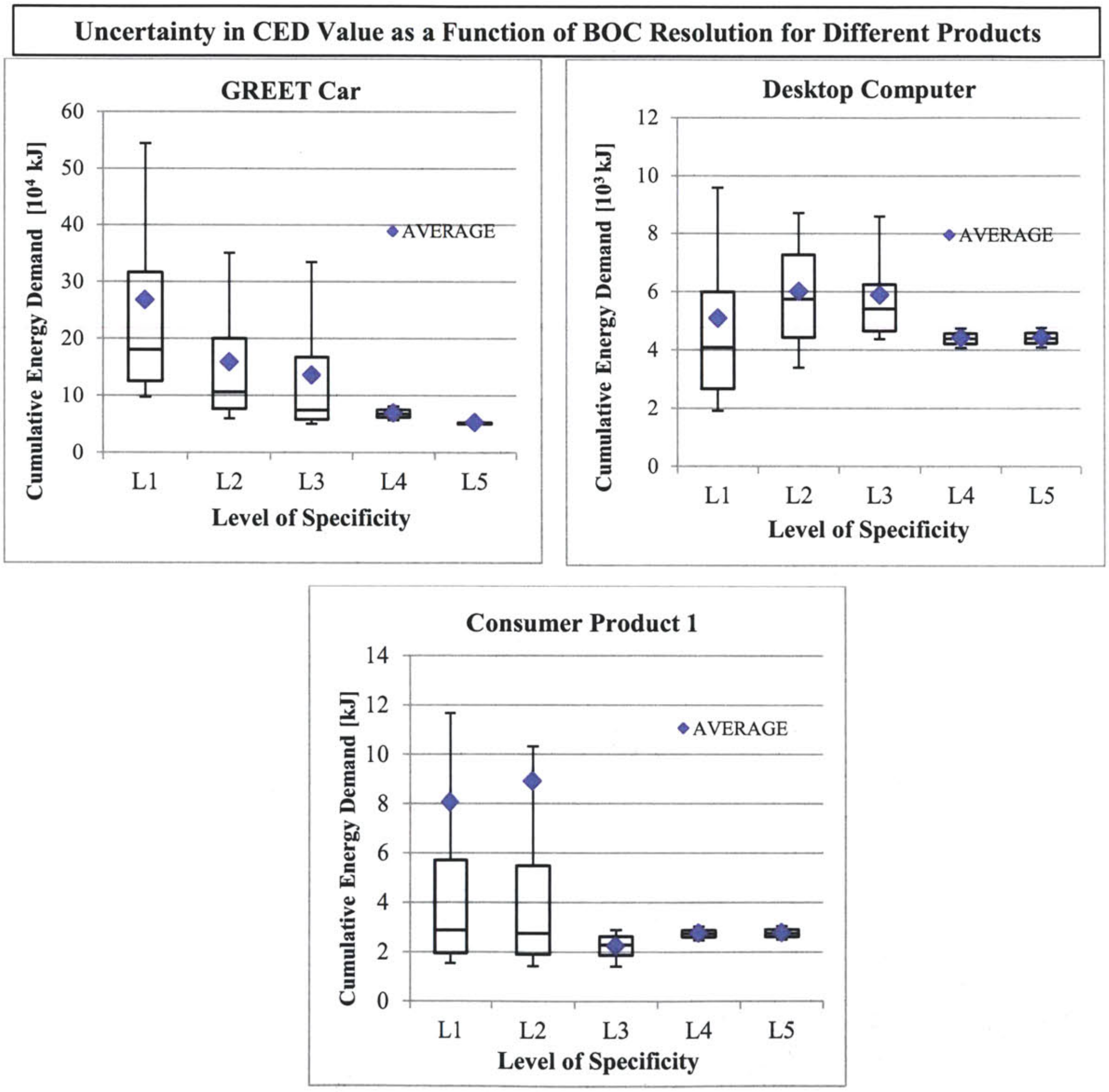

Figure 5-4 Box and whisker plots showing the spread in total CED of three products. Notice the difference in magnitude of the CED values due to the differences in products. Note the narrowing of the spread in uncertainty as the BOC gets more specified.

the 25th percentile. The line in between the edges of the box is the median value of the dataset, while the upper edge of the box represents the 3rd quartile of the data, or the 75th percentile of the dataset. The edges of the upper and lower whiskers are the 90th and the 10th percentile of the data respectively. Notice that the CED values of the products are at different orders of magnitude as noted by the y-axes. The average values of the CED for the computer and car do fall within the 3rd quartile of the dataset, showing a somewhat more normal distribution when compared to Consumer Product 1 (CP1).

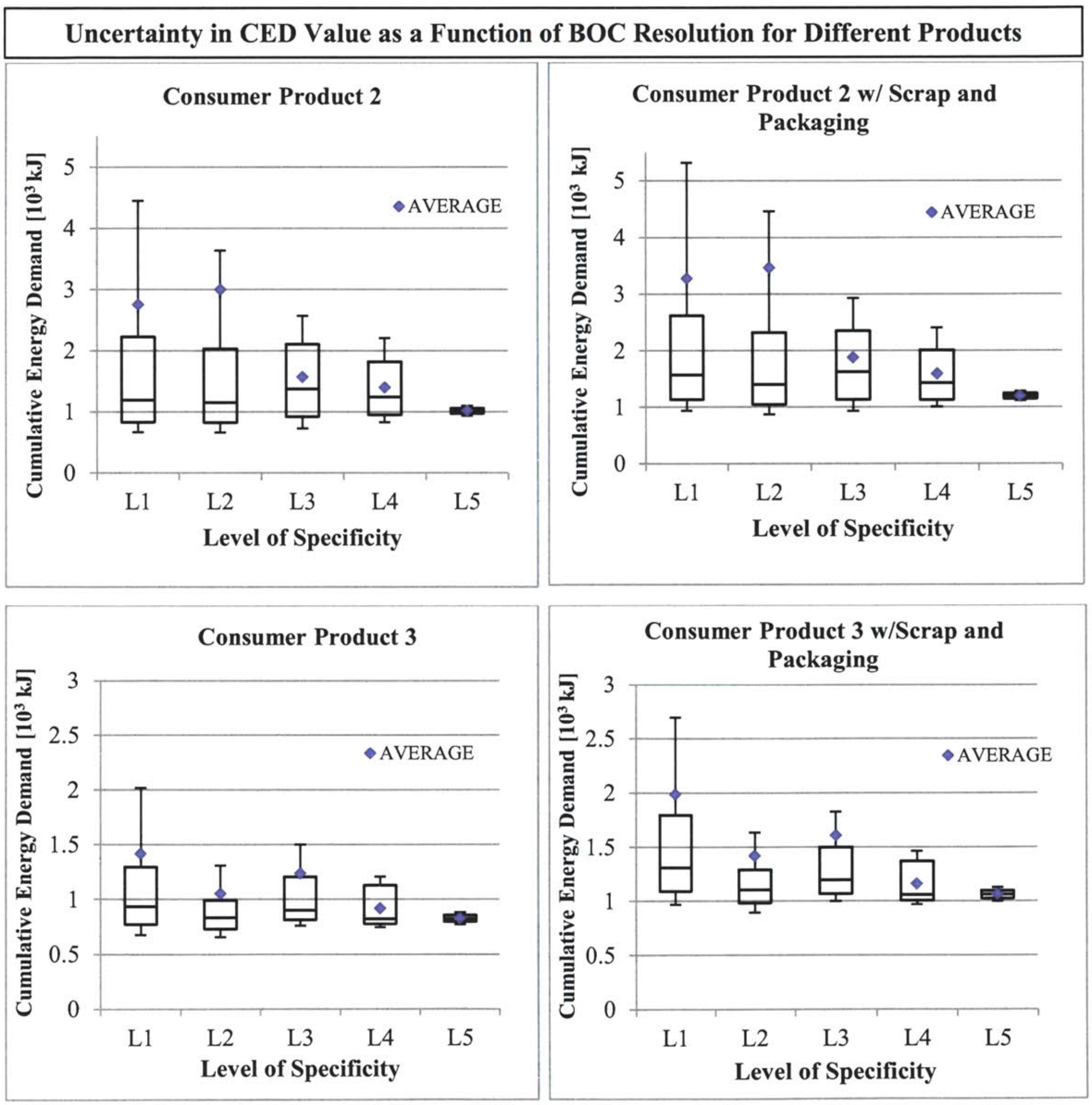

Figure 5-5 Box and whisker plots of Consumer Product 2 and Consumer Product 3 along with the versions of the BOC that include scrap and packaging.

Consumer Product 2 (CP2), Consumer Product 2 with Scrap and Packaging (CP2SP), Consumer Product 3 (CP3), and Consumer Product 3 with Scrap and Packaging (CP3SP) are grouped together in Figure 5-5 because each represents the same functional product, however the main structural component of CP3 is a polymer, while the main CP2 structural component can be described as a metal in the most underspecified level. CP2SP and CP3SP demonstrate that including the scrap and packaging associated with the product could lead to significantly different expectation values for the CED. The most notable difference is in the impact of CP3. When the packaging and scrap was included there was about an increase of around 200 kJ of energy per product while CP2 did not show such an increase when scrap was taken into account. This suggests that the scrap of CP3 may be more impactful or that there is a lot of scrap waste in the production of CP3.

5.2.1 Absolute Deviation from the Best Estimate

Figure 5-6 shows the distribution of absolute deviations of the median (ADM) as the measurement of how good the median is as the estimator of the impact of the product at the most specified level (L5). The ADM calculation is described in equation [5-3]:

$$ADM = \frac{|Median(CED_{LX}) - (Median\ CED_{L5})|}{(Median\ CED_{L5})} \quad [5\text{-}3]$$

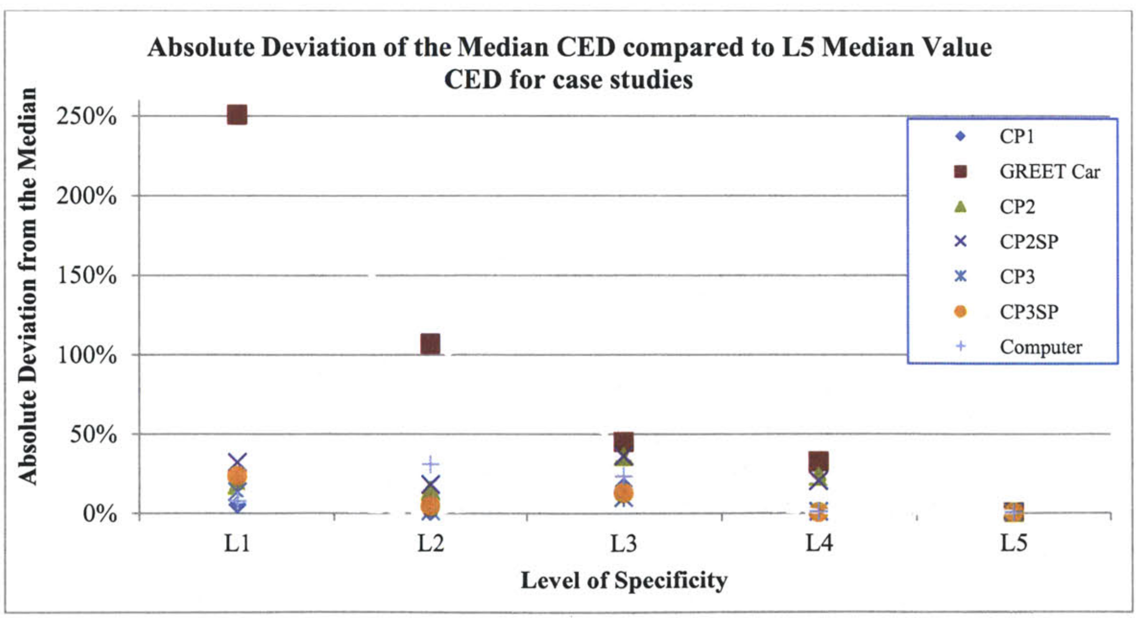

Figure 5-6 The absolute deviation of the median estimator for CED at each level of specification for all case study products. The median gives good estimates but they have low confidence at low specificity.

The ADM for all the products is below 50% deviation except for the L1 and L2 estimations for the car. This suggests that the median give a fairly good estimate of the L5 CED median value. The large uncertainty in the car case may be due to the majority of the car being made up of one group of materials: metals. This group of material can have a large range of CED impact values there is no data beyond the fact that the component is metal and the components' weights. Although, as the car becomes better specified, it is observed that the ADM significantly decreases. Even though the other case studies have only about 50% ADM starting at L1, the confidence in the estimates may be quite low as demonstrated in the following subsection.

5.2.2 MAD-Coefficient of Variation

MAD-COV is calculated for the portfolio of products, shown below in Figure 5-7. The general trend is that as the product gets better specified the variability in the expected impact decreases, represented by the dashed blue line. This average MAD-COV derived from a simple mean calculation of the MAD-COV of all the products for each level of specificity. There are slight increases in the MAD-COV of CP1 and the computer going from L1 to L2, whereas CP2, CP2SP, and CP3SP all have higher MAD-COV values going from L2 to L3. This increase is only slight and may be due to the phenomena described in Figure 5-3, where the materials that contributed to mid-value impacts are taken out and the extreme values remain, leaving the higher specified levels with larger uncertainties.

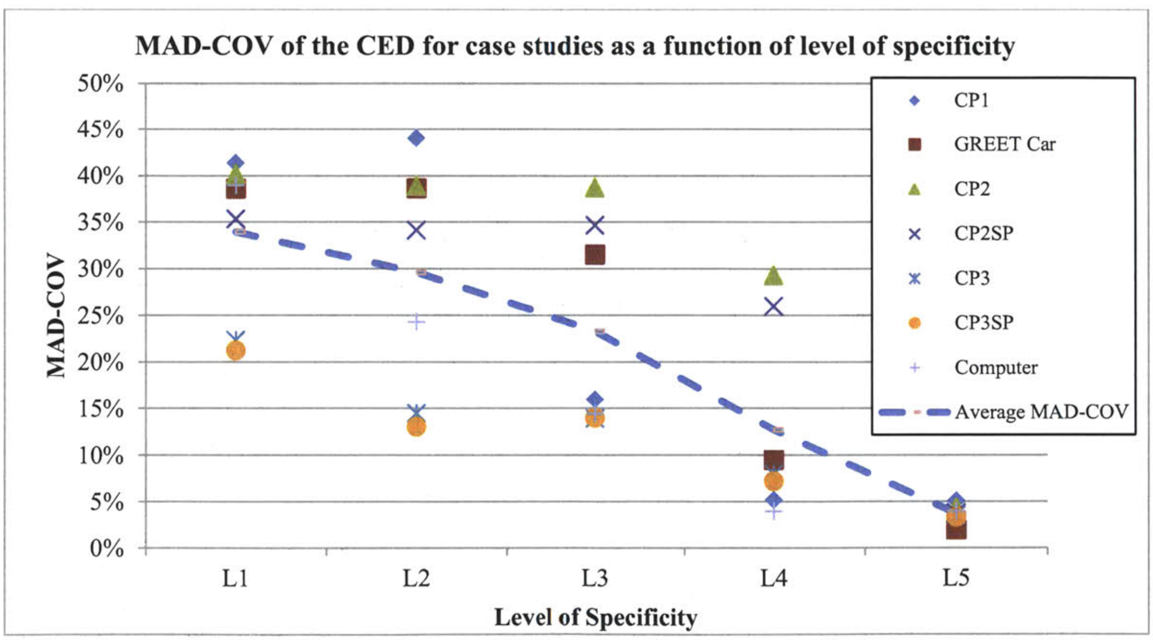

Figure 5-7 The MAD-COV of the impact of each product evaluated at different levels of specificity. The blue dotted line is the average MAD-COV for the products.

The AMD of the CED impact evaluation of the products suggests that it may be possible to use the median as a fairly accurate estimate of the expected value of the product even with the lowest level of the product's BOC. However, the MAD-COV, shown Figure 5-4 and Figure 5-5 demonstrate high level of uncertainty in the CED values at high underspecification. Thus, we do not have much confidence in the median estimate value even though it has proximity to the L5 CED. If these materials impact calculations were going to be used for any decision making, it may be necessary to further specify the BOC of the underspecified product to obtain a better confidence level and resolve the uncertainty. The fact that this is possible leads to the exploration of the application of the streamlining methodology to the GREET car in Section 5.3 to test out the effectiveness of streamlining using probabilistic underspecification as a tool to arrive at an accurate and precise estimate of the impact.

5.3 Methodology Training Case: GREET Car

The GREET Car was chosen as the methodology-training case study because it consists of the largest number of components in our portfolio of BOCs and has the most uniform BOC

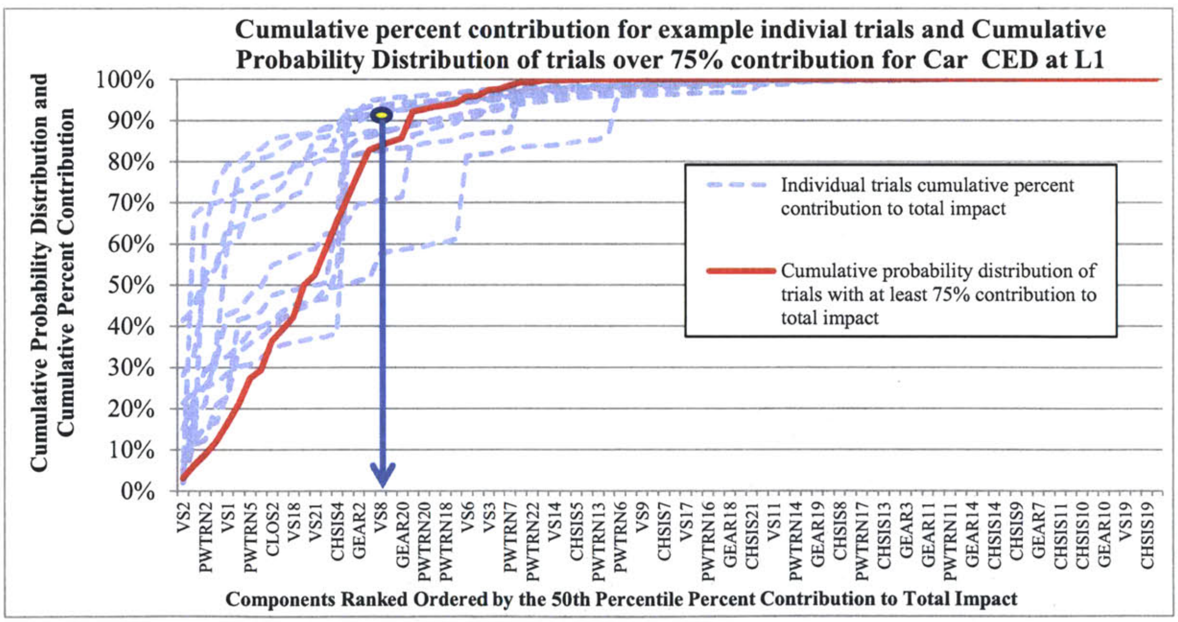

Figure 5-8 Cumulative percent contribution for each individual trials and cumulative probability distribution of trials over 75% contribution for car CED at L1.

according to the normalized Herfindahl Index. These two factors make it the best candidate for analysis among the product BOCs available to this thesis. The large number or components, coupled with the uniformity in mass of the components, can potentially make it difficult for the

SOI to be determined. This difficulty could present itself as a large SOI or SOI that is inaccurate at predicting the high impacting components.

The L1 CED Monte Carlo simulations were analyzed to probabilistically determine which products were the most impactful contributors to CED, contributing to 75% of the product's impact 90% of the time. Each component is ranked by their 50th percentile total-trial percent contribution for all the trials. Figure 5-8 represents the GREET car components that are ranked ordered by the 50th percentile percent contribution to the total impact for all the trials.

The dashed blue line represents examples of the individual trials' cumulative percent contribution to the total as more and more components' impacts are compiled according to the rank order. The solid red curve represents the cumulative probability distribution of the cumulative percent contribution, as the components are added up, to have at least 75% contribution to the total impact of the particular trials. The yellow circle marks the point when the cumulative probability graph passes the 90% threshold for confidence. Thus, all the components to the left of the green arrow are determined to be the important components and constitute the SOI. The SOI for the car under the parameters described here is 22 components, or 24% of the BOC.

The SOI is then further resolved to L5 resolution of specificity to see how much improvement in fidelity of the impact estimate comes from resolving only the SOI. The resulting spread in expected CED for the L1/L5 hybrid BOC is presented in Figure 5-9, comparing it to the other levels of specificity. Notice that by only specifying 24% of the BOC, the accuracy of the estimate can be significantly improved.

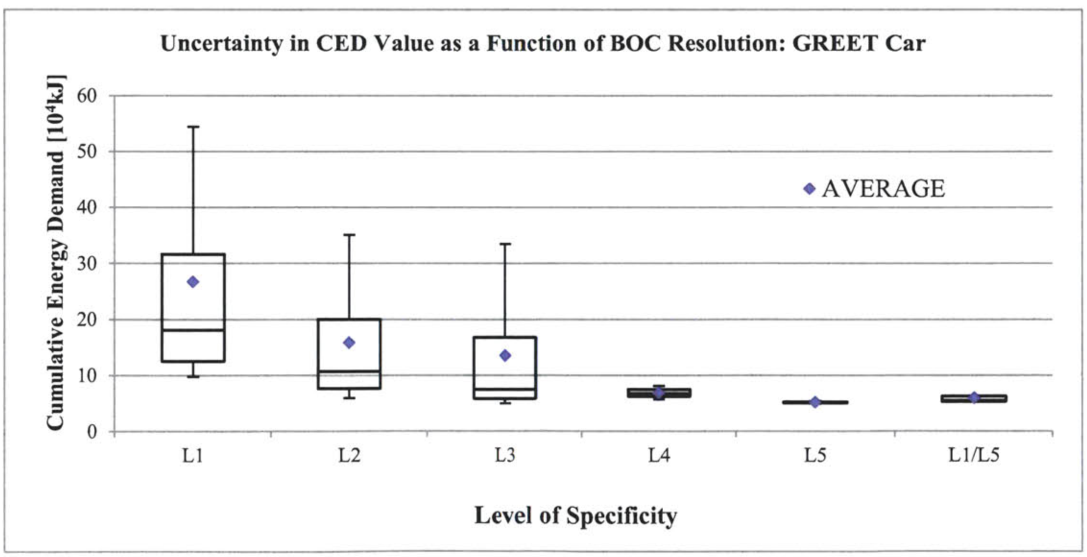

Figure 5-9 The hybrid L1/L5 BOC CED is compared to the other pure levels of specificity. By only specifying 24.4% of the BOC at L5, we were able to obtain significant resolution.

5.3.1 Effectiveness of Strategy

One of the motivations for using the underspecified impact database to determine the SOI is that it takes into account the range of impact values of the material. As briefly discussed, the mass of a component is roughly related to its impact; however, there are examples where light materials can have considerably higher impact compared to other materials of the same mass. Precious metals are a prime example of where the environmental impact per weight is high. Therefore, methods like using weight to rank components to determine the SOI may not perform very well.

