ENABLING STREAMLINED LIFE CYCLE ASSESSMENT: MATERIALS-CLASSIFICATION DERIVED STRUCTURED UNDERSPECIFICATION

by

Abhishek Rampuria

SUBMITTED TO THE
DEPARTMENT OF MATERIALS SCIENCE AND ENGINEERING
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

BACHELOR OF SCIENCE IN MATERIALS SCIENCE AND ENGINEERING
AT THE

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
June 2012

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ABSTRACT

As environmental footprint considerations for companies gain greater importance, the need for quantitative impact assessment tools such as life cycle assessment (LCA) has become a higher priority. Currently, the cost and time burden associated with LCA has prevented it from becoming more prevalent. While several streamlining approaches have been suggested, questions regarding the effectiveness and efficiency of the streamlined results are still of concern. The streamlining method of probabilistic underspecification has shown initial success in its ability to reduce LCA efforts while simultaneously increasing certainty in the final impact assessment. Probabilistic underspecification streamlines LCA by prioritizing targets of more refined data collection and by implementing the use of underspecified surrogate data within LCI analysis. This thesis concentrates on further developing and improving the streamlining methodology of probabilistic underspecification through refinement of the materials classification systems for polymers and minerals and through additional case study analysis. The classification system allows for a better understanding of the relationship between the degree of materials specificity and the uncertainty in the resulting impact values. Additionally, the resulting polymer and mineral classifications were combined with existing materials classifications to conduct an alkaline battery case study in order to test the effectiveness of the streamlining method. The material classifications created through this research provide a logical and practical approach to underspecification while maintaining consistent and reasonable levels of uncertainty. Furthermore, the case study analysis showed that the streamlining methodology significantly lowered LCA burden by systematically reducing the number of product components requiring full specification. This research provides further evidence that probabilistic underspecification may provide a promising LCA streamlining method among a set of such strategies that can significantly reduce LCA efforts while maintaining the accuracy of the overall impact assessment.

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ACKNOWLEDGEMENTS

I would like to first thank Dr. Randolph Kirchain and Prof. Joel Clark, my thesis supervisors, for the opportunity to perform my undergraduate thesis research under them, and for providing me with the ability to pursue a thesis topic that both engaged me and closely aligned with my interests. Admittedly, this thesis would not have become a reality without the help of Elsa Olivetti. She has continually supported me throughout this project with her knowledge, patience and guidance, and I am extremely appreciative of all she has done. Finally, I would like to sincerely thank my parents, my brother, my friends and everyone else who have influenced and supported me over the years.

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1 INTRODUCTION

Over the past few decades, with the rise of oil prices and the pressure for alternative energy sources, there has been a transition in the manner in which the world views energy consumption and its effects on the environment. As a result, environmental assessment of products and services considerations has become increasingly important for companies across all industries and practices. Furthermore, as consumers become more aware and conscientious of the importance of environmentally friendly materials and manufacturing processes for products they purchase, companies are facing an increased market pressure to make environmental footprint information about their products accessible to the public (Borland & Wallace, 1999; Finster & Eagen et al, 2001; Gaustad & Olivetti et al, 2010). As a result, firms are increasing efforts around quantitative environmental evaluations of products in order to reduce environmental impact, cut supply chain costs, and improve their overall image and brand. One such evaluation method, life cycle assessment (LCA), is a technique to calculate and quantify the environmental impact associated with a product's (or service's) entire lifespan ranging from materials extraction and processing all the way through to disposal and recycling. According to the ISO standards for life-cycle assessments, LCAs are performed in four phases which include: Goal and Scope Definition, Inventory Analysis, Impact Assessment, and Interpretation. By completing these steps for each product, companies are able to make more informed decisions regarding the design and manufacturing of their products.

One large hurdle that has prevented LCAs from becoming more widespread is the large expense and time that is required to collect the necessary data and perform the analysis. The reason for this is because complex products such as automobiles and computers not only involve thousands of individual components, but oftentimes the parts are bought from 3rd party manufacturers where the exact materials or specifications may not be readily available (Todd & Curran, 1999). Due to the fact that LCA takes into consideration every input and output of a product's entire life cycle, even LCAs of less complex products can require extensive resources that may not always be readily available. In conjunction with this problem, another common hurdle that companies face is that even after spending a large amount of time and money on these analyses, the results are not always completely reliable and in some cases can be too precise and irreproducible. As a result of these difficulties associated with gathering the necessary information to complete a LCA, researchers have examined ways to streamline the LCA process in order to reduce the effort and cost needed to collect the life cycle inventory (LCI) data, while maintaining credibility and precision of the LCA results. This thesis builds upon the work of previous research within the Materials Systems Lab at MIT to investigate the viability of streamlined LCA.

1.1 LCA Streamlining

In most cases, streamlining in LCA is considered to be successful if the results are of approximate equivalence to the results from a full, non-streamlined LCA, and if the streamlining lowered the time and cost of collecting the necessary data for the assessment. Most current LCA streamlining work that is done aims to reduce the effort needed to characterize the data associated with the life cycle inventory for life cycle assessment, but even characterizing the bill of materials (BOM) for a complex product can be a challenge.

Since full life cycle assessments require precise and quantitative environmental impact values, streamlining work in LCA has focused on taking a qualitative or semi-quantitative approach (Graedel, Streamlined Life-Cycle Assessment, 1998). Qualitative LCA techniques such as matrix-type LCAs are effective streamlining methods because they can provide a rough and rapid evaluation of a product's impact since they require much less comprehensiveness in the amount and precision of the data that is collected for the assessment (Graedel, Allenby, & et al., 1995). Qualitative methods of LCA often streamline the data collection process by using qualitative scoring questionnaires (such as yes or no questions) to estimate LCI data that allows for approximations of the overall impact. Alternatively, semi-quantitative streamlining methods have also been developed which combine aspects from both qualitative and quantitative techniques in order meet the increasing demand for quantitative environmental impact values. Semi-quantitative methods will often take into consideration previously conducted LCAs in order to narrow the BOA to those activities that are most likely to have the largest effect on the product's overall impact.

The problem, however, with qualitative and semi-quantitative streamlining methods is that they are not always sufficient in situations that require quantitative results (Hunt, Boguski, & et al, 1998). As a consequence, the most common approach that has been taken to streamline quantitative LCA has been to substitute primary data (which is often prohibitively expensive and time-consuming to collect) with surrogate or proxy data (Todd & Curran, 1999; Weckenmann & Schwan, 2001; Hochschorner & Finnveden, 2003). This surrogate data is most often obtained from comprehensive life cycle inventories such as the ecoinvent 2.2 database or the United States Life Cycle Inventory (USLCI) database. While the use of surrogate data is a valid technique for streamlining quantitative LCA, like all other streamlining methods, it adds uncertainty and inaccuracies to the results which can negatively affect the validity of the study (Heijungs & Huijbregts, 2004).

In 1999, The Society of Environmental Toxicology and Chemistry (SETAC) released a report summarizing the various different streamlining LCA methods that were in use at the time, along with an analysis of the benefits and drawbacks of each method (Todd & Curran, 1999). Table 1 below from the report shows that, broadly speaking, the two main streamlining methods used for LCA were a) to more closely define the goal and scope of the assessment and b) to use surrogate data to reduce the burden of LCI data collection.

Streamlining Approach	**Application Procedure**
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.
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 represent 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.

Table 1: LCA streamlining methods reproduced from SETAC’s 1999 North America Streamlined LCA Workgroup (Todd & Curran, 1999)

The LCA streamlining methods described in Table 1, that, for the most part, fall into the categories of either limiting the scope of the LCA or using surrogate inventory data, still come with their own set of obstacles. When comparing results of studies that make use of these methods to a full LCA, limiting the scope becomes problematic especially when considering the fact that a full and complete LCA accounts for every single possible life cycle impact activity – a feature that is not possible for a scope-limited assessment (Weitz & Sharma, 1998). The best way to avoid this problem with scope-limiting streamlining is to screen and prioritize the bill of activities (BOA, which includes thing like the bill of materials as well as energy, transportation, use parameters, etc.) based on an activity's contribution to total in order to determine which activities require detailed analysis and which activities are of little importance. This screening process can be difficult to accomplish because it is based on the assumption that the total environmental impact of the product is already known, making the need for screening the BOA redundant and unnecessary. For the case of surrogate data streamlining, as mentioned earlier, the major problem with the method is the high level of uncertainty that exists in the results of the LCA (Heijungs & Huijbregts, 2004).

Last year, in order to address these concerns with scope-limiting and surrogate data LCA streamlining methods, Siamrut Patanavanich at MIT investigated the method of triage-based streamlining in order to determine its feasibility as a reliable LCA streamlining technique (Patanavanich, 2011).

1.2 Patanavanich Research

In order to determine the feasibility of triage-based LCA streamlining, Patanavanich studied a streamlining approach that coupled *probabilistic triage* as a way of identifying the high impact set of life cycle activities with low-fidelity characterization of the BOA through *underspecification* of the surrogate data during LCI analysis. To accomplish the task of probabilistic triage, Patanavanich proposed a method of qualitatively and/or quantitatively identifying a set of interest (SOI) that includes those life cycle activities that are targets of detailed data collection. SOI activities are selected using a statistical ranking system that determines the ranking based on the probability that a certain life cycle activity contributes at least a pre-defined minimum to the total environmental impact of the product. Since the SOI includes only those activities which most contribute to the total impact, only the activities within the SOI must be fully specified, as opposed to every activity within the BOA, resulting in an overall reduction in the burden associated with the assessment.

Additionally, in order to achieve the low-fidelity characterization of the BOA, Patanavanich proposed the use of structured underspecification of surrogate data, as opposed to the use of proxy data. Essentially, instead of using the closest proxy for a given activity or material, Patanavanich suggests using the set of inventory data that could be classified along with the given activity or material, but at a lower level of specification. The analysis takes into consideration a varying range of degrees of underspecification, where higher degrees of underspecification correspond to higher uncertainty in the results given the larger range of potential impact values, and lower degrees of underspecification correspond to lower uncertainty in the results given the smaller range of potential impact values. For example, consider the situation where a certain product component is made out of aluminum, but the exact procurement and production process of the aluminum is unknown. Instead of expending considerable effort and money to collect further information about the component in question, the component could instead be underspecified as a generic aluminum alloy (slightly underspecified), a non-ferrous metal (moderately underspecified), or even just as a metal (most underspecified). While each varying level of underspecification obviously affects the overall uncertainty of the impact of the component, this method makes it possible to understand the range and distribution of the environmental impact values of the product. The reasoning behind this methodology is that using structured underspecification as a surrogate, rather than proxy data as a surrogate, may help to reduce the innate bias associated with human judgment and overconfidence (Weidema & Wesnaes, 1996).

With this hypothesis, Patanavanich used a case-based analysis to determine whether the method of probabilistic triage, coupled with structured underspecification can result in a more effective and efficient streamlined LCA. With the understanding that mass can be a key indicator of environmental impact, products of varying mass composition or varying degrees of mass uniformity (measured using an adaption of the Herfindahl index) were chosen for the case studies. The results of his research showed that the approach was able to drastically reduce the number of components (and the associated burden) that required full specification, while still maintaining a relatively high level of confidence in the results of the analysis.

As a result of Patanavanich's research, it has become clear that using underspecified data as surrogate data in LCA is a promising method for both reducing the burden associated with LCA while simultaneously increasing the certainty and significance of the total environmental impact values of the assessment as a whole. By reducing the burden associated with LCA, the rate at which life cycle assessment can be conducted will be improved, hopefully resulting in its more widespread adoption and use. This work will build upon Patanavanich's research through additional case study analysis.

1.3 Materials Classification Motivation

The results of Patanavanich's research are an indication that underspecification of data in LCA and then subsequently using this underspecification to triage a more refined data collection is a streamlining method worth investigating and refining even further. When considering the bill of activities for a given product, underspecification can be used for a wide variety of activities including materials, transportation, processing, use and disposal. Probabilistic underspecification relies on an effective classification scheme for each activity type that results in the lowest possible uncertainty for each level of specification, while still lowering the burden of data collection. This thesis aims to improve this LCA streamlining approach by creating more effective classifications that both decrease the uncertainty of the results while maintaining the ability to streamline and the reliability of the resulting impact values. However, given the time constraints of this thesis, it was not possible to create an underspecification classification scheme for *every* activity type. In order to limit the scope of the thesis, it was necessary to methodologically prioritize the activity types for further study.

In order to determine the best activity type to systematically classify for this thesis, past LCA case studies were cataloged and analyzed. This analysis was performed to understand which activity(ies) is(are) most commonly the primary driver of environmental impact for a wide range of products to direct the structured underspecification classification work. The methodology that was used to select the life cycle activity that would be the best candidate for underspecification classification was to review and catalog a wide variety of previous LCA case studies. To find relevant LCA case studies, a range of scientific journals were reviewed, including the International Journal of Life Cycle Assessment, the journal of Environmental Science and Technology (ES&T) and the Journal of Cleaner Production. Case studies dating back to 2007 were included in the literature screen, as well as a wide variety of product types. Some of the case study sectors include industries such as construction, energy, electronics, toys and medical equipment. Overall, the sample set of LCA case studies consisted of a range of different published life cycle assessments from varying years, industries and journals. Table 2 below provides a glimpse of some of the LCA case studies that were used to determine the life cycle activity that most commonly acts as the driver of environmental impact.

Name of Case Study	**Author/s**	**Date**	**Product**	**Sector**	**Driving Impact Factor**
Life cycle assessment of granite application in sidewalks	Mendoza, Oliver-Sola, Gabarrell, Josa	Feb-12	Granite Application for sidewalks	Construction	Construction Materials
Life cycle assessment of electricity transmission and distribution - part 1: power lines and cables	Jorge, Hawkins, Hertwich	Jan-12	Power lines and cables	Energy	Production of metal for masts and conductors, production of foundations, power losses
Life cycle assessment of ceramic tiles. Environmental and statistical analysis	Ibanez-Fores, Bovea, Simo	Nov-11	Ceramic Tiles	Construction	Manufacturing of the tile, followed by atomising of the clay and distribution of the product
Recycling in buildings: an LCA case study of a thermal insulation panel made of polyester fiber,	Intini, Kuhtz	Mar-11	Recycled PET Fiber Thermal Insulation	Construction	Fiber-spinning phase of production

recycled from post-consumer PET bottles					
Books from an environmental perspective - Part 1: environmental impacts of paper books sold in traditional and internet bookshops	Borggren, Moberg, Finnveden	Feb-11	Paper Books	Books	Pulp and paper production, transportation (depending on distance from bookstore)
LCA study of a plasma television device	Hischier, Baudin	Apr-10	Plasma TVs	Electronics	Use, Production of wiring boards
LCA and ecodesign in the toy industry: case study of a teddy bear incorporating electric and electronic components	Munoz, Gazulla, Bala, Puig, Fullana	Jul-08	Teddy bear	Toys	Use

Table 2: A sample set of LCA case studies that were cataloged and analyzed to determine the life cycle activity that most commonly acts as the primary driver of environmental impact.

Further analysis of the LCA case studies revealed that the materials used to create the given product were most commonly the largest contributor to the product's overall environmental impact, particularly when the product did not consume energy in the use phase. While other activities such as manufacturing and use are also important drivers of environmental impact, materials were the dominating factor in the majority of LCA case studies that were included in the sample set. As summarized in Figure 1 below, of the LCA case studies cataloged in the sample set, life cycle activities associated with the materials used in the production of the given product were the primary driver of environmental impact in 54% of the case studies. This percentage jumps to 70% when case studies that consume energy in the use phase are excluded from the grouping.

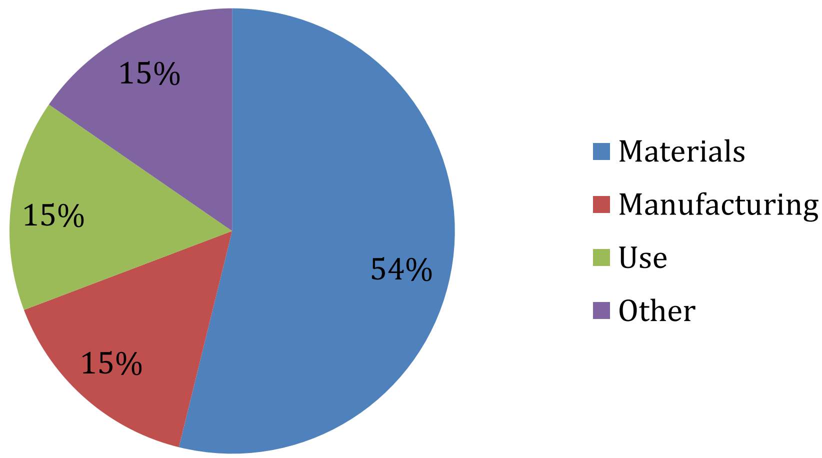

Figure 1: Prior LCA case studies were cataloged and analyzed in order to determine the life cycle activity that was most commonly the driver of the product's overall environmental impact. Results indicate that materials are the driving factor the majority of the time

Based on the results of this past LCA cataloging activity, the study prioritized the classification of materials over other types of life cycle activities. Specifically, this thesis focuses on creating an underspecification classification scheme for two classes of materials: polymers and minerals. Polymers and minerals were chosen over other materials types such as metals or chemicals because a) they are both commonly used in many complex products for which LCA is becoming increasingly important and b) both polymers and minerals were quite weakly classified in Patanavanich's original research.

The overall goal of this thesis is to create effective structured underspecification classification schemes for the polymer and mineral material types. The classifications will be achieved through the application of broader materials science ideology, coupled with statistical testing via virtual simulations to determine the degree of uncertainty in the results. The final classifications are then tested using a case-based approach on an actual product in order to quantify the effectiveness and efficiency of the classifications as well as the underspecification method as a whole.

Ultimately, by improving the underspecification classifications for polymers and minerals, probabilistic underspecification will be further evaluated and improved as a method for conducting streamlined LCA.

2 METHODOLOGY

In today's world of LCA, complete LCA is challenging due to the fact that the collection of primary data for every single life cycle activity is both very time consuming and very expensive, especially when the primary data is not readily available. Instead, LCA practitioners have almost ubiquitously chosen to perform LCA with the use of secondary or proxy data as opposed to primary data in order to reduce the burden associated with the assessment. A limitation, however, with the use of surrogate data in LCA is the varying types of uncertainty that come along with it. Instead, underspecification and probabilistic triage aims to define appropriate proxy data based on the impact distributions of data classification sets. Ultimately, through underspecification, it is possible to avoid the statistical bias associated with surrogate data, and instead capture and account for the uncertainty that comes with using proxy data as an LCA streamlining method.

Structured underspecification enables the categorization of materials life cycle data, allowing for a greater understanding of the varying degrees of uncertainty associated with the level of specificity. In order to test this methodology, the specific proxy data was first assembled in order to create a comprehensive database where the structured underspecification of the materials could be implemented. To build the comprehensive materials database, each individual materials description and corresponding cumulative energy demand (CED) were obtained from the following life cycle databases: the United States Life Cycle Inventory (USLCI), Industry Data 2.0, European Life Cycle Reference Data (ELCD) (Wolf & Pennington, 2008) and ecoinvent 2.2 (Frischknect, 2007). Once the necessary information was gathered from the various databases, the information was organized into five (or four) different levels of specificity, labeled Level 1 (L1) through Level 4 (L4) or Level 5 (L5). With this breakdown, L1 represents the most underspecified level (such as the type of material), and L4 or L5 consist of the most specified data which are the individual materials entries that were collected from the various different LCA databases. Given that the L5 (or L4 in some cases) entries are taken directly from the LCA databases, they can best estimate the surrogate data that act as a proxy for the primary data of a certain product component. In addition, comparison of the streamlined results with the L5 (or L4) entries is the best way to determine the overall success or failure of the methodology.

2.1 Systematic Materials Classification

The systematic classification of the materials, specifically polymers and minerals in the case of this thesis, was achieved by first applying the general categorization scheme outlined in Patanavanich's research and then refined by using resources such as the built-in categorization structure provided in SimaPro (a commercially available life cycle assessment software tool), materials classification literature by Michael Ashby, and other existing materials classification schemes such as the Nickel-Strunz classification for minerals. Additionally, knowledge of materials properties and processing as informed by the sources above is also important to consider when creating the classification scheme. The general categorization outline that Patanavanich presents is composed of five levels of specificity (L1 to L5) that are broken down into material category (L1), material property (L2), material type (L3), material processing (L4) and the specific database entry (L5). This systematic classification structure is schematically shown in Figure 2 below.

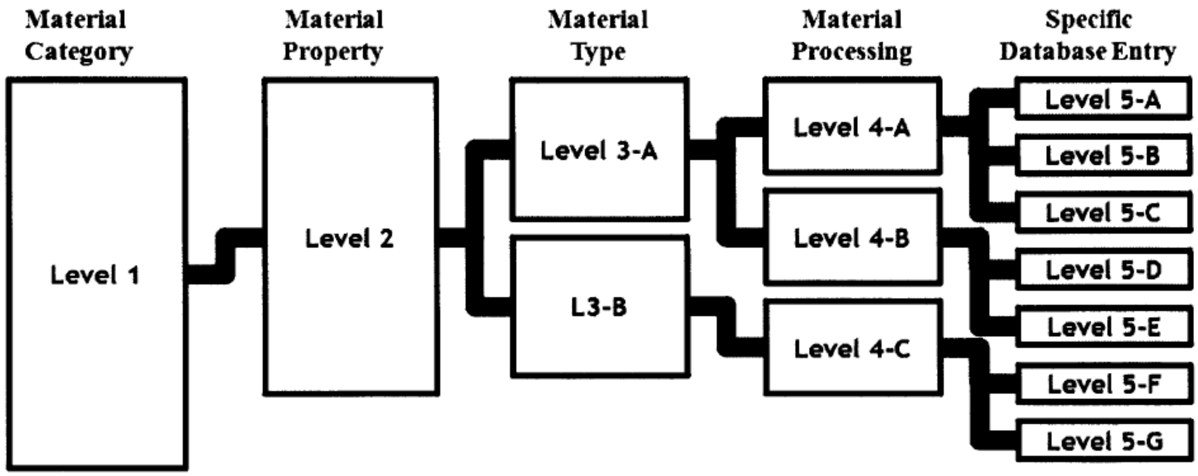

Figure 2: Schematic example of the database information hierarchy for structuring underspecification. Reproduced from (Patanavanich, 2011)

In the categorization structure shown above, the level of specificity increases with each additional level. While the categorization uses five different levels, it is also possible to use more or a fewer number of classification levels. In the case of polymers, five levels were used, and in the case of minerals only four levels were used in the classification scheme. In the case of polymers, the categorization structure outlined in Figure 2 was used. The material category (L1) for all materials is simply composed of the broadest categorization type for the material, such as "Polymer" or "Metal." At Level 2, the material property is used as a mechanism to further specify the material type, which in the case of metals could include classifications such as "Ferrous Metals" and "Non-Ferrous Metals." In a similar manner, the Level 3 and Level 4 classifications increase specificity by further differentiating by material type and processing method.

In the case of minerals, a slightly different categorization methodology was used due to the fact that there are existing mineral classification schemes such as the Nickel-Strunz

Classification of minerals. As a result, instead of following the categorization criteria in Figure 2, the minerals classification levels more closely follow the classification breakdown outlined in the Nickel-Strunz minerals classification documentation (Ralph & Chau). A complete list of the final classification divisions for both polymers and minerals is located in the Appendix.

Despite the slight variances in classification methodology, both the classifications for polymers and minerals follow the tree structure categorization shown in Figure 2. The advantage of the tree structure categorization is that it makes it easier to account for the uncertainty that is involved with underspecification since the possible proxy database entries included in the impact analysis is dependent on the level of specificity. For example, in the hypothetical schematic shown in Figure 2, if a product component is classified using the Level 1 or Level 2 specificity, then it has the potential to be any of the Level 5 database materials. However, if the component is instead classified using Level 4-B specificity, then the only possible materials that could act as proxy data entries would be materials 5-D and 5-E. As a result of this tree structure categorization, the level of uncertainty of the proxy data is a known value, and it can be statistically integrated into the model of the product's environmental impact.

2.2 Refinement of Materials Classifications

In order to test the effectiveness and accuracy of each iteration of the systematic materials classifications, Monte Carlo simulations were performed to determine the precision of the classification scheme. After creating the desired material classification scheme in Excel, a random number generator (Excel's RANDBETWEEN function) was used to randomly select an L5 (or L4) proxy material from the list of database entries that belongs within the particular classification designation – this can work due to the tree structure of the categorization scheme described earlier. It is important to note here, however, that even though the L5 material entries are pulled directly from the database, they still contain some level of uncertainty. This uncertainty is due to a range of different reasons, including discrepancies in measurement, geography, or reliability. In order to simplify this problem with L5 uncertainty for the purposes of this study, midrange uncertainty assumptions were used.

At this point, Oracle's Crystal Ball software is used to run a Monte Carlo simulation on the randomly selected L5 database material in order to generate an impact value for that material at every level of specificity. The simulation is run 10,000 times in order to account for the fact that at higher levels of underspecification, impact values are the result of a larger distribution of the L5 (or L4) materials. The inputs of the Crystal Ball simulation include the arithmetic mean, the arithmetic standard deviation and the location. The arithmetic mean and standard deviations are transformed from the geometric standard deviation. The simulation is run simultaneously for every L5 (or L4) database entry for the given material type (in this case, polymers or minerals). Once the simulation is complete, the 10,000 individual trial values are extracted for each unique entry at every level of specification. For example, at level 1 there is only one unique entry, so only the trial values from one of the L5 (or L4) entries need to be extracted. However, at level 2 there are five unique material classification entries, meaning that the corresponding trial values for at least five L5 (or L4) materials need to be extracted.

After extracting the individual trial values at the different levels of underspecification, they are used to determine how the distribution of impact values changes with the levels of specificity. The expectation is that higher degrees of underspecification will correlate with a larger variety of possible database entries and as a result, a larger range of possible impact values. For this reason, the distribution of impact values should decrease as the material is less underspecified. Instead of representing the impact value distribution with the mean or standard deviation, the trial values were instead used to calculate the median absolute deviation (MAD) of impact values for each level of underspecification. The median absolute deviation is similar to the standard deviation since it can be used to illustrate the distribution of the data, but differs in that it lessens the impact of outliers in the data set. The MAD is then used to derive the median absolute deviation-coefficient of variation (MAD-COV), which indicates the median percent variation of the data from its median. The MAD and MAD-COV are defined by the following equations (Patanavanich, 2011):

$$\boldsymbol{MAD = median_i(\left|X_{i\text{-}} - \ median_j(X_j)\right|)} \qquad \textbf{Equation 1}$$

$$\boldsymbol{MAD - COV = \frac{MAD}{median_j(X_j)}} \qquad \textbf{Equation 2}$$

Lastly, the MAD-COV values of each categorization at each level of underspecification are plotted in order to observe the impact value distribution trend as the level of underspecification changes. If for some reason the distribution (represented by the MAD-COV) increases at a lower level of underspecification, then changes to the classification scheme are considered in order to improve the its quality and associated uncertainty. This increase is an indication of a potential misclassification or an error in the order at which things should be specified. For example, if the classification scheme for a material such as metals causes the MAD-COV to increase at a lower level of underspecification, then it is possible that the order in which things are classified might be incorrect. A possible remedy to this problem could be to classify by recycling type earlier at level 2 as opposed to L3 or L4.

2.3 Case Study Analysis

With the creation of the polymer and mineral classifications complete, the next step towards achieving a more effective and efficient streamlined LCA by coupling structured underspecification with the method of probabilistic triage is to apply the method to an actual product case study to test whether the LCA burden can be reduced while maintaining reliable LCA results. In order to test this methodology and the classification schemes created for polymers and minerals, an alkaline battery was chosen for the product case study. The alkaline battery was chosen as the product for the case study because out of the available products where the bill of components is known, the alkaline battery has a larger number of components, many of which are made out of materials such as metals, polymers and minerals. Given that the battery is made primarily of materials where the underspecification classification schemes have been well defined, it stood out as a good candidate to test the success of the streamlining methodology.

In order to test the streamlining methodology on the alkaline battery, a similar approach to the refining of the materials classifications is taken. The first step is to use the

BOC of the battery (inclusive of both product component materials and corresponding masses) in order to estimate the impact value of each component of the battery. Once again, Monte Carlo simulations using Oracle's Crystal Ball software are performed in order to derive the environmental impact value of each component of the battery. Using the same methodology as the materials classification refinement, the random number generator is used to choose a proxy database entry at level 5 and the simulation is repeated 10,000 times in order to generate 10,000 different impact profiles for the product. The impact profiles at each level of specificity are then plotted to observe that the uncertainty in the LCA results decreases as the level of specificity increases. The final step in understanding the effectiveness of the structured underspecification is to combine it with the probabilistic triage method as a way of fully streamlining LCA.

2.3.1 Selection of the Set of Interest

In order to reduce the burden associated with LCA, the method of probabilistic triage suggests that by limiting the number of product components that need to be comprehensively defined in LCA, the time and expense involved with the assessment can be significantly reduced. In order to accomplish this task, a set of interest (SOI) must be defined, which consists of the subset of product components that most contribute to the product's overall impact. Given that the Monte Carlo simulations produce a distribution of possible impact values for the product, the SOI that results from each iteration of the simulation may contain a different set of components. In order to resolve this issue of uncertainty due to underspecification, the SOI is composed of the set of components that probabilistically fulfill a pre-defined fraction of the product's total impact value. More simply, the SOI consists of the smallest number of product components for which the cumulative impact value of the SOI components represents a minimum threshold fraction of the total impact of the product (Patanavanich, 2011).

To systematically determine which components to include in the SOI, the product components are ranked in descending order by the median of their level 1 impact values. In order to determine the cutoff for the SOI, the ranked impact medians are then cumulatively summed so that the minimum threshold can be found. For the purposes of this case study, the minimum impact cutoff was defined as 75% of the total impact of the product at a confidence level of 90%. For example, if the total impact of a given product is 10kJ, then the SOI will consist of the smallest number of components whose individual impact contributions add up to at least 7.5kJ at a confidence level of 90%. By identifying the components that contribute to the majority of the impact, the burden associated with data collection can be drastically reduced since fewer components need to be fully defined.

2.3.2 Triaged Hybrid Comparison

With the constituents of the SOI at level 1 known, the components of the SOI can then by fully specified at level 5, while the remaining components of the BOC remain at their level 1 specification, resulting in an L1/L5 triaged hybrid BOC. The resulting impact from this hybrid BOC is a good indication of how effective this streamlined LCA can be when the majority of the burden is involved with fully specifying the SOI while the remainder of the BOC remains underspecified at L1. This method can be further evaluated by comparing the uncertainty of the triaged hybrid situation with the benchmark of the fully specified (at L5) BOC. This comparison provides insight into the effectiveness and efficiency of the triaged hybrid model depending on its uncertainty similarity to the fully specified L5 situation and the relative size of the BOC.

3 RESULTS & ANALYSIS

The following section presents the results of the process of creating a systematic classification scheme for two types of materials – polymers and minerals. It also goes on to show the results of applying these new materials classifications in tandem with the streamlining method of underspecification on the LCA product case study. The results of the case study are integral in determining the effectiveness and efficiency of not only the classifications themselves, but also of the methodology as a whole.

3.1 Systematic Classification of Polymers

Systematic classification of polymers was achieved using a five level format, where level 1 is the most underspecified classification and level 5 is the most specified classification. The classification was successfully achieved using the same level breakdowns as the classification schematic shown in Figure 2. At L1, the category is at its highest level of underspecification, where all entries are singularly classified as a Polymer. At level 2, material property differentiations are made, resulting in the following five categories: Thermoplastics, Resins, Elastomers, High-Temperature Thermoplastics and Thermosets. As shown in Table 4 below, of the 111 polymers included in the data set, 67% of them fall into the thermoplastic category. Additionally, separate L2 categories were created for resins and high temperature thermoplastics to account for the sheer difference in processing method and energy demand. At level 3, polymer types are further differentiated, resulting in 20 categories including polymer types such as polystyrene and nylon. At level 4, polymer processing techniques are considered, which differentiates polymers made of the same material, but processed into different final forms. For example, the differentiation between polypropylene granulates and polypropylene fibers is made at level 4. Level 4 contains 45 distinct categories, each of which is differentiated at the material processing level. Lastly the level 5 categories consist of the individual polymer material entries obtained from the LCA databases, representing the lowest level of underspecification. A full listing of the classification can be found in the Appendix.

Level	# of Polymer Categories
1	1
2	5
3	20
4	45
5	111

Table 3: Polymer classification breakdown by level

Level 2 Category	# of L5 Entries Contained
Thermoplastic	74
Resin	19
Elastomer	10
High Temp Thermoplastic	4
Thermoset	4
Total	111

Table 4: Polymer level 2 classification breakdown

In order to determine the validity and effectiveness of this classification scheme, the impact value distribution for each level of underspecification was plotted using the MAD-COV metric. The MAD-COV plot of the polymer classification scheme is shown in Figure 3 below. At level 1, there is a MAD-COV of approximately 20%, which continues to decline with each level of specificity until level 5, where the MAD-COV of the entries are all close to approximately 8%. The results of the graph indicate that the final classification scheme successfully underspecifies the polymer material class. Given that the impact value distribution continually decreases with each level of specificity, this classification can now be applied in a streamlined LCA using probabilistic underspecification.

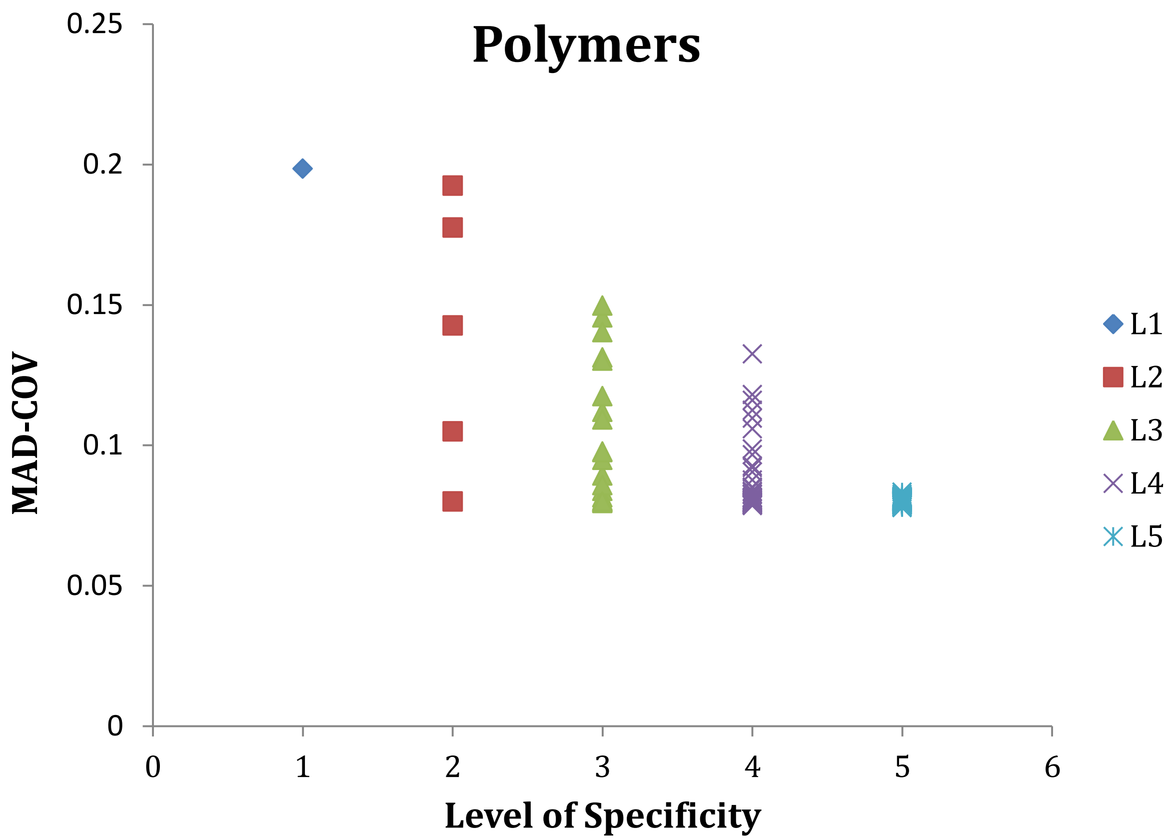

Figure 3: Median Absolute Deviation – COV plot of the polymer classification scheme shown by level of specificity

3.2 Systematic Classification of Minerals

Unlike the systematic classification of polymers, the classification of minerals was not achieved using the same five-level format. Instead, the systematic classification of minerals consists of four levels, each of which is differentiated using the Nickel-Strunz mineral classification methodology. The Nickel-Strunz classification scheme categorizes minerals based on their chemical compositions. One main difference, however, is that for the mineral category of materials, two separate L1 categories were made in order to account for the drastic difference in energy impact between semi-finished minerals and minerals from an ore or concentrate. As a result, the two categories are completely separate, in the same manner that the polymer and metal L1 categories are separate. It is important to note, however, that this classification decision and corresponding results were influenced in part by the particular CED database values that were available, and different database values may influence the classification differently.

For the two mineral categories, a four-level Nickel-Strunz classification was applied, where level 1 is the most underspecified category and level 4 is the most specified classification. At level 1, the category is at its highest level of underspecification, where all entries are singularly classified as either a Semifinished Mineral or as an Ore/Concentrate Mineral. At level 2, Nickel-Strunz chemical composition distinctions are made, resulting in the following six categories for Ore/Concentrate minerals: Volcanic, Rock, Silicate, Sulfate, Oxide and Element. And the following ten categories for the Semi-Finished Minerals: Carbonate, Sulfate, Rock, Element, Silicate, Sulfide, Oxide, Halide, Volcanic and Rare Earth. For the Ore/Concentrate minerals, the Rock level 2 category includes the majority of the 23 minerals included in the data set. However, for the semi-finished minerals, there is no single category that includes the majority of the 51 semi-finished minerals included in the dataset. Table 5 below shows the breakdown of the level 2 categories for both mineral types. At level 3, the mineral types are further differentiated, resulting in 18 different categories for the ore/concentrate minerals, and 36 different level 3 categories for the semi-finished minerals. Lastly, the level 4 categories for both mineral types consist of the individual mineral material entries obtained from the LCA databases, representing the lowest level of underspecification. A full listing of the mineral classifications can be found in the Appendix.

Level	# of Ore/Concentrate Categories	# of Semi-Finished Categories
1	1	1
2	6	10
3	18	36
4	23	51

Table 5: Mineral classification breakdown by level

Level 2 Category	# of L4 Entries Contained
Volcanic	2
Rock	13
Silicate	3
Sulfate	2
Oxide	2
Element	1
Total	23

Table 6: Ore/Concentrate Minerals level 2 classification breakdown

Level 2 Category	# of L4 Entries Contained
Carbonate	8
Sulfate	11
Rock	3
Element	4
Silicate	8
Sulfide	3
Oxide	10
Halide	2
Volcanic	1
Rare Earth	1
Total	51

Table 7: Semi-Finished Minerals level 2 classification breakdown

Similar to the method used for the polymer classification scheme, in order to determine the effectiveness of the mineral classification schemes, MAD-COV calculations were used to plot the impact value distribution for each level of underspecification. The MAD-COV plot for the Ore/Concentrate minerals is shown in Figure 4 and the MAD-COV plot for the Semi-Finished minerals is shown in Figure 5 below. In the plot of the Ore/Concentrate minerals, at level 1, there is a MAD-COV of approximately 68% which variably declines in levels 2 and 3 until reaching a low MAD-COV of approximately 8% at level 4. The MAD-COV plot of the Semi-Finished minerals follows a similar trajectory, except for the fact that the level 1 variance is higher at approximately 91%. In the ores/concentrates MAD-COV plot, the L3 category with a MAD-COV that is larger than the highest L2 category is the result of two different values for the mineral bauxite, that come from two different LCA databases. This type of discrepancy cannot be avoided by the classification scheme, if all database entries are to be included in the analysis. Similarly, in the semi-finished minerals MAD-COV plot, the L2 category with a MAD-COV that is larger than the MAD-COV of the L1 category is the result of the inclusion of both limestone and lime in the carbonate L2 category.

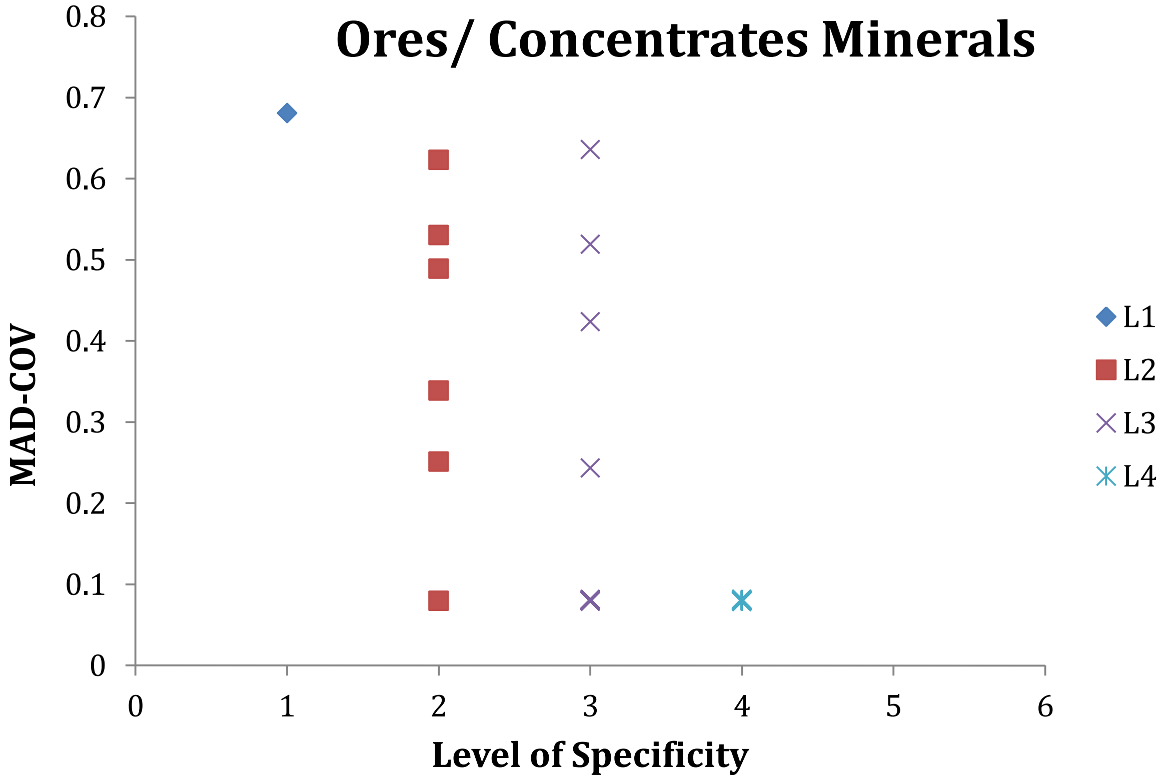

Figure 4: Median Absolute Deviation – COV plot of the ore/concentrate mineral classification by level of specificity

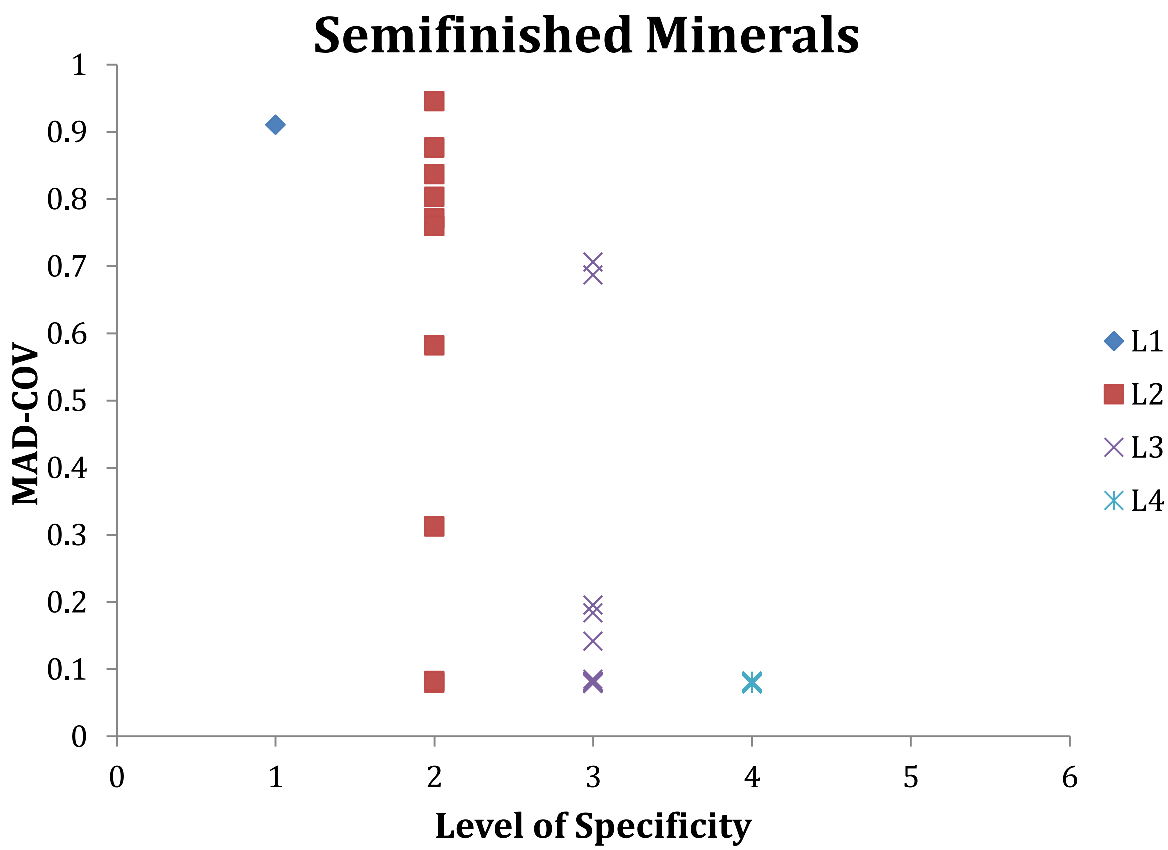

Figure 5: Median Absolute Deviation – COV plot of the semi-finished mineral classification by level of specificity

3.3 Case Study Results

The following section summarizes the results of the product case study analysis that was performed in order to determine the effectiveness and efficiency of the probabilistic underspecification-based streamlining method discussed earlier. The total impact and methodology effectiveness is measured for the case study product, which in this case is an alkaline battery.

The total cumulative energy demand (CED) was calculated for the materials contained within an alkaline battery at each level of specificity using the structured underspecification methodology. Only the materials phase of the alkaline battery was examined as previous LCA results indicated that materials were the primary driver of life cycle burden (Olivetti, Gregory, & Kirchain, 2011). The data is shown through box and whisker plots in Figure 6 which incorporates the standard deviation, mean, median, ninetieth percentile and tenth percentile for the 10,000 iterations of the simulation at each specificity level. The median impact is represented by the line in the middle of the box, while the average is indicated by the blue point; additionally, the lower and upper whiskers represent the tenth and ninetieth percentiles of the CED. As expected, the CED distribution decreases as the level of specificity increases along the x-axis.

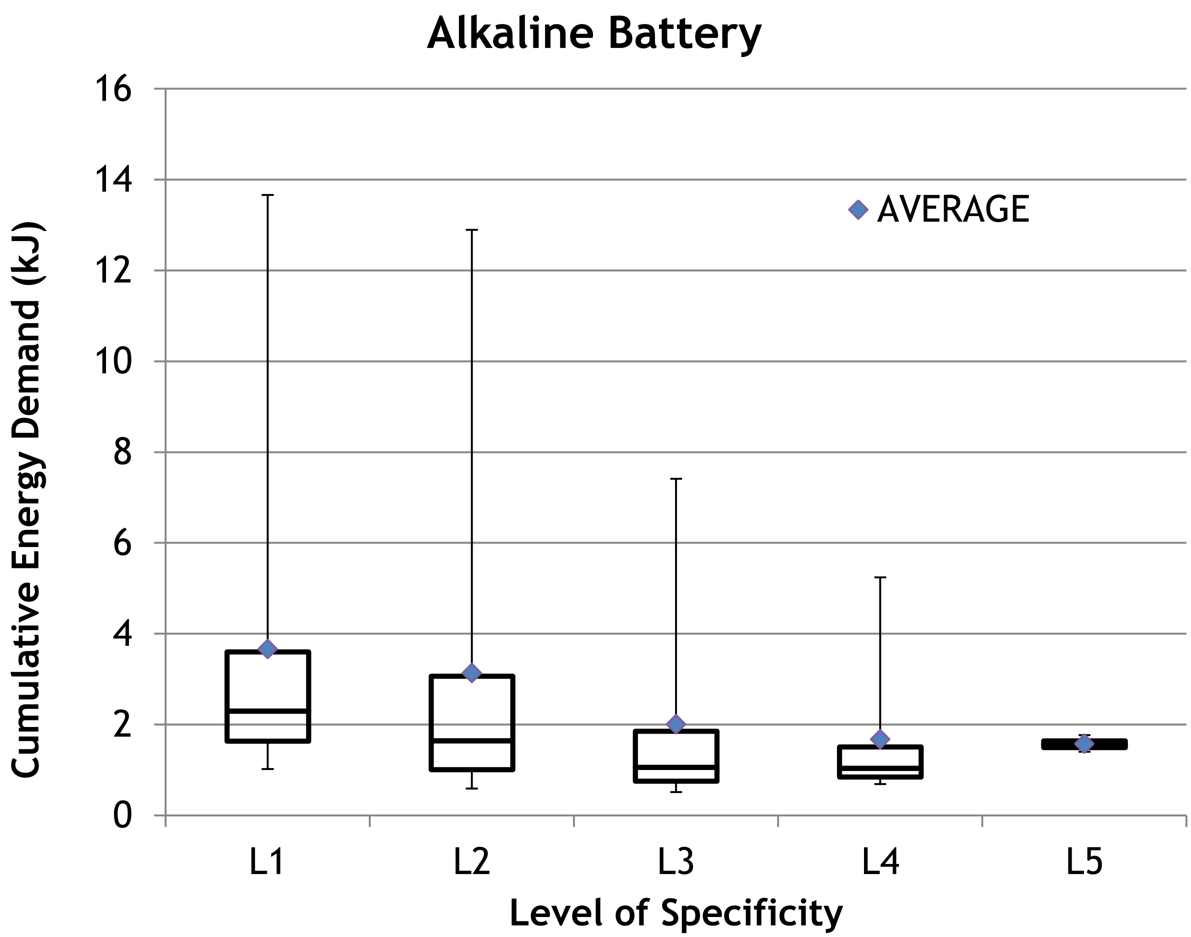

Figure 6: Box and Whisker plot showing the CED distribution by level of specificity for the alkaline battery case study. Trend shows decreasing uncertainty with increasing specificity

3.3.1 Case Study Effort Reduction

One of the main advantages of the probabilistic underspecification methods of LCA streamlining is its ability to reduce the burden associated with LCA by systematically decreasing the number of product components that need to be fully defined (with increased research and precision of impact values). The SOI, which consists of only those components that need to be fully defined, can be represented as a fraction of the total number of components in the BOC. The smaller the fraction, the lower the burden associated with performing the LCA for the given product. For the case of the alkaline battery, the BOC consisted of 37 unique components, and the SOI represented only 7 components, or 19% of the BOC. Figure 7 below shows the BOC breakdown for the alkaline battery, in comparison with the results of other product case studies from Patanavanich's thesis research**.** The alkaline battery falls in the middle in terms of total number of BOC components, and has the smallest SOI percentage of all of the product case studies. Another trend that is shown in Figure 7 is the fact that the SOI percent of BOC and the number of components in the BOC are inversely related – that is, the products with larger BOCs tend to have a SOI that comprises a smaller percentage of the product's overall BOC.

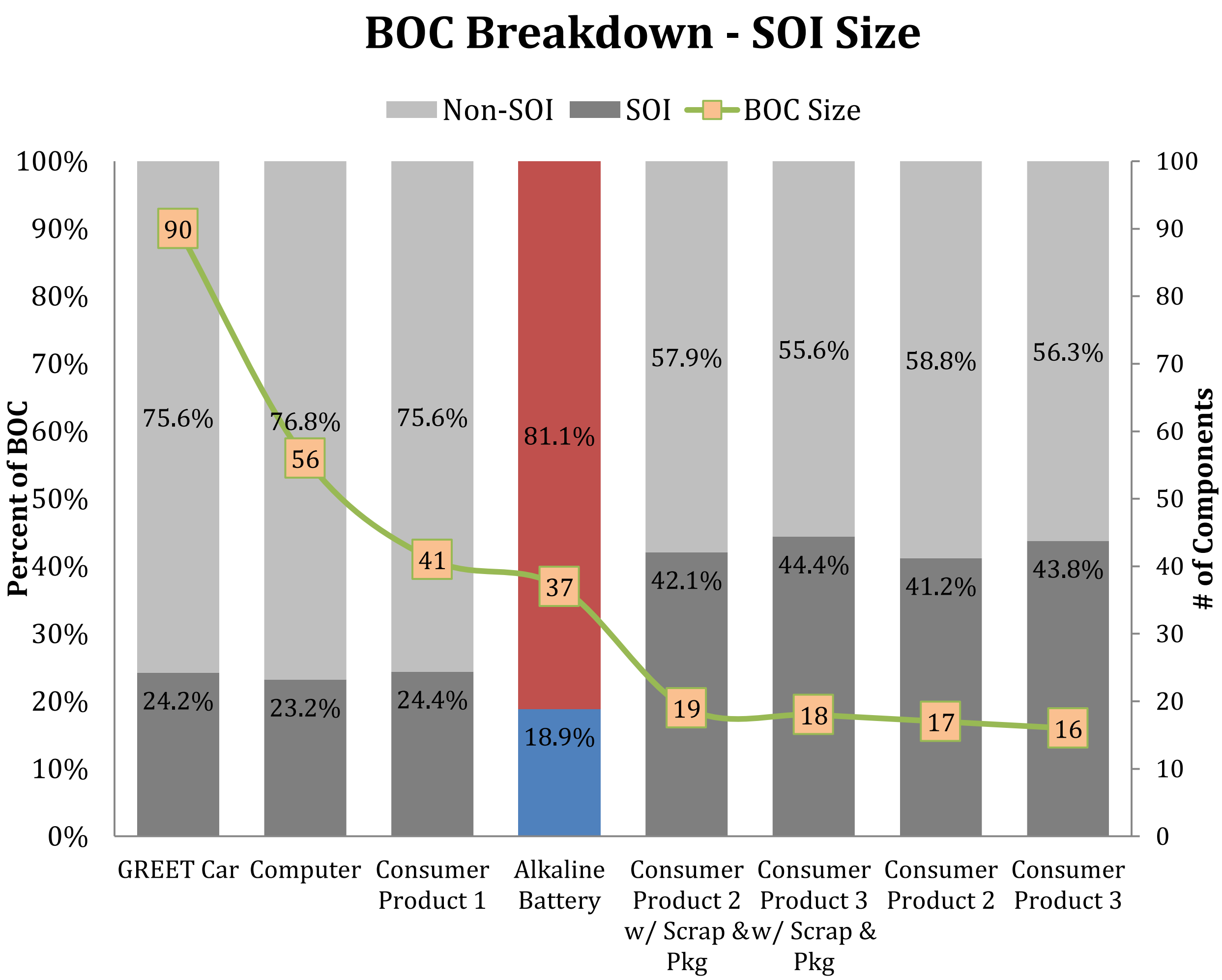

Figure 7: Breakdown of BOCs for various product case studies, showing the SOI percentage of the BOC, ranked by decreasing BOC size. Alkaline Battery case study results incorporated with results from Patanavanich's case studies (Patanavanich, 2011)

3.3.2 Triaged Hybrid Results

As discussed in the methodology, the SOI can be used to create a L1/L5 triaged hybrid BOC that can be used to understand the effectiveness of the streamlined LCA through comparison of the resulting hybrid impact values with the impact values of the fully specified L5 scenario. Figure 8 below shows the impact uncertainty for the alkaline battery at the five levels of specification as well as the uncertainty associated with the

L1/L5 hybrid BOC. As shown in the graph, with each additional level of specification, the accuracy of the impact assessment improves while the associated level of uncertainty decreases. Additionally, the L1/L5 hybrid BOC produces an impact assessment and distribution that is extremely similar to the results produced by the L5 BOC (both in terms of accuracy and uncertainty). Based on these results, it is clear that the use of the level 1 specificity level and associated uncertainty is a successful mechanism for determining the SOI, given that the triage hybrid BOC significantly reduced the burden associated with the LCA while still producing an accurate estimate of the total environmental impact.

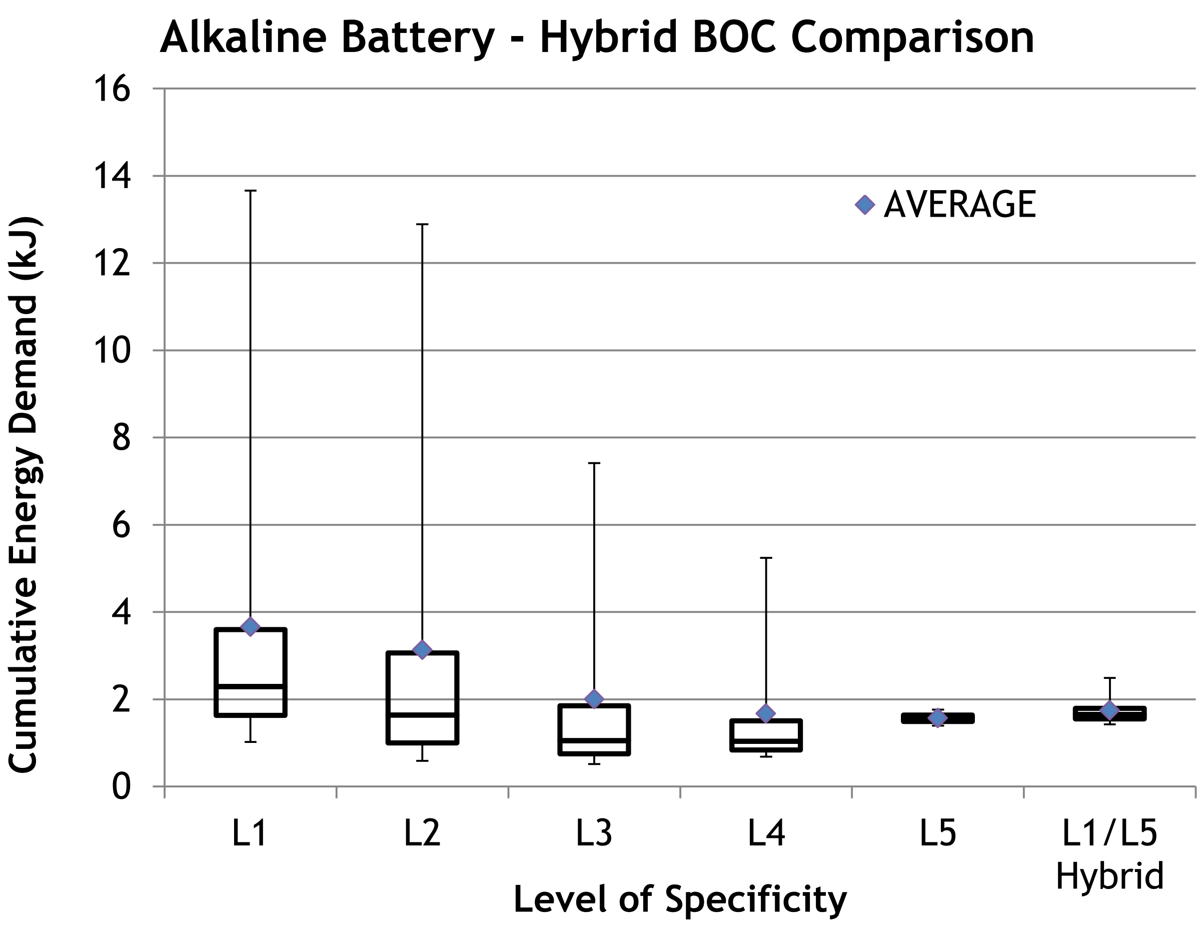

Figure 8: Box and Whisker plot comparing the streamlined CEDs for L1-L5 and L1/L5 hybrid BOCs. Hybrid BOC produces an impact assessment of close proximity to the fully defined L5 BOC

3.3.3 Case Study Uncertainty Analysis

While the impact assessment values of the product case study are a good indication of the precision of the streamlining method, the best way to measure the uncertainty associated with the method of probabilistic streamlining is to measure the Median Absolute Deviation-Coefficient of Variation (MAD-COV) of the CED. Figure 9 below shows the results of the MAD-COV analysis for the alkaline battery case study, in comparison with seven other case studies analyzed in Patanavanich's thesis research (Patanavanich, 2011).

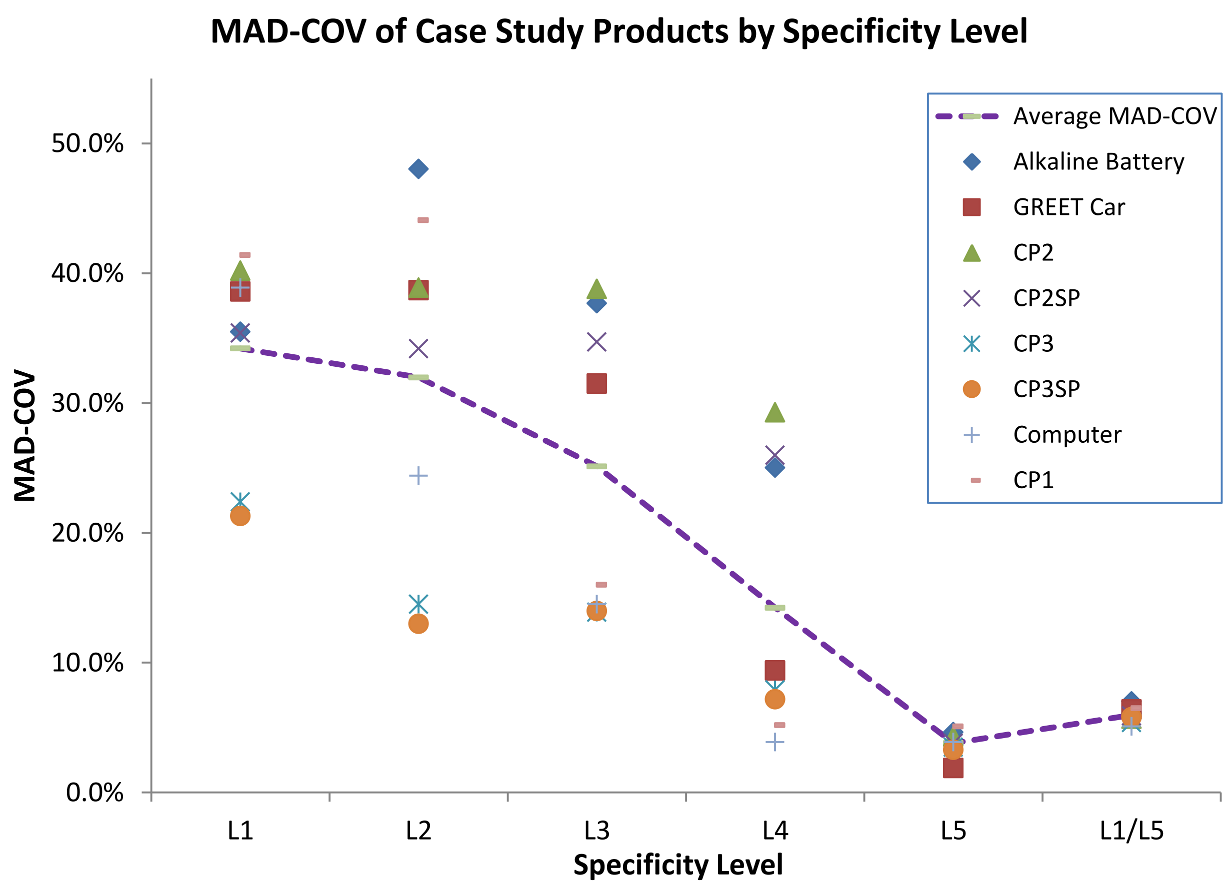

Figure 9: MAD-COV of CED results for Alkaline Battery case study with streamlined L1/L5 hybrid results. Alkaline battery results incorporated with other case study results from (Patanavanich, 2011)

As seen in the figure above, the results of the MAD-COV analysis suggest that the probabilistic streamlining method was successfully able to reduce the uncertainty in the CED values for the alkaline battery case study. The L1/L5 hybrid BOC produces a CED with a MAD-COV that comparable to the L5 MAD-COV values, while remaining lower than the L4 MAD-COV values. These results show that the use of the SOI as a means of reducing the burden involved with LCA can produce impact results to a predictably high level of certainty. Additionally, the dotted line in the figure above indicates the trend for the average MAD-COV of all eight of the case studies. One important discrepancy to note is the fact that for several of the case studies, including the alkaline battery study, the L2 MAD-COV is higher than the L1 MAD-COV. For the alkaline battery case, this upward trend at L2 is most likely due to the fact that 43% of the BOC is chemical materials – a material type that still requires though classification. Lastly, Table 8 below provides a view of the specific MAD-COV values for all of the case studies, at each level of specificity. Overall, the average MAD-COV for the L1/L5 hybrid BOC was only 2.2% higher than the average MAD-COV of the fully specified L5 BOC. This slight increase in uncertainty for the hybrid BOC seems reasonable, given that the hybrid model significantly reduced LCA burden by only requiring 32.8% (on average) of the BOC to be fully specified.

MAD-COV	L1	L2	L3	L4	L5	L1/L5
Alkaline Battery	35.5%	48.0%	37.7%	25.0%	4.7%	7.0%
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	***34.2%***	***32.0%***	***25.1%***	***14.2%***	***3.8%***	***6.0%***

Table 8: MAD-COV of CED values for alkaline battery case study with streamlined L1/L5 hybrid results. Alkaline battery results incorporated with other case study results from (Patanavanich, 2011)

4 CONCLUSIONS

This thesis attempts to improve the viability of LCA streamlining through probabilistic underspecification by improving the classification schemes for the polymer and mineral material types. Through the process of creating, refining and testing the classification schemes for the two types of materials, the results suggest that the underspecification streamlining approach can produce effective and efficient LCA results. Further analysis of the resulting underspecification databases for polymers and minerals shows that the variability of results decreases, on average, as a product becomes less underspecified, as displayed in the MAD-COV plots for the material classifications. The methodology used to create these classifications is confirmed to be a valid approach that can be applied to better classify other material types such as chemicals.

The classification schemes, which are a component of the probabilistic underspecification streamlining methodology, are then applied to an alkaline battery case study to determine the effectiveness and efficiency of the methodology at reducing the burden associated with LCA. A set of interest, composed of select components from the BOC, is selected based on a 50th percentile ranking of the components at L1 impact values, a 75% cumulative threshold of total product impact and a 90% confidence level in the uncertainty of the results. The resulting SOI only composes 19% of the 37 components in the BOC and the L1/L5 triaged hybrid model outputs a suitable total impact assessment with a variation that is only 2.3% higher than the fully defined L5 estimate. Additionally, the uncertainty in the triaged hybrid impact results for the alkaline battery is lower than that of the L1, L2, L3 and L4 values at only 7%, as indicated by the MAD-COV values.

Ultimately, the results suggest the viability of probabilistic underspecification as an acceptable streamlining method for LCA.

4.1 Future Work

The scope of this thesis limited the underspecification classification research to the materials of polymers and minerals. Future work should look at creating more refined classification schemes for other material categories such as chemicals, construction materials, glass materials, textiles, etc. Additionally, the focus on materials classification was chosen for this work due to its predominance as a primary driver of total product impact for many different product types. However, other LCA activities such as transportation, use and disposal can also be significant drivers of total environmental impact. Future work should explore creating similar underspecification classification schemes for these LCA activities as well.

With regards to probabilistic underspecification, this work has continued on prior research to show its ability to successfully reduce LCA burden while increasing certainty in the results, through additional case study analysis. However, future work should continue to analyze many more case studies using this streamlining approach to better understand the flaws in the methodology. Lastly, future work should explore the viability of probabilistic underspecification when used with environmental impact categories other than the cumulative energy demand.

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6 APPENDIX

6.1 Full Polymer Classification

Level 1	Level 2	Level 3	Level 4	Level 5
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	Bitumen	Bitumen4	Bitumen sealing, at plant/RER U
Polymers	Elastomer	Polybutadiene	Polybutadiene4	Polybutadiene E
Polymers	Elastomer	Polybutadiene	Polybutadiene granulate	Polybutadiene granulate (PB), production mix, at plant RER
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	High Temp Thermoplastic	Polyamide	Polyamide glass	Glass fibre reinforced plastic, polyamide, injection moulding, at plant/RER U
Polymers	High Temp Thermoplastic	Polyamide	Polyamide4	Polyamide 6.6 fibres (PA 6.6), from adipic acid and hexamethylene diamine (HMDA), prod. mix, EU-27 S
Polymers	High Temp Thermoplastic	TFE	TFE Film	Tetrafluoroethylene film, on glass/RER U
Polymers	High Temp Thermoplastic	TFE	TFE4	Tetrafluoroethylene, at plant/RER U
Polymers	Resin	ABS	ABS Copolymer resin	Acrylonitrile-butadiene-styrene copolymer resin, at plant/RNA
Polymers	Resin	Polyethylene	Polyester resin	Alkyd resin, long oil, 70% in white spirit, at plant/RER U
Polymers	Resin	Polyethylene	Polyester glass	Glass fibre reinforced plastic, polyester resin, hand lay-up, at plant/RER U
Polymers	Resin	Polyethylene	HDPE	HDPE resin E
Polymers	Resin	Polyethylene	HDPE	High density polyethylene resin, at plant/RNA
Polymers	Resin	Polystyrene	HIPS	High impact polystyrene resin, at plant/RNA
Polymers	Resin	Polyethylene	LDPE	LDPE resin E
Polymers	Resin	Polyethylene	LLDPE	Linear low density polyethylene resin, at plant/RNA
Polymers	Resin	Polyethylene	LLDPE	LLDPE resin E
Polymers	Resin	Polyethylene	LDPE	Low density polyethylene resin, at plant/RNA
Polymers	Resin	Polymer resin	Phenolic resin	Phenolic resin, at plant/RER U

Polymers	Resin	Polyethylene	Polyester resin	Polyester resin, unsaturated, at plant/RER U
Polymers	Resin	Polypropylene	Polypropylene resin	Polypropylene resin E
Polymers	Resin	Polypropylene	Polypropylene resin	Polypropylene resin, at plant/RNA
Polymers	Resin	PVC	PVC resin	Polyvinyl chloride resin, at plant/RNA
Polymers	Resin	PVC	PVC resin	Polyvinylchloride resin (B-PVC), bulk polymerisation, production mix, at plant RER
Polymers	Resin	PVC	PVC resin	Polyvinylchloride resin (E-PVC), emulsion polymerisation, production mix, at plant RER
Polymers	Resin	PVC	PVC resin	Polyvinylchloride resin (S-PVC), suspension polymerisation, production mix, at plant RER
Polymers	Resin	Formaldehyde resin	Urea formaldehyde resin	Urea formaldehyde resin, at plant/RER U
Polymers	Thermoplastic	Polyacrylonitrile	AN	Acrylonitrile E
Polymers	Thermoplastic	Polyacrylonitrile	AN	Acrylonitrile from Sohio process, at plant/RER U
Polymers	Thermoplastic	EVA	EVA4	Ethylene vinyl acetate copolymer, at plant/RER U
Polymers	Thermoplastic	EVA	EVA foil	Ethylvinylacetate, foil, at plant/RER U
Polymers	Thermoplastic	Polystyrene	EPS	Expandable polystyrene (EPS) E
Polymers	Thermoplastic	Polyethylene	PET	Fleece, polyethylene, at plant/RER U
Polymers	Thermoplastic	Polystyrene	GPPS	General purpose polystyrene, at plant/RNA
Polymers	Thermoplastic	Polyethylene	HDPE	HDPE bottles E
Polymers	Thermoplastic	Polyethylene	HDPE	HDPE pipes E
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	Polyethylene	LDPE	LDPE bottles E
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 glas 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	Polypropylene	Polypropylene film	Oriented polypropylene film E
Polymers	Thermoplastic	Polyethylene	LDPE	Packaging film, LDPE, 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
Polymers	Thermoplastic	Polyethylene	PET	PET film (production only) E
Polymers	Thermoplastic	PMMA	PMMA beads	PMMA beads E
Polymers	Thermoplastic	PMMA	PMMA sheet	PMMA sheet E
Polymers	Thermoplastic	Polyacrylonitrile	PAN	Polyacrylonitrile fibres (PAN), from acrylonitrile and methacrylate, prod. mix, PAN w/o additives EU-27 S
Polymers	Thermoplastic	Polycarbonate	Polycarbonate4	Polycarbonate E
Polymers	Thermoplastic	Polycarbonate	Polycarbonate granulate	Polycarbonate granulate (PC), production mix, at plant RER
Polymers	Thermoplastic	Polycarbonate	Polycarbonate4	Polycarbonate, at plant/RER U
Polymers	Thermoplastic	Polyethylene	HDPE	Polyethylene high density granulate (PE-HD), production mix, at plant RER
Polymers	Thermoplastic	Polyethylene	LDPE	Polyethylene low density granulate (PE-LD), production mix, at plant RER
Polymers	Thermoplastic	Polyethylene	LLDPE	Polyethylene low linear density granulate (PE-LLD), production mix, at plant RER
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	HDPE	Polyethylene, HDPE, granulate, at plant/RER U
Polymers	Thermoplastic	Polyethylene	LDPE	Polyethylene, LDPE, granulate, at plant/RER U
Polymers	Thermoplastic	Polyethylene	LLDPE	Polyethylene, LLDPE, granulate, at plant/RER U
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	Polymethyl methacrylate, sheet, 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 granulate	Polypropylene granulate (PP), production mix, at plant RER
Polymers	Thermoplastic	Polypropylene	Polypropylene molded	Polypropylene injection moulding E
Polymers	Thermoplastic	Polypropylene	Polypropylene granulate	Polypropylene, granulate, at plant/RER U
Polymers	Thermoplastic	Polystyrene	GPPS	Polystyrene (general purpose) granulate (GPPS), prod. mix, RER
Polymers	Thermoplastic	Polystyrene	EPS	Polystyrene expandable granulate (EPS), production mix, at plant RER
Polymers	Thermoplastic	Polystyrene	Polystyrene thermoforming	Polystyrene thermoforming E
Polymers	Thermoplastic	Polystyrene	EPS	Polystyrene, expandable, at plant/RER U
Polymers	Thermoplastic	Polystyrene	GPPS	Polystyrene, general purpose, GPPS, at plant/RER U
Polymers	Thermoplastic	Polystyrene	HIPS	Polystyrene, high impact, HIPS, at plant/RER U
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	PVDC	Polyvinylidenchloride, granulate, at plant/RER U
Polymers	Thermoplastic	PVC	PVDC	Polyvinylidene chloride (PVDC) E
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	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	Thermoset	Polyurethane	Polyurethane flexible foam	Polyurethane flexible foam E
Polymers	Thermoset	Polyurethane	Polyurethane rigid foam	Polyurethane rigid foam E
Polymers	Thermoset	Polyurethane	Polyurethane flexible foam	Polyurethane, flexible foam, at plant/RER U
Polymers	Thermoset	Polyurethane	Polyurethane rigid foam	Polyurethane, rigid foam, at plant/RER U

6.2 Full Ore/Concentrate Minerals Classification

Level 1	Level 2	Level 3	Level 4
Ores/Concentrates	Element	Sulphur	Sulphur, from crude oil, consumption mix, at refinery, elemental sulphur EU-15 S
Ores/Concentrates	Oxide	Sand	Sand, at mine/CH U
Ores/Concentrates	Oxide	Chromite	Chromite, ore concentrate, at beneficiation/GLO U
Ores/Concentrates	Rock	Limestone	Limestone, at mine/CH U
Ores/Concentrates	Rock	Anhydrite	Anhydrite rock, at mine/CH U
Ores/Concentrates	Rock	Gravel	Gravel, round, at mine/CH U
Ores/Concentrates	Rock	Iron Ore	Iron ore, 46% Fe, at mine/GLO U
Ores/Concentrates	Rock	Gravel	Gravel, unspecified, at mine/CH U
Ores/Concentrates	Rock	Limestone	Limestone, at mine/US
Ores/Concentrates	Rock	Bauxite	Bauxite, at mine/GLO U
Ores/Concentrates	Rock	Basalt	Basalt, at mine/RER U
Ores/Concentrates	Rock	Gravel	Gravel, crushed, at mine/CH U
Ores/Concentrates	Rock	Iron Ore	Iron ore, 65% Fe, at beneficiation/GLO U
Ores/Concentrates	Rock	Bauxite	Bauxite, at mine/GLO
Ores/Concentrates	Rock	Phosphate rock	Phosphate rock, as P2O5, beneficiated, dry, at plant/MA U
Ores/Concentrates	Rock	Rare Earth Concentrate	Rare earth concentrate, 70% REO, from bastnasite, at beneficiation/CN U
Ores/Concentrates	Silicate	Vermiculite	Vermiculite, at mine/ZA U
Ores/Concentrates	Silicate	Clay	Clay, at mine/CH U
Ores/Concentrates	Silicate	Bentonite	Bentonite, at mine/DE U
Ores/Concentrates	Sulfate	Gypsum	Gypsum, mineral, at mine/CH U
Ores/Concentrates	Sulfate	Stibnite	Stibnite ore, 70% stibnite, at mine/CN U
Ores/Concentrates	Volcanic	Pumice	Pumice, at mine/DE U
Ores/Concentrates	Volcanic	Perlite	Perlite, at mine/DE U

6.3 Full Semi-Finished Minerals Classification

Level 1	Level 2	Level 3	Level 4
Semifinished Minerals	Carbonate	Limestone	Limestone, crushed, for mill/CH U
Semifinished Minerals	Carbonate	Limestone	Limestone, crushed, washed/CH U
Semifinished Minerals	Sulfate	Gypsum	Gypsum stone (CaSO4-dihydrate) DE S
Semifinished Minerals	Rock	Gravel	Gravel 2/32, wet and dry quarry, production mix, at plant, undried RER S
Semifinished Minerals	Rock	Crushed Stone	Crushed stone 16/32, open pit mining, production mix, at plant, undried RER S
Semifinished Minerals	Carbonate	Limestone	Limestone, milled, loose, at plant/CH U
Semifinished Minerals	Sulfate	Anhydrite	Anhydrite, at plant/CH U
Semifinished Minerals	Sulfate	Asbestos	Asbestos, crysotile type, at plant/GLO U
Semifinished Minerals	Carbonate	Dolomite	Dolomite, at plant/RER U
Semifinished Minerals	Element	Graphite	Graphite, at plant/RER U
Semifinished Minerals	Silicate	Spodumene	Spodumene, at plant/RER U
Semifinished Minerals	Sulfide	Pyrite	Intral, at plant/RER U
Semifinished Minerals	Silicate	Feldspar	Feldspar, at plant/RER S
Semifinished Minerals	Carbonate	Limestone	Limestone, milled, packed, at plant/CH U
Semifinished Minerals	Oxide	Chromite	Portachrom, at plant/RER U
Semifinished Minerals	Silicate	Calcium Silicate	Calcium silicate, blocks and elements, production mix, at plant, density 1400 to 2000 kg/m3 RER S
Semifinished Minerals	Sulfate	Anhydrite	Anhydrite, burned, at plant/CH U
Semifinished Minerals	Sulfate	Anhydrite	Anhydrite (CaSO4), technology mix of natural, thermal and synthetic produced anhydrite DE S
Semifinished Minerals	Halide	Fluorite	Fluorspar, 97%, at plant/GLO U
Semifinished Minerals	Sulfate	Thenardite	Sodium sulphate, from natural sources, at plant/RER U
Semifinished Minerals	Oxide	Magnesium oxide	Magnesium oxide, at plant/RER U
Semifinished Minerals	Oxide	Limenite	Ilmenite, 54% titanium dioxide, at plant/AU U

Semifinished Minerals	Silicate	Kaolin	Kaolin, at plant/RER U
Semifinished Minerals	Carbonate	Lime	Lime, hydrated, loose, at plant/CH U
Semifinished Minerals	Carbonate	Lime	Lime, hydrated, packed, at plant/CH U
Semifinished Minerals	Carbonate	Lime	Lime, hydraulic, at plant/CH U
Semifinished Minerals	Silicate	Clay	Expanded clay, at plant/DE U
Semifinished Minerals	Rock	Phosphate rock	Phosphate rock, as P2O5, beneficiated, wet, at plant/US U
Semifinished Minerals	Sulfate	Magnesium sulphate	Magnesium sulphate, at plant/RER U
Semifinished Minerals	Silicate	Vermiculite	Expanded vermiculite, at plant/CH U
Semifinished Minerals	Sulfate	Thenardite	Sodium sulphat from viscose production, at plant/GLO U
Semifinished Minerals	Sulfate	Thenardite	Sodium sulphate, from Mannheim process, at plant/RER U
Semifinished Minerals	Sulfate	Thenardite	Sodium sulphate, powder, production mix, at plant/RER U
Semifinished Minerals	Silicate	Bentonite	Bentonite, at processing/DE U
Semifinished Minerals	Sulfate	Thenardite	Sodium sulphate from sulfuric acid digestion of spodumene/GLO U
Semifinished Minerals	Oxide	Magnetite	Magnetite, at plant/GLO U
Semifinished Minerals	Volcanic	Perlite	Expanded perlite, at plant/CH U
Semifinished Minerals	Silicate	Zircon	Zircon, 50% zirconium, at plant/AU U
Semifinished Minerals	Oxide	Rutile	Rutile, 95% titanium dioxide, at plant/AU U
Semifinished Minerals	Element	Selenium	Selenium, at plant/RER U
Semifinished Minerals	Oxide	Zincite	Zinc oxide, at plant/RER U
Semifinished Minerals	Halide	Cryolite	Cryolite, at plant/RER U
Semifinished Minerals	Sulfide	Molybdenite	Molybdenite, at plant/GLO U
Semifinished Minerals	Element	Graphite	Graphite, battery grade, at plant/CN U
Semifinished Minerals	Oxide	Baddeleyite	Zirconium oxide, at plant/AU U
Semifinished Minerals	Sulfide	Sphalerite	Zinc sulphide, ZnS, at plant/RER U

Semifinished Minerals	Oxide	Rutile	Titanium dioxide at plant, sulphate process, at plant/RER S
Semifinished Minerals	Oxide	Rutile	Titanium dioxide, production mix, at plant/RER U
Semifinished Minerals	Oxide	Rutile	Titanium dioxide, chloride process, at plant/RER S
Semifinished Minerals	Element	Moissanite	Silicon carbide, at plant/RER U
Semifinished Minerals	Rare Earth	Samarium	Samarium europium gadolinium concentrate, 94% rare earth oxide, at plant/CN U