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Analysis of Interactions between Raw Material and Energy Demands for Data Centers

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To all of them my everlasting gratitude.

To my beloved parents,
whose invaluable understanding knows
neither bounds, distances, or doubts.

Abstract

The amount of professional data centers in Germany is continuously increasing. This results in a growing demand for ICT components, such as servers and storage units. This, in addition to their short service times and high intensity of critical raw material content, results in a higher demand for valuable raw materials and primary energy for their production. The evaluation of the energy and material demands comes with challenges regarding poor data quality, a focus on operational phases, and lack of proper information on End-of-Life strategies. Recovery of valuable materials from high grade electronic components is considered strategic because of their high concentration of critical metals but at the same time represents a knowledge gap.

The goal of this dissertation is to analyze the raw material and primary energy demands for the cradle-to-grave lifecycle of professional data centers and its equipment, outside of the operational phase, and to analyze possible resource savings that come from different End-Of-Life strategies. The interdependencies of these resource demands within several scenarios is to be analyzed. To achieve this, Life Cycle Assessment of different data center systems and their components is conducted, with consideration of the infrastructure and inventorial composition of such facilities.

This requires gathering and updating data on raw material content and on devices composition, preparation of models for analysis, and evaluation of results through appropriate Life Cycle Impact Assessment Methods that reflect the use of material and energy resources, as current indicators consider mostly the operational phase, and omit the importance of different materials to the economy. Different scenarios for technologies applied for End-of-Life treatment and recycling are evaluated. Due to the number of models required and the volume of input and output data, automation of model building, calculations, and of results evaluation is required. An assessment of input data quality allows evaluating the results quality and validity, which serves to provide an overview of the data improvements. The information system used to calculate resource consumption is evaluated within the scope of this research. This provides a validated methodological basis for holistic resource consumption evaluation.

Zusammenfassung

Die Anzahl professioneller Rechenzentren in Deutschland nimmt kontinuierlich zu. Daraus resultiert ein wachsender Bedarf an IKT-Komponenten wie Servern und Speichereinheiten. Dies führt neben ihren kurzen Standzeiten und der hohen Intensität an kritischen Rohstoffgehalten zu einem höheren Bedarf an wertvollen Rohstoffen und Primärenergie für ihre Herstellung. Die Bewertung des Energie- und Materialbedarfs ist mit Herausforderungen in Bezug auf schlechte Datenqualität, Fokus auf Betriebsphasen und Mangel an angemessenen Informationen über End-of-Life-Strategien verbunden. Die Rückgewinnung wertvoller Materialien aus hochwertigen elektronischen Komponenten wird aufgrund ihrer hohen Konzentration an kritischen Metallen als strategisch angesehen, stellt aber gleichzeitig eine Wissenslücke dar.

Ziel dieser Dissertation ist es, den Rohstoff- und Primärenergiebedarf für den Cradle-to-Grave-Lebenszyklus professioneller Rechenzentren und ihrer Geräte außerhalb der Betriebsphase zu analysieren und mögliche Ressourceneinsparungen zu analysieren, die sich aus verschiedenen Strategien ergeben. Die Interdependenzen dieser Ressourcenanforderungen innerhalb mehrerer End-Of-Life Szenarien sollen analysiert werden. Um dies zu erreichen, werden Lebenszyklusanalysen verschiedener Rechenzentrumssysteme und ihrer Komponenten unter Berücksichtigung der Infrastruktur und Bestandszusammensetzung solcher Einrichtungen durchgeführt.

Dies erfordert das Sammeln und Aktualisieren von Daten zum Rohstoffgehalt und zur Gerätezusammensetzung, die Erstellung von Modellen für die Analyse und die Bewertung der Ergebnisse durch geeignete Methoden zur Bewertung der Auswirkungen auf den Lebenszyklus, die die Nutzung von Material- und Energieressourcen widerspiegeln, da aktuelle Indikatoren hauptsächlich die Betriebsphase berücksichtigen und die Bedeutung verschiedener Materialien für die Wirtschaft außer Acht lassen. Es werden verschiedene Szenarien für Technologien bewertet, die für die Behandlung und das Recycling von End-of-Life angewendet werden. Aufgrund der Anzahl der benötigten Modelle und der Menge an Ein- und Ausgabedaten ist eine Automatisierung der Modellbildung, der Berechnungen und der Ergebnisauswertung erforderlich. Eine Bewertung der Eingangsdatenqualität ermöglicht die Bewertung der Ergebnisqualität und -validität, was dazu dient, einen Überblick über die Datenverbesserungen zu geben. Im Rahmen dieser Untersuchung wird das Informationssystem zur Berechnung des Ressourcenverbrauchs evaluiert. Damit steht eine validierte methodische Grundlage für eine ganzheitliche Ressourcenverbrauchsbewertung zur Verfügung.

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1. Introduction

1.1. Motivation

Data centers have become an integral part of everyday life. Streaming services, automation, or real-time analysis such as traffic density are just a few of the many topics that are taken for granted today. The data centers run in the background and are increasingly struggling with their energy demands due to the high computing power. Data centers have thus an important role in the implementation of the EU climate protection goals and on the achievement of the efficiency goals of the German Federal Government [HH18]. More than 14 TWh/a are consumed yearly by around 53 000 Data Centers in Germany, representing 2.5% of the country's electricity consumption in 2018. This quantity is expected to grow to 21 TWh/a by 2030 [Hi21, Hi20b]. This despite an overall increment in energy efficiency of data center infrastructure of about 21% [Hi20a, HH20, BSB08]. Energy use indicators, such as Power Usage Efficiency, improved from 1.98 to 1.70 between 2010 and 2018. The increasing energy consumption has been documented in several studies not only for Germany, but also for Europe and the rest of the world [Hi14, Pr14, Co14].

The increasing energy demand of data centers poses a challenge when it comes to achieving climate protection goals and implementing the energy transition. This challenge is reinforced by two aspects. On the one hand, particularly in the area of IT products with their very short life cycles, not only the energy requirement in the operation phase is relevant [Ga12]. The so-called grey energy, i.e., the energy that is required for the manufacture, transport, storage, and disposal of the components, can also make up a considerable proportion of the total energy requirement, especially when operation lifetime can be as short as two years [FH14].

Between 2003 and 2013, the IT surface area of German professional data centers grew by 42% to 1.8 million m^2 [HC14], with over 2.3 million servers in operation by 2014. These trends result in an increasing demand for raw materials for these applications. One reason for this is the rapidly increasing need to store and process substantial amounts of data. In 2020, the energy requirements of the storage systems accounted for around 33% of the energy requirements of data centers [Mo20]. For the data center operators involved in the consortium of the project TEMPRO[1] (Total Energy Management for Professional Data Centers), a German project, the energy requirement of the storage systems is currently around 30% of the total electricity requirement [Pe20].

[1] https://tempro.uni-oldenburg.de/

In addition to ever-increasing energy consumption, however, the demand for material resources for manufacturing data center components is coming to the forefront. Even before a data center has used a kWh for data processing or storage, the structure of a data center contains an important amount of embedded energy.

This aspect is becoming increasingly important as the material intensity of data centers increases. Associated with a clear trend towards larger data centers, there has been a significant increase in IT (Information Technology) infrastructures such as servers, storage, and network components. The number of servers alone increased by 15% between 2010 and 2018 and will continue to increase until 2025 [Mo20]. This leads to an ever-increasing demand for raw materials, some of them considered critical due to their scarcity and economic importance. However, quantifying the amount of energy and raw material demands presents challenges regarding the methodologies to assess these values, and the limited amount of information available from manufacturers.

The high specific content of valuable materials makes data center equipment attractive for recycling, since the material content of the End-Of -Life (EoL) products makes them be categorized as High Grade Waste Electrical and Electronical Equipment (WEEE) [BBC12]. The possible material recovery is thus only considered from an economic point of view, and normally aspects such as recovery of critical materials with sustainability considerations are overlooked. Moreover, the benefits that proper EoL strategies can have on the overall primary energy demand are to be studied.

1.2. Related research and research gaps

The topic of resource depletion and environmental impacts of data centers has been widely researched, although most of the research focuses on operational energy efficiency [SN16, JN16] and assessment and improvement of carbon footprint of operational energy uses [JSN14]. Recent is the discussion of material use and incorporating concepts such as material supply risks has gained attention, mostly when considering production and recycling of WEEE.

1.2.1. Energy efficiency in data centers

The energy use during operation of a data center has been thoroughly studied due to economic and ecological issues. Due to the considerable amounts of electricity and the additional requirement to cool the IT devices, data centers present opportunities for energy saving which directly represent savings for the operators. This generates great interest in the development of indicators and metrics that reflect the performance of a data center that can help to keep track of a data center energy performance. There is abundant research on reducing data center operational energy consumption, such as the work presented in [Sc16], which developed operation indicators dependent on IT load. Consolidation and virtualization provide solutions for optimization of resource use while considering operational stability [Ja17, Bo21].

Measurements for operational energy efficiency and for reducing the environmental impacts of data centers operations are focused on the supply of power and cooling energy into data centers [SUO17].

1.2.2. Data center material composition

Data Centers structure can be divided into: IT, Energy Supply, Climatization, and Infrastructure systems [BI13]. IT components consist of equipment such as servers, storage units, and network units. Data centers use IT equipment fabricated mostly from non-renewable raw materials. These components contain high concentrations of valuable materials, such as precious metals, which make them a potential source from recovery. Some of these raw materials are labeled as “critical materials” by the European Union due to its economic importance and supply risk [EC14, EC17, Bu12, Os13]. There is however a lack of information regarding material composition of data centers, so no proper information on material demands or contents is available, and consequently no certain information on material availability for recovery exists. [FHS10] conducted a study for an assessment the material content of data centers in Germany, where the amounts of valuable metals such as copper, iron, gold, silver, and palladium present in data centers, were evaluated. This study already concluded that along with the increasing energy demand for operation, the demand for raw materials for the manufacturing of these components was rising, and therefore these materials are accumulating in the installed or in the decommissioned IT equipment, creating the potential for urban mining. The number of servers grew by 28% for the period 2010-2014, with the trend to build bigger facilities [Hi15]. This is accompanied by the increasing material intensity in data centers, so the material demand for these applications keeps rising in parallel.