The value of probabilistic ranking using the 50th percentile in the GREET car case study is demonstrated in Figure 5-10. The components were ranked by their mass and by their median

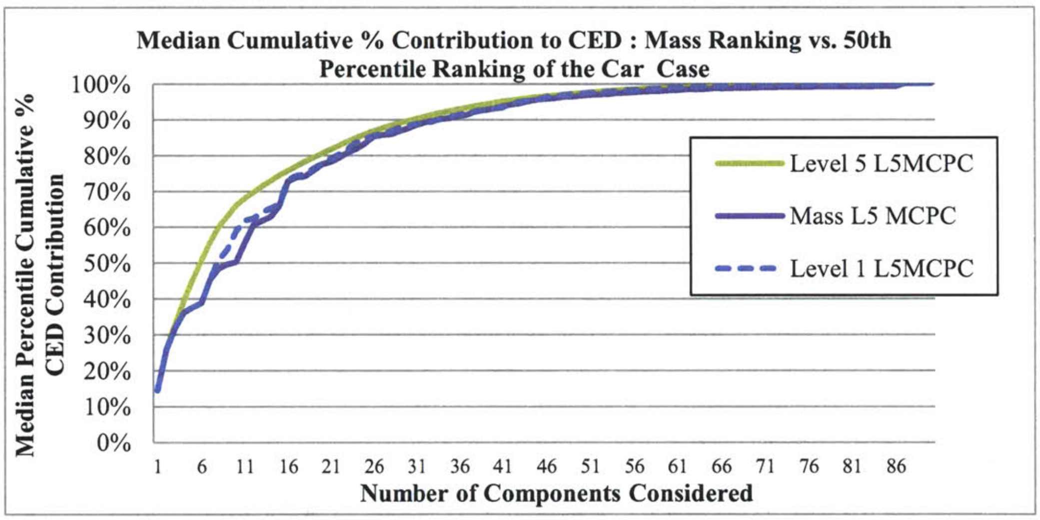

Figure 5-10 Cumulative % CED curve comparing the mass ranking method to the 50th percentile ranking method.

percent contribution to the product's impact at the L1 level. The median percentile cumulative percent contribution (MCPC) at L5 resolution were calculated for each methodology of ranking by mass or Level 1 median percent contribution. The purple curve demonstrates how well mass functions as an indicator of impact, which is referred to as Mass L5MCPC. The dashed blue curve represents the ranking by median percent contribution of each component L1. These two curves are compared to the green curve, Level 5 L5MCPC. This curve was derived by ranking the 50th percentile percent contribution of the components at L5 resolution (Level 5 L5MCPC). The curve for Level 5 L5MCPC represents the correct ranking of materials in terms of contribution to impact. Notice how the change in the slope of the line is negative for the entire curve, indicating decreasing marginal contribution to the total. The mass MCPC does not present a compelling decreasing marginal contribution curve. It is observed that the Level 1 L5MCPC is stochastically dominant over the Mass L5 MCPC, suggesting that mass is less effective at correctly ranking the most important components to impact contribution.

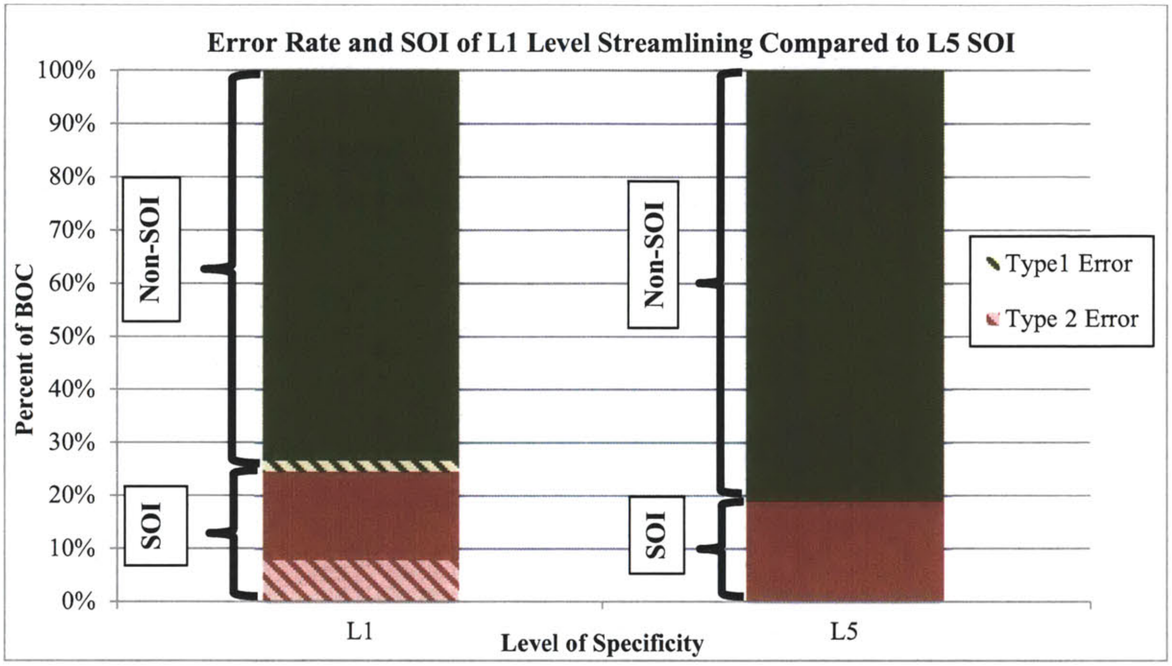

Figure 5-11 The error rates and SOI for L1 level of streamlining compared to the L5 SOI.

The error rates were also calculated to see how well the SOI determined at L1 compared to the SOI of L5 at capturing the high impacting components. The result of the L1 streamlining is diagramed in Figure 5-11. Only 24% of the BOC is determined by the probabilistic underspecification methodology to need further specification to meet the criteria established in this case study. However, some components that constitute the SOI are actually extraneous and constitute Type 2 error or wasted effort. Meanwhile, the non-SOI portion of the BOC contains the Type 1 error, or false rejection of importance. In this specific case, the methodology missed two components of importance while incorporated seven unnecessary materials. Although both types of errors are not ideal, in terms of risk mitigation, Type 1 avoidance is preferred while Type 2 error is can be more tolerated.

5.4 Case Study Results

The demonstrated efficacy of the application of the methodology to the car model motivates the further application of the methodology to the rest of the case studies. The following subsection presents the results of the methodology as applied to the products described in the methodology section.

5.4.1 Effort Reduction: Case Studies

The goal of probabilistic streamlining is to decrease the effort necessary to conduct LCA. Figure 5-12 shows the L1 SOI as a fraction of the BOC. This is the portion of the BOC that is determined to be important to invest additional research efforts to increase the precision of the impact estimates. For all the case studies, the L1 SOI constitutes less than half of the components of the BOC. Notice that the products that have high SOI percentages also have low component numbers (16-19 components) to begin with. Therefore considering the increase in resolution and confidence the impact estimate, the methodology seems effective in reducing LCA effort assuming that there is the same amount of effort to gain information for all components.

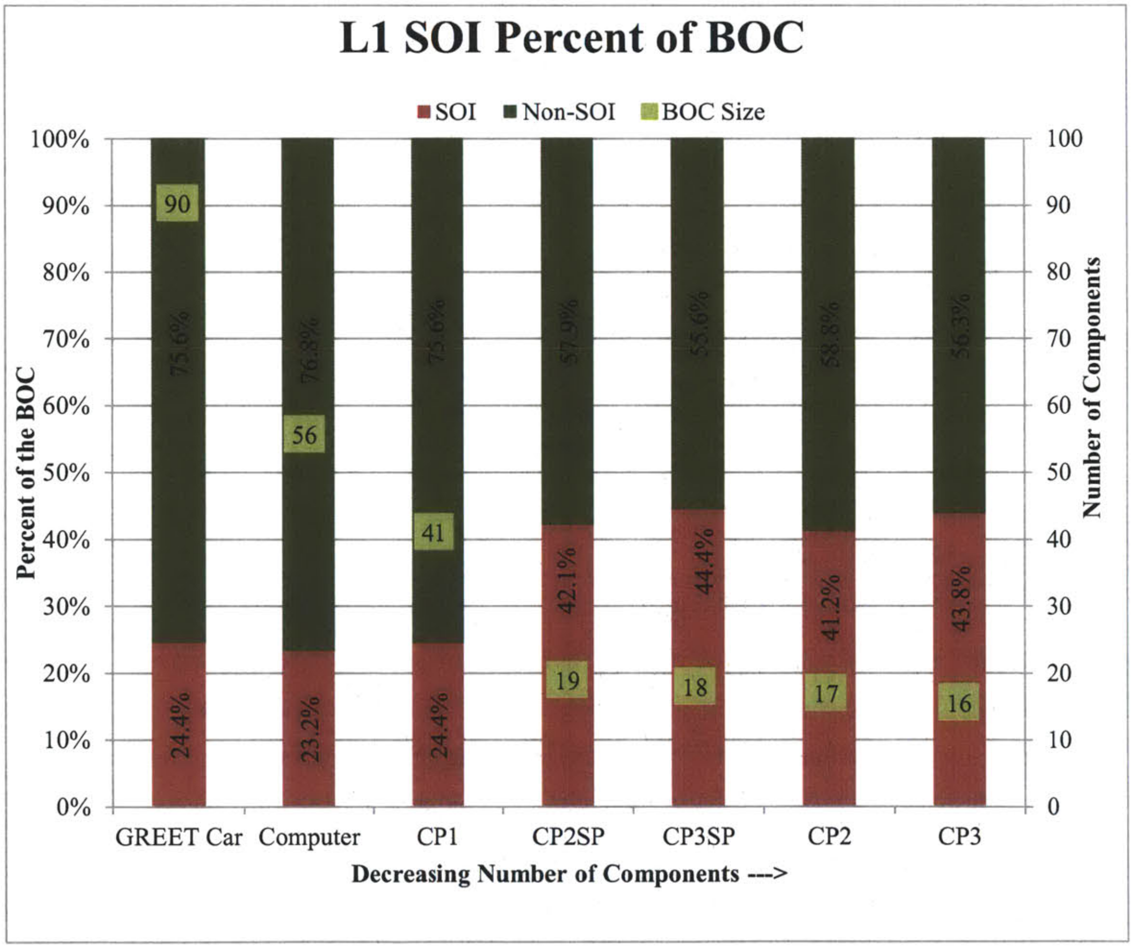

Figure 5-12 L1 SOI as a percentage of the products total BOC: the products are arranged in order of decreasing BOC size.

5.4.2 Error Rate: Case Studies

The Type 1, or false rejections, from the SOI and Type 2, or false acceptances, to the SOI were calculated comparing the L1 SOI and the L5 SOI. Figure 5-13 displays the error rates of the SOI as a percentage of the BOC. The red-hashed areas (Type 2) are the non-SOI parts of the product that were identified to be part of the SOI. The green-hashed areas are the SOI parts that were not identified as such. Clearly, for the cases that were examined, there are many more Type 2 errors than Type 1 errors. This suggest that the methodology that is applied has a bias for incorporating more components than necessary for the SOI, while it rarely rejects the components

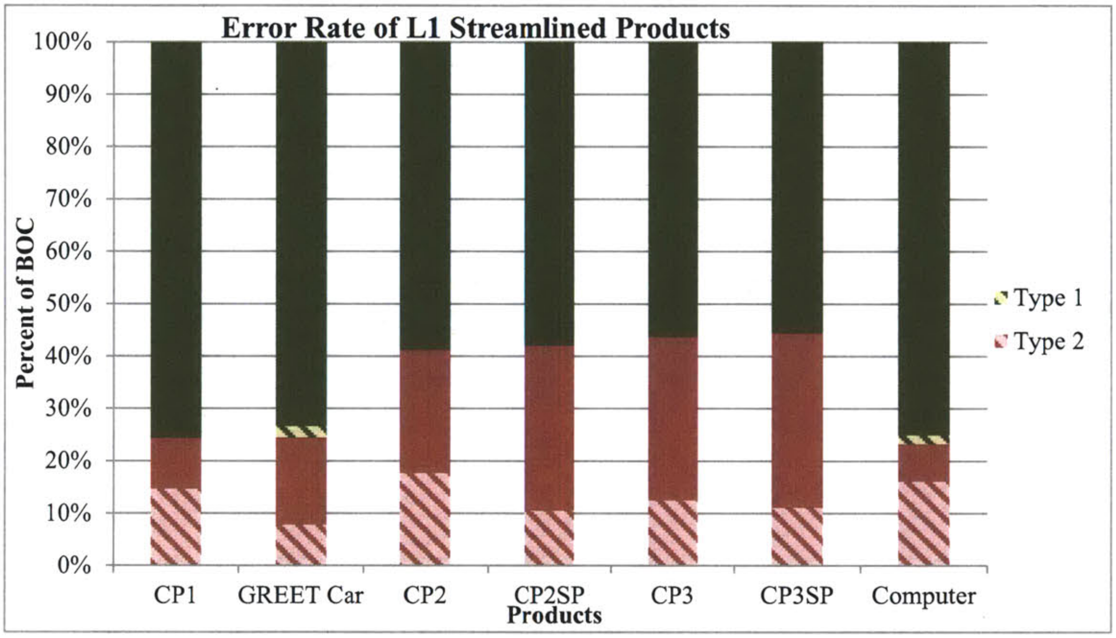

Figure 5-13 Type 1 and Type 2 error rates for all the products as a percentage of the BOC. The green parts are the non-SOI and the red parts are SOI. The striped areas are where the errors in those sets.

that are important and should be in the SOI. The only components with Type 1 errors are products with the most number of components, in this case the computer and car. None of the consumer product case studies showed any Type 1 errors, which may be due to their smaller number of components. The CP2, CP2SP, CP3, and CP3SP case studies all have the highest percent SOI of BOC. However, the Type 2 errors are among the lowest in the case study portfolio, except for the CP2. The two products in which the Type 2 error is greater than 50% of the SOI is the CP1 and the computer.

5.4.3 Impact Estimates

The same constraints were applied to both the case studies and the GREET car study. Figure 5-14 compares the impact uncertainty for the L1, L5, and L1/L5 hybrid BOCs. The case studies show similar ability for the L1 level of specificity and uncertainty estimates to determine an SOI for the product that significantly reduced the effort to obtain an accurate estimate of the L5 results with a lower level of uncertainty.

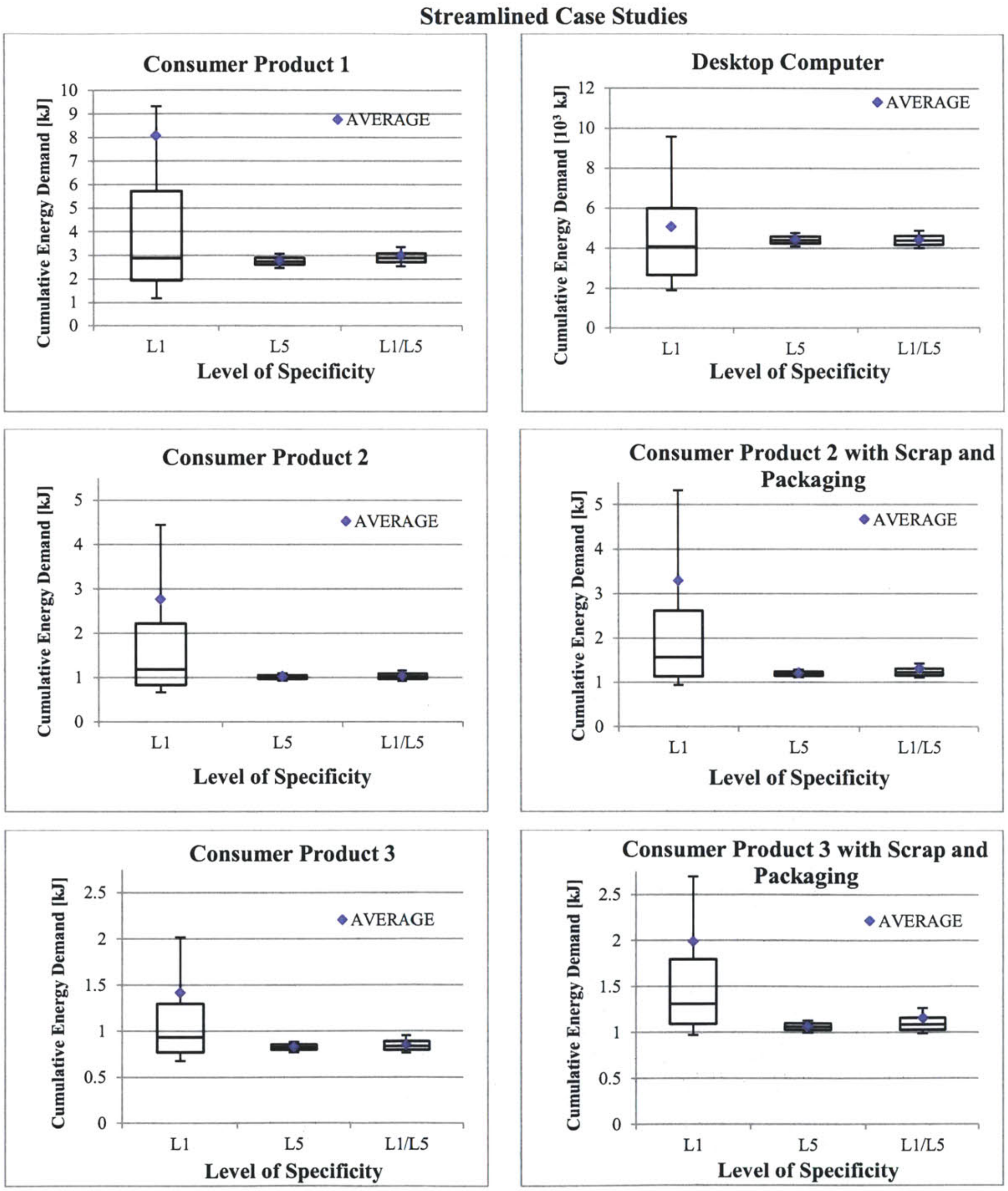

Figure 5-14 The streamlined CED comparisons of L1, L5, and the hybrid L1/L5 resolution of the BOCs. Notice the proximity of the streamlined results to the L5 results.

5.4.4 ADM-Case Studies

The ADM values for the case studies, comparing the hybrid L1/L5 BOC median as estimates for the L5 medians, show that an accurate estimate of the L5 value can be obtained by well specifying a small portion of the BOC. The absolute variation away from the L5 median ranges from 0.8% (Computer) to 7.9% (Car). Figure 5-15 compares the ADM for all the levels of specificity with the L1/L5 hybrid BOC. Table 5-1 gives the numerical absolute percentage deviation from the L5 median for each level of specificity including L1/L5.

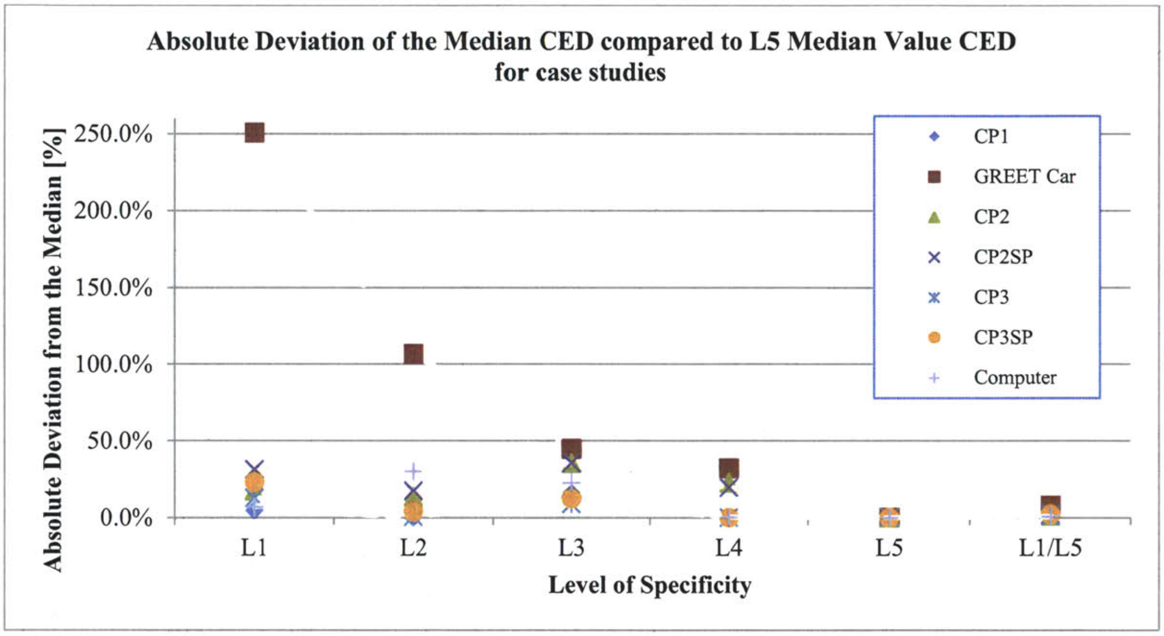

Figure 5-15 The ADM of the Case Studies including the L1/L5 Hybrid BOC as comparison to L5 and the other levels of uncertainty.

Table 5-1 Absolute Deviation from the L5 median CED of the median CED of other levels of specificity.

Absolute Deviation from L5 Median	L1	L2	L3	L4	L5	L1/L5
CP1	5.0%	0.4%	16.5%	0.3%	0.0%	4.9%
GREET Car	250.6%	106.7%	44.7%	32.2%	0.0%	7.9%
CP2	17.6%	13.8%	35.6%	22.9%	0.0%	1.4%
CP2SP	31.6%	17.7%	35.7%	19.8%	0.0%	2.3%
CP3	13.1%	0.9%	9.3%	0.3%	0.0%	1.3%
CP3SP	23.4%	4.1%	12.6%	0.2%	0.0%	2.2%
Computer	7.3%	30.4%	23.0%	0.5%	0.0%	0.8%
Average ADM	**49.8%**	**24.9%**	**25.3%**	**10.9%**	**0.0%**	**3.0%**

5.4.5 MAD-COV: Case Studies

The MAD-COV suggests that the hybrid BOCs resulting from probabilistic streamlining are able to significantly reduce the spread and uncertainty in the CED output data in the other case study products aside from the initial GREET Car example. Figure 5-16 is the MAD-COV plot of the case studies with the L1/L5 hybrid MAD-COV values. Although these values are not as low as the L5 MAD-COV values they are comparable and on average the L1/L5 MAD-COV values are lower than L4 level of specificity. The average MAD-COV values are represented by the dotted line in Figure 5-16, the L5 to L1/L5 line is marked in red to indicate that it is not

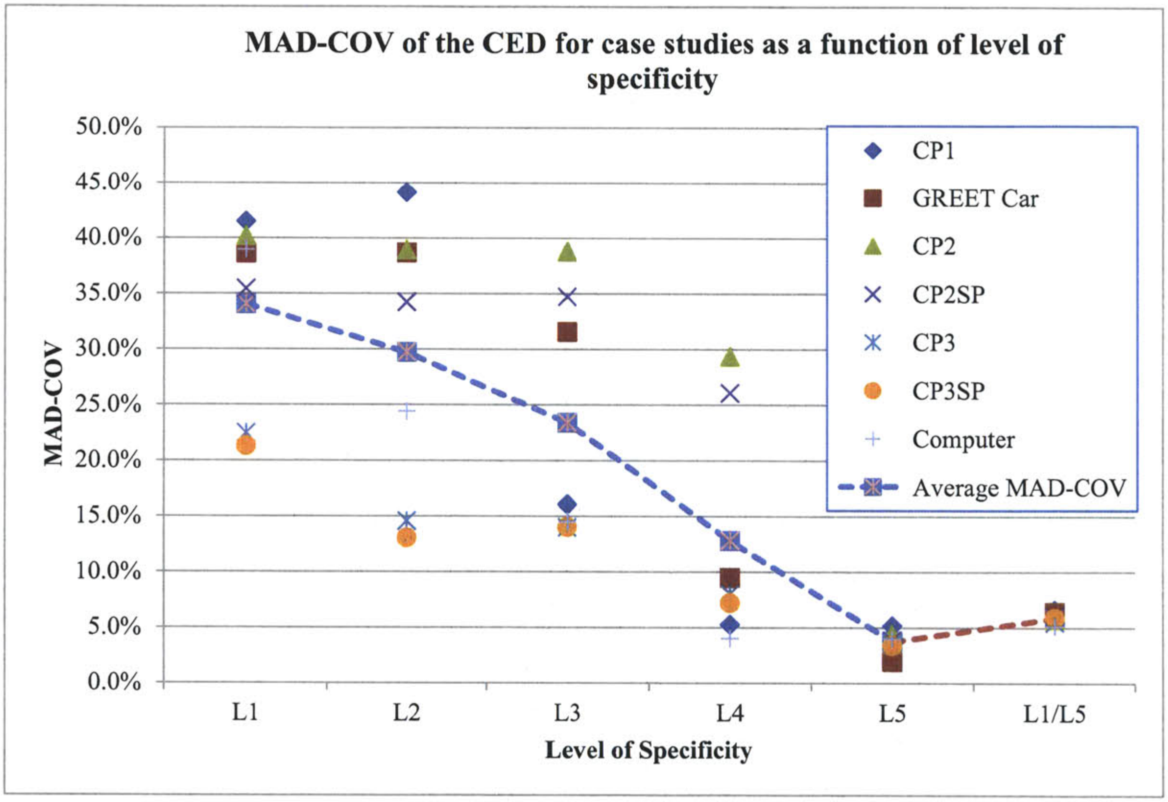

Figure 5-16 MAD-COV of the CED for the case studies with the hybrid L1/L5 impact result for comparison.

increasing in specificity. The median absolute deviations from the L5 median for the L1/L5 hybrids are around six per cent on average; this represents only a two per cent increase over the average MAD-COV for the fully specified L5 results. The values of the MAD-COV for all the levels and the hybrid BOCs are tabulated in Figure 5-16 along with the specificity level MAD-COV.

Table 5-2 MAD-COV Values for the case studies with the L1/L5 streamlined hybrid BOC and average MAD-COV

MAD-COV	L1	L2	L3	L4	L5	L1/L5
CP1	41.4%	44.1%	16.0%	5.2%	5.1%	6.5%
GREET Car	38.6%	38.7%	31.5%	9.4%	1.9%	6.4%
CP2	40.2%	38.9%	38.8%	29.3%	4.3%	5.7%
CP2SP	35.4%	34.2%	34.7%	26.0%	3.8%	5.9%
CP3	22.4%	14.5%	13.9%	7.9%	3.5%	5.4%
CP3SP	21.3%	13.0%	14.0%	7.2%	3.3%	5.8%
Computer	38.9%	24.4%	14.5%	3.9%	3.9%	5.1%
Average MAD-COV	**34.0%**	**29.7%**	**23.3%**	**12.7%**	**3.7%**	**5.8%**

5.5 Sensitivities to Model Parameters

The robustness of the method is assessed by understanding the sensitivity of probabilistic underspecification-based screening approach to changes in the parameters defining ranking criteria, cumulative threshold, and confidence level. The performance in picking the SOI will be measured by the magnitude of the Type1 and Type II errors because the size of the SOI does not say much about its quality of the selection. The ideal parameter values would be the ones that will minimize both types of errors.

5.5.1 Ranking Criteria

The components' importance ranking criteria used thus far in the case studies have been by the 50th percentile of the percent contribution by the particular component to the total impact the product. The 50th percentile of the percent contribution represents the median value of the product's possible contribution to the BOC. It can be imagined that using a higher or lower percentile contribution could lead to better results in terms of selecting the optimal SOI that will match the top contributors at the most specified level. For example, by ranking components by their 10th percentile percent contribution, the methodology is considering which components are contributing greatest at their 10th percentile percent value. It can be expected that this would give a conservative estimate of contribution, ranking the components with the largest 10th percentile values first. In essence, the ranking criterion asks: is it *possible* for a component to contribute a higher impact at its 10th percentile value than another component? If yes, then that particular component is ranked ahead. The implicit assumption in this ranking scheme is that the distribution of possible impact values does not change very much. On the other hand, if the components were ranked according to its 90th percentile percent contribution, one is supposing that the actual components may turn out to cluster around the higher values of the percent impact distributions.

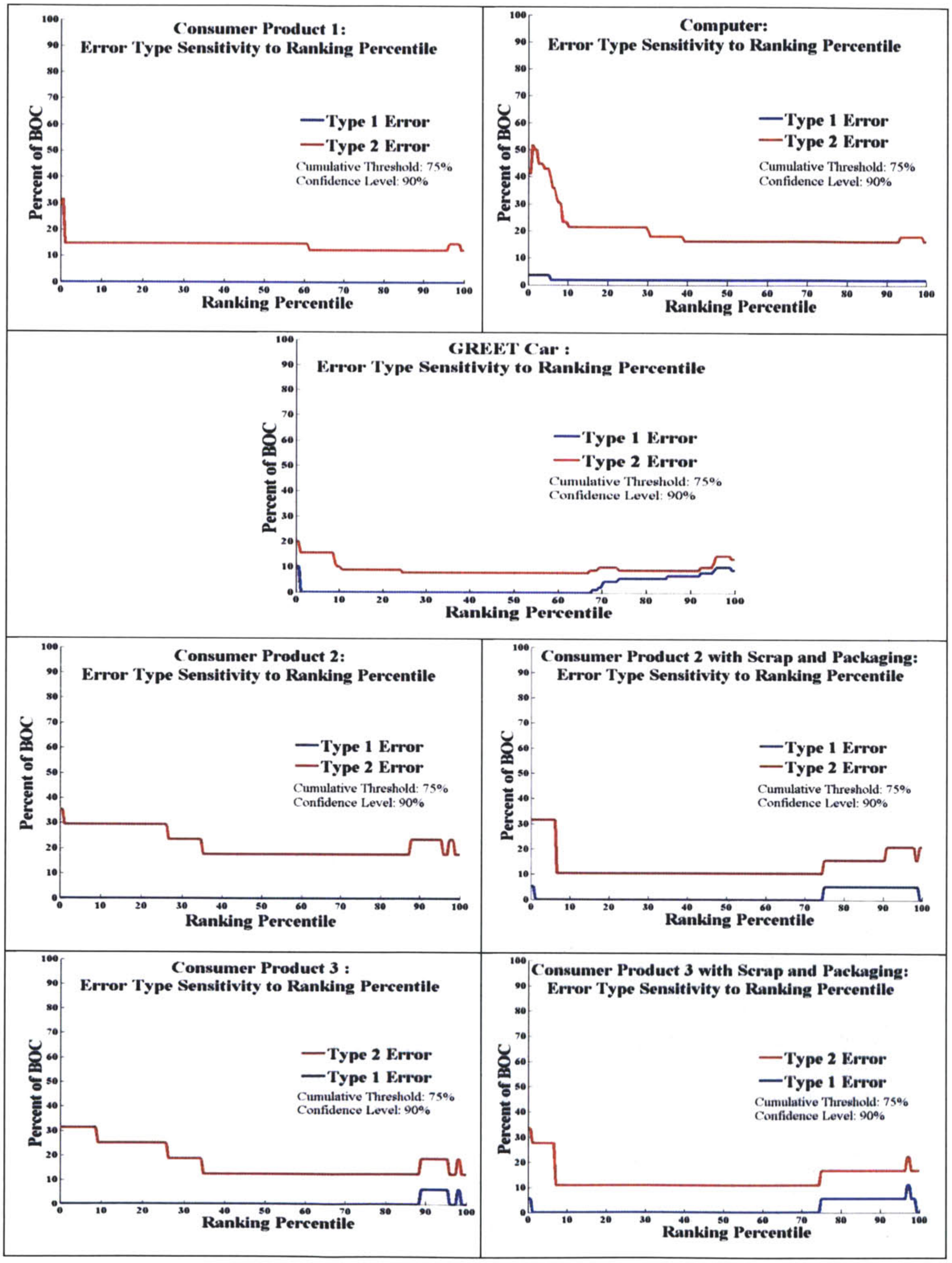

Figure 5-17 Type 1 and Type 2 error sensitivity to ranking percentile for case studies.

The results of the two types of error rate sensitivity on the percentile ranking while keeping the cumulative threshold at 75% and confidence level at 90% are displayed in Figure 5-17 for all the case studies. To review, Type 1 error is the fraction of the non-SOI portion of the BOC that is misclassified as not being important, while Type 2 error is fraction of the SOI that is misclassified as being important. This number is presented as a fraction of the BOC that is getting misclassified. Type 2 errors are more acceptable than large Type 1 errors because they merely represent wasted effort but no loss in the accuracy of the results. However, if there were a high Type 1 error, then the results would be less accurate because the components that are important to the total contribution are being neglected.

For all case studies the Type 1 error rate is always lower than the Type 2 error rates for all the ranking percentiles. The plateaus in the error rates around the 40^{th} percentile up to 70^{th} percentile for most of the cases indicate relative insensitivities to varying the ranking percentile. The error rates at the lower and higher percentile rankings increases for all the cases suggesting that the extreme values lead to SOI classification errors. Ranking by higher percentiles seems to always lead to higher Type 1 error starting from around 70^{th} percentile, except for the CP1 and computer case. The increase in error rates towards the two extremes may be due to the inability to predict which way the component's distribution of possible impact value will move as the product gets more specified. Having the 50^{th} percentile as the ranking criteria may allow for the mitigation buffering of the risk of the component's impact distribution moving either up or down.

5.5.2 Cumulative Threshold

The cumulative threshold criterion serves as the cut-off point in determining the size of the SOI. Depending on the goal of the LCA, the cumulative threshold criteria may vary. For example, if the LCA is being conducted in the product development phase of a project, a lower threshold of some value above 50% contribution would be enough. However, if there is a need to reduce significantly the uncertainty in the final impact results, the cut-off cumulative threshold criteria may be higher depending on the contribution to variance of each component. In Figure 5-18 and Figure 5-19, the sensitivities to cumulative threshold of the L1 SOI percent of each BOC are presented with their L5 SOI alongside the SOI size sensitivity.

For all the cases, as the cumulative threshold increases, so does the size of the SOI. This makes intuitive sense because one would need to incorporate more components into the SOI to account for a larger contribution to the product's total impact. Notice how the curve is smoother for the L5 SOI sensitivity than for the L1 SOI sensitivity as a function of the cumulative threshold.

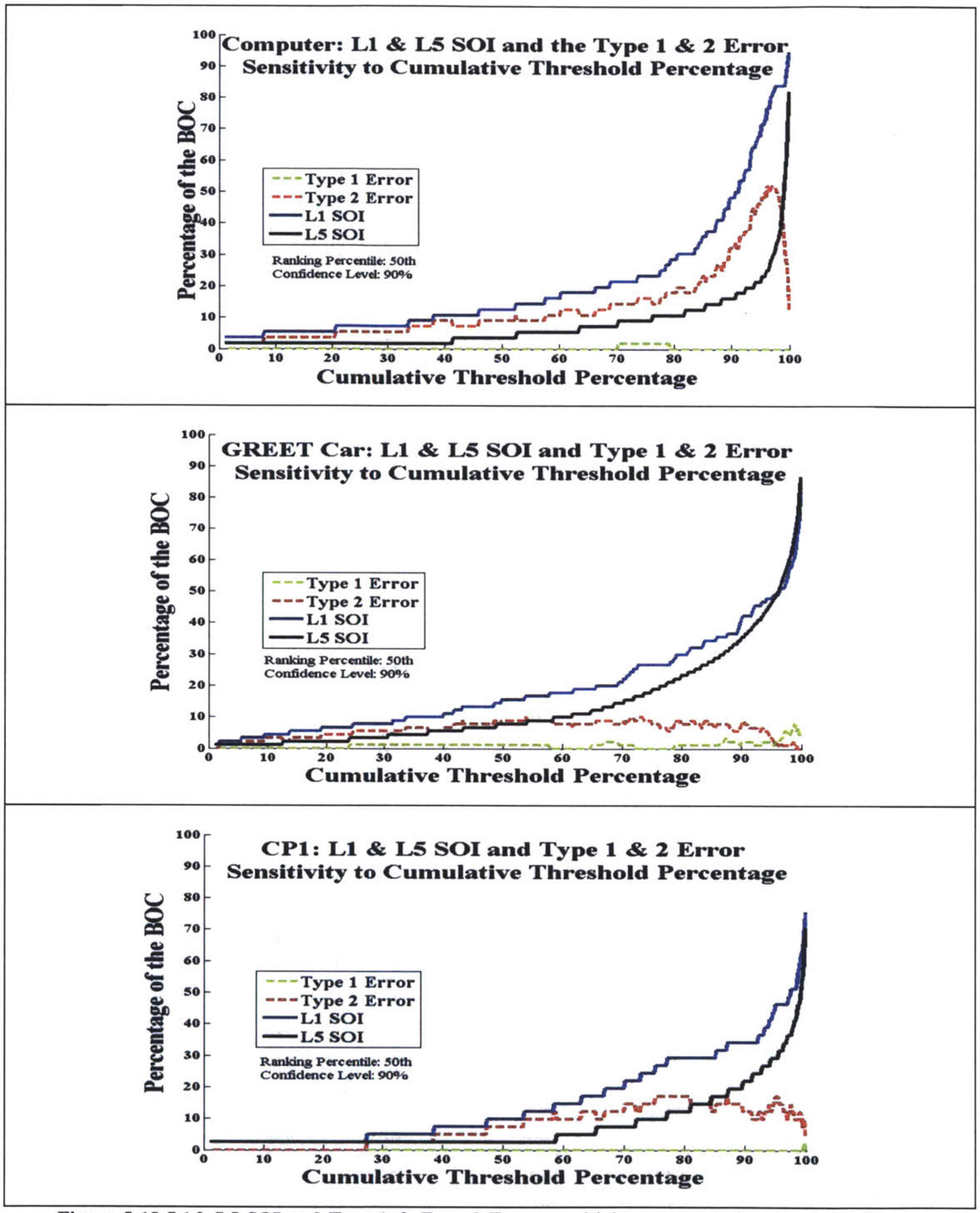

Figure 5-18 L1& L5 SOI and Type 1 & Type 2 Error sensitivity to cumulative threshold for the three products among the case studies with the largest BOCs.

This is because the L5 ranking scheme is perfectly ranking the components in the order of greatest to least percent contribution to impact, whereas the L1 ranking of the components may be positioning the components slightly out of order. It makes sense that the L1 SOI will be larger than the L5 SOI, and, in fact, this observed in all the case studies. Although there is an interesting cross over point for the L1SOI and L5SOI for the GREET car case Figure 5-18 . This is correlated with the cross over Type 1 and Type 2 error rates at the cumulative threshold percentage of 96%. This error is probably due to errors in the ranking of small-contributing components.

In Figure 5-18, the error rates seem to be relatively insensitive to ranking until reaching the high cumulative threshold where the Type 2 errors seem to increase until a certain point beyond 95% contribution, where the Type 2 error drops off. The exception to the relative insensitivity seems to be the computer case study, where the Type 2 error rate increases quickly starting at the 90th cumulative threshold. However, the Type 2 error rate eventually drops off as well. This is due to the fact that the components that were previously erroneously incorporated into the SOI start to become part of the L5SOI and no longer constitute an error. The Type 1 errors for all three cases were zero or close to zero over all cumulative threshold percentage.

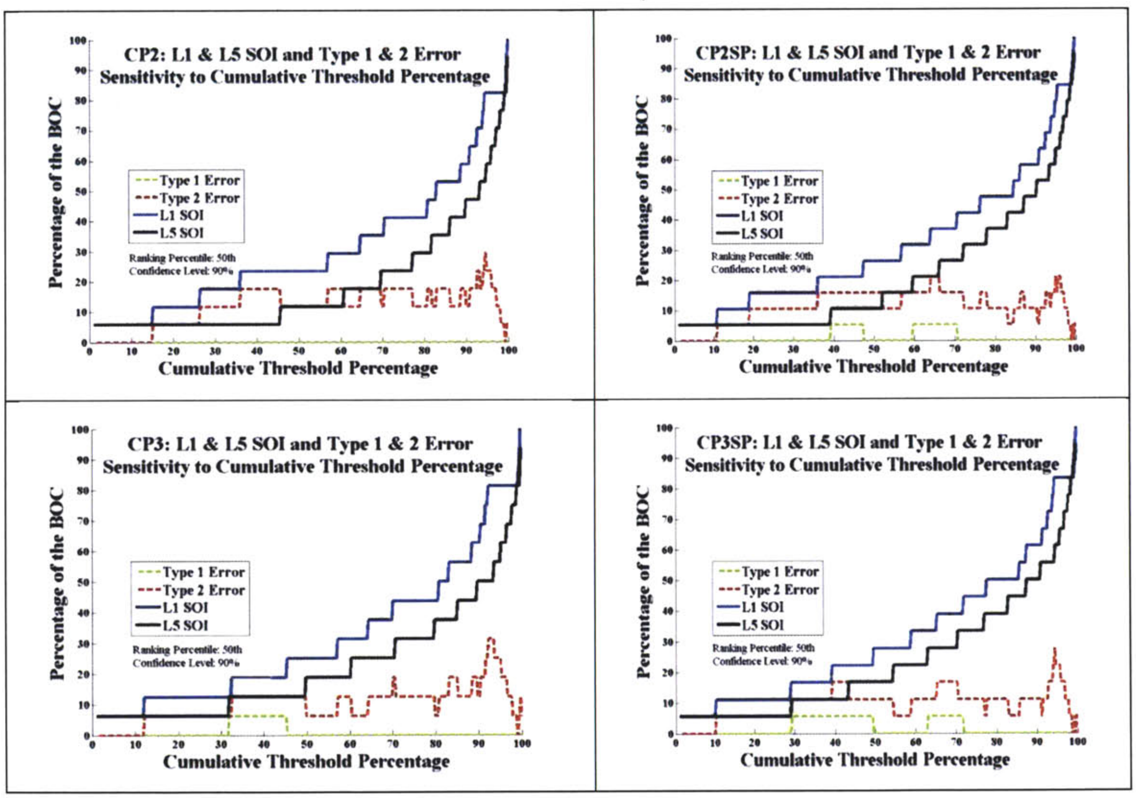

Figure 5-19 L1& L5 SOI and Type 1 & Type 2 Error sensitivity to cumulative threshold for same functional products that are made out of different materials and with(out) scrap and packaging consideration.

Considering the Figure 5-19 group of products, the general trends remain the same: the stochastic dominance of L1SOI over L5SOI, the larger Type 2 errors than Type 1 errors, relative insensitivities in Type 1 errors and Type 2 errors to the cumulative threshold, and the drop off in the Type 2 errors above 95% cumulative threshold.

From the sensitivity analysis of the SOI size and the error rates, it seems that in terms of choosing the cumulative threshold percentage, the LCA practitioner should be able to choose a cumulative threshold percentage that makes sense for the application of the LCA results because the error rates appear to be insensitive to this parameter. The dominant type of error is Type 2 error, with the Type 1 error for all the case studies being effectively zero except for the GREET car case. This is encouraging because by having zero Type 1 error, the practitioner is not falsely ignoring components which are actually important. However, it must be cautioned that the cumulative threshold criteria should not be higher than 90% because this is around the point where Type 2 error begins to increase. It also should be noted that the cumulative threshold criterion is only used to determine the size of the SOI and is applied at the particular level where the BOC is being viewed. After the resolution of the SOI to a higher level of specificity, it may be that the SOI is contributing more to the cumulative threshold criterion that was being used to identify the important components.

5.5.3 Confidence Level

The confidence level is another criterion that determines the size of the SOI. The SOI is chosen such that, at a given cumulative threshold, the confidence-level percentage of the trials will meet the cumulative threshold criterion. The size of the L1SOI is evaluated as a function of cumulative threshold and confidence level. The confidence levels range from 40% to 99%. Lower values are not explored because the SOI should be chosen such that the majority of the time, the SOI will meet or exceed the cumulative threshold criterion. The plots of the L1SOI sensitivity curves to the cumulative threshold at different confidence level are shown in Figure 5-20 and Figure 5-21 along with their L5SOI curves. The black arrows in the graphs indicate plots of increasing confidence level criterion.

For all the case studies, as the confidence level is increased, the L1SOI increases. This is because as the confidence level parameter becomes more stringent, the model must include more components into the SOI to contribute to the cumulative threshold. Notice that for most of the case studies, the lowest L1SOI curve does not fall below the L5SOI curve as the confidence level decreases. This phenomenon is only due to the fact that the lowest confidence level value is 40%. As demonstrated by the GREET car case, the L1SOI sensitivity curve could be less than the L5SOI. This is due to the overconfidence in the impact of the GREET car's L1 components to contribute to the total impact. In reality, the components that get ranked high and incorporated into the SOI may not contribute as much as they should and the components that should be included do not get included. This is illustrated in the increase in Type 1 error as the confidence level gets lower, as shown in Figure 5-22.

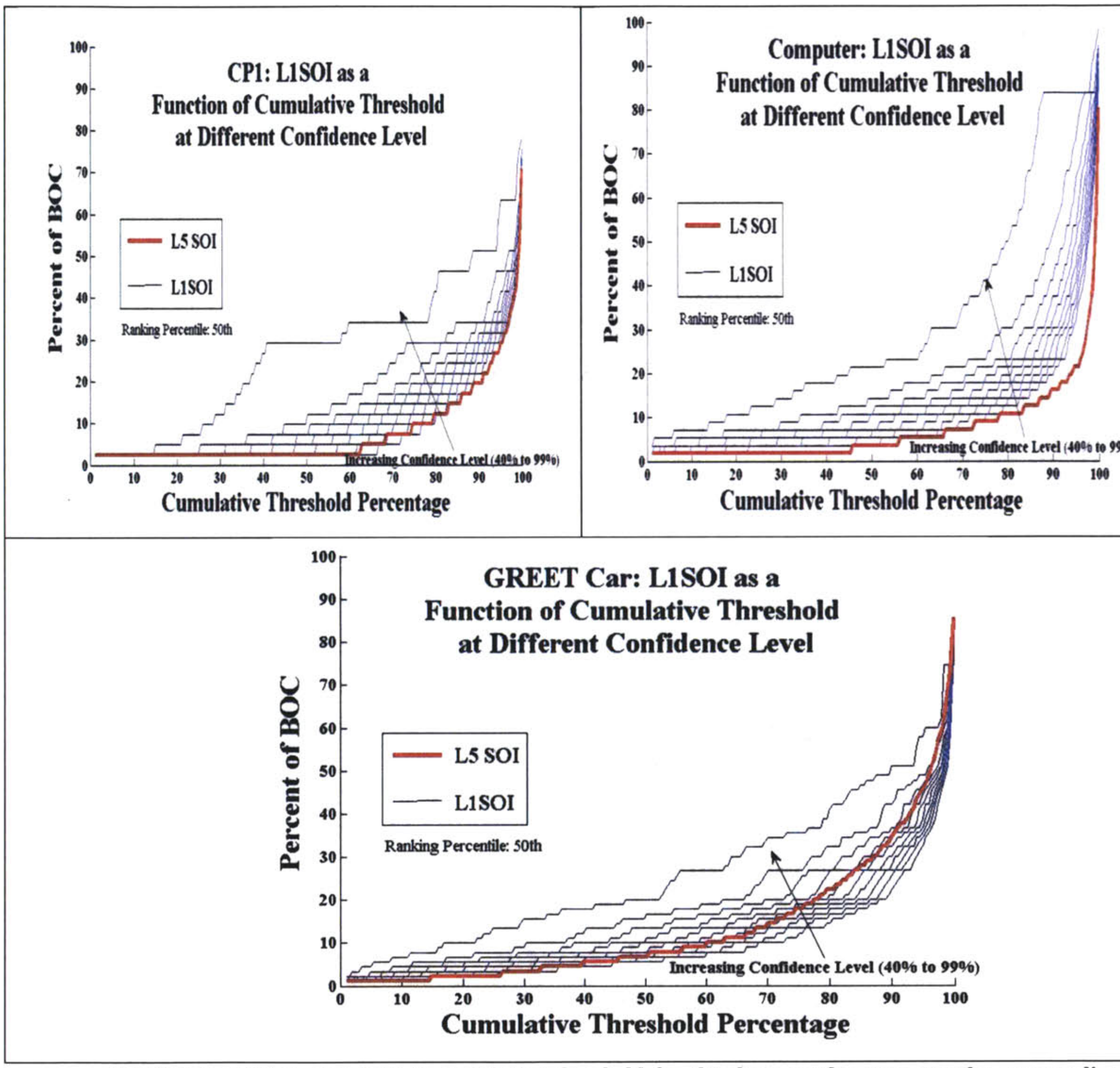

Figure 5-20 L1SOI sensitivity to cumulative threshold for the three products among the case studies with the largest BOCs at different confidence levels.

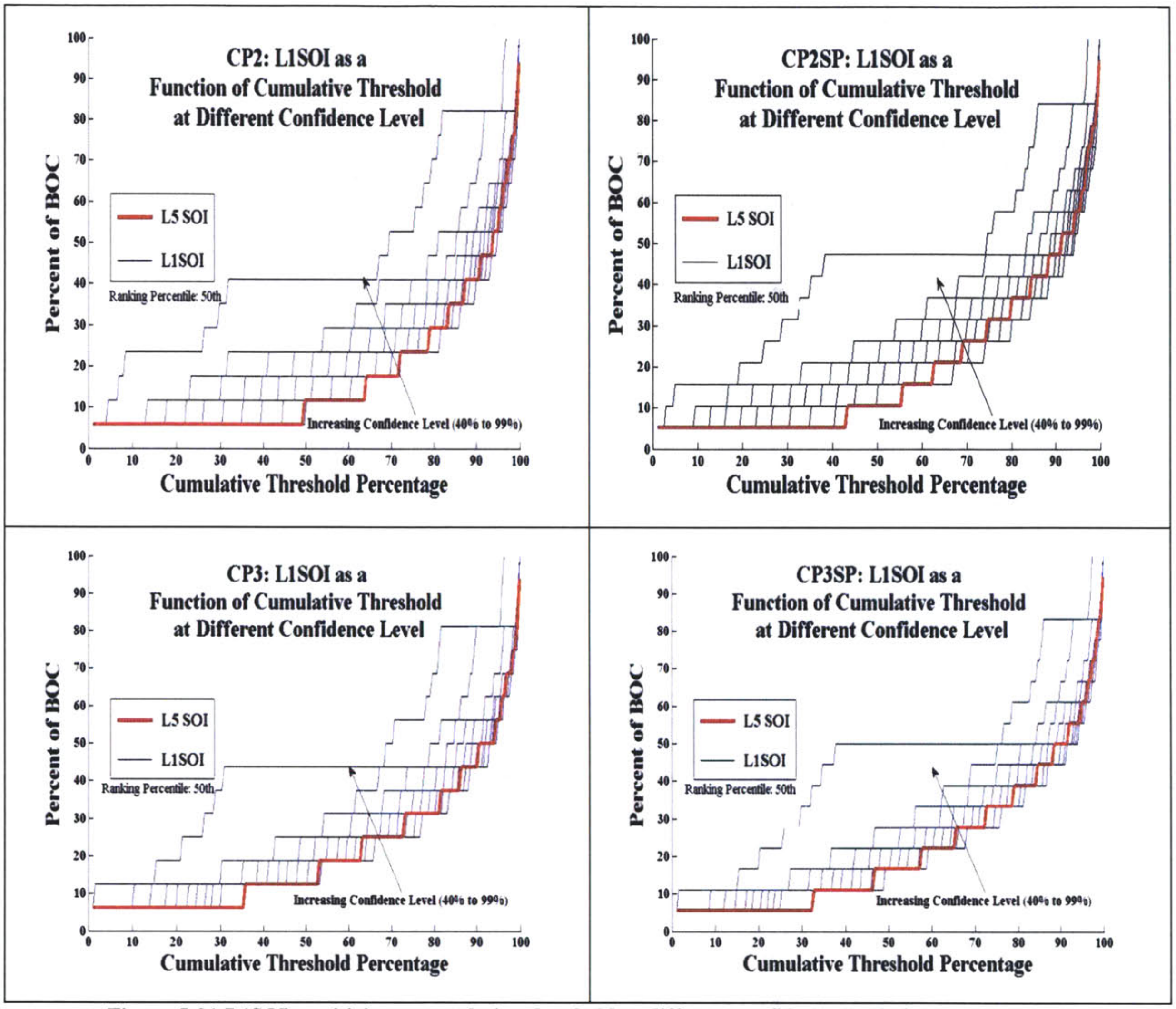

Figure 5-21 L1SOI sensitivity to cumulative threshold at different confidence levels for same functional products that are made out of different materials and with(out) scrap and packaging consideration.

When considering the size of the SOI, it is also necessary to consider the errors associated with the separation of the important components and the non-important components. The plots of the two error types at different confidence levels can be found in Figure 5-22 and Figure 5-23. The 50th percentile is used to rank the L1 components and to determine the L1SOI in the analysis. The Type 2 error again dominates the Type 1 error for all of the case studies for most of the cumulative threshold values. This indicates that the current methodology does prove to be conservative at selecting the SOI and, in the process, incorporates more components than necessary. For all the case studies, there appears to be an almost exponential increase in the number of components at a given cumulative threshold value as the confidence is monotonically increased. This can be clearly observed in the computer case shown in Figure 5-22. Furthermore, the model seems to be good at mitigating Type 1 error. For the most part, the model is effective in not neglecting the important components by leaving them out of the SOI. However, the Type 1 error rates do increase slightly as the confidence level decreases. Although it should be noted that the car case does exhibit a relatively high Type 1 error as the cumulative threshold percentage increases and the confidence level is decreased.

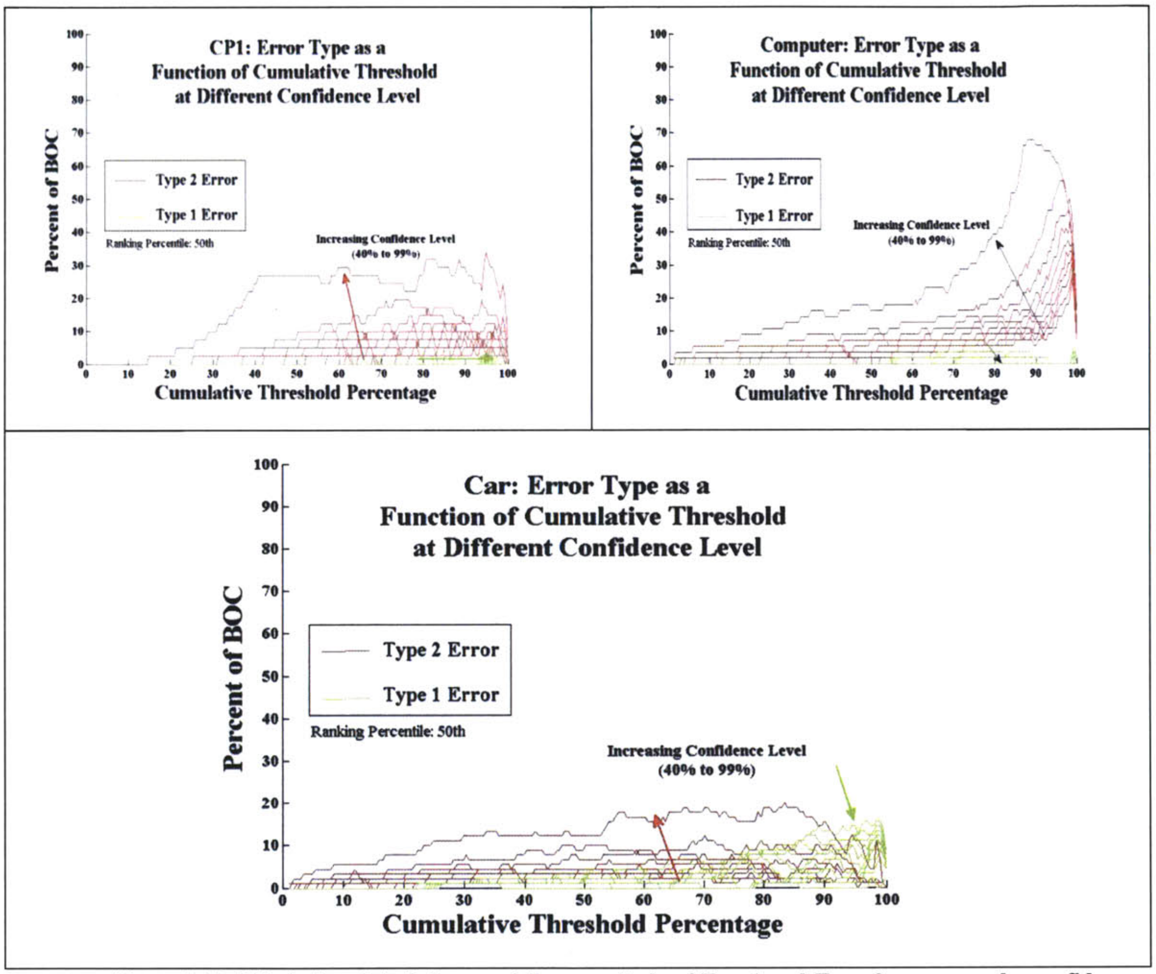

Figure 5-22 This is the plot of change of the magnitude of Type1 and Type 2 errors as the confidence level is varied for three product of the case studies that have 41-90 components. The arrows indicate the direction the curves are moving as the confidence level is increased.

In the case studies group of smaller BOCs shown in Figure 5-23, the behavior of the results do follow the case studies in Figure 5-22, however due to having a small number of components in the BOC, the results are more discretized and harder to interpret. The observation of low Type 1 error and higher Type 2 error holds. One interesting behavior to note is the increase in Type 1 error as the scrap and packaging is considered in both the Consumer Product 2 and Consumer Product 3 cases.

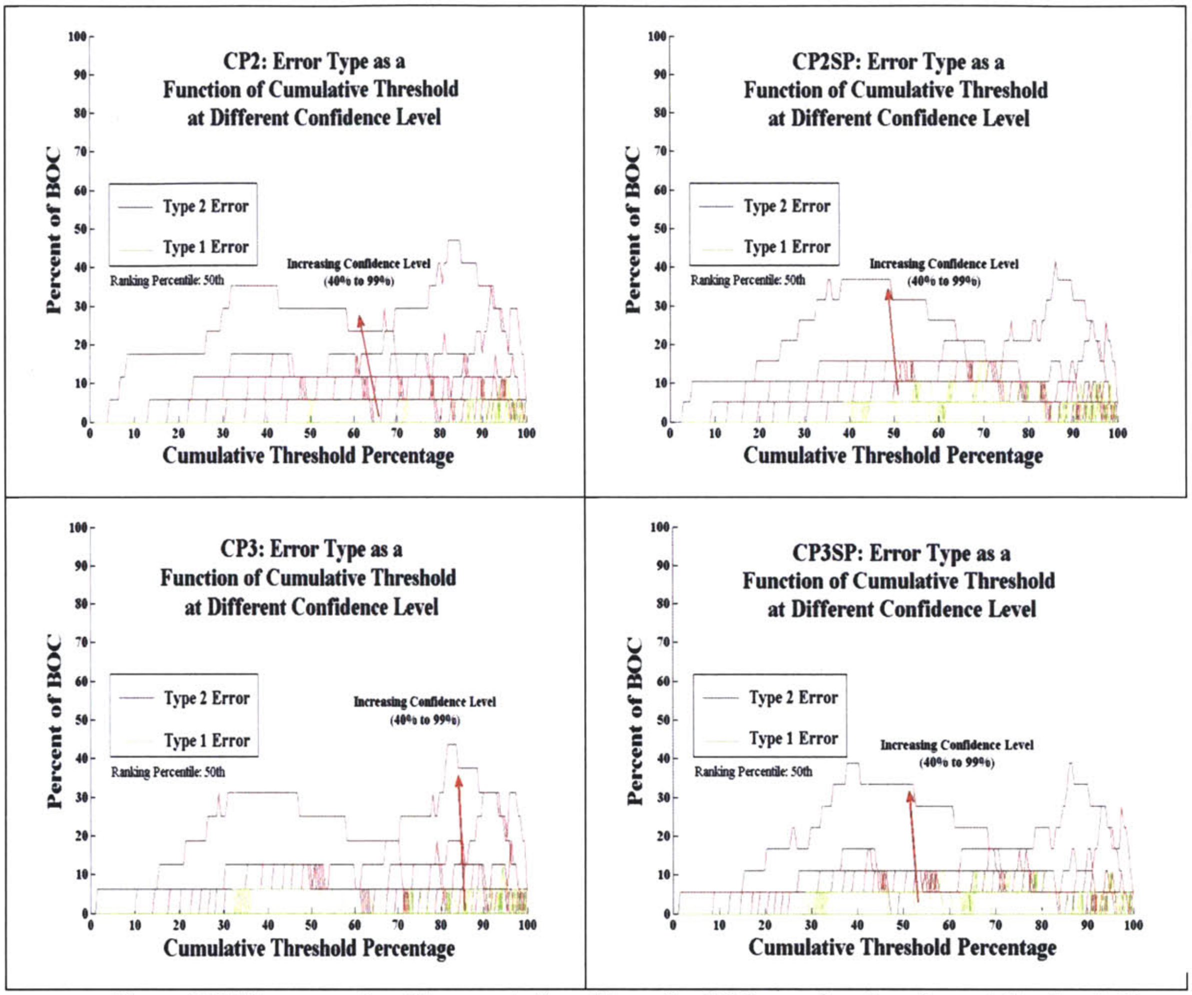

Figure 5-23 The error rates of the case studies with smaller BOCs as a function of cumulative threshold percentage and confidence level.

5.5.4 Herfindahl Trend

The products chosen for the case studies were picked from a range of mass uniformity among the components to take into account the role of mass uniformity in the ability to streamline LCA. However, from the case studies examined within this thesis, there seems to be no clear relationship in the ability to streamline the mass uniformity of the BOC. A more clear distinction seems to be that the ability to streamline more easily for the products with the most components. These products all have a roughly 75% reduction in the number of components needed to specify to L5 when the probabilistic underspecification is applied at L1 specificity. On the other hand the products with the smaller number of components only have a reduction of around 55% in the number of components needed to specify. The insensitivity to streamlining of the mass uniformity of the product is encouraging because it could indicate that the methodology may be robust against this factor. Unfortunately this limited dataset is only suggestive and far from conclusive.

6 CONCLUSIONS

The analysis of the structured underspecification database suggests that there is a general trend towards decreasing magnitude of variability as a product becomes less underspecified. When the structured underspecification model is applied to the selected case studies, the precision of the estimate of the product environmental performance is improved when compared to the estimate at the lower levels of specification. Although the distance of the median estimate of the CED, as measured by the absolute deviation of the median ADM, from L1 to L4 ranges from 0.2% to 50% for the range of products, it can go up to as high as 250% in the GREET car case. The proximity of the estimates is overshadowed by the uncertainties in their value. The variability in the CED values, as measured by the MAD-COV, decreases, on average, as the products' components become better specified. Thus, it is demonstrated that when a product becomes better specified, the uncertainty in the impact estimate decreases along with increase precision.

The probabilistic underspecification streamlining methodology is applied to several studies to determine if an effective SOI can be chosen only by observing the product at reduced or L1 specificity in our case. The methodology is applied with the parameters of 50th percentile ranking, 75% cumulative percentage impact threshold, and 90% confidence level. The SOI identified from the L1 impact data are less than 1/3 of the BOC for CP1, computer, and GREET Car. These products have 41, 56, and 90 components respectively. While the other case study products, CP2, CP2SP, CP3, and CP3SP, although have L1SOIs that are around 50% of the BOC, they all have a small number of components in the BOC to begin with. Resolving the SOI to L5 specificity proved to yield significant improvements in the precision of the estimate for the products' impacts when compared to L5. The residual variation in the L1/L5 hybrid estimate compared to the L5 estimate is only on average 3%. The average confidence in that value described by the average MAD-COV value for L1/15 impact results is 5.8%. This uncertainty is lower than the average MAD-COV values for L1 through L4 values for the case studies.

Another question this thesis attempts to answer is whether there is robustness of the methodology under different conditions regarding the modeling parameters of ranking criteria, cumulative threshold, and confidence level? The ranking criteria of 50th percentile percentage contribution afforded the lowest error rate in the sensitivity analysis. It is discovered that cumulative threshold for cutting of the percentage contribution to the total impact of the product was robust against Type 1 error and Type 2 errors. However, the cumulative threshold should not be set above 90% because that will lead to higher rates of Type 2 error and decrease the degree of streamlining. It is also demonstrated that the degree of streamlining will decrease with the increase in the confidence level almost exponentially due to the increase in Type 2 error. It is also promising that, for all the case studies, the confidence level is relatively robust to false rejections of the important components.

6.1 Future Work

Although probabilistic underspecification methodology for streamlining LCA has proved to be promising in the case studies in reducing LCA effort and increasing confidence in the LCA estimate, this thesis work is only a preliminary exploration. In order to have confidence in this streamlining approach, many more case studies will need to be analyzed using the proposed methods. However, this could prove very labor intensive. Instead, a mock bill of components could be developed to adequately map out the streamlining realm of possibilities for assessing materials impact. It would also be interesting to extend the methodology to other life cycle impact categories, such as global warming potential or toxicity, since it cannot be assumed that the ability to tease out the SOI would be the same for other impact factors. Further, this thesis only considered the materials production part of the life cycle. Future work should eventually extend to the entire bill of activities of the life cycle. Finally, in this thesis SOI is taken to the level of specificity of L5; however, it may also be interesting to see the effect of underspecifying the components to L2, L3 or L4 to see how this affects the resolution of the estimate of the product's impact.

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8 APPENDIX A: Table of Database Classification

Level 1	Level 2	Level 3	Level 4	Level 5
Construction	Binders	Cement	Cement blast	Blast furnace slag cement, at plant/CH U
Construction	Binders	Cement	Cement mortar	Cement mortar, at plant/CH U
Construction	Binders	Cement	Cement unspecified	Cement, unspecified, at plant/CH U
Construction	Binders	Cement	Portland cement	Portland calcareous cement, at plant/CH U
Construction	Binders	Cement	Portland cement	Portland cement (CEM I), CEMBUREAU technology mix, CEMBUREAU production mix, at plant, EN 197-1 RER S
Construction	Binders	Cement	Portland cement	Portland cement, at plant/US
Construction	Binders	Cement	Portland cement	Portland cement, strength class Z 42.5, at plant/CH U
Construction	Binders	Cement	Portland cement	Portland cement, strength class Z 52.5, at plant/CH U
Construction	Binders	Cement	Portland cement	Portland slag sand cement, at plant/CH U
Construction	Binders	Mortar	Mortar adhesive	Adhesive mortar, at plant/CH U
Construction	Binders	Mortar	Mortar light	Light mortar, at plant/CH U
Construction	Binders	Mortar	Mortar lime	Lime mortar, at plant/CH U
Construction	Binders	Stucco	Stucco-plant	Stucco, at plant/CH U
Construction	Bricks	Brick 3	Brick generic	Brick, at plant/RER U
Construction	Bricks	Brick 3	Brick light clay	Light clay brick, at plant/DE U
Construction	Bricks	Brick 3	Brick-sand-lime	Sand-lime brick, at plant/DE U
Construction	Bricks	Refractory	Refractory basic	Refractory, basic, packed, at plant/DE U
Construction	Bricks	Refractory	Refractory fireclay	Refractory, fireclay, packed, at plant/DE U
Construction	Bricks	Refractory	Refractory high aluminium oxide	Refractory, high aluminium oxide, packed, at plant/DE U
Construction	Cladding	Cladding 3	Cladding crossbar-pole	Cladding, crossbar-pole, aluminium, at plant/RER U
Construction	Concrete	Concrete 3	Concrete extracting	Concrete, exacting, at plant/CH U
Construction	Concrete	Concrete 3	Concrete extracting	Concrete, exacting, with de-icing salt contact, at plant/CH U
Construction	Concrete	Concrete 3	Concrete normal	Concrete, normal, at plant/CH U
Construction	Concrete	Concrete 3	Concrete sole plate	Concrete, sole plate and foundation, at plant/CH U
Construction	Concrete	Concrete Block	Aerated concrete block	Aerated concrete block, mix of P2 04 and P4 05, production mix, at plant, average density 433 kg/m3 RER S
Construction	Concrete	Concrete Block	Aerated concrete block	Aerated concrete block, type P4 05 reinforced, production mix, at plant, average density 485 kg/m3 RER S
Construction	Concrete	Concrete Block	Aerated concrete block	Autoclaved aerated concrete block, at plant/CH U
Construction	Concrete	Concrete Block	Concrete block generic	Concrete block, at plant/DE U
Construction	Concrete	Concrete Block	Lightweight concrete block-expanded clay	Lightweight concrete block, expanded clay as base material, production mix, at plant RER S

Level 1	Level 2	Level 3	Level 4	Level 5
Construction	Concrete	Concrete Block	Lightweight concrete block-expanded perlite	Lightweight concrete block, expanded perlite, at plant/CH U
Construction	Concrete	Concrete Block	Lightweight concrete block-expanded vermiculite	Lightweight concrete block, expanded vermiculite, at plant/CH U
Construction	Concrete	Concrete Block	Lightweight concrete block-polystyrene	Lightweight concrete block, polystyrene, at plant/CH U
Construction	Concrete	Concrete Block	Lightweight concrete block-pumice	Lightweight concrete block, pumice, at plant/DE U
Construction	Concrete	Poor concrete	Poor concrete plant	Poor concrete, at plant/CH U
Construction	Concrete	Precast concrete	Precast concrete min reinf	Pre-cast concrete, min. reinf., prod. mix, concrete type C20/25, w/o consideration of casings RER S
Construction	Covering	Acrylic filler3	Acrylic filler plant	Acrylic filler, at plant/RER U
Construction	Covering	Corrugated slab	Corrugated slab fiber cement	Fibre cement corrugated slab, at plant/CH U
Construction	Covering	Cover coat	Cover coat mineral	Cover coat, mineral, at plant/CH U
Construction	Covering	Cover coat	Cover coat organic	Cover coat, organic, at plant/CH U
Construction	Covering	Fiberboard	Fiberboard gypsum	Gypsum fibre board, at plant/CH U
Construction	Covering	Plaster	Plaster base	Base plaster, at plant/CH U
Construction	Covering	Plaster	Plaster cement cast	Cement cast plaster floor, at plant/CH U
Construction	Covering	Plaster	Plaster clay	Clay plaster, at plant/CH U
Construction	Covering	Plaster	Plaster gypsum	Gypsum plaster ($CaSO_4$ alpha hemihydrates) DE S
Construction	Covering	Plaster	Plaster gypsum	Gypsum plaster ($CaSO_4$ beta hemihydrates) DE S
Construction	Covering	Plaster	Plaster gypsum	Gypsum plaster board, at plant/CH U
Construction	Covering	Plaster	Plaster thermal	Thermal plaster, at plant/CH U
Construction	Covering	Slate	Slate fiber cement	Fibre cement roof slate, at plant/CH U
Construction	Covering	Tile	Tile ceramic	Ceramic tiles, at regional storage/CH U
Construction	Covering	Tile	Tile fiber cement	Fibre cement facing tile, at plant/CH U
Construction	Covering	Tile	Tile fiber cement	Fibre cement facing tile, large format, at plant/CH U
Construction	Covering	Tile	Tile fiber cement	Fibre cement facing tile, small format, at plant/CH U
Construction	Covering	Tile	Tile quarry	Quarry tile, at plant/CH U
Construction	Covering	Tile	Tile roof	Roof tile, at plant/RER U
Construction	Covering	Tile	Tile roof concrete	Concrete roof tile, at plant/CH U
Construction	Door	Inner door	Inner door glass-wood	Door, inner, glass-wood, at plant/RER U
Construction	Door	Inner door	Inner door wood	Door, inner, wood, at plant/RER U
Construction	Door	Outer door	Outer door wood-aluminum	Door, outer, wood-aluminium, at plant/RER U
Construction	Door	Outer door	Outer door wood-glass	Door, outer, wood-glass, at plant/RER U
Construction	Insulation	Elastomer Sealing	Tube insulation	Tube insulation, elastomere, at plant/DE U
Construction	Insulation	Glass Insulation	Glass foam	Foam glass, at plant/RER U

Level 1	Level 2	Level 3	Level 4	Level 5
Construction	Insulation	Glass Insulation	Glass foam	Foam glass, at regional storage/AT U
Construction	Insulation	Glass Insulation	Glass foam	Foam glass, at regional storage/CH U
Construction	Insulation	Glass Insulation	Glass wool	Glass wool mat, at plant/CH U
Construction	Insulation	Glass Insulation	Glass wool	Glass wool, fleece, production mix, at plant, density between 10 to 100 kg/m3 RER S
Construction	Insulation	Organic Insulation	Cellulose fiber	Cellulose fibre, inclusive blowing in, at plant/CH U
Construction	Insulation	Organic Insulation	Cork slab	Cork slab, at plant/RER U
Construction	Insulation	Polystyrene	Polystyrene extruded	Polystyrene, extruded (XPS) CO2 blown, at plant/RER U
Construction	Insulation	Polystyrene	Polystyrene extruded	Polystyrene, extruded (XPS), at plant/RER U
Construction	Insulation	Polystyrene	Polystyrene extruded	Polystyrene, extruded (XPS), HFC-134a blown, at plant/RER U
Construction	Insulation	Polystyrene	Polystyrene extruded	Polystyrene, extruded (XPS), HFC-152a blown, at plant/RER U
Construction	Insulation	Polystyrene	Polystyrene foam slab	Polystyrene foam slab, 100% recycled, at plant/CH U
Construction	Insulation	Polystyrene	Polystyrene foam slab	Polystyrene foam slab, 45% recycled, at plant/CH U
Construction	Insulation	Polystyrene	Polystyrene foam slab	Polystyrene foam slab, at plant/RER U
Construction	Insulation	Rock wool	Rock wool fleece	Rock wool, fleece, production mix, at plant, density between 30 to 180 kg/m3 RER S
Construction	Insulation	Rock wool	Rock wool general	Rock wool, at plant/CH U
Construction	Insulation	Rock wool	Rock wool packed	Rock wool, packed, at plant/CH U
Construction	Insulation	Urea formaldehyde	UF in situ	Urea formaldehyde foam, in situ foaming, at plant/CH U
Construction	Insulation	Urea formaldehyde	UF slab	Urea formaldehyde foam slab, hard, at plant/CH U
Construction	Other	Asphalt	Mastic asphalt	Mastic asphalt, at plant/CH U
Construction	Other	Cobwork 3	Cobwork	Cobwork, at plant/CH U
Construction	Other	Floor	Anhydrite floor	Anhydrite floor, at plant/CH U
Construction	Other	Plate	Plate cut	Natural stone plate, cut, at regional storage/CH U
Construction	Other	Plate	Plate grounded	Natural stone plate, grounded, at regional storage/CH U
Construction	Other	Plate	Plate polished	Natural stone plate, polished, at regional storage/CH U
Construction	Paint	Alkyd piant	Alkyd paint white	Alkyd paint, white, 60% in H2O, at plant/RER U
Construction	Paint	Alkyd piant	Alkyd paint white	Alkyd paint, white, 60% in solvent, at plant/RER U
Construction	Paint	Arylic varnish	Acrylic varnish 87.5 water	Acrylic varnish, 87.5% in H2O, at plant/RER U
Construction	Sealing	Bitumen	Bitumen adhesive	Bitumen adhesive compound, cold, at plant/RER U
Construction	Sealing	Bitumen	Bitumen adhesive	Bitumen adhesive compound, hot, at plant/RER U
Construction	Sealing	Bitumen	Bitumen-refinery	Bitumen, at refinery/CH U
Construction	Sealing	Bitumen	Bitumen-refinery	Bitumen, at refinery/kg/US
Construction	Sealing	Bitumen	Bitumen-refinery	Bitumen, at refinery/RER U
Construction	Sealing	Bitumen	Bitumen-sealing	Bitumen sealing Alu80, at plant/RER U
Construction	Sealing	Bitumen	Bitumen-sealing	Bitumen sealing V60, at plant/RER U

Level 1	Level 2	Level 3	Level 4	Level 5
Construction	Sealing	Bitumen	Bitumen-sealing	Bitumen sealing VA4, at plant/RER U
Construction	Sealing	Bitumen	Bitumen-sealing	Bitumen sealing, polymer EP4 flame retardant, at plant/RER U
Construction	Sealing	Elastomer Sealing	Natural rubber sealing	Natural rubber based sealing, at plant/DE U
Construction	Sealing	Elastomer Sealing	Polysulphide	Polysulphide, sealing compound, at plant/RER U
Construction	Ventilation	Air distribution	Air distribution steel	Air distribution housing, steel, 120 m3/h, at plant/CH U
Construction	Ventilation	Air filter	Air filter central unit	Air filter, central unit, 600 m3/h, at plant/RER U
Construction	Ventilation	Air filter	Air filter decentralize	Air filter, decentralized unit, 180-250 m3/h, at plant/RER U
Construction	Ventilation	Air filter	Air filter decentralize	Air filter, decentralized unit, 250 m3/h, at plant/RER U
Construction	Ventilation	Air filter	Air filter exhaust valve	Air filter, in exhaust air valve, at plant/RER U
Construction	Ventilation	Air intake	Air intake steel	Outside air intake, stainless steel, DN 370, at plant/RER U
Construction	Ventilation	Air intake	Air intake steel	Supply air inlet, steel/SS, DN 75, at plant/RER U
Construction	Ventilation	Connection piece	Connection piece steel	Connection piece, steel, 100x50 mm, at plant/RER U
Construction	Ventilation	Control and wiring	Control and wiring central unit	Control and wiring, central unit, at plant/RER U
Construction	Ventilation	Control and wiring	Control and wiring decentralized unit	Control and wiring, decentralized unit, at plant/RER U
Construction	Ventilation	Duct	Duct corrugated tube	Ventilation duct, PE corrugated tube, DN 75, at plant/RER U
Construction	Ventilation	Duct	Duct spiral seem	Spiral-seam duct, steel, DN 125, at plant/RER U
Construction	Ventilation	Duct	Duct spiral seem	Spiral-seam duct, steel, DN 400, at plant/RER U
Construction	Ventilation	Duct	Duct steel	Ventilation duct, steel, 100x50 mm, at plant/RER U
Construction	Ventilation	Elbow	Elbowsteel	Elbow 90°, steel, 100x50 mm, at plant/RER U
Construction	Ventilation	Exhaust	Exhaust outlet	Exhaust air outlet, steel/aluminum, 85x365 mm, at plant/CH U
Construction	Ventilation	Exhaust	Exhaust roofhood	Exhaust air roof hood, steel, DN 400, at plant/CH U
Construction	Ventilation	Exhaust	Exhaust valve	Exhaust air valve, in-wall housing, plastic/steel, DN 125, at plant/CH U
Construction	Ventilation	Flexible duct	Flexible duct aluminum	Flexible duct, aluminum/PET, DN of 125, at plant/RER U
Construction	Ventilation	Heat exchanger	Heat exchanger ground	Ground heat exchanger, PE, DN 200, at plant/RER U
Construction	Ventilation	Insulation	Insulation spiral seam	Insulation spiral-seam duct, rockwool, DN 400, 30 mm, at plant/RER U
Construction	Ventilation	Overflow element	Overflow element steel	Overflow element, steel, approx. 40 m3/h, at plant/RER U
Construction	Ventilation	Sealing tape	Sealing tape aluminum	Sealing tape, aluminum/PE, 50 mm wide, at plant/RER U
Construction	Ventilation	Silencer	Silencer steel	Silencer, steel, DN 125, at plant/CH U
Construction	Ventilation	Silencer	Silencer steel	Silencer, steel, DN 315, 50 mm, at plant/CH U
Construction	Ventilation	Ventilation equipment	Ventilation equipment avent	Ventilation equipment, Avent E 97, at plant/RER U

Level 1	Level 2	Level 3	Level 4	Level 5
Construction	Ventilation	Ventilation equipment	Ventilation equipment central	Ventilation equipment, central, 600-1200 m3/h, at plant/RER U
Construction	Ventilation	Ventilation equipment	Ventilation equipment decentralized	Ventilation equipment, decentralized, 180-250 m3/h, at plant/RER U
Construction	Ventilation	Ventilation equipment	Ventilation equipment GE	Ventilation equipment, GE 250 RH, at plant/CH U
Construction	Ventilation	Ventilation equipment	Ventilation equipment KWL	Ventilation equipment, KWL 250, at plant/RER U
Construction	Ventilation	Ventilation equipment	Ventilation equipment KWLC	Ventilation equipment, KWLC 1200, at plant/RER U
Construction	Ventilation	Ventilation equipment	Ventilation equipment storkair	Ventilation equipment, Storkair G 90, at plant/RER U
Construction	Ventilation	Ventilation equipment	Ventilation equipment twl	Ventilation equipment, Twl-700, at plant/RER U
Construction	Window frame	Window frame 3	Window aluminium	Window frame, aluminium, U=1.6 W/m2K, at plant/RER U
Construction	Window frame	Window frame 3	Window plastic	Window frame, plastic (PVC), U=1.6 W/m2K, at plant/RER U
Construction	Window frame	Window frame 3	Window wood	Window frame, wood, U=1.5 W/m2K, at plant/RER U
Construction	Window frame	Window frame 3	Window wood-metal	Window frame, wood-metal, U=1.6 W/m2K, at plant/RER U
Electronics	Components	Anode	Anode-lithium ion battery	Anode, lithium-ion battery, graphite, at plant/CN U
Electronics	Components	Backlight	Backlight-LCD screen	Backlight, LCD screen, at plant/GLO U
Electronics	Components	Cable	Cable printer	Cable, printer cable, without plugs, at plant/GLO U
Electronics	Components	Cable	Cable ribbon	Cable, ribbon cable, 20-pin, with plugs, at plant/GLO U
Electronics	Components	Cable	Cable three conductor	Cable, three-conductor cable, at plant/GLO U
Electronics	Components	Cable	Cable-connector for computer	Cable, connector for computer, without plugs, at plant/GLO U
Electronics	Components	Cable	Cable-data	Cable, data cable in infrastructure, at plant/GLO U
Electronics	Components	Cable	Cable-network cat 5	Cable, network cable, category 5, without plugs, at plant/GLO U
Electronics	Components	Capacitor	Capacitor film	Capacitor, film, through-hole mounting, at plant/GLO U
Electronics	Components	Capacitor	Capacitor SMD type	Capacitor, SMD type, surface-mounting, at plant/GLO U
Electronics	Components	Capacitor	Capacitor tantalum	Capacitor, Tantalum-, through-hole mounting, at plant/GLO U
Electronics	Components	Capacitor	Capacitor electrolyte type	Capacitor, electrolyte type, < 2cm height, at plant/GLO U
Electronics	Components	Capacitor	Capacitor electrolyte type	Capacitor, electrolyte type, > 2cm height, at plant/GLO U
Electronics	Components	Capacitor	Capacitor unspecified	Capacitor, unspecified, at plant/GLO U
Electronics	Components	Cathode	Cathode-Lithium ion battery	Cathode, lithium-ion battery, lithium manganese oxide, at plant/CN U
Electronics	Components	CD/DVD drive	CD/DVD drive desktop	CD-ROM/DVD-ROM drive, desktop computer, at plant/GLO U

Level 1	Level 2	Level 3	Level 4	Level 5
Electronics	Components	Connector	Connector PCI bus	Connector, PCI bus, at plant/GLO U
Electronics	Components	Connector	Connector-clamp connection	Connector, clamp connection, at plant/GLO U
Electronics	Components	Connector	Connector-computer	Connector, computer, peripherical type, at plant/GLO U
Electronics	Components	Diode	Diode-glass	Diode, glass-, SMD type, surface mounting, at plant/GLO U
Electronics	Components	Diode	Diode-glass	Diode, glass-, through-hole mounting, at plant/GLO U
Electronics	Components	Diode	Diode-unspecified	Diode, unspecified, at plant/GLO U
Electronics	Components	Electrode	Electrode-positive	Electrode, positive, LaNi5, at plant/GLO U
Electronics	Components	Electrolyte	Electrolyte-KOH	Electrolyte, KOH, LiOH additive, at plant/GLO U
Electronics	Components	Electron gun	Eletrogun-CRT tube	Electron gun, for CRT tube production, at plant/GLO U
Electronics	Components	Electronic Component	EC-active	Electronic component, active, unspecified, at plant/GLO U
Electronics	Components	Electronic Component	EC-passive	Electronic component, passive, unspecified, at plant/GLO U
Electronics	Components	Electronic Component	EC-unspecified	Electronic component, unspecified, at plant/GLO U
Electronics	Components	Frit	Frit-CRT tube production	Frit, for CRT tube production, at plant/GLO U
Electronics	Components	Funnel glass	Funnel glass-CRT screen	Funnel glass, CRT screen, at plant/GLO U
Electronics	Components	Inductor	Inductor unspecified	Inductor, unspecified, at plant/GLO U
Electronics	Components	Inductor	Inductor-low value multilayer chip	Inductor, low value multilayer chip type, LMCI, at plant/GLO U
Electronics	Components	Inductor	Inductor-miniature chip	Inductor, miniature RF chip type, MRFI, at plant/GLO U
Electronics	Components	Inductor	Inductor-ring core choke	Inductor, ring core choke type, at plant/GLO U
Electronics	Components	Integrated circuit	IC-logic type	Integrated circuit, IC, logic type, at plant/GLO U
Electronics	Components	Integrated circuit	IC-memory type	Integrated circuit, IC, memory type, at plant/GLO U
Electronics	Components	LED	LED-plant	Light emitting diode, LED, at plant/GLO U
Electronics	Components	Panel components	Panel component-plant	Panel components, at plant/GLO U
Electronics	Components	Panel glass	Panel glass-CRT	Panel glass, CRT screen, at plant/GLO U
Electronics	Components	Panel glass	Panel glass-LCD	LCD glass, at plant/GLO U
Electronics	Components	Plugs	Plugs-computer cable	Plugs, inlet and outlet, for computer cable, at plant/GLO U
Electronics	Components	Plugs	Plugs-network cable	Plugs, inlet and outlet, for network cable, at plant/GLO U
Electronics	Components	Plugs	Plugs-printer cable	Plugs, inlet and outlet, for printer cable, at plant/GLO U
Electronics	Components	Potentiometer	Potentiometer-unspecified	Potentiometer, unspecified, at plant/GLO U
Electronics	Components	Power adapter	Power adapter-laptop	Power adapter, for laptop, at plant/GLO U
Electronics	Components	Resistor	Resistor-metal film	Resistor, metal film type, through-hole mounting, at plant/GLO U

Level 1	Level 2	Level 3	Level 4	Level 5
Electronics	Components	Resistor	Resistor-SMD type	Resistor, SMD type, surface mounting, at plant/GLO U
Electronics	Components	Resistor	Resistor-unspecified	Resistor, unspecified, at plant/GLO U
Electronics	Components	Resistor	Resistor-wirewound	Resistor, wirewound, through-hole mounting, at plant/GLO U
Electronics	Components	Separator	Separator-Lithium ion battery	Separator, lithium-ion battery, at plant/CN U
Electronics	Components	Switch	Switch-toggle type	Switch, toggle type, at plant/GLO U
Electronics	Components	Transformer	Transformer-high voltage	Transformer, high voltage use, at plant/GLO U
Electronics	Components	Transformer	Transformer-low voltage	Transformer, low voltage use, at plant/GLO U
Electronics	Components	Transistor	Transistor-small size	Transistor, wired, small size, through-hole mounting, at plant/GLO U
Electronics	Components	Transistor	Transistor-SMD type	Transistor, SMD type, surface mounting, at plant/GLO U
Electronics	Components	Transistor	Transistor-unspecified	Transistor, unspecified, at plant/GLO U
Electronics	Components	Transistor	Transistor-wired big	Transistor, wired, big size, through-hole mounting, at plant/GLO U
Electronics	Devices	Computer	Desktop-screenless	Desktop computer, without screen, at plant/GLO U
Electronics	Devices	Computer	Laptop	Laptop computer, at plant/GLO U
Electronics	Devices	Keyboard	Keyboard-standard	Keyboard, standard version, at plant/GLO U
Electronics	Devices	Mouse	Mouse-optical w/cable	Mouse device, optical, with cable, at plant/GLO U
Electronics	Devices	Network access device	NAD-internet	Network access devices, internet, at user/CH/I U
Electronics	Devices	Printer	Printer-laser jet	Printer, laser jet, b/w, at plant/GLO U
Electronics	Devices	Printer	Printer-laser jet	Printer, laser jet, colour, at plant/GLO U
Electronics	Devices	Router	Router-IP network	Router, IP network, at server/CH/I U
Electronics	Devices	Screen	CRT-17in	CRT screen, 17 inches, at plant/GLO U
Electronics	Devices	Screen	LCD-flat-17in	LCD flat screen, 17 inches, at plant/GLO U
Electronics	Modules	Battery	Battery-lithium ion	Single cell, lithium-ion battery, lithium manganese oxide/graphite, at plant/CN U
Electronics	Modules	Battery	Battery-rechargeable	Battery, LiIo, rechargeable, prismatic, at plant/GLO U
Electronics	Modules	Battery	Battery-rechargeable	Battery, NiMH, rechargeable, prismatic, at plant/GLO U
Electronics	Modules	Chassis	Chassis network main devices	Chassis, network main devices/RER U
Electronics	Modules	CRT 3	CRT	Cathode-ray tube, CRT screen, at plant/GLO U
Electronics	Modules	Electrode	Electrode-negative	Electrode, negative, LiC6, at plant/GLO U
Electronics	Modules	Electrode	Electrode-negative	Electrode, negative, Ni, at plant/GLO U
Electronics	Modules	Electrode	Electrode-positive	Electrode, positive, LiMn2O4, at plant/GLO U
Electronics	Modules	Fan	Fan-plant	Fan, at plant/GLO U
Electronics	Modules	HDD	HDD-desktop	HDD, desktop computer, at plant/GLO U
Electronics	Modules	HDD	HDD-laptop	HDD, laptop computer, at plant/GLO U
Electronics	Modules	ITO	ITO-powder	ITO powder, for target production, at plant/RER U

Level 1	Level 2	Level 3	Level 4	Level 5
Electronics	Modules	ITO	ITO-sintered target	ITO, sintered target, at plant/RER U
Electronics	Modules	Power supply unit	Power supply unit-plant	Power supply unit, at plant/CN U
Electronics	Modules	Screen	LCD module	Assembly, LCD module/GLO U
Electronics	Modules	Screen	LCD module	LCD module, at plant/GLO U
Electronics	Modules	Screen	LCD screen	Assembly, LCD screen/GLO U
Electronics	Modules	Toner	Toner-laser jet	Toner module, laser jet, b/w, at plant/GLO U
Electronics	Modules	Toner	Toner-laser jet	Toner module, laser jet, colour, at plant/GLO U
Electronics	Photovoltaic	Metallization paste	Metallization paste-backside	Metallization paste, back side, aluminium, at plant/RER U
Electronics	Photovoltaic	Metallization paste	Metallization paste-backside	Metallization paste, back side, at plant/RER U
Electronics	Photovoltaic	Metallization paste	Metallization paste-frontside	Metallization paste, front side, at plant/RER U
Electronics	Photovoltaic	Photovoltaic	Photocell-multi Si	Photovoltaic cell, multi-Si, at plant/RER U
Electronics	Photovoltaic	Photovoltaic	Photocell-ribbon Si	Photovoltaic cell, ribbon-Si, at plant/RER U
Electronics	Photovoltaic	Photovoltaic	Photocell-single Si	Photovoltaic cell, single-Si, at plant/RER U
Electronics	Photovoltaic	Silicon	Si-multi wafer	Multi-Si wafer, at plant/RER U
Electronics	Photovoltaic	Silicon	Si-multi wafer	Multi-Si wafer, ribbon, at plant/RER U
Electronics	Photovoltaic	Silicon	Si-single crystal-electronics	CZ single crystalline silicon, electronics, at plant/RER U
Electronics	Photovoltaic	Silicon	Si-single crystal-electronics	Single-Si wafer, electronics, at plant/RER U
Electronics	Photovoltaic	Silicon	Si-single crystal-photovoltaics	CZ single crystalline silicon, photovoltaics, at plant/RER U
Electronics	Photovoltaic	Silicon	Si-single crystal-photovoltaics	Single-Si wafer, photovoltaics, at plant/RER U
Electronics	Printed Wiring Board	Controls Electronic	Controls Electronic units	Electronics for control units/RER U
Electronics	Printed Wiring Board	PWB-mounted	PWB-mounted-Desktop PC mainboard	Printed wiring board, mounted, Desktop PC mainboard, at plant/GLO U
Electronics	Printed Wiring Board	PWB-mounted	PWB-mounted-Desktop PC mainboard	Printed wiring board, mounted, Desktop PC mainboard, Pb containing, at plant/GLO U
Electronics	Printed Wiring Board	PWB-mounted	PWB-mounted-Desktop PC mainboard	Printed wiring board, mounted, Desktop PC mainboard, Pb free, at plant/GLO U
Electronics	Printed Wiring Board	PWB-mounted	PWB-mounted-Laptop PC mainboard	Printed wiring board, mounted, Laptop PC mainboard, at plant/GLO U
Electronics	Printed Wiring Board	PWB-mounted	PWB-mounted-Laptop PC mainboard	Printed wiring board, mounted, Laptop PC mainboard, Pb containing, at plant/GLO U

Level 1	Level 2	Level 3	Level 4	Level 5
Electronics	Printed Wiring Board	PWB-mounted	PWB-mounted-unspecified	Printed wiring board, mixed mounted, unspec., solder mix, at plant/GLO U
Electronics	Printed Wiring Board	PWB-power supply unit	PWB-power supply unit desktop PC	Printed wiring board, power supply unit desktop PC, Pb containing, at plant/GLO U
Electronics	Printed Wiring Board	PWB-power supply unit	PWB-power supply unit desktop PC	Printed wiring board, power supply unit desktop PC, Pb free, at plant/GLO U
Electronics	Printed Wiring Board	PWB-power supply unit	PWB-power supply unit desktop PC	Printed wiring board, power supply unit desktop PC, solder mix, at plant/GLO U
Electronics	Printed Wiring Board	PWB-surface mount	PWB-surface mount-lead	Printed wiring board, surface mount, lead-containing surface, at plant/GLO U
Electronics	Printed Wiring Board	PWB-surface mount	PWB-surface mount-lead	Printed wiring board, surface mounted, unspec., Pb containing, at plant/GLO U
Electronics	Printed Wiring Board	PWB-surface mount	PWB-surface mount-lead free	Printed wiring board, surface mount, lead-free surface, at plant/GLO U
Electronics	Printed Wiring Board	PWB-surface mount	PWB-surface mount-lead free	Printed wiring board, surface mounted, unspec., Pb free, at plant/GLO U
Electronics	Printed Wiring Board	PWB-surface mount	PWB-surface mount-plant	Printed wiring board, surface mount, at plant/GLO U
Electronics	Printed Wiring Board	PWB-surface mount	PWB-surface mount-solder mix	Printed wiring board, surface mounted, unspec., solder mix, at plant/GLO U
Electronics	Printed Wiring Board	PWB-through-hole mounted	PWB-through-hole-at plant	Printed wiring board, through-hole, at plant/GLO U
Electronics	Printed Wiring Board	PWB-through-hole mounted	PWB-through-hole-lead	Printed wiring board, through-hole mounted, unspec., Pb containing, at plant/GLO U
Electronics	Printed Wiring Board	PWB-through-hole mounted	PWB-through-hole-lead	Printed wiring board, through-hole, lead-containing surface, at plant/GLO U
Electronics	Printed Wiring Board	PWB-through-hole mounted	PWB-through-hole-lead free	Printed wiring board, through-hole mounted, unspec., Pb free, at plant/GLO U
Electronics	Printed Wiring Board	PWB-through-hole mounted	PWB-through-hole-lead free	Printed wiring board, through-hole, lead-free surface, at plant/GLO U
Electronics	Printed Wiring Board	PWB-through-hole mounted	PWB-through-hole-solder mix	Printed wiring board, through-hole mounted, unspec., solder mix, at plant/GLO U
Electronics	Silicons 2	General Silicon	Silicon-electronic grade	Silicon, electronic grade, at plant/DE U
Electronics	Silicons 2	General Silicon	Silicon-electronic grade	Silicon, electronic grade, off-grade, at plant/DE U
Electronics	Silicons 2	General Silicon	Silicon-MG	MG-silicon, at plant/NO U
Electronics	Silicons 2	General Silicon	Silicon-multi Si	Silicon, multi-Si, casted, at plant/RER U

Level 1	Level 2	Level 3	Level 4	Level 5
Electronics	Silicons 2	General Silicon	Silicon-photovoltaics	Silicon, production mix, photovoltaics, at plant/GLO U
Electronics	Silicons 2	General Silicon	Silicon-photovoltaics	Silicon, solar grade, modified Siemens process, at plant/RER U
Glass	Construction Glass	Flat Glass	Flat Glass coated	Flat glass, coated, at plant/RER U
Glass	Construction Glass	Flat Glass	Flat Glass uncoated	Flat glass, uncoated, at plant/RER U
Glass	Construction Glass	Glass Fiber	Glass Fiber plant	Glass fibre, at plant/RER U
Glass	Construction Glass	Glass Tube	Glass tube borosilicate	Glass tube, borosilicate, at plant/DE U
Glass	Construction Glass	Glass tube	Glass tube solar w/ silver mirror	Solar collector glass tube, with silver mirror, at plant/DE U
Glass	Construction Glass	Glazing Glass	Glazing Glass double	Glazing, double (2-IV), U<1.1 W/m2K, at plant/RER U
Glass	Construction Glass	Glazing Glass	Glazing Glass double	Glazing, double (2-IV), U<1.1 W/m2K, laminated safety glass, at plant/RER U
Glass	Construction Glass	Glazing Glass	Glazing Glass triple	Glazing, triple (3-IV), U<0.5 W/m2K, at plant/RER U
Glass	Construction Glass	Solar Glass	Solar Glass low-iron	Solar glass, low-iron, at regional storage/RER U
Glass	Packaging Glass	PG-brown	PG-brown plant	Packaging glass, brown, at plant/CH S
Glass	Packaging Glass	PG-brown	PG-brown plant	Packaging glass, brown, at plant/DE U
Glass	Packaging Glass	PG-brown	PG-brown plant	Packaging glass, brown, at plant/RER U
Glass	Packaging Glass	PG-brown	PG-brown regional storage	Packaging glass, brown, at regional storage/CH S
Glass	Packaging Glass	PG-green	PG-green plant	Packaging glass, green, at plant/CH S
Glass	Packaging Glass	PG-green	PG-green plant	Packaging glass, green, at plant/DE U
Glass	Packaging Glass	PG-green	PG-green plant	Packaging glass, green, at plant/RER U
Glass	Packaging Glass	PG-green	PG-green regional storage	Packaging glass, green, at regional storage/CH S
Glass	Packaging Glass	PG-white	PG-white plant	Packaging glass, white, at plant/CH S
Glass	Packaging Glass	PG-white	PG-white plant	Packaging glass, white, at plant/DE U
Glass	Packaging Glass	PG-white	PG-white plant	Packaging glass, white, at plant/RER U
Glass	Packaging Glass	PG-white	PG-white regional storage	Packaging glass, white, at regional storage/CH S
Glass	Waste Glass	Waste Glass 3	Glass cullet	Glass cullets, sorted, at sorting plant/RER U
Glass	Waste Glass	Waste Glass 3	Glass from public unsorted	Glass, from public collection, unsorted/RER U
Metal	Ferrous metals	Iron	Iron cast	Cast iron, at plant/RER U
Metal	Ferrous metals	Iron	Iron cast	Iron, sand casted/US

Level 1	Level 2	Level 3	Level 4	Level 5
Metal	Ferrous metals	Iron	Iron pig	Pig iron, at plant/GLO U
Metal	Ferrous metals	Iron	Iron4	Ferrite, at plant/GLO U
Metal	Ferrous metals	Iron	Iron4	Iron and steel, production mix/US
Metal	Ferrous metals	Steel	Steel	Reinforcing steel, at plant/RER U
Metal	Ferrous metals	Steel	Steel chromium	Chromium steel 18/8, at plant/RER U
Metal	Ferrous metals	Steel	Steel coil	Stainless steel hot rolled coil, annealed & pickled, elec. arc furnace route, prod. mix, grade 304 RER S
Metal	Ferrous metals	Steel	Steel coil	Steel hot rolled coil, blast furnace route, prod. mix, thickness 2-7 mm, width 600-2100 mm RER S
Metal	Ferrous metals	Steel	Steel converter	Steel, converter, chromium steel 18/8, at plant/RER U
Metal	Ferrous metals	Steel	Steel converter	Steel, converter, low-alloyed, at plant/RER U
Metal	Ferrous metals	Steel	Steel converter	Steel, converter, unalloyed, at plant/RER U
Metal	Ferrous metals	Steel	Steel electric	Steel, electric, chromium steel 18/8, at plant/RER U
Metal	Ferrous metals	Steel	Steel electric	Steel, electric, un- and low-alloyed, at plant/RER U
Metal	Ferrous metals	Steel	Steel low alloyed	Steel, low-alloyed, at plant/RER U
Metal	Ferrous metals	Steel	Steel rebar	Steel rebar, blast furnace and electric arc furnace route, production mix, at plant GLO S
Metal	Ferrous metals	Steel	Steel section	Steel hot rolled section, blast furnace and electric arc furnace route, production mix, at plant GLO S
Metal	Ferrous metals	Steel	Steel sheet	Galvanized steel sheet, at plant/RNA
Metal	Ferrous metals	Steel	Steel sheet	Hot rolled sheet, steel, at plant/RNA
Metal	Ferrous metals	Steel	Steel tin plated	Tin plated chromium steel sheet, 2 mm, at plant/RER U
Metal	Metal Alloys	Aluminum Alloy	Aluminum alloy	Aluminium alloy, AlMg3, at plant/RER U
Metal	Metal Alloys	Ferrous Alloys	Ferrochromium	Ferrochromium, high-carbon, 68% Cr, at plant/GLO U
Metal	Metal Alloys	Ferrous Alloys	Ferrochromium	Ferrochromium, high-carbon, 68% Cr, at regional storage/RER U
Metal	Metal Alloys	Ferrous Alloys	Ferromanganese	Ferromanganese, high-coal, 74.5% Mn, at regional storage/RER U
Metal	Metal Alloys	Ferrous Alloys	Ferronickel	Ferronickel, 25% Ni, at plant/GLO U
Metal	Metal Alloys	Ferrous Alloys	Iron-Nickel-Chromium	Iron-nickel-chromium alloy, at plant/RER U
Metal	Metal Alloys	Magnesium Alloy 3	Magnesium alloy 4	Magnesium-alloy, AZ91, at plant/RER U
Metal	Metal Alloys	Magnesium Alloy 3	Magnesium alloy 4	Magnesium-alloy, AZ91, diecasting, at plant/RER U
Metal	Metal Alloys	Solder	Solder bar	Solder, bar, Sn63Pb37, for electronics industry, at plant/GLO U

Level 1	Level 2	Level 3	Level 4	Level 5
Metal	Metal Alloys	Solder	Solder bar	Solder, bar, Sn95.5Ag3.9Cu0.6, for electronics industry, at plant/GLO U
Metal	Metal Alloys	Solder	Solder cadmium free	Brazing solder, cadmium free, at plant/RER U
Metal	Metal Alloys	Solder	Solder paste	Solder, paste, Sn63Pb37, for electronics industry, at plant/GLO U
Metal	Metal Alloys	Solder	Solder paste	Solder, paste, Sn95.5Ag3.9Cu0.6, for electronics industry, at plant/GLO U
Metal	Metal Alloys	Solder	Solder soft	Soft solder, Sn97Cu3, at plant/RER U
Metal	Non-Ferrous metals	Aluminum	Aluminum primary	Aluminium, primary, at plant/RER U
Metal	Non-Ferrous metals	Aluminum	Aluminum primary	Aluminium, primary, liquid, at plant/RER U
Metal	Non-Ferrous metals	Aluminum	Aluminum primary	Aluminum, primary, ingot, at plant/RNA
Metal	Non-Ferrous metals	Aluminum	Aluminum primary	Aluminum, primary, smelt, at plant/RNA
Metal	Non-Ferrous metals	Aluminum	Aluminum production mix	Aluminium, production mix, at plant/RER U
Metal	Non-Ferrous metals	Aluminum	Aluminum production mix	Aluminium, production mix, cast alloy, at plant/RER U
Metal	Non-Ferrous metals	Aluminum	Aluminum production mix	Aluminium, production mix, wrought alloy, at plant/RER U
Metal	Non-Ferrous metals	Aluminum	Aluminum secondary	Aluminium, secondary, from old scrap, at plant/RER U
Metal	Non-Ferrous metals	Aluminum	Aluminum secondary	Aluminum, secondary, ingot, at plant/RNA
Metal	Non-Ferrous metals	Aluminum	Aluminum secondary	Aluminum, secondary, ingot, from automotive scrap, at plant/RNA
Metal	Non-Ferrous metals	Aluminum	Aluminum secondary	Aluminum, secondary, ingot, from beverage cans, at plant/RNA
Metal	Non-Ferrous metals	Aluminum	Aluminum secondary shaped	Aluminum, secondary, extruded/RNA
Metal	Non-Ferrous metals	Aluminum	Aluminum secondary shaped	Aluminum, secondary, rolled/RNA
Metal	Non-Ferrous metals	Aluminum	Aluminum secondary shaped	Aluminum, secondary, shape casted/RNA
Metal	Non-Ferrous metals	Aluminum	Aluminum shaped	Aluminium extrusion profile, primary prod., prod. mix, aluminium semi-finished extrusion product RER S
Metal	Non-Ferrous metals	Aluminum	Aluminum shaped	Aluminium sheet, primary prod., prod. mix, aluminium semi-finished sheet product RER S
Metal	Non-Ferrous metals	Aluminum	Aluminum shaped	Aluminum ingot, production mix, at plant/US
Metal	Non-Ferrous metals	Aluminum	Aluminum shaped	Aluminum, cast, lost foam, at plant/kg/US

Level 1	Level 2	Level 3	Level 4	Level 5
Metal	Non-Ferrous metals	Aluminum	Aluminum shaped	Aluminum, cast, precision sand casting/kg/US
Metal	Non-Ferrous metals	Aluminum	Aluminum shaped	Aluminum, cast, semi-permanent mold (SPM), at plant/kg/US
Metal	Non-Ferrous metals	Brass	Brass4	Brass, at plant/CH U
Metal	Non-Ferrous metals	Bronze	Bronze4	Bronze, at plant/CH U
Metal	Non-Ferrous metals	Cadmium	Cadmium chloride	Cadmium chloride, semiconductor-grade, at plant/US U
Metal	Non-Ferrous metals	Cadmium	Cadmium primary	Cadmium, primary, at plant/GLO U
Metal	Non-Ferrous metals	Cadmium	Cadmium semiconductor grade	Cadmium, semiconductor-grade, at plant/US U
Metal	Non-Ferrous metals	Cadmium	Cadmium sulphide	Cadmium sulphide, semiconductor-grade, at plant/US U
Metal	Non-Ferrous metals	Cadmium	Cadmium telluride	Cadmium telluride, semiconductor-grade, at plant/US U
Metal	Non-Ferrous metals	Chromium	Chromium4	Chromium, at regional storage/RER U
Metal	Non-Ferrous metals	Cobalt	Cobalt4	Cobalt, at plant/GLO U
Metal	Non-Ferrous metals	Copper	Copper primary	Copper, at regional storage/RER U
Metal	Non-Ferrous metals	Copper	Copper primary	Copper, blister-copper, at primary smelter/RER U
Metal	Non-Ferrous metals	Copper	Copper primary	Copper, from imported concentrates, at refinery/DE U
Metal	Non-Ferrous metals	Copper	Copper primary	Copper, primary, at refinery/GLO U
Metal	Non-Ferrous metals	Copper	Copper primary	Copper, primary, at refinery/ID U
Metal	Non-Ferrous metals	Copper	Copper primary	Copper, primary, at refinery/RAS U
Metal	Non-Ferrous metals	Copper	Copper primary	Copper, primary, at refinery/RER U
Metal	Non-Ferrous metals	Copper	Copper primary	Copper, primary, at refinery/RLA U
Metal	Non-Ferrous metals	Copper	Copper primary	Copper, primary, at refinery/RNA U
Metal	Non-Ferrous metals	Copper	Copper primary CombineProd	Copper, from combined metal production, at beneficiation/SE U
Metal	Non-Ferrous metals	Copper	Copper primary CombineProd	Copper, from combined metal production, at refinery/SE U

Level 1	Level 2	Level 3	Level 4	Level 5
Metal	Non-Ferrous metals	Copper	Copper primary CombineProd	Copper, primary, from platinum group metal production/RU U
Metal	Non-Ferrous metals	Copper	Copper primary CombineProd	Copper, primary, from platinum group metal production/ZA U
Metal	Non-Ferrous metals	Copper	Copper processed	Copper sheet, technology mix, consumption mix, at plant, 0,6 mm thickness EU-15 S
Metal	Non-Ferrous metals	Copper	Copper processed	Copper telluride cement, from copper production/GLO U
Metal	Non-Ferrous metals	Copper	Copper processed	Copper tube, technology mix, consumption mix, at plant, diameter 15 mm, 1 mm thickness EU-15 S
Metal	Non-Ferrous metals	Copper	Copper processed	Copper wire, technology mix, consumption mix, at plant, cross section 1 mm² EU-15 S
Metal	Non-Ferrous metals	Copper	Copper secondary	Copper, secondary, at refinery/RER U
Metal	Non-Ferrous metals	Copper	Copper solvent extracted	Copper, SX-EW, at refinery/GLO U
Metal	Non-Ferrous metals	Gallium	Gallium semiconductor grade	Gallium, semiconductor-grade, at plant/GLO U
Metal	Non-Ferrous metals	Gallium	Gallium semiconductor grade	Gallium, semiconductor-grade, at regional storage/RER U
Metal	Non-Ferrous metals	Indium	Indium regional storage	Indium, at regional storage/RER U
Metal	Non-Ferrous metals	Lead	Lead combined production	Lead, from combined metal production, at beneficiation/SE U
Metal	Non-Ferrous metals	Lead	Lead combined production	Lead, from combined metal production, at refinery/SE U
Metal	Non-Ferrous metals	Lead	Lead primary	Lead, primary, at plant/GLO U
Metal	Non-Ferrous metals	Lead	Lead primary	Lead, primary, consumption mix, at plant DE S
Metal	Non-Ferrous metals	Lead	Lead regional storage	Lead, at regional storage/RER U
Metal	Non-Ferrous metals	Lead	Lead secondary	Lead, secondary, at plant/RER U
Metal	Non-Ferrous metals	Lithium	Lithium4	Lithium, at plant/GLO U
Metal	Non-Ferrous metals	Magnesium 3	Magnesium 4	Magnesium, at plant/RER U
Metal	Non-Ferrous metals	Manganese	Manganese regional storage	Manganese, at regional storage/RER U
Metal	Non-Ferrous metals	Mercury	Mercury4	Mercury, liquid, at plant/GLO U
Metal	Non-Ferrous metals	Mischmetal	Mischmetal4	Mischmetal, primary, at plant/GLO U

Level 1	Level 2	Level 3	Level 4	Level 5
Metal	Non-Ferrous metals	Molybdenum	Molybdenum regional storage	Molybdenum, at regional storage/RER U
Metal	Non-Ferrous metals	Nickel	Nickel primary	Nickel, primary, from platinum group metal production/RU U
Metal	Non-Ferrous metals	Nickel	Nickel primary	Nickel, primary, from platinum group metal production/ZA U
Metal	Non-Ferrous metals	Nickel	Nickel secondary	Nickel, secondary, from electronic and electric scrap recycling, at refinery/SE U
Metal	Non-Ferrous metals	Nickel	Nickel4	Nickel, 99.5%, at plant/GLO U
Metal	Non-Ferrous metals	Tantalum	Tantalum powder	Tantalum, powder, capacitor-grade, at regional storage/GLO U
Metal	Non-Ferrous metals	Tellurium	Tellurium semiconductor grade	Tellurium, semiconductor-grade, at plant/GLO U
Metal	Non-Ferrous metals	Tin	Tin regional storage	Tin, at regional storage/RER U
Metal	Non-Ferrous metals	Titanium	Titanium zinc plate	Titanium zinc plate, without pre-weathering, at plant/DE U
Metal	Non-Ferrous metals	Zinc	Zinc combined production	Zinc, from combined metal production, at beneficiation/SE U
Metal	Non-Ferrous metals	Zinc	Zinc combined production	Zinc, from combined metal production, at refinery/SE U
Metal	Non-Ferrous metals	Zinc	Zinc high grade	Special high grade zinc, primary production, production mix, at plant GLO S
Metal	Non-Ferrous metals	Zinc	Zinc primary	Zinc, primary, at regional storage/RER U
Paper and Board	Board	Base Fiber	Chipboard4	Whitelined chipboard, WLC, at plant/RER U
Paper and Board	Board	Core Board	Core Board4	Core board, at plant/RER U
Paper and Board	Board	Liquid Board	Liquid Board4	Liquid packaging board, at plant/RER U
Paper and Board	Board	Solid Board	SB-Bleached	Solid bleached board, SBB, at plant/RER U
Paper and Board	Board	Solid Board	SB-Unbleached	Solid unbleached board, SUB, at plant/RER U
Paper and Board	Corrugated board	Base Fiber	Kraftliner	Corrugated board base paper, kraftliner, at plant/RER U
Paper and Board	Corrugated board	Base Fiber	SemiChemFluting	Corrugated board base paper, semichemical fluting, at plant/RER U
Paper and Board	Corrugated board	Base Fiber	Testliner	Corrugated board base paper, testliner, at plant/RER U
Paper and Board	Corrugated board	Base Fiber	Wellenstoff	Corrugated board base paper, wellenstoff, at plant/RER U
Paper and Board	Corrugated board	Double Wall	Recycling Fiber-DW	Corrugated board, recycling fibre, double wall, at plant/CH U
Paper and Board	Corrugated board	Double Wall	Recycling Fiber-DW	Corrugated board, recycling fibre, double wall, at plant/RER U
Paper and Board	Corrugated board	Single Wall	Fresh Fiber	Corrugated board, fresh fibre, single wall, at plant/CH U
Paper and Board	Corrugated board	Single Wall	Fresh Fiber	Corrugated board, fresh fibre, single wall, at plant/RER U

Level 1	Level 2	Level 3	Level 4	Level 5
Paper and Board	Corrugated board	Single Wall	Mixed Fiber	Corrugated board, mixed fibre, single wall, at plant/CH U
Paper and Board	Corrugated board	Single Wall	Mixed Fiber	Corrugated board, mixed fibre, single wall, at plant/RER U
Paper and Board	Corrugated board	Single Wall	Recycling Fiber-SW	Corrugated board, recycling fibre, single wall, at plant/CH U
Paper and Board	Corrugated board	Single Wall	Recycling Fiber-SW	Corrugated board, recycling fibre, single wall, at plant/RER U
Paper and Board	Graphic Paper	Graphic Recycling	Deinking	Paper, recycling, with deinking, at plant/RER U
Paper and Board	Graphic Paper	Graphic Recycling	No-Deinking	Paper, recycling, no deinking, at plant/RER U
Paper and Board	Graphic Paper	News Print	DIP-Containing	Paper, newsprint, DIP containing, at plant/RER U
Paper and Board	Graphic Paper	News Print	News Print-At Plant	Paper, newsprint, 0% DIP, at plant/RER U
Paper and Board	Graphic Paper	News Print	News Print-At Plant	Paper, newsprint, at plant/CH U
Paper and Board	Graphic Paper	News Print	News Print-Regional Storage	Paper, newsprint, at regional storage/CH U
Paper and Board	Graphic Paper	News Print	News Print-Regional Storage	Paper, newsprint, at regional storage/RER U
Paper and Board	Graphic Paper	Wood Containing	WC-LWC	Paper, wood-containing, LWC, at plant/RER U
Paper and Board	Graphic Paper	Wood Containing	WC-LWC	Paper, wood-containing, LWC, at regional storage/CH U
Paper and Board	Graphic Paper	Wood Containing	WC-LWC	Paper, wood-containing, LWC, at regional storage/RER U
Paper and Board	Graphic Paper	Wood Containing	WC-SC	Paper, woodcontaining, supercalendred (SC), at plant/RER U
Paper and Board	Graphic Paper	Wood Containing	WC-SC	Paper, wood-containing, supercalendred (SC), at regional storage/CH U
Paper and Board	Graphic Paper	Wood Containing	WC-SC	Paper, wood-containing, supercalendred (SC), at regional storage/RER U
Paper and Board	Graphic Paper	Wood Free	WF-Coated	Paper, woodfree, coated, at integrated mill/RER U
Paper and Board	Graphic Paper	Wood Free	WF-Coated	Paper, woodfree, coated, at non-integrated mill/RER U
Paper and Board	Graphic Paper	Wood Free	WF-Coated	Paper, woodfree, coated, at regional storage/CH U
Paper and Board	Graphic Paper	Wood Free	WF-Coated	Paper, woodfree, coated, at regional storage/RER U
Paper and Board	Graphic Paper	Wood Free	WF-Uncoated	Paper, woodfree, uncoated, at integrated mill/RER U
Paper and Board	Graphic Paper	Wood Free	WF-Uncoated	Paper, woodfree, uncoated, at non-integrated mill/RER U
Paper and Board	Graphic Paper	Wood Free	WF-Uncoated	Paper, woodfree, uncoated, at regional storage/CH U
Paper and Board	Graphic Paper	Wood Free	WF-Uncoated	Paper, woodfree, uncoated, at regional storage/RER U
Paper and Board	Packaging Paper	Corrugated	Corrugated board, mixed fiber	Packaging, corrugated board, mixed fibre, single wall, at plant/CH U
Paper and Board	Packaging Paper	Corrugated	Corrugated board, mixed fiber	Packaging, corrugated board, mixed fibre, single wall, at plant/RER U

Level 1	Level 2	Level 3	Level 4	Level 5
Paper and Board	Packaging Paper	Corrugated	Corrugated boxes, technology mix	Corrugated board boxes, technology mix, prod. mix, 16,6 % primary fibre, 83,4 % recycled fibre EU-25 S
Paper and Board	Packaging Paper	Graphic Packaging	Kraft-bleached	Kraft paper, bleached, at plant/RER U
Paper and Board	Packaging Paper	Graphic Packaging	Kraft-unbleached	Kraft paper, unbleached, at plant/RER U
Paper and Board	Packaging Paper	Liquid Packing	Liquid Packing 4	Production of liquid packaging board containers, at plant/RER U
Paper and Board	Pulp	Chemi-Thermomech pulp	Chemi-Thermomech pulp 4	Chemi-thermomechanical pulp, at plant/RER U
Paper and Board	Pulp	Sulphate pulp	Sulphate pulp, average	Sulphate pulp, average, at regional storage/CH U
Paper and Board	Pulp	Sulphate pulp	Sulphate pulp, average	Sulphate pulp, average, at regional storage/RER U
Paper and Board	Pulp	Sulphate pulp	Sulphate pulp, ECF bleached	Sulphate pulp, ECF bleached, at plant/RER U
Paper and Board	Pulp	Sulphate pulp	Sulphate pulp, eucalyptus	Sulphate pulp, from eucalyptus ssp. (SFM), unbleached, at pulpmill/TH U
Paper and Board	Pulp	Sulphate pulp	Sulphate pulp, eucalyptus	Sulphate pulp, from eucalyptus ssp. (SFM), unbleached, TH, at maritime harbour/RER U
Paper and Board	Pulp	Sulphate pulp	Sulphate pulp, TCF bleached	Sulphate pulp, TCF bleached, at plant/RER U
Paper and Board	Pulp	Sulphate pulp	Sulphate pulp, unbleached	Sulphate pulp, unbleached, at plant/RER U
Paper and Board	Pulp	Suphite pulp	Sulphite pulp, bleached	Sulphite pulp, bleached, at plant/RER U
Paper and Board	Pulp	Thermo-mechanical pulp	Thermo-mechanical pulp4	Thermo-mechanical pulp, at plant/RER U
Paper and Board	Pulp	Wood Pulp	Stone Ground	Stone groundwood pulp, SGW, at plant/RER U
Paper and Board	Waste Paper	WP-for further treatment	WP-mixed	Waste paper, mixed, from public collection, for further treatment/CH U
Paper and Board	Waste Paper	WP-for further treatment	WP-mixed	Waste paper, mixed, from public collection, for further treatment/RER U
Paper and Board	Waste Paper	WP-for further treatment	WP-sorted	Waste paper, sorted, for further treatment/CH U
Paper and Board	Waste Paper	WP-for further treatment	WP-sorted	Waste paper, sorted, for further treatment/RER U
Plant Product	Fruiting products	Fruit	Fruit4	Harvesting, fresh fruit bunch, at farm/RNA
Plant Product	Fruiting products	Nuts	Nuts4	Husked nuts harvesting, at farm/PH U
Plant Product	Fruiting products	Palm	Palm fruit	Palm fruit bunches, at farm/MY U
Plant Product	Fruiting products	Palm	Palm kernel	Palm kernel, at plant/RNA
Plant Product	Fruiting products	Rape Seed	Rape Seed conventional	Rape seed conventional, at farm/DE U
Plant Product	Fruiting products	Rape Seed	Rape Seed conventional	Rape seed conventional, Barrois, at farm/FR U
Plant Product	Fruiting products	Rape Seed	Rape Seed conventional	Rape seed conventional, Saxony-Anhalt, at farm/DE U
Plant Product	Fruiting products	Rape Seed	Rape Seed extensive	Rape seed extensive, at farm/CH U

Level 1	Level 2	Level 3	Level 4	Level 5
Plant Product	Fruiting products	Rape Seed	Rape Seed organic	Rape seed, organic, at farm/CH U
Plant Product	Fruiting products	Rape Seed	Rape Seed4	Rape seed IP, at farm/CH U
Plant Product	Fruiting products	Rape Seed	Rape Seed4	Rape seed, at farm/US U
Plant Product	Fruiting products	Rape Seed	Rape Seed4	Rapeseed, at field/kg/US
Plant Product	Fruiting products	Seeds	Seeds4	Seedlings, at greenhouse, US PNW/US
Plant Product	Fruiting products	Seeds	Seeds4	Seedlings, at greenhouse, US SE/US
Plant Product	Grains	Barley	Barley grains	Barley grains IP, at farm/CH U
Plant Product	Grains	Barley	Barley grains conventional	Barley grains conventional, Barrois, at farm/FR U
Plant Product	Grains	Barley	Barley grains conventional	Barley grains conventional, Castilla-y-Leon, at farm/ES U
Plant Product	Grains	Barley	Barley grains conventional	Barley grains conventional, Saxony-Anhalt, at farm/DE U
Plant Product	Grains	Barley	Barley grains extensive	Barley grains extensive, at farm/CH U
Plant Product	Grains	Barley	Barley grains organic	Barley grains organic, at farm/CH U
Plant Product	Grains	Corn	Corn grain	Grain maize IP, at farm/CH U
Plant Product	Grains	Corn	Corn grain organic	Grain maize organic, at farm/CH U
Plant Product	Grains	Corn	Corn4	Corn, at farm/US U
Plant Product	Grains	Corn	Corn4	Corn, at field/kg/US
Plant Product	Grains	Rice	Rice grain	Rice grain, at field/kg/US
Plant Product	Grains	Rice	Rice4	Rice, at farm/US U
Plant Product	Grains	Rye	Rye grain	Rye grains IP, at farm/CH U
Plant Product	Grains	Rye	Rye grain conventional	Rye grains conventional, at farm/RER U
Plant Product	Grains	Rye	Rye grain extensive	Rye grains extensive, at farm/CH U
Plant Product	Grains	Rye	Rye grain organic	Rye grains organic, at farm/CH U
Plant Product	Grains	Sorghum	Sorghum grain	Sweet sorghum grains, at farm/CN U
Plant Product	Grains	Wheat grain	Wheat grain	Wheat grains IP, at farm/CH U
Plant Product	Grains	Wheat grain	Wheat grain	Wheat grains, at farm/US U
Plant Product	Grains	Wheat grain	Wheat grain	Wheat grains, at field/kg/US
Plant Product	Grains	Wheat grain	Wheat grain conventional	Wheat grains conventional, Barrois, at farm/FR U
Plant Product	Grains	Wheat grain	Wheat grain conventional	Wheat grains conventional, Castilla-y-Leon, at farm/ES U
Plant Product	Grains	Wheat grain	Wheat grain conventional	Wheat grains conventional, Saxony-Anhalt, at farm/DE U
Plant Product	Grains	Wheat grain	Wheat grain extensive	Wheat grains extensive, at farm/CH U
Plant Product	Grains	Wheat grain	Wheat grain organic	Wheat grains organic, at farm/CH U
Plant Product	Legume	Fava beans	Fava beans organic	Fava beans organic, at farm/CH U

Level 1	Level 2	Level 3	Level 4	Level 5
Plant Product	Legume	Fava beans	Fava beans4	Fava beans IP, at farm/CH U
Plant Product	Legume	Pea	Pea protein conventional	Protein peas conventional, Barrois, at farm/FR U
Plant Product	Legume	Pea	Pea protein conventional	Protein peas conventional, Castilla-y-Leon, at farm/ES U
Plant Product	Legume	Pea	Pea protein conventional	Protein peas conventional, Saxony-Anhalt, at farm/DE U
Plant Product	Legume	Pea	Pea protien	Protein peas, IP, at farm/CH U
Plant Product	Legume	Pea	Pea protien organic	Protein peas, organic, at farm/CH U
Plant Product	Legume	Soybean	Soybean organic	Soy beans organic, at farm/CH U
Plant Product	Legume	Soybean	Soybean4	Soy beans IP, at farm/CH U
Plant Product	Legume	Soybean	Soybean4	Soybean grains, at field/kg/US
Plant Product	Legume	Soybean	Soybean4	Soybeans, at farm/BR U
Plant Product	Legume	Soybean	Soybean4	Soybeans, at farm/US U
Plant Product	Plant fibers	Cotton	Cotton fibers	Cotton fibres, at farm/US U
Plant Product	Plant fibers	Cotton	Cotton fibers	Cotton fibres, ginned, at farm/CN U
Plant Product	Plant fibers	Cotton	Cotton4	Cotton, at field/kg/US
Plant Product	Plant fibers	Fibers	Jute fibers	Jute fibres, irrigated system, at farm/IN U
Plant Product	Plant fibers	Fibers	Jute fibers	Jute fibres, rainfed system, at farm/IN U
Plant Product	Plant fibers	Fibers	Kenaf fibers	Kenaf fibres, at farm/IN U
Plant Product	Plant matter	Corn silage	Corn silage	Silage maize IP, at farm/CH U
Plant Product	Plant matter	Corn silage	Corn silage organic	Silage maize organic, at farm/CH U
Plant Product	Plant matter	Fertilizer	Green Manure	Green manure IP, until April/CH U
Plant Product	Plant matter	Fertilizer	Green Manure	Green manure IP, until February/CH U
Plant Product	Plant matter	Fertilizer	Green Manure	Green manure IP, until January/CH U
Plant Product	Plant matter	Fertilizer	Green Manure	Green manure IP, until march/CH U
Plant Product	Plant matter	Fertilizer	Green Manure organic	Green manure organic, until April/CH U
Plant Product	Plant matter	Fertilizer	Green Manure organic	Green manure organic, until February/CH U
Plant Product	Plant matter	Fertilizer	Green Manure organic	Green manure organic, until January/CH U
Plant Product	Plant matter	Fertilizer	Green Manure organic	Green manure organic, until march/CH U
Plant Product	Plant matter	Hay	Hay extensive	Hay extensive, at farm/CH U
Plant Product	Plant matter	Hay	Hay intensive	Hay intensive IP, at farm/CH U
Plant Product	Plant matter	Hay	Hay intensive organic	Hay intensive organic, at farm/CH U
Plant Product	Plant matter	Stem	Jute stalks	Jute stalks, from fibre production, irrigated system, at farm/IN U
Plant Product	Plant matter	Stem	Jute stalks	Jute stalks, from fibre production, rainfed system, at farm/IN U
Plant Product	Plant matter	Stem	Kenaf stalks	Kenaf stalks, from fibre production, at farm/IN U
Plant Product	Plant matter	Stem	Sorghum stem	Sweet sorghum stem, at farm/CN U
Plant Product	Plant matter	Straw	Barley Straw	Barley straw extensive, at farm/CH U

Level 1	Level 2	Level 3	Level 4	Level 5
Plant Product	Plant matter	Straw	Barley Straw	Barley straw IP, at farm/CH U
Plant Product	Plant matter	Straw	Barley Straw	Barley straw organic, at farm/CH U
Plant Product	Plant matter	Straw	Rye straw	Rye straw IP, at farm/CH U
Plant Product	Plant matter	Straw	Rye straw conventional	Rye straw conventional, at farm/RER U
Plant Product	Plant matter	Straw	Rye straw extensive	Rye straw extensive, at farm/CH U
Plant Product	Plant matter	Straw	Rye straw organic	Rye straw organic, at farm/CH U
Plant Product	Plant matter	Straw	Straw organic	Straw organic, at farm/CH U
Plant Product	Plant matter	Straw	Straw4	Straw IP, at farm/CH U
Plant Product	Plant matter	Straw	Straw4	Straw, from straw areas, at field/CH U
Plant Product	Plant matter	Straw	Wheat straw	Wheat straw extensive, at farm/CH U
Plant Product	Plant matter	Straw	Wheat straw	Wheat straw IP, at farm/CH U
Plant Product	Plant matter	Straw	Wheat straw organic	Wheat straw organic, at farm/CH U
Plant Product	Plant matter	Sugarcane	Sugarcane4	Sugarcane, at farm/BR U
Plant Product	Plant matter	Sunflower	Sunflower conventional	Sunflower conventional, Castilla-y-Leon, at farm/ES U
Plant Product	Plant matter	Sunflower	Sunflower4	Sunflower IP, at farm/CH U
Plant Product	Processed	Plant oil	Coconut oil4	Crude coconut oil, at plant/PH U
Plant Product	Processed	Plant oil	Palm oil4	Crude palm kernel oil, at plant/RNA
Plant Product	Processed	Plant oil	Palm oil4	Palm kernel oil, at oil mill/MY U
Plant Product	Processed	Plant oil	Palm oil4	Palm kernel oil, processed, at plant/RNA
Plant Product	Processed	Plant oil	Palm oil4	Palm oil, at oil mill/MY U
Plant Product	Processed	Plant oil	Rape Seed oil4	Rape oil, at oil mill/CH U
Plant Product	Processed	Plant oil	Rape Seed oil4	Rape oil, at oil mill/RER U
Plant Product	Processed	Plant oil	Rape Seed oil4	Rape oil, at regional storage/CH U
Plant Product	Processed	Plant oil	Soybean oil4	Soya oil, at plant/RER U
Plant Product	Processed	Plant oil	Soybean oil4	Soybean oil, at oil mill/BR U
Plant Product	Processed	Plant oil	Soybean oil4	Soybean oil, at oil mill/US U
Plant Product	Processed	Starch	Corn starch	Maize starch, at plant/DE U
Plant Product	Processed	Starch	Potato starch	Potato starch, at plant/DE U
Plant Product	Root	Beet	Beet fodder	Fodder beets IP, at farm/CH U
Plant Product	Root	Beet	Beet sugar	Sugar beets IP, at farm/CH U
Plant Product	Root	Potato	Potato organic	Potatoes organic, at farm/CH U
Plant Product	Root	Potato	Potato4	Potato, at field/kg/US
Plant Product	Root	Potato	Potato4	Potatoes IP, at farm/CH U
Plant Product	Root	Potato	Potato4	Potatoes, at farm/US U
Polymers	Elastomer	ABS	ABS Copolymer	Acrylonitrile-butadiene-styrene copolymer, ABS, at plant/RER U
Polymers	Elastomer	ABS	ABS Copolymer granulate	Acrylonitrile-butadiene-styrene granulate (ABS), production mix, at plant RER
Polymers	Elastomer	ABS	ABS Copolymer resin	Acrylonitrile-butadiene-styrene copolymer resin, at plant/RNA
Polymers	Elastomer	Bitumen	Bitumen4	Bitumen sealing, at plant/RER U

Level 1	Level 2	Level 3	Level 4	Level 5
Polymers	Elastomer	Polybutadiene	Polybutadiene granulate	Polybutadiene granulate (PB), production mix, at plant RER
Polymers	Elastomer	Polybutadiene	Polybutadiene4	Polybutadiene E
Polymers	Elastomer	Polybutadiene	Polybutadiene4	Polybutadiene, at plant/RER U
Polymers	Elastomer	Polybutadiene	Polybutadiene4	Polybutadiene, at plant/RNA
Polymers	Elastomer	SAN	SAN copolymer4	Styrene-acrylonitrile copolymer (SAN) E
Polymers	Elastomer	SAN	SAN copolymer4	Styrene-acrylonitrile copolymer, SAN, at plant/RER U
Polymers	Elastomer	Synthetic rubber	Synthetic rubber4	Synthetic rubber, at plant/RER U
Polymers	Thermoplastic	EVA	EVA foil	Ethylvinylacetate, foil, at plant/RER U
Polymers	Thermoplastic	EVA	EVA4	Ethylene vinyl acetate copolymer, at plant/RER U
Polymers	Thermoplastic	Nylon	Nylon 6	Nylon 6 + 30% glass fibre E
Polymers	Thermoplastic	Nylon	Nylon 6	Nylon 6 E
Polymers	Thermoplastic	Nylon	Nylon 6	Nylon 6 glass filled (PA 6 GF), production mix, at plant RER
Polymers	Thermoplastic	Nylon	Nylon 6	Nylon 6 granulate (PA 6), production mix, at plant RER
Polymers	Thermoplastic	Nylon	Nylon 6	Nylon 6, at plant/RER U
Polymers	Thermoplastic	Nylon	Nylon 6	Nylon 6, glass-filled, at plant/RER U
Polymers	Thermoplastic	Nylon	Nylon 66	Nylon 66 E
Polymers	Thermoplastic	Nylon	Nylon 66	Nylon 66 GF 30 compound (PA 66 GF 30), production mix, at plant RER
Polymers	Thermoplastic	Nylon	Nylon 66	Nylon 66 granulate (PA 66), production mix, at plant RER
Polymers	Thermoplastic	Nylon	Nylon 66	Nylon 66, at plant/RER U
Polymers	Thermoplastic	Nylon	Nylon 66	Nylon 66, glass-filled, at plant/RER U
Polymers	Thermoplastic	Nylon	Nylon 66	Nylon 66/glass fibre composite E
Polymers	Thermoplastic	PMMA	PMMA beads	PMMA beads E
Polymers	Thermoplastic	PMMA	PMMA beads	Polymethyl methacrylate (PMMA) beads, production mix, at plant RER
Polymers	Thermoplastic	PMMA	PMMA beads	Polymethyl methacrylate, beads, at plant/RER U
Polymers	Thermoplastic	PMMA	PMMA sheet	PMMA sheet E
Polymers	Thermoplastic	PMMA	PMMA sheet	Polymethyl methacrylate, sheet, at plant/RER U
Polymers	Thermoplastic	Polyacrylonitrile	AN	Acrylonitrile E
Polymers	Thermoplastic	Polyacrylonitrile	AN	Acrylonitrile from Sohio process, at plant/RER U

Level 1	Level 2	Level 3	Level 4	Level 5
Polymers	Thermoplastic	Polyacrylonitrile	PAN	Polyacrylonitrile fibres (PAN), from acrylonitrile and methacrylate, prod. mix, PAN w/o additives EU-27 S
Polymers	Thermoplastic	Polyamide	Polyamide glass	Glass fibre reinforced plastic, polyamide, injection moulding, at plant/RER U
Polymers	Thermoplastic	Polyamide	Polyamide4	Polyamide 6.6 fibres (PA 6.6), from adipic acid and hexamethylene diamine (HMDA), prod. mix, EU-27 S
Polymers	Thermoplastic	Polycarbonate	Polycarbonate granulate	Polycarbonate granulate (PC), production mix, at plant RER
Polymers	Thermoplastic	Polycarbonate	Polycarbonate4	Polycarbonate E
Polymers	Thermoplastic	Polycarbonate	Polycarbonate4	Polycarbonate, at plant/RER U
Polymers	Thermoplastic	Polyethylene	HDPE	HDPE bottles E
Polymers	Thermoplastic	Polyethylene	HDPE	HDPE pipes E
Polymers	Thermoplastic	Polyethylene	HDPE	HDPE resin E
Polymers	Thermoplastic	Polyethylene	HDPE	High density polyethylene resin, at plant/RNA
Polymers	Thermoplastic	Polyethylene	HDPE	Polyethylene high density granulate (PE-HD), production mix, at plant RER
Polymers	Thermoplastic	Polyethylene	HDPE	Polyethylene, HDPE, granulate, at plant/RER U
Polymers	Thermoplastic	Polyethylene	LDPE	LDPE bottles E
Polymers	Thermoplastic	Polyethylene	LDPE	LDPE resin E
Polymers	Thermoplastic	Polyethylene	LDPE	Low density polyethylene resin, at plant/RNA
Polymers	Thermoplastic	Polyethylene	LDPE	Packaging film, LDPE, at plant/RER U
Polymers	Thermoplastic	Polyethylene	LDPE	Polyethylene low density granulate (PE-LD), production mix, at plant RER
Polymers	Thermoplastic	Polyethylene	LDPE	Polyethylene, LDPE, granulate, at plant/RER U
Polymers	Thermoplastic	Polyethylene	LLDPE	Linear low density polyethylene resin, at plant/RNA
Polymers	Thermoplastic	Polyethylene	LLDPE	LLDPE resin E
Polymers	Thermoplastic	Polyethylene	LLDPE	Polyethylene low linear density granulate (PE-LLD), production mix, at plant RER
Polymers	Thermoplastic	Polyethylene	LLDPE	Polyethylene, LLDPE, granulate, at plant/RER U
Polymers	Thermoplastic	Polyethylene	PET	Fleece, polyethylene, at plant/RER U
Polymers	Thermoplastic	Polyethylene	PET	PET (amorphous) E
Polymers	Thermoplastic	Polyethylene	PET	PET (bottle grade) E
Polymers	Thermoplastic	Polyethylene	PET	PET bottles E

Level 1	Level 2	Level 3	Level 4	Level 5
Polymers	Thermoplastic	Polyethylene	PET	PET film (production only) E
Polymers	Thermoplastic	Polyethylene	PET	Polyethylene terephthalate (PET) granulate, production mix, at plant, amorphous RER
Polymers	Thermoplastic	Polyethylene	PET	Polyethylene terephthalate (PET) granulate, production mix, at plant, bottle grade RER
Polymers	Thermoplastic	Polyethylene	PET	Polyethylene terephthalate fibres (PET), via dimethyl terephthalate (DMT), prod. mix, EU-27 S
Polymers	Thermoplastic	Polyethylene	PET	Polyethylene terephthalate, granulate, amorphous, at plant/RER U
Polymers	Thermoplastic	Polyethylene	PET	Polyethylene terephthalate, granulate, bottle grade, at plant/RER U
Polymers	Thermoplastic	Polyethylene	Polyester glass	Glass fibre reinforced plastic, polyester resin, hand lay-up, at plant/RER U
Polymers	Thermoplastic	Polyethylene	Polyester resin	Alkyd resin, long oil, 70% in white spirit, at plant/RER U
Polymers	Thermoplastic	Polyethylene	Polyester resin	Polyester resin, unsaturated, at plant/RER U
Polymers	Thermoplastic	Polyphenylene sulfide	Polyphenylene sulfide4	Polyphenylene sulfide, at plant/GLO U
Polymers	Thermoplastic	Polypropylene	Polypropylene fibers	Polypropylene fibres (PP), crude oil based, production mix, at plant, PP granulate without additives EU-27 S
Polymers	Thermoplastic	Polypropylene	Polypropylene film	Oriented polypropylene film E
Polymers	Thermoplastic	Polypropylene	Polypropylene granulate	Polypropylene granulate (PP), production mix, at plant RER
Polymers	Thermoplastic	Polypropylene	Polypropylene granulate	Polypropylene, granulate, at plant/RER U
Polymers	Thermoplastic	Polypropylene	Polypropylene molded	Polypropylene injection moulding E
Polymers	Thermoplastic	Polypropylene	Polypropylene resin	Polypropylene resin E
Polymers	Thermoplastic	Polypropylene	Polypropylene resin	Polypropylene resin, at plant/RNA
Polymers	Thermoplastic	Polystyrene	EPS	Expandable polystyrene (EPS) E
Polymers	Thermoplastic	Polystyrene	EPS	Polystyrene expandable granulate (EPS), production mix, at plant RER
Polymers	Thermoplastic	Polystyrene	EPS	Polystyrene, expandable, at plant/RER U
Polymers	Thermoplastic	Polystyrene	GPPS	General purpose polystyrene, at plant/RNA
Polymers	Thermoplastic	Polystyrene	GPPS	Polystyrene (general purpose) granulate (GPPS), prod. mix, RER
Polymers	Thermoplastic	Polystyrene	GPPS	Polystyrene, general purpose, GPPS, at plant/RER U
Polymers	Thermoplastic	Polystyrene	HIPS	High impact polystyrene (HIPS) E
Polymers	Thermoplastic	Polystyrene	HIPS	High impact polystyrene granulate (HIPS), production mix, at plant RER
Polymers	Thermoplastic	Polystyrene	HIPS	High impact polystyrene resin, at plant/RNA

Level 1	**Level 2**	**Level 3**	**Level 4**	**Level 5**
Polymers	Thermoplastic	Polystyrene	HIPS	Polystyrene, high impact, HIPS, at plant/RER U
Polymers	Thermoplastic	Polystyrene	Polystyrene scrap	Polystyrene scrap, old, at plant/CH U
Polymers	Thermoplastic	Polystyrene	Polystyrene thermoforming	Polystyrene thermoforming E
Polymers	Thermoplastic	PVC	PVC resin	Polyvinyl chloride resin, at plant/RNA
Polymers	Thermoplastic	PVC	PVC resin	Polyvinylchloride resin (B-PVC), bulk polymerisation, production mix, at plant RER
Polymers	Thermoplastic	PVC	PVC resin	Polyvinylchloride resin (E-PVC), emulsion polymerisation, production mix, at plant RER
Polymers	Thermoplastic	PVC	PVC resin	Polyvinylchloride resin (S-PVC), suspension polymerisation, production mix, at plant RER
Polymers	Thermoplastic	PVC	PVC shaped	PVC calendered sheet E
Polymers	Thermoplastic	PVC	PVC shaped	PVC film E
Polymers	Thermoplastic	PVC	PVC shaped	PVC injection moulding E
Polymers	Thermoplastic	PVC	PVC shaped	PVC pipe E
Polymers	Thermoplastic	PVC	PVC4	Polyvinylchloride, at regional storage/RER U
Polymers	Thermoplastic	PVC	PVC4	Polyvinylchloride, bulk polymerised, at plant/RER U
Polymers	Thermoplastic	PVC	PVC4	Polyvinylchloride, emulsion polymerised, at plant/RER U
Polymers	Thermoplastic	PVC	PVC4	Polyvinylchloride, suspension polymerised, at plant/RER U
Polymers	Thermoplastic	PVC	PVC4	PVC (bulk polymerisation) E
Polymers	Thermoplastic	PVC	PVC4	PVC (emulsion polyerisation) E
Polymers	Thermoplastic	PVC	PVC4	PVC (suspension polymerisation) E
Polymers	Thermoplastic	PVC	PVDC	Polyvinylidenchloride, granulate, at plant/RER U
Polymers	Thermoplastic	PVC	PVDC	Polyvinylidene chloride (PVDC) E
Polymers	Thermoplastic	TFE	TFE Film	Tetrafluoroethylene film, on glass/RER U
Polymers	Thermoplastic	TFE	TFE4	Tetrafluoroethylene, at plant/RER U
Polymers	Thermoset	Epoxy	Epoxy resin	Epoxy resin insulator (Al2O3), at plant/RER U
Polymers	Thermoset	Epoxy	Epoxy resin	Epoxy resin insulator (SiO2), at plant/RER U
Polymers	Thermoset	Epoxy	Epoxy resin liquid	Epoxy resin, liquid, at plant/RER U
Polymers	Thermoset	Epoxy	Epoxy resin liquid	Epoxy resin, liquid, disaggregated data, at plant/RER U
Polymers	Thermoset	Epoxy	Epoxy resin liquid	Liquid epoxy resins E
Polymers	Thermoset	Formaldehyde resin	Malamine-urea-formaldehyde	Melamine formaldehyde resin, at plant/RER U

Level 1	Level 2	Level 3	Level 4	Level 5
Polymers	Thermoset	Formaldehyde resin	Malamine-urea-formaldehyde	Melamine-urea-formaldehyde hardener, at plant/US
Polymers	Thermoset	Formaldehyde resin	Malamine-urea-formaldehyde	Melamine-urea-formaldehyde resin, at plant/US
Polymers	Thermoset	Formaldehyde resin	Urea formaldehyde resin	Urea formaldehyde resin, at plant/RER U
Polymers	Thermoset	Polymer resin	Phenolic resin	Phenolic resin, at plant/RER U
Polymers	Thermoset	Polymer resin	Resin	Resin size, at plant/RER U
Polymers	Thermoset	Polyurethane	Polyurethane flexible foam	Polyurethane flexible foam E
Polymers	Thermoset	Polyurethane	Polyurethane flexible foam	Polyurethane, flexible foam, at plant/RER U
Polymers	Thermoset	Polyurethane	Polyurethane rigid foam	Polyurethane rigid foam E
Polymers	Thermoset	Polyurethane	Polyurethane rigid foam	Polyurethane, rigid foam, at plant/RER U
Precious Metals	Precious metals 2	Gold	Gold combined production	Gold, from combined gold-silver production, at refinery/CL U
Precious Metals	Precious metals 2	Gold	Gold combined production	Gold, from combined gold-silver production, at refinery/PE U
Precious Metals	Precious metals 2	Gold	Gold combined production	Gold, from combined gold-silver production, at refinery/PG U
Precious Metals	Precious metals 2	Gold	Gold combined production	Gold, from combined metal production, at beneficiation/SE U
Precious Metals	Precious metals 2	Gold	Gold combined production	Gold, from combined metal production, at refinery/SE U
Precious Metals	Precious metals 2	Gold	Gold primary	Gold, primary, at refinery/GLO U
Precious Metals	Precious metals 2	Gold	Gold refinery	Gold, at refinery/AU U
Precious Metals	Precious metals 2	Gold	Gold refinery	Gold, at refinery/CA U
Precious Metals	Precious metals 2	Gold	Gold refinery	Gold, at refinery/TZ U
Precious Metals	Precious metals 2	Gold	Gold refinery	Gold, at refinery/US U
Precious Metals	Precious metals 2	Gold	Gold refinery	Gold, at refinery/ZA U
Precious Metals	Precious metals 2	Gold	Gold regional storage	Gold, at regional storage/RER U
Precious Metals	Precious metals 2	Gold	Gold secondary	Gold, secondary, at precious metal refinery/SE U
Precious Metals	Precious metals 2	Palladium	Palladium primary	Palladium, primary, at refinery/RU U
Precious Metals	Precious metals 2	Palladium	Palladium primary	Palladium, primary, at refinery/ZA U
Precious Metals	Precious metals 2	Palladium	Palladium regional storage	Palladium, at regional storage/RER U
Precious Metals	Precious metals 2	Palladium	Palladium secondary	Palladium, secondary, at precious metal refinery/SE U
Precious Metals	Precious metals 2	Palladium	Palladium secondary	Palladium, secondary, at refinery/RER U
Precious Metals	Precious metals 2	Platinum	Platinum primary	Platinum, primary, at refinery/RU U

Level 1	Level 2	Level 3	Level 4	Level 5
Precious Metals	Precious metals 2	Platinum	Platinum primary	Platinum, primary, at refinery/ZA U
Precious Metals	Precious metals 2	Platinum	Platinum regional storage	Platinum, at regional storage/RER U
Precious Metals	Precious metals 2	Platinum	Platinum secondary	Platinum, secondary, at refinery/RER U
Precious Metals	Precious metals 2	Rhodium	Rhodium primary	Rhodium, primary, at refinery/RU U
Precious Metals	Precious metals 2	Rhodium	Rhodium primary	Rhodium, primary, at refinery/ZA U
Precious Metals	Precious metals 2	Rhodium	Rhodium regional storage	Rhodium, at regional storage/RER U
Precious Metals	Precious metals 2	Rhodium	Rhodium secondary	Rhodium, secondary, at refinery/RER U
Precious Metals	Precious metals 2	Silver	Silver combined production	Silver, from combined gold-silver production, at refinery/CL U
Precious Metals	Precious metals 2	Silver	Silver combined production	Silver, from combined gold-silver production, at refinery/GLO U
Precious Metals	Precious metals 2	Silver	Silver combined production	Silver, from combined gold-silver production, at refinery/PE U
Precious Metals	Precious metals 2	Silver	Silver combined production	Silver, from combined gold-silver production, at refinery/PG U
Precious Metals	Precious metals 2	Silver	Silver combined production	Silver, from combined metal production, at beneficiation/SE U
Precious Metals	Precious metals 2	Silver	Silver combined production	Silver, from combined metal production, at refinery/SE U
Precious Metals	Precious metals 2	Silver	Silver combined production	Silver, from copper production, at refinery/GLO U
Precious Metals	Precious metals 2	Silver	Silver combined production	Silver, from lead production, at refinery/GLO U
Precious Metals	Precious metals 2	Silver	Silver regional storage	Silver, at regional storage/RER U
Precious Metals	Precious metals 2	Silver	Silver secondary	Silver, secondary, at precious metal refinery/SE U
Wood Products	Beam	Beam glue laminated	Beam GL-plant	Glue laminated beam, at plant, US PNW/kg/US
Wood Products	Beam	Fiberboard soft	Fiberboard without adhesive	Fibreboard soft, without adhesives, at plant (u=7%)/CH U
Wood Products	EUR	EUR 3	EUR flat pallet	EUR-flat pallet/RER U
Wood Products	Fiberboard	Fiberboard hard	Fiberboard hard plant	Fibreboard hard, at plant/RER U
Wood Products	Fiberboard	Fiberboard medium density	Fiberboard medium density-plant	Medium density fibreboard, at plant/RER U
Wood Products	Fiberboard	Fiberboard soft	Fiberboard soft latex bonded	Fibreboard soft, latex bonded, at plant (u=7%)/CH U
Wood Products	Fiberboard	Fiberboard soft	Fiberboard soft plant	Fibreboard soft, at plant (u=7%)/CH U
Wood Products	Laminatedboard	Laminatedboard three layer	Laminatedboard three layer at plant	Three layered laminated board, at plant/RER U
Wood Products	l-joist	Composite-l-joist	Composite-l-joist-plant	Composite wood I-joist, at plant, US PNW/kg/US
Wood Products	l-joist	Composite-l-joist	Composite-l-joist-plant	Composite wood I-joist, at plant, US SE/kg/US

Level 1	Level 2	Level 3	Level 4	Level 5
Wood Products	Log	Conditioned Log	Conditioned Log-plywood	Conditioned log, at plywood plant, US PNW/US
Wood Products	Log	Conditioned Log	Conditioned Log-plywood	Conditioned log, at plywood plant, US SE/US
Wood Products	Lumber	Lumber Dry Rough	Lumber-DR-kiln	Dry rough lumber, at kiln, US PNW/US
Wood Products	Lumber	Lumber Dry Rough	Lumber-DR-kiln	Dry rough lumber, at kiln, US SE/US
Wood Products	Lumber	Lumber rough green	Lumber RG-sawmill	Rough green lumber, at sawmill, US SE/kg/US
Wood Products	Lumber	Lumber rough green	Lumber RG-softwood	Rough green lumber, softwood, at sawmill, US PNW/kg/US
Wood Products	Lumber	Lumber surface dried	LSD-planer mill	Surfaced dried lumber, at planer mill, US PNW/kg/US
Wood Products	Lumber	Lumber surface dried	LSD-planer mill	Surfaced dried lumber, at planer mill, US SE/kg/US
Wood Products	Lumber	Lumber surface green	LSG-planer mill	Surfaced green lumber, at planer mill, US PNW/kg/US
Wood Products	Lumber	Lumber veneer laminated	lumber veneer-plant	Laminated veneer lumber, at plant, US PNW/kg/US
Wood Products	Lumber	Lumber veneer laminated	lumber veneer-plant	Laminated veneer lumber, at plant, US SE/kg/US
Wood Products	Particleboard	Particleboard 3	Particleboard cement bonded	Particle board, cement bonded, at plant/RER S
Wood Products	Particleboard	Particleboard 3	Particleboard indoor use	Particle board, indoor use, at plant/RER U
Wood Products	Particleboard	Particleboard 3	Particleboard outdoor use	Particle board, outdoor use, at plant/RER U
Wood Products	Particleboard	Particleboard 3	Particleboard P2	Particle board, P2 (Standard FPY), production mix, at plant, 7,8% water content EU-27 S
Wood Products	Particleboard	Particleboard 3	Particleboard P5	Particle board, P5 (V100), production mix, at plant, 7,8% water content EU-27 S
Wood Products	Plywood	Plywood 3	Plywood-indoor	Plywood, indoor use, at plant/RER U
Wood Products	Plywood	Plywood 3	Plywood-outdoor	Plywood, outdoor use, at plant/RER U
Wood Products	Plywood	Plywood 3	Plywood-plant	Plywood, at plywood plant, US PNW/kg/US
Wood Products	Plywood	Plywood 3	Plywood-plant	Plywood, at plywood plant, US SE/kg/US
Wood Products	Plywood	Plywood pressed raw	Plywood PR-layup	Pressed raw plywood, from lay-up, at plywood plant, US PNW/US
Wood Products	Plywood	Plywood pressed raw	Plywood PR-layup	Pressed raw plywood, from lay-up, at plywood plant, US SE/US
Wood Products	Strandboard	Strandboard oriented	Strandboard oriented 4	Oriented strand board product, US SE/kg/US
Wood Products	Strandboard	Strandboard oriented	Strandboard oriented 4	Oriented strand board, at plant/RER U
Wood Products	Strandboard	Strandboard oriented	Strandboard oriented OSB mix	Oriented strand board, OSB III, production mix, at plant, 4,8% water content EU-27 S
Wood Products	Timber	Beam glue laminated	Beam GL-plant	Glue laminated beam, at plant, US SE/kg/US
Wood Products	Timber	Timber glue laminated	Timber GL-indoor use	Glued laminated timber, indoor use, at plant/RER U
Wood Products	Timber	Timber laminated	Timber laminated transversally prestressed	Laminated timber element, transversally prestressed, for outdoor use, at plant/RER U

Level 1	Level 2	Level 3	Level 4	Level 5
Wood Products	Timber	Timber sawn	TSH-parana pine	Sawn timber, paraná pine (SFM), kiln dried, u=15%, at sawmill/BR U
Wood Products	Timber	Timber sawn	TSH-parana pine	Sawn timber, paraná pine (SFM), u=15%, BR, at maritime harbour/RER U
Wood Products	Timber	Timber sawn azobe	TSA-air dried	Sawn timber (SFM), azobe, planed, air dried, u=15%, CM, at sawmill/RER U
Wood Products	Timber	Timber sawn hardwood	TSH-planed kiln dried	Sawn timber, hardwood, planed, air / kiln dried, u=10%, at plant/RER U
Wood Products	Timber	Timber sawn hardwood	TSH-planed kiln dried	Sawn timber, hardwood, planed, kiln dried, u=10%, at plant/RER U
Wood Products	Timber	Timber sawn hardwood	TSH-raw air dried	Sawn timber, hardwood, raw, air dried, u=20%, at plant/RER U
Wood Products	Timber	Timber sawn hardwood	TSH-raw kiln dried	Sawn timber, hardwood, raw, air / kiln dried, u=10%, at plant/RER U
Wood Products	Timber	Timber sawn hardwood	TSH-raw kiln dried	Sawn timber, hardwood, raw, kiln dried, u=10%, at plant/RER U
Wood Products	Timber	Timber sawn hardwood	TSH-raw plant debarked	Sawn timber, hardwood, raw, plant-debarked, u=70%, at plant/RER U
Wood Products	Timber	Timber sawn softwood	TSH-planed	Sawn timber, softwood, planed, air dried, at plant/RER U
Wood Products	Timber	Timber sawn softwood	TSH-planed	Sawn timber, softwood, planed, kiln dried, at plant/RER U
Wood Products	Timber	Timber sawn softwood	TSH-raw	Sawn timber, softwood, raw, air dried, u=20%, at plant/RER U
Wood Products	Timber	Timber sawn softwood	TSH-raw	Sawn timber, softwood, raw, forest-debarked, u=70%, at plant/RER U
Wood Products	Timber	Timber sawn softwood	TSH-raw	Sawn timber, softwood, raw, kiln dried, u=10%, at plant/RER U
Wood Products	Timber	Timber sawn softwood	TSH-raw	Sawn timber, softwood, raw, kiln dried, u=20%, at plant/RER U
Wood Products	Timber	Timber sawn softwood	TSH-raw	Sawn timber, softwood, raw, plant-debarked, u=70%, at plant/RER U
Wood Products	Timber	Timber sawn softwood	TSH-Scandinavian	Sawn timber, Scandinavian softwood, raw, plant-debarked, u=70%, at plant/NORDEL U
Wood Products	Timber	Timber sprucewood	Timber spruce-production mix	Spruce wood, timber, production mix, at saw mill, 40% water content DE S
Wood Products	Timber	Timber-pine	Timber-pine production mix	Pine wood, timber, production mix, at saw mill, 40% water content DE S
Wood Products	Veneer	Timber glue laminated	Timber GL-outdoor use	Glued laminated timber, outdoor use, at plant/RER U
Wood Products	Veneer	Veneer Dry	Veneer Dry-plywood	Dry veneer, at plywood plant, US PNW/kg/US
Wood Products	Veneer	Veneer Dry	Veneer Dry-plywood	Dry veneer, at plywood plant, US SE/US
Wood Products	Veneer	Veneer Dry	Veneer Dry-sold plywood	Dry veneer, sold, at plywood plant, US PNW/kg/US
Wood Products	Veneer	Veneer green	Veneer green-plywood	Green veneer, at plywood plant, US PNW/kg/US
Wood Products	Veneer	Veneer green	Veneer green-plywood	Green veneer, at plywood plant, US SE/kg/US
Wood Products	Veneer	Veneer green	Veneer green-sold plywood	Green veneer, sold, at plywood plant, US PNW/kg/US
Wood Products	Veneer	Veneer green	Veneer green-sold plywood	Green veneer, sold, at plywood plant, US SE/kg/US

Level 1	Level 2	Level 3	Level 4	Level 5
Wood Products	Wood pellet	Wood pellet 3	Wood pellet storehouse	Wood pellets, u=10%, at storehouse/RER U
Wood Products	Wood wool	Wood wool 3	Wood wool cement bonded	Wood wool boards, cement bonded, at plant/RER S
Wood Products	Wood wool	Wood wool 3	Wood wool plant	Wood wool, u=20%, at plant/RER U