1.2.3. Life cycle assessment for data centers and embodied energy

Increasing the overall energy efficiency of a data center is part of the Sustainable Development Goals. Additionally, the topic of raw material efficiency gains importance as increasing circularity of materials has also benefits on reduction of energy consumption. Studies on IT devices during its life cycle prove that as the equipment becomes more operationally efficient, the specific material demands increase, the embodied stage will play a larger role in the full life cycle [WAS15].

The average lifespan of central processing units in computers has decreased from 4-6 years in 1997 to 2 years in 2005 [Ba14, RPA07], which has been reduced even further (**Figure 1-1**). IT products used in data centers have a comparatively short lifetime (2-5 years) [Ga12]. [FBK18] conducted a study for assessing the lifetime of different consumer electronics, considering IT for data centers as one single category with a maximum probability of lifetime at 4.6 years. The result of this technology driven paradigm is that Electrical and Electronic Equipment (EEE) becomes obsolete at an early stage in their product life cycle, sometimes within only a few months of their release indicating that the energy consumption outside of the service phase is also of relevance. The contributions to the embodied energy demands comes in part from the required efforts for mining and processing of raw minerals into materials for manufacturing. The assessment of this energy is required to evaluate potential benefits that recovery and recycling of these materials can have on the overall life cycle of data center equipment. Consequently, indicators need to be developed that display these dependencies.

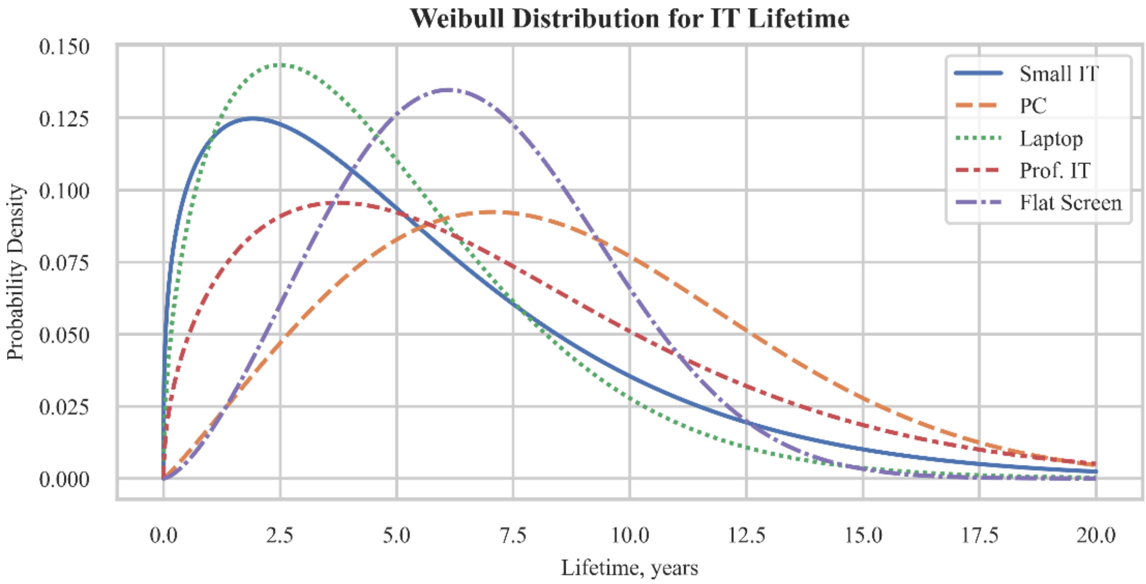


Figure 1-1: Example of product lifespans in years, represented as a Weibull distribution. Source: Data from [FBK18].

1.2.4. Data center resource use indicators

Indictors for evaluation of environmental impacts for data centers have been developed for the operation phase, with a focus on the greenhouse emissions from energy use for the services and for the cooling of facilities. Widely known are indicators such as Power Usage Effectiveness (PUE) and Data Center Infrastructure Efficiency (DCIE) [Re17a, Be08]. Some indicators are linked with a reference unit that quantifies the useful work done by a data center, although a unified indicator is difficult to stablish [WDD12]. [Ar15] introduced metrics for the assessment of flexibility and sustainability of data centers, which consider the inputs of renewable energy sources and account for avoided emissions.

Metrics to assess the circularity of materials are so far bounded to the operational aspects of a data center, with a focus on the amount in weight of data center components sent for recovery, such as the Electronics Disposal Efficiency (EDE) [Re17a, Br13]. Most of the metrics regarding material recovery stop at the operation phase and omit the posterior processes of recycling recovery, so no information on EoL processes is included.

1.2.5. Life cycle impact resource indicators

The concept of embodied energy attached to the steps of raw parts production, manufacturing, transporting, decommissioning, and recycling are often excluded when analyzing energy consumption or improvements on energy efficiency, which focuses mostly on the use phase, and overlooks the importance of the critical material content of IT applications. To study the relationship between material requirements and total primary energy consumption for manufacturing is complex due to different data center configurations, different material composition of the devices, and in general a poor data quality regarding high grade IT equipment. This analysis requires the execution of Life Cycle Assessments (LCA), that consider the products lifecycle and its stages.

There are indicators that have been developed for evaluation of primary energy demand across the lifecycle of a system, which can be applied to a data center and its components. Indicators such as the cumulated energy demand have been used for assessing total primary energy demand in distinct stages of the lifecycle. Indicators such as the cumulated material demand present a methodology for evaluating raw material demand consumption for product manufacturing [Gi12]. These indicators of material resource use overlook aspects such as material importance or material supply risks, so they are unable to include aspects such as material scarcity in their assessments.

1.2.6. Recycling and recovery

Electronic components have greater concentrations of precious metals than natural ores, which makes their recycling as secondary sources significant for both economic and environmental motivations [LZ12]. Components from data centers coming for recycling can be cataloged as High-Grade generated Waste Electrical and Electronic Equipment (WEEE) [BBC12] . When discussing WEEE, there is research regarding processes for recovering valuable materials, especially copper and gold, from printed circuit boards [Iş16]. There are several methodologies that yield each one different performance [La14, MCB19]. Nevertheless, these studies focus in generic WEEE components, and do not reflect the potential of recovering valuable metals from printed circuit boards (PCBs) coming from data center components [An16, Ba16]. Recovering of scarce metals, such as rare earths, from WEEE hast gained attention due to supply constraints, and there are several studies addressing the potential for recovery of these materials [Bi13, Ch20, Li19]. A complementary analysis of the relation between material recovery and energy gains for recovery from data center components is also often missing, although the sustainability of recovery of materials from other sources has been analyzed, with focus in savings of greenhouse emissions [Un17, DCG18]. However, since the information on recovery is mostly focused on generic WEEE, the data quality is deficient.

1.2.7. Data quality and methods

A dedicated analysis of data quality for specific IT components for data centers has not been conducted. Moreover, commercial databases for LCA, such as GaBi and ecoinvent, do not include product systems representing the devices used in data centers. These databases include data quality assessments of the included products [Ci21, We16]. Most of the electronic components present on different studies are limited to laptops, personal computers, and cellphones. Therefore, when performing modelling of IT components from data centers, many assumptions are taken and proxy data is used, which diminishes further the quality of the results. Methodologies for assessing data quality are based on a qualitative evaluation of the data [AW16], with a relation of data quality and uncertainty of results being used in LCA for results uncertainty evaluation [CMW12, GM12]. This provides a guideline for assessing the data quality of new data generated in this research, and to evaluate the improvements. **Table 1-1** provides a summary of the related research and an overview of the research gaps found.

1.3. Research questions

From the thematic problems described in Section 1.1 and with the overview of the current state of research briefly described in Section 1.2, the following subsections detail the research questions defined for analysis in this dissertation:

1.3.1. Main research question (MRQ)

MRQ: How are the primary energy consumption and raw material demand in professional data centers divided between the distinct phases of their lifecycle outside of the operational phase?

From this main research question, the scope of this research lies on analyzing the various stages of data center equipment, from raw material gathering, production, mounting, and all the stages related to life after operational phase, including decommissioning, disposal, recycling, and recovery of materials. This research focuses on energy consumption and material demands in data centers located in Germany. This requires developing LCA models to analyze products used in datacenters, assess data centers inventories, data center components material composition, and use of appropriate indicators to evaluate these energy consumption and material demand impacts. Relations to the resource consumption on the use phase, specially energy use, can be studied using the dimensioning of the data center. On parallel, data quality and results quality need to be evaluated through this research.

The following three sub-questions result from the main research question, with consideration of the various aspects related to the current state of the research, which specifically deepens various aspects of the question. These three questions build on each other in terms of content and help to guide the objectives of this research.

Table 1-1: Overview of existing literature. Legend: Related, Outdated, Covered/Applicable.

Concept		[Sc16] [Ja17]	[SUO17] [Pe20]	[BI13]	[FHS10]	[WAS15] [Ga12]	[Ma12] [Eu14] [Eu17] [Os13] [Eu17]	[Re17] [Be08] [Ar15]	[Re17, Br13]	[Gi12]	[LZ12] [BBC12]	[An16] [Ba16] [Iş16] [La14] [MCB19]	[Un17] [DCG18]	[Ci21] [We16]	[AW16] [CMW12] [GM12]
Data Sources/ Inventories	Energy Efficiency	Operational Indicators	Operational Improvements			Operational Efficiency Indicators									
	Embodied Energy					Embodied Energy Calculations									
	Material Composition			General DC structure	Material Content of DC							WEEE Material Content		Proxy Systems	
	Material Recovery					Material Recycling Indicators			Electronics Disposal Efficiency		High Grade WEEE Recovery	WEEE Recovery Processes Yields	Emissions Savings		
Indicators	Indicators for Energy Consumption							PUE, DCIE, RE Use		KEA				CED, CExD	
	Indicators for Material Impacts						Material Criticality			KRA					
Data Quality	Data Quality													Data Quality of Products	
	Methods														General Methods

1.3.2. Secondary research questions (SRQ)

The secondary research questions part from the main research question and are formulated to answer specific issues related to the obtaining of research goals.

SRQ 1: Which are the dependencies between the values of the indicators of raw material consumption and primary energy demand during the distinct stages of the lifecycle?

For this evaluation, LCA models representing the different components of data centers need to be developed. The goal is to evaluate the different production chains and manufacturing process, so the total amounts of energy required, and material demand are quantified. To evaluate these parameters, indicators need to be applied or further developed, so they can also represent the materials demands not only by their physical amount, but also by including aspects such as criticality.

SRQ 2: What are the benefits of different scenarios for recycling, when considering energy savings, greenhouse emission savings, and material recovery potential?

SRQ 2 is related to the aspects of sustainable production, which shall include recovery of materials as part of the production chains. Building up on the developed models, different scenarios for recycling are to be further constructed. These scenarios allow further experimentation on parameters such as recycling rates and on the technologies used for recycling. Information on industrial recycling process for various kinds of electronic equipment is therefore required, with the possibility of evaluating established and experimental technologies. This allows evaluating with a high degree of confidence the amount of material present on these components, so a proper assessment may be conducted. Improvements on energy consumption through appropriate recycling strategies are here evaluated, complementing the aspects of the Secondary Research Question 1.

SRQ3: Which have been the improvements of data quality of the results, after improvements on current data sources are conducted.

Given the existing issues on data quality [FHS10], and the requirement to use proxy data for developing models for LCA, results with low data quality are obtained in general. This produces a problem when assessing the potential of data center EoL equipment as a potential source for minerals. This issue is replicated for electronic equipment when considering urban mines as a material source [SBF11]. Reliable data on waste production, treatment facilities and management are partial requirements for the implementation of a community legislation and for the evaluation of the waste management [OJ93]. As part of the measures to be taken by actors across the lifecycle of a product to facilitate the preparation for re-use and correct treatment, for products in the category of Electrical and Electronic Equipment (EEE) and the generated Waste Electrical and Electronic Equipment (WEEE), data and statistics on their lifecycle are necessary to monitor the achievement of the objectives of the European Union Directive [EC12]. This research attempts to improve the data quality on material content and on process for manufacturing of data center equipment to present better data on material content and improve the results on evaluation of energy demand and material demands for this application, as specified on the Secondary Research Questions 1 and 2.

1.4. Research objectives

The methodology for the analysis is based on LCA and includes the development of a new database for performing impact assessments of IT equipment used in data centers, including a new analysis of material composition. Results on raw material depletion, the embodied energy and the cumulative energy demands represent indicators for integration in a comprehensive lifecycle analysis. This is a first-time approach to include the EoL phase and laboratory results on material composition into the LCA of professional data centers. Emphasis is placed on analyzing the dependencies of the results on embodied energy in combination with the results on the evaluation of the quantities of materials required for the production and operational phases.

Following the requirements of the main research question detailed in Section 1.3.1 and of the secondary research questions in Section 1.3.2, specific objectives are formulated for achieving the research goals. These can be understood as specific tasks for the development of this research, and as requirements for developing the models and executing the different calculations required for the experimentation and scenario evaluation. Following objectives can be therefore established, which will serve as a path for the development of this dissertation.

1.4.1. Update of inventory and material composition data

The SRQ 3 indicates a requirement of an improvement of the data available for evaluation of material and energy demands of data center components. As expressed in Section 1.2.2, the most common databases do not possess information on data center components [We16, th19], and proxy data used (coming from other electronic products) may produce results with lower data quality. Using decommissioned devices from data centers, an analysis of the parts and components of these devices is to be executed. Inventories on data centers are to be gathered from data center operators in Germany, which will allow to construct models representing their infrastructure. To get precise information on material composition of these components, laboratory analysis to quantify and determine their material content is to be conducted. This information is to be systematized in databases built with the required structure to access and store the information and to be used for model building and further calculations.

1.4.2. Building LCA models for data centers and their devices

To start the evaluation of resource consumption outlined in the MRQ, different models for the lifecycle of devices and systems need to be built using the information gathered from the results required in the objective 1.4.1. This with the objective of performing LCA of the various products and evaluating the inputs/outputs of flows of resources during their lifecycle. These models will be based on the bill-of-materials (BoM) and on the inventories of data centers. To allow escalation of the results, these components need to be modular, so different data center configurations can be later evaluated.

1.4.3. Modelling material recovery

The SRQ 2 requires the development of models for processes of material recovery for data center components to study the end-of-life stages, where different scenarios of material recovery and recovery processes can be analyzed. Information on recovery processes and their recovery factors, gathered also in objective 1.4.1, is here to be used as input for modelling and further calculations. These models will be based on the different recycling and recovery processes from literature sources and industrial processes [BBC12, Al14, Li19], and are to be developed with consideration of the particularities of the high critical material content of data center components.

1.4.4. Evaluation of current resource assessment indicators and development of critical material consumption indicators

To evaluate properly the dependencies between raw material and energy use, as outlined in the SRQ 2, an assessment of the existing indicators for evaluation of material and energy consumption through the life cycle of a product is to be conducted. This with the goal of evaluating whether the current existing indicators can reflect the issues that come with material use, such as material scarcity or economic value of materials. Additionally, new indicators are to be proposed, implemented, and evaluated. These will serve the purposes of this dissertation and reflect current issues with energy consumption and material scarcity. The new indicators to be proposed will try to overcome the drawbacks and limitations of the state-of-the-art indicators with regards to energy consumption and material scarcity.

1.4.5. Results evaluation and analysis of dependencies

Following the requirements of the MRQ and of the SRQ 1, the developed models from the objectives 1.4.2 and 1.4.3, and the formulation of indicators developed in objective 1.4.4, calculations on total resource demand for different systems under different scenarios can be evaluated, for whole data centers or for a particular device. Life Cycle Impact Assessment (LCIA) for these systems allow evaluation of these quantities and an evaluation of the results and their interactions. Given the amount of product systems and parameters to evaluate, automation of the calculations is desired, and storing and automated analysis of the results is also required.

1.4.6. Data quality assessment and uncertainty modelling

SRQ 3 requires simultaneously the developments previously explained and the evaluation of the quality of the input data in objective 1.4.1. This quality evaluation follows the methodologies in [Ci21, Mu16]. Following the calculations in objective 1.4.5, the results quality also needs to be evaluated. To assess improvements in data quality, comparisons with previous studies or previous databases need to be conducted. Statistical parameters such as uncertainty of results are also evaluated.

1.4.7. Build an information system for energy and material demands evaluation

The information gathered from objective 1.4.1 is to be systematized in different databases of material composition, devices BoM, and data center inventories. Similar systems for the development of indicators are to be developed. The values used for creation of new indicators in objective 1.4.4 also need to be linked with the proper material they represent. Given the amount of data and results required, the results of the calculations from objective 1.4.5 and objective 1.4.6 need to be saved on proper databases for further evaluation of results. The models developed in the objectives 1.4.2 and 1.4.3 need to be saved and exported to appropriate databases that include the models of the different devices, data centers, and recovery processes in the appropriate formats. The algorithmic implementation of the connections between these databases for the creation of models, execution of impact assessment calculations, and saving and evaluation of results is to be developed to automate the calculations. The specifics of this information system are detailed in the following chapters.

1.5. Structure of the research

Following the relation outline of the research objectives in Section 1.4, the design of this research follows broadly first the structure of a Life Cycle Assessment Study, which follows the steps of [ISO14040]. This also provides a framework for conducting and evaluating various aspects of this research. The requirements also call for engineering methods to design and produce an information system that allows a proper management of the information gathered and generated. This requires the development of a software solution that helps with the management of the information here included, as required by objective 1.4.7.

Figure 1-2 details the general structure of this dissertation, with relations to the research questions here detailed, the research objectives, and the distinct stages of LCA and Software Development.

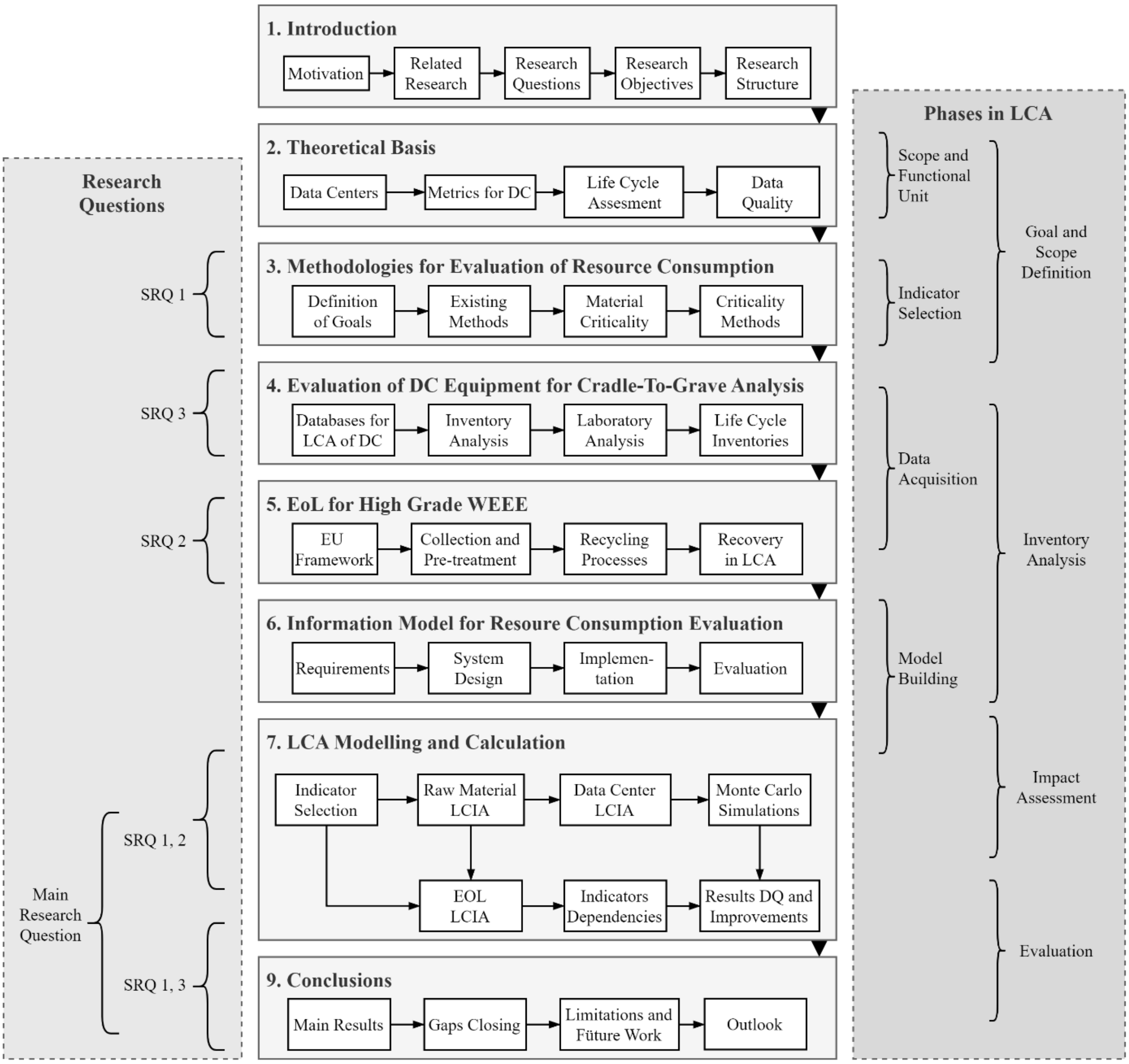


Figure 1-2: Structure of this dissertation with relation to the main and secondary research questions and the development of a Life Cycle Assessment Study with an information system.

After this introduction, **Chapter 2** provides an overview of data centers, their structure, and the indicators used for resource consumption evaluation. Accordingly, LCA as a scientific methodology is described. **Chapter 3** details the specific targets for research and evaluates the existing methods for resource consumption evaluation. material criticality and criticality assessment methods are introduced here. **Chapter 4** evaluates existing databases for LCA of data center and its equipment, and attempts closing gaps on data by presenting inventories of operational data centers, and on material content data gathered from laboratory analysis performed. Improvements to data quality are first assessed. **Chapter 5** presents an overview of EoL processes for data center components, review on industrial and experimental processes, and recovery potential. **Chapter 6** summarizes the architecture of the information system built to manage the information gathered and save and evaluate the results and the calculated models. **Chapter 7** gives an overview of the modelling and calculation, the scenarios and experiments performed, and the selection of the indicators for evaluation. The results are analyzed and evaluated accordingly, and aspects like interdependency of indicators, scenario results, and results data quality are evaluated. This dissertation concludes in **Chapter 8** with an overview of the most important results, and a reflection on scientific contributions, limitations, and future work.

On the right side of **Figure 1-2**, the chapters of this dissertation and their relationship with the steps of a LCA research study are detailed. The specification of these steps is deepened in **Chapter 2**. On the left side of **Figure 1-2** are the research questions formulated in **Section 1.3**, and the relation that the chapters have with these questions. The content formulated in **Chapters 3** and **7** allow evaluating the resource consumption indicators and their interdependencies. **Chapters 5** and **7** also allow evaluation of EoL scenarios. **Chapters 3**, **7** and **8** provide an outlook on data quality and on the improvements achieved during this research. **Chapter 6** has overlapping content with the objectives, as it is about the development of artifacts to facilitate and improve data management regarding life cycle inventories, material content, models, and results. Answers to the main research question are derived from the results evaluation and the conclusions in **Chapters 7** and **8**.

2. Theoretical Foundations

This section details the fundamental concepts on data centers, existing indicators to evaluate data center performance, and on LCA as a tool to evaluate the environmental impacts of processes and products, which are later used as methods to evaluate data center energy and material resource use. This has the goal of providing a better overview of the technological and scientific contexts to advance the development of the scientific tools and models to achieve the objectives of this dissertation. These foundations are used as basis for the development of indicators for assessment of material and energy demands for data center manufacturing, inventories for LCA of data centers at different stages of their lifecycle, and for the evaluation of results quality (**Figure 2-1**).

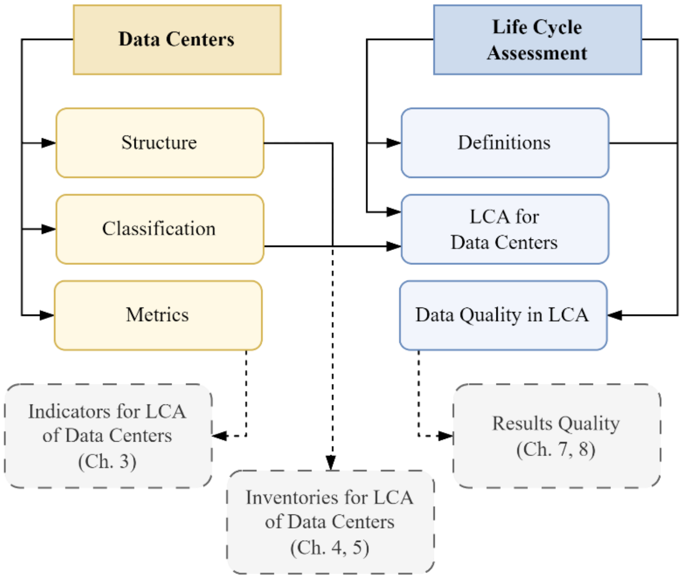


Figure 2-1: Conceptual development for the theoretical framework and linkage to other chapters.

2.1. Data centers

Data centers are the backbone of IT networks across the globe [CSD13]. A data center is space which houses the central data processing technology for an organization. Data centers contain IT equipment for the processing and storage of data, and for communications networks [Bro07]. Data centers house servers, networking, and storage equipment. It must consist at least of a room of its own with a secure electricity supply and climate control [Hi15, HF10]. Data Centers include the supporting infrastructures required to power and cool the IT equipment, plus the required infrastructure for safety and hosting of the devices. The computing capacities (server, storage, network) and the infrastructure for its operation (power supply, climatization, security) are centrally located [Re17a, Sc16, Ko08]. A more complete definition states that [ec08]:

> *"A data center is at least one independent, structurally separate room with simple air conditioning, a simple power supply, an UPS with a five-minute bridging time, fire detection and protection devices, access protection and stable network connection."*

Data centers may fulfill one of the different functions [Hi15, Wh14]:

- The physical housing of IT equipment, including servers, switches, routers, data storage devices, racks, and related equipment.
- The storage, management, processing, and exchange of digital data.
- The provision of application services or management for data processing, such as web hosting, internet, intranet, and telecommunication.

The size of the IT load capacity depends on the type and number of installed servers. This determines the energetic dimensioning of the supporting devices and the infrastructure required [Ja17].

2.2. Data center structure

A data center can be as simple as a single rack in a server closet or as complex as a large warehouse with floor area reaching 150 000 m^2, typically having built-in redundancy for the avoidance of downtime. Hardly any robust data and statistics on the structure of data centers is available [HC14]. Therefore, studies on the impacts of use of data centers usually focus on analyzing individual data or determining the total electricity consumption. Traditionally, the systems on a data center can be divided into IT, power supply, climatization, and additional infrastructure.

2.2.1. IT hardware for data centers

Under IT are the devices responsible for executing the data center operations and processing tasks. The applications and services run on servers[2]. There are various server types on the market, varying in terms of capacity, size, and energy requirements. In addition to the usual plug-in servers for racks (sizes given in units of height, e.g., 1U, 2U, 5U), there are also complete server cabinets (mainframes), or compact and exchangeable blade servers. This work considers diverse types of servers, their parts, and their inventory for analysis of material resource demand. Servers have the characteristic that their electrical power consumption is load sensitive. In addition, IT includes storage devices that consist of hard disk arrays for data storage and backups.

IT hardware also includes network devices such as switches and routers. These devices are usually also located in the racks in the IT rooms. The network devices are often static consumers, since they have the task of data transmission, which is not load sensitive [Sc16, Ja17].

[2] Server may also refer to a virtual server is executed in a virtual machine. Since this work focuses on analyzing physical infrastructure and their resource demands, the term server here refers to a physical server.

The individual rack always forms the basis for secure installation of the IT systems. [BI13] refers to these as server racks, network racks, or power supply and power distribution racks. Due to their standardized size, they offer possibilities for scalability of the IT infrastructure.

2.2.2. Power supply

The power supply architecture in data centers includes power distribution, sub-distribution, and infrastructure for emergency power supply and its redundancy. Newer architectures integrate uninterruptible power supply systems (UPS) devices into the racks or into the servers [Go12, Go10]. Transformers and power converters are required for the power supply. The medium voltage is transformed to 400 V in the transformer stations and routed to the data center via cables or bus bars via the low-voltage distribution board. The sub-distribution lines also supply the UPS with power [BI13].

Electricity suppliers are unable to guarantee an uninterrupted supply of electrical energy [BI13]. UPSs bridge the time until the emergency generator is active in the event of a power failure. The electricity required for this is usually temporarily stored in accumulators [Sc16]. UPSs also filter out disturbances, such as voltage surges or voltage dips, and bridge interruptions in the network. This reduces transmission errors, computer crashes and data loss. The energetic dimensioning of the UPS thus depends primarily on the devices to be supplied. Due to redundancy requirements for the data center, several UPS systems share the entire workload. This means that a single UPS system utilization normally lies beyond a certain limit. Typical levels of utilization are below 50%, which affects the operational efficiency.

There are two levels of emergency power supply for mains power failures: For short failures of a maximum of a few minutes, battery units are kept available, which are switched on by UPS units. In the event of longer failures, emergency power systems must be used. In data centers, these are usually large diesel generators located outside of the actual data center complex and can be started up in less than a minute [Go12]. They enable further data center operation, sometimes from several hours to a few days.

UPS systems use various technologies. The most used is that of the static UPS. Rechargeable batteries store electric energy. In the event of a power failure, a static converter (inverter) makes the storage energy available at the output of the UPS system. Typical bridging times are in the range of 10 to 30 min. Electrochemical storage used in conjunction with UPS systems include lead-acid and nickel-cadmium batteries. The use of lithium-ion batteries has not yet established itself [BI13]. The air conditioning is supplied by the emergency power generator in the event of a power failure. Until the emergency power generator starts, air conditioning is provided exclusively by the server fans. **Figure 2-2** provides an overview of the energy flows in a data center, with the power supply system included.

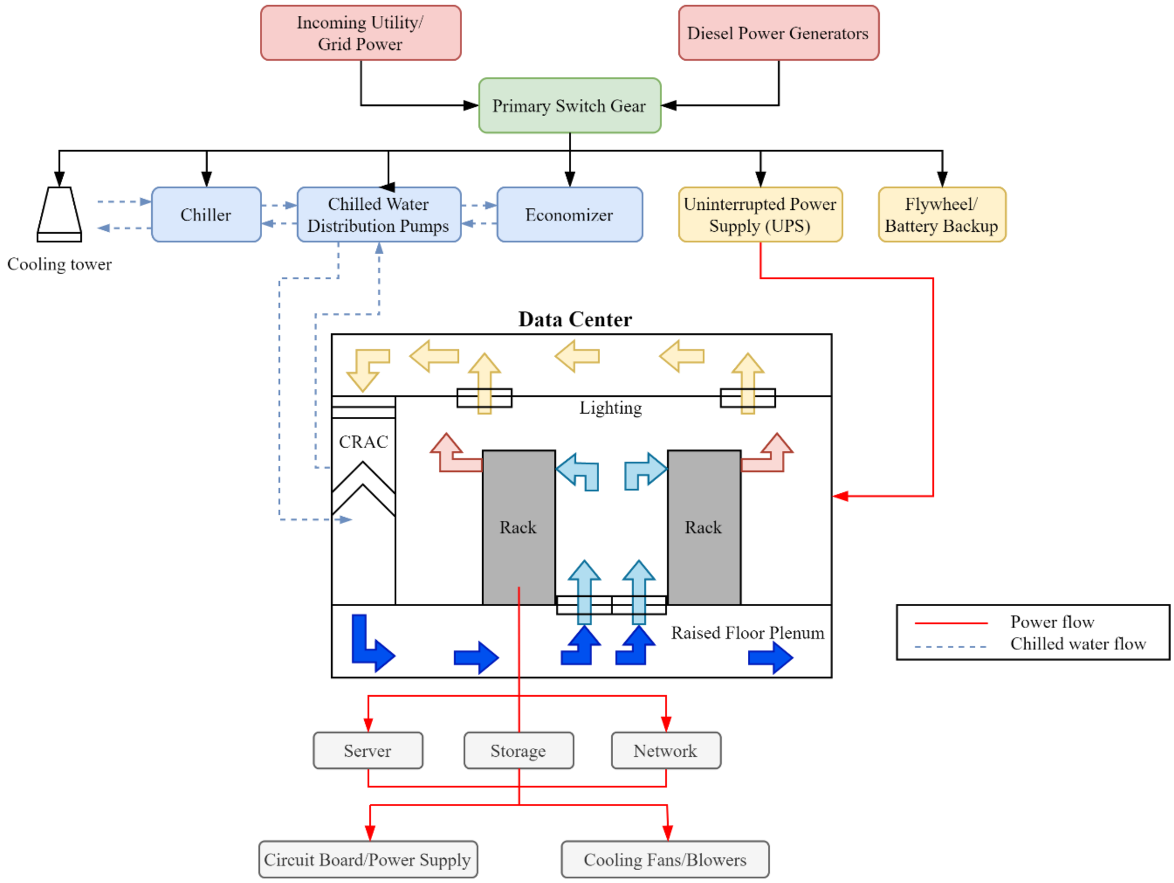


Figure 2-2: Energy flows in a data center. Source: Adapted from [DWF16, JK12].

2.2.3. Climatization

Data centers use cooling and air conditioning to dissipate the waste heat produced from the operation of the IT devices. The air conditioning of IT systems is an essential criterion for their availability and operational reliability [BI13]. The increasing heat density in IT rooms makes this task challenging [HPF08, PBB03]. Typical power densities can vary between 0.5-11 kW/m^2, with the higher values associated to the latest IT technologies [Gl21, Ra05]. Since the energy input of the servers is dissipated as heat and must be transported away to maintain the temperatures stable, the cooling must be adjusted accordingly. Circulating air conditioning systems differ significantly in terms of their structure and the system to be used must consider the expected heat loads, the climatic outside conditions, and the structural possibilities of the IT room.

In larger data centers, a central air conditioning chain supplies cold air in the IT rooms through circulating air-cooling devices (Figure 2-3). This cools down the warm air generated by the waste heat from the servers in the IT room using heat exchangers and cooling water. A central water chiller or free cooling unit provide the energy required to cool down the thermal fluid, often cooling water. [Li12]. Pumps transport the cooling water from the chiller to the IT rooms. The cooling fluid (usually a water-glycol mixture) leaves the chiller at the set cold temperature. The coolant heats up after passing through air-liquid heat exchangers, which transfer the energy contained in the air and previously dissipated by the IT equipment to the circulating cool fluid.

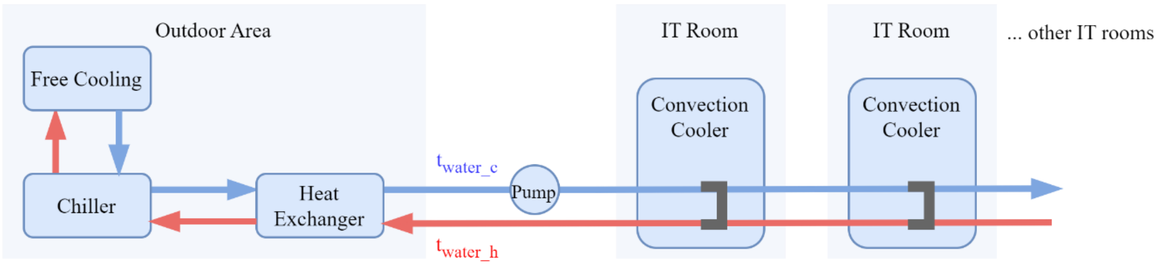


Figure 2-3: Air conditioning chain in a Data Center. Source: Adapted from [Ja17].

Compression chillers are usually used in data centers [Pe09], which compress a gas and then expand it within a heat exchanger. Free cooling can be used in data center locations where the outdoor temperature is often relatively low during the year. Efficient air conditioning systems reduce the operating times of the cooling generation to a minimum using free cooling. There are two different options [PBB03]:

- Direct use of external air as cold air in the IT room when the external temperature is below the temperature required for the operation of the IT equipment [Zh12]. This requires air filtering and humidity control [PBB03].
- Use of external air to cool down the coolant (chilled water): This common method maintains the indoor air climate. A free cooling unit for the water (usually a cooling tower) is used instead of by the chillers.

Other functions of the air conditioning systems are filtering, reheating, humidifying, and dehumidifying.

2.2.4. Additional infrastructure

Several installations are required to guarantee the safe functioning of a data center. Complementary services, such as lightning, security, and fire protection services are required.

Reliable and effective fire protection is an indispensable prerequisite for the safe operation of the data center. For security purposes, fire detection and extinguishing technology is necessary. This includes smoke detectors, which mostly use the scattered light principle. For fire protection, an oxygen-poor atmosphere is recommended to have an inert atmosphere in which fire is unlikely to occur. Means which use fluids are considered dangerous. Other means include extinguishing systems with gaseous extinguishing agents.

Although the building may also be considered part of the infrastructure, for most analysis the impacts of the construction of civil facilities are often set aside, as their long-term impacts are negligible in comparison. The housing of data center systems may be included, if not already shared by the organization infrastructure. Regenerative architecture (e.g., vegetated roof, water management practices, etc.) may be included if they are part of an energy management plan that includes the data center operation [ABD12].

2.3. Types of data centers

Given the previous description in Section 2.2 regarding the composition of data centers, it comes as a result that configurations may vary widely from one system to another. Data centers are each planned and built individually for the specific operator and the required applications. They are subject to constant further development due to rapid technological development. Each data center is therefore unique.

There is no uniform system for classification or taxonomy of data centers, either nationally or worldwide. Criteria for classification of data centers may include superficial area, number of racks, number of servers, number of processors, IT power, annual energy consumption, operation capacity, etc. Additionally, operative characteristics may be used, such as application, location, availability. Four categories are presented here.

2.3.1. Classification by size

Size is used for classification for statistical purposes. These typologies have mainly been used to make statements about the energy consumption of data centers [BSB08]. [Ba07] provided a first example of this categorization, with rather vague statements on IT and infrastructure equipment. [HF10] expanded on these criteria to build a classification system appropriate to the German market (**Table 2-1**).

Table 2-1: Classification of Data Centers by Type. Sources: [Hi22, HF10]

Data Center Type	N° of Servers	Average N° of Servers	IT Power (kW)	Area (m2)	Number of DC in Germany (2013)	Yearly growth
Server Cabin	3-10	4,8	1,5	5	30500	-8%
Server Room	11-100	19	6	20	18100	0%
Small DC	105-450	150	50	150	2150	+23%
Medium DC	450-5000	600	240	600	280	+27%
Big DC	>5000	6000	2500	6000	70	+40%

This approach is based on the number of servers in the data centers. The average connected load of the IT and the size of the data center are given also as classification criteria. This approach benefits from its simplicity, and on the availability of market data [HF12]. This typology is based on the inventory of IT material and provides a base for extrapolation. The types selected are comparable with other approaches and studies: [Hi23] estimates that for Germany, there are more than 3 000 data centers with more than 40 kW of IT load, and around 50 000 smaller data centers for 2022 (**Figure 2-4**).

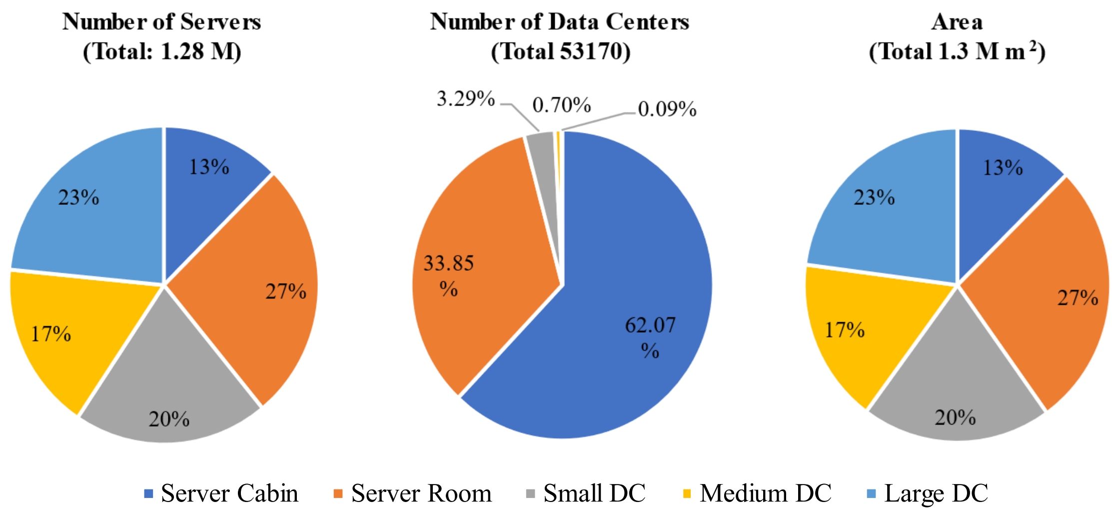


Figure 2-4: Proportion of servers by category according to their size. Source: Data from [HC14, Hi23].

2.3.2. Classification by availability

Availability refers to the probability that a system can be used as planned at a given time. The demand for continuous data center availability for organizations is increasing rapidly, with outages of merely minutes being undesired. The availability has a direct impact on the composition of a data center. Redundancies in the air conditioning and power supply, double feeds and uninterrupted maintenance of the systems are the standard for highly available IT infrastructures.

Several authors define different degrees of availability of data centers [Tu06, In10, BI09]. In most cases, these typologies are based on the maximum permissible downtime of a data center. **Table 2-2** presents a Tier classification based on availability.

Table 2-2: Tier Classification of Data Centers by Availability. Source: Data from [Tu06, HF10, BI13].

Category	Availability	Downtime per year	Description
Tier I	99.671%	28h	simple power supply path, simple cooling supply, no redundant components
Tier II	99.741%	22h	simple power supply path, simple cooling supply, redundant components
Tier III	99.982%	1h30	multiple paths available, but only one active, redundant components Maintenance possible without interruption,
Tier IV	99.995%	0h26	multiple active power & chilled water distribution paths, redundant components fault tolerant

2.3.3. Classification by purpose

Data Centers can also be typologized regarding their application. This can be, for example, the type of application or the underlying business model. [ec08] classifies the data centers as multi-purpose or single business purpose (**Figure 2-5**).

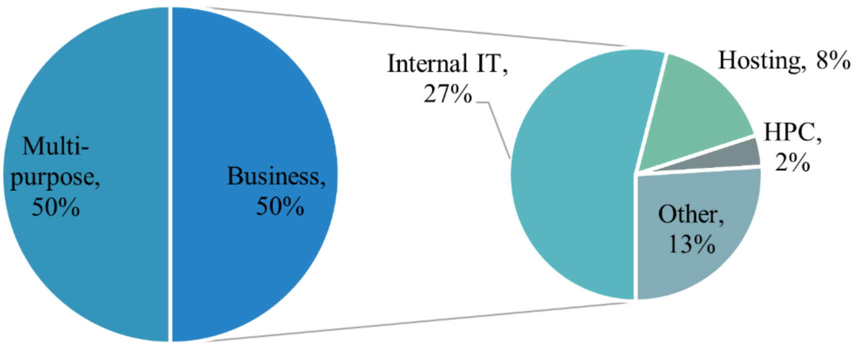


Figure 2-5: Typology of Data Centers by Purpose. Source: Data from [ec08].

2.3.4. Classification by type of operator:

Data center and equipment suppliers often describe clients in terms of the type of operator. This can be, for example, the industry (banking, automotive, telecommunications, research) or the distinction between authorities and companies. This is because the requirements, applications, and legal and other framework conditions for data centers with similar operators are often similar.

2.3.5. Categorization of data centers applied to LCA

The categorization according to size allows an easier typology, which agrees with the objectives of this dissertation. The evaluation of material resources goes in hand with the inventory of a data center, which can be coupled with its dimensioning. This typology is also geared towards the servers. Due to the high proportion of electronics in a data center, it can be expected that IT equipment will present the greatest environmental relevance in terms of resource consumption. This categorization can also help to provide an overview of the complete material availability in data centers. It is also useful for comparing the primary energy consumption to the operational energy consumption [HF10]. Availability also refers to the infrastructure of the data centers, and it is useful to define inventories based on their classification.

Classification by purpose or by type of operator of data centers is unsuited for the present study because it has no direct relation to the material used or the embedded energy consumed for manufacturing. It focuses very strongly on the information technology used and on the software level and ignores the existing infrastructure in the data center.

2.4. Metrics for evaluation of data center performance

An efficient and eco-friendly operation of data centers requires monitoring of all their components. By applying specific oriented metrics and making accurate measurements, it is possible to better utilize data center infrastructure and reduce the recurring costs of IT and facility management [Re17a]. Most of the metrics developed refer to individual systems in the data center, such as the cooling, power supply, servers, or the type of energy use. Various systems can be aggregated in groups to provide metrics of the data center infrastructure. These key figures are often unsuited to provide overall assessment of the energy efficiency of data centers [HH18]. Another group of metrics has the purpose of defining a performance measure for the IT of a data center. These metrics consider a defined output unit and are suitable to evaluate the overall efficiency of a data center.

[Re17a] presented an analysis of metrics that are commonly used in data centers, from the power grid up to the service delivery. This work identifies various metrics relating to a data center and presents a classification based on the different core dimensions of data center operations. Based on this taxonomy schema, the following dimensions are here considered as core: a) Efficiency (Energy Efficiency and Greenness), b) Air Conditioning (Thermal Management and Cooling), c) Performance (Operation, Network, Storage, Security), and d) Financial Impact. The infrastructure of a data center is considered as background **(Figure 2-6**), with the possible subdivisions regarding the system that these represent (Section 2.2). **Figure 2-7** presents a visualization of the taxonomy of the metrics used to evaluate data center operation. Annex A details the acronyms used.

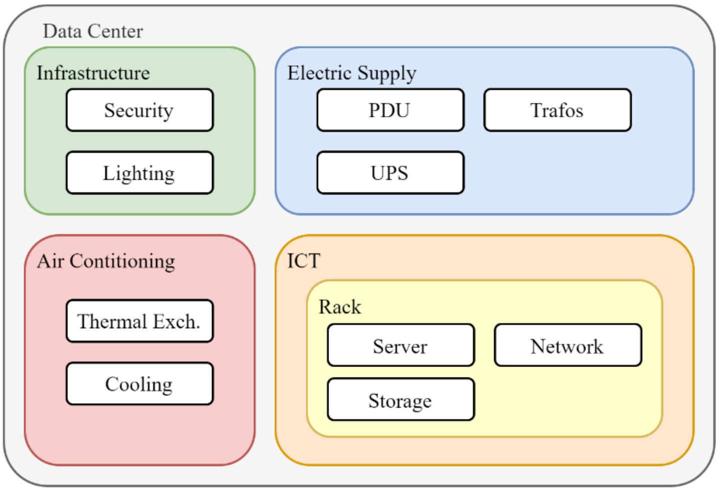


Figure 2-6: Topology of a Data Center for Classification of KPIs.

2.4.1. Energy efficiency metrics

The energy efficiency of a system is defined as the ratio of useful work done by a system to the total energy delivered to the system. For data centers, the energy efficiency translates into the useful work performed by different subsystems [Re17a]. A variety of different Key Performance Indicators have been developed [Da09, EDP13, Li09, SCI05, Az11, WK13, DDW12, St15]. Even if many of these key figures consider the energy requirements of IT, few key figures pursue the approach to put the performance of IT in a relationship to the energy requirement [HH18].

The most popular energy efficiency metric, PUE, relates the amount of power used by IT devices to the total energy consumed by the facility [Av12]. The Data Center Infrastructure Efficiency (DCiE) is the inverse of PUE [Av12]. Server Power Usage Efficiency [Wi14] and Partial PUE [Av12] metrics are based on the same principles as the PUE metric. The Data Center Performance per Energy [Grn12] metric is a combination of four other metrics: DCiE, Green Energy Coefficient (GEC), IT Equipment Energy (ITEE), and IT Equipment Utilization (ITEU). PUE and DCiE help operators know the efficiency of the data center, where partial PUE measures the energy efficiency of a zone in a data center [Re17a].

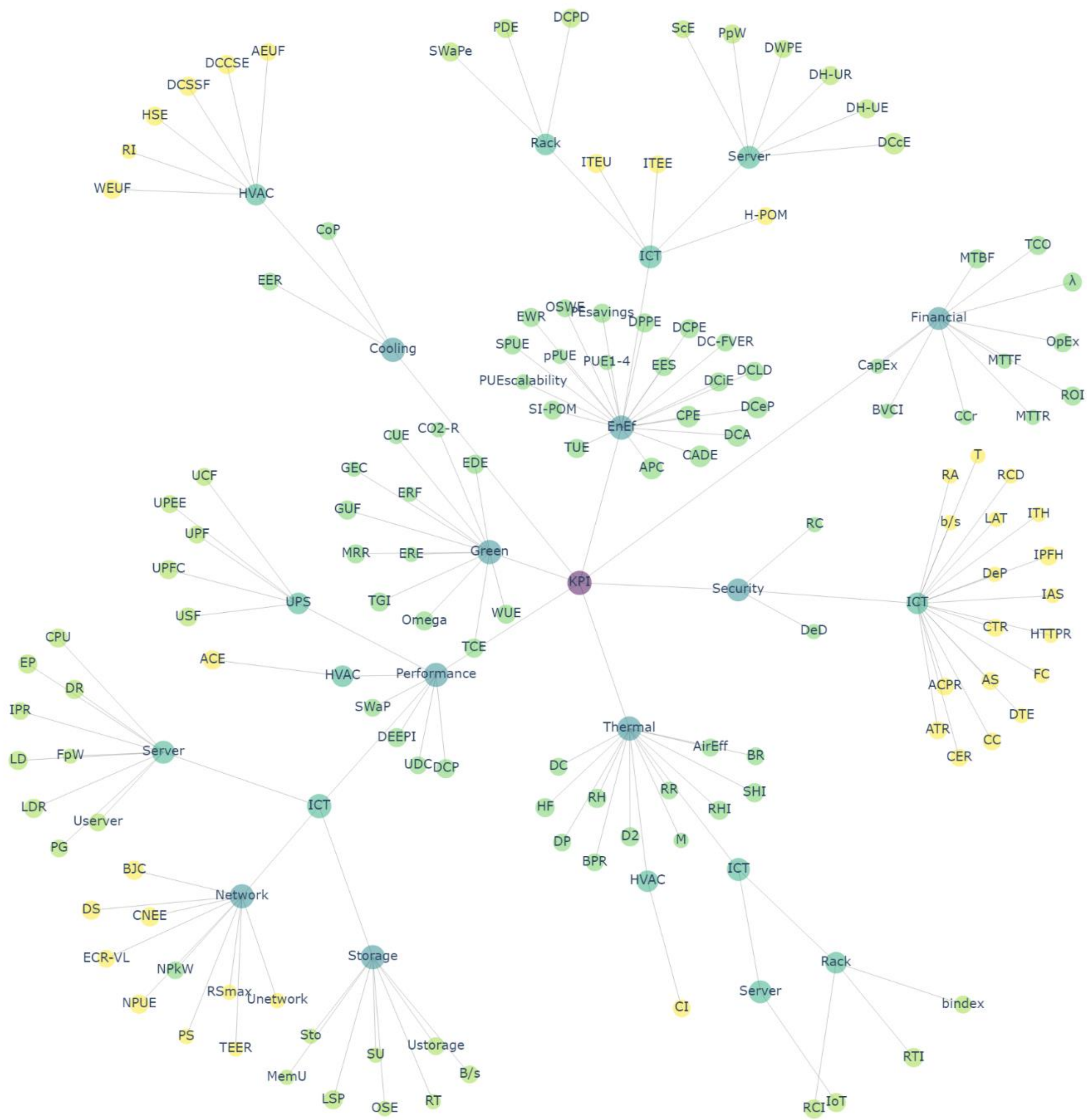


Figure 2-7: Taxonomy of Data Center Metrics. Source: Data from [Re17a]. Acronyms are detailed in **Annex 1**.

2.4.2. Green metrics

The carbon footprint has become subject to governmental regulations and taxes. As a result, the "greenness" of a data center is becoming increasingly important. "Greenness" mostly refers to a subjective categorization related to low greenhouse emission during operation. Green IT benefits the environment by improving energy efficiency, lowering greenhouse gas emissions, using renewable resources, and by encouraging reuse and recycling [Mu08]. Green metrics measure the environmental impact of a data center and its components [Re17a]. These can be used to decrease the environmental impact of data centers.

Metrics such as Carbon Usage Effectiveness (CUE) [Az10], Water Usage Effectiveness (WUE) [ABP11], and Electronics Disposal Efficiency (EDE) [Ba12], measure the CO2 footprint, the water consumption per year, and the disposal efficiency of the data centers, respectively [Re17a].

2.4.3. Thermal management metrics

Thermal and air management metrics measure environmental conditions of the data center. These metrics are based on the relationship between air flow rate and ambient temperature. Measurements like temperature (T), relative humidity (RH), dew point (DP) and heat flux are used to prevent the over-heating, maintain the humidity levels, or assess the cooling system [SS11]. Air management metrics address air flow efficiency and separation of hot and cold air streams [Re17a].

2.4.4. Cooling metrics

The complex interconnection of heat, ventilation, and air conditioning (HVAC) systems ensures optimal conditions for the computing environment in a data center, guaranteeing the life span, scalability, and flexibility of the servers [KK15]. Cooling metrics are related to the efficiency of the cooling devices (such as the Coefficient of Performance, COP) [PP09], or of the whole infrastructure, such as Data Center Cooling System Efficiency (DCCSE) [Ma09].

2.4.5. Performance Metrics

The performance of a data center is the total effectiveness of the system, including throughput, response time, and availability [WK13]. Measuring performance and productivity is crucial as sub-optimal performance has operational and financial implications for a data center [Re17a]. Different metrics consider the outputs of the data center as a functional unit that fits the purpose of the data center. Indicators such as the Data Center Energy Efficiency and Productivity Index (DEEPI) [Br07] and the Flops per Watt (flops/W) [BC10] directly relate output to direct energy consumption. These metrics can also include subsections such as Network, Storage, and Security (**Figure 2-6**).

2.4.6. Financial impact metrics

Most of the organizations depend on non-financial, operational metrics except in setting up budgets and measuring the projects [AP09]. Employing financial metrics can enable the operators to put other key metrics such as outage reports and service quality metrics in a financial perspective. Metrics such as

Total Cost of Ownership (TCO) [Ra11], Capital expenditure (CapEx) and Operational expenditure (OpEx) keep tracks of the financial impacts of a Data Center [Re17a].

2.4.7. Applicability of data center metrics to this study

There is no single metric to cover all dimensions of the operation of a data center. Mapping the different indicators according to their category allows an overview of their relations and of the area they cover. While many differ on the inputs, these indicators separately can serve to define operational goals and as benchmarks with other data centers. Some of these metrics also require seasonal benchmarking to capture region and season changes. Green metrics are also dependent energy sources [Re17a].

Regarding performance metrics, "useful computing work" is not defined uniquely. [HH18] presented a metric which considers environmental impacts based on server tasks and uses the CO_2 footprint of energy used. Financial metrics are difficult to present as benchmarks since confidentiality concerns associated with revealing costs for a particular facility limit openness. Carbon Credits used for carbon trading may vary based on local governmental policies, requiring more disclosure.

While most of these indicators consider energy inputs, only a few consider related environmental impacts of energy use, and none considers the impacts of production of the devices related to data center. Impacts on material consumption are overlooked, and they focus on the operational energy use. Moreover, energy consumption data disaggregated by data center sub-components may not be available, so a granular comparison is often not possible.

2.5. Life Cycle Assessment

Life Cycle Assessment (LCA) is a structured, comprehensive, and internationally standardized method. It quantifies all relevant emissions and resources consumed and the related environmental and health impacts associated with any goods or services. LCA is a systematic and iterative process [EC10]. The [ISO14040] and [ISO14044] standards provide the indispensable framework for LCA. [EC10], in their publication "*International Reference Life Cycle Data System (ILCD) Handbook*", provides a common basis for consistent, robust, and quality-assured LCA. LCA is the scientific approach behind modern environmental policies and business decision support related to Sustainable Consumption and Production (SCP) [EC10]. The main aim of LCA is to reduce the environmental impact of products through guiding the decision making process towards more sustainable solutions [Me11].

A life cycle approach enables product designers, service providers, government agents, and individuals to make choices for the longer term [va13]. LCA provides a framework for micro-level decision support, answering questions related to specific products of an organization; and meso/macro-level decision support, which is support at a strategic level, e.g., raw materials strategies, technology scenarios, policy options, amongst others [EC10].

LCA considers a product's full life cycle: from the extraction of resources, through production, use, and recycling, up to the disposal of remaining waste (**Figure 2-8**). The boundary of analysis is typically from cradle to grave, considering extraction, production, distribution, consumption and disposal [Re17c].It is based on physical metrics of material and energy flows during the life cycle of a product or service system [Re04, ISO14040]. LCA thereby helps to avoid resolving one environmental problem while creating others. LCA is always structured around a functional unit that defines what is examined [va13]. Due to its systemic approach, the methodology is considered suitable to provide a valuable support in integrating sustainability of resources into design, innovation and evaluation of products and services [KSB14, SFZ13].

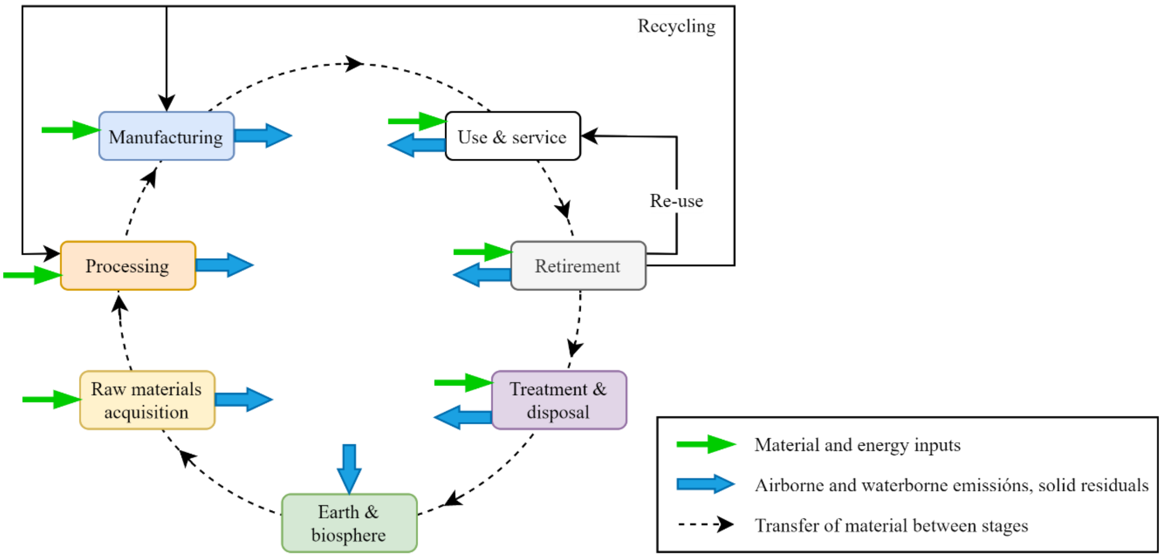


Figure 2-8: Phases considering during a Life Cycle Analysis. Source: Modified from [NJR07]

[ISO14040] standardized the methodology into a framework of four interdependent phases: Goal and Scope Definition, Life Cycle Inventory (LCI), Life Cycle Impact Assessment (LCIA), and Interpretation. [EC10] separates Goal and Scope Definition in two separate phases (**Figure 2-9**). The most critical phase in an LCA study is the LCIA, where the inventory results of a system are transformed into understandable impact categories that represent the impact on the environment [Me11].

2.5.1. Goal Definition

During the goal definition the decision-context and intended application of the study are identified and the targeted audience are to be named. This guides all the detailed aspects of the scope definition, which in turn sets the frame for the LCI work and LCIA work. The quality control of the work is performed in view of the requirements derived from the goal. The interpretation is in close relation to the goal.

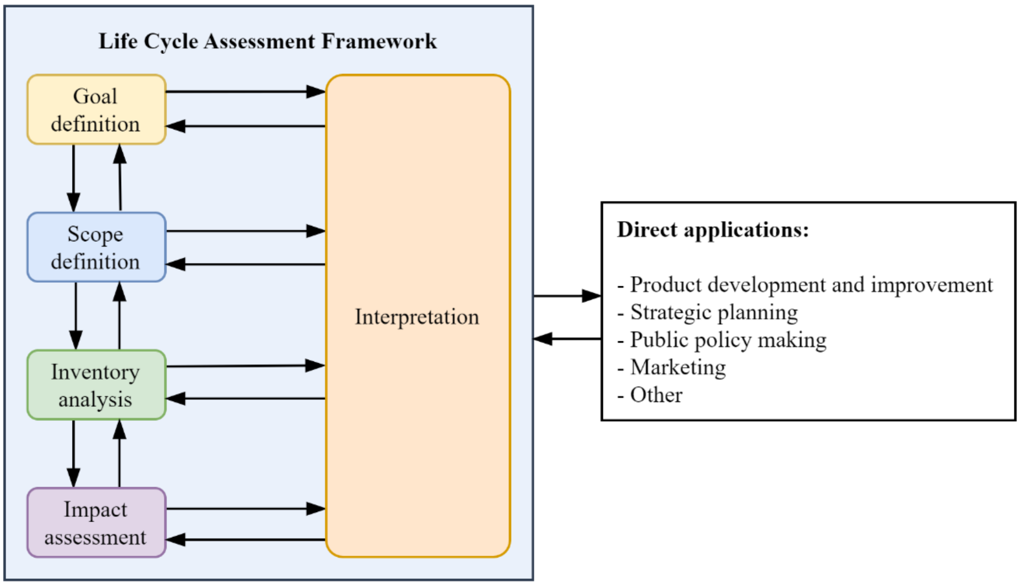


Figure 2-9: Framework for Life Cycle Assessment. Source: Modified from [EC10].

Goal definition shall consider intended application, limitations, reasons for carrying out the study, target audience for the results, publication strategies, and stakeholders [EC10].

2.5.2. Scope definition

In the scope definition it is decided what to analyze and how. The object of the LCA study is identified and defined. This shall be done in line with the goal. A main part is to derive the requirements on methodology, quality, reporting, and review in accordance with the goal [EC10]. Main types and sources of data and other information should be identified. Normalization data and weighting factors may be required but may hinder the transparency of the study.

The derivation of the scope of an LCA study from the goal includes: defining the types of the deliverable; the system or process studied and its function; functional units and reference flows; modelling framework; system boundaries, completeness requirements and cut-off rules; impact categories to be covered and selection of specific LCIA methods to be applied; types, quality and sources of required data and information; and planning reporting of the results [EC10].

The functional unit indicates the quantity of the product under consideration in the LCA. The quantitative definition of a product's functional unit should refer to technical standards wherever possible [Re17c].

2.5.3. Life Cycle Inventory

The inventory phase involves the collection of the required data and modelling of the system [EC10]. This is to be done in line with the goal definition and meeting the requirements derived in the scope.

Types of required data comprise inventory information, statistical data, technical process and system information, market information, allocation-related information, and legal and other boundary conditions. For process based LCA, the flow of materials and energy inputs and outputs is also involved.

Typically, the Life Cycle Inventory (LCI) phase requires the highest efforts and resources of an LCA for data collection, acquisition, and modelling. Some missing data may be present. For all processes that have been identified, the inventory data must be collected. Additional measurements, third party data, or use of proxy data may be employed here. The quality requirements on inventory data can only be identified after the first rough model of the life cycle has been established. It is then revised in context of the iterative improvement of the inventory [EC10].

Unit process data are at the basis of all LCI work. This produces data for input and outputs of separated processes, which combined represent the entire system. The specific kind of life cycle inventory include:

- Identifying the processes of the system within its boundaries
- Planning, collection, and averaging of the background and foreground data, generic and complementary data. Here databases can be used for background data, and process measurement as foreground data.
- Modelling the system in a framework by connecting and scaling the data sets, and by connecting the system to the functional unit (**Figure 2-10**).
- Calculating LCI results, i.e., summing up all material and energy inputs and outputs of all processes within the system boundaries. If entirely modelled, only the reference flow (main output) and elementary flows (inputs from nature) remain in the inventory.

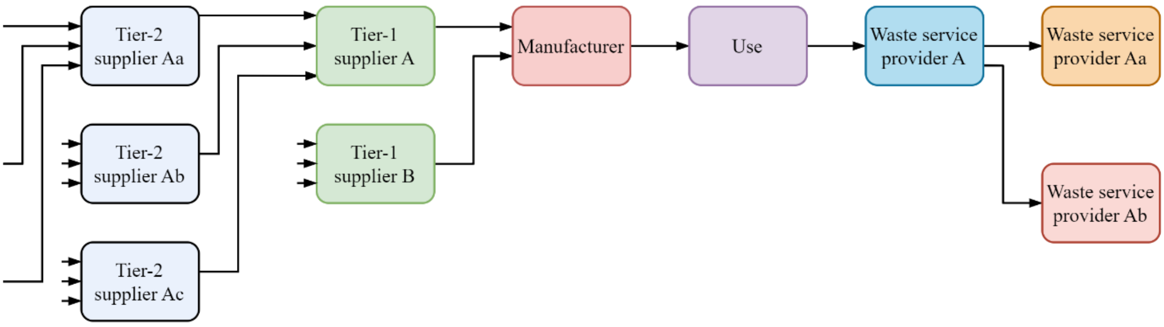


Figure 2-10: Simplified supply chain life cycle model of a Product. Source: Modified from [EC10].

The LCI results are the input to the subsequent LCIA phase. The results of the LCI work also provide feedback to the scope phase as initial scope settings often need adjustments. The quality of the LCI depends on the data quality. Data quality is composed of accuracy, precision, with technological, geographical, and time-related representativeness, and with the completeness of the inventory. All of these contribute to the overall quality and typically the weakest of them determines the overall data quality. On a system's level, the inventory data must be representative of the processes, which actually relate to the life cycle of the system [EC10]. For specific unit process data measurements at the operated processes are the as preferred option.

2.5.4. Life Cycle Impact Assessment

The inputs and outputs of elementary flows that collected and reported in the inventory are translated into potential environmental impact indicator results related to human health, natural environment, and resource depletion. The results of LCIA are considered impact potential indicators. LCIA is composed of several steps:

- Based on classification and characterization of the individual elementary flows, the LCIA results are calculated by multiplying the individual inventory data of the LCI results with the characterization factors. These are found in literature or from other scientific sources.
- LCIA results can then be multiplied with normalization factors to obtain dimensionless, normalized LCIA results. The selection of impact categories and normalization and weighting sets shall be consistent with the goal of the LCA study.
- The LCIA results can be multiplied by weighting factors, that indicate the different relevance that the different impact categories (midpoint level related weighting) or areas-of-protection (endpoint level related weighting) may have, obtaining normalized and weighted LCIA results [EC10].

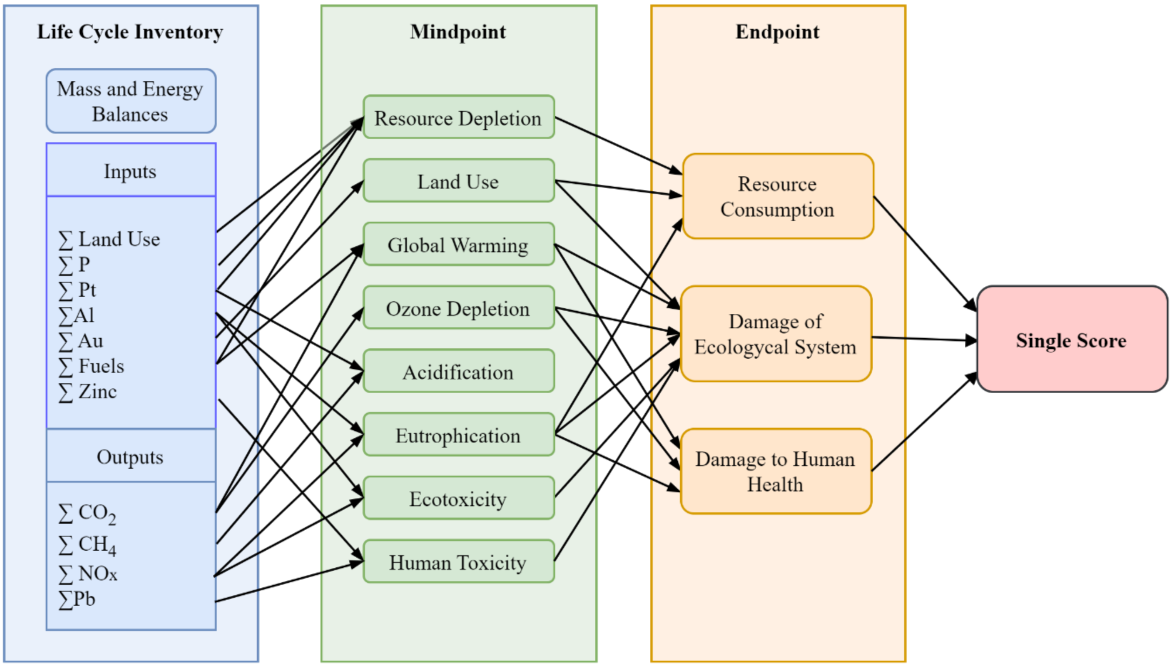


Figure 2-11: Life cycle impact assessment. Schematic steps from inventory to category endpoints. Source: Modified from [EC10]

2.5.5. Interpretation

The interpretation phase of an LCA has two main purposes: to self-improve the Life Cycle Inventory to meet the needs derived from the study goal; and to communicate results to the intended audience through reporting. The interpretation phase serves then to derive robust conclusions and often recommendations.

Criteria for analysis and interpretation include accuracy, completeness and precision of the applied data, and evaluation of the assumptions made throughout. The LCIA results are appraised to answer questions posed in the goal definition. The interpretation relates to the intended applications of the study and is used to develop recommendations.

Reporting needs to consider and address the needs of different audiences when presenting or disseminating the study. Target audiences can be internal, (defined) external, or public, and technical or non-technical. Good reporting of LCA studies provides the relevant project details, the process followed, approaches and methods applied, and results produced. This is essential to ensure reproducibility of the results and to provide the required information to reviewers to judge the quality of the results and appropriateness of conclusions and recommendations.

2.5.6. Applicability of LCA to the case of data centers

The [ISO14040] and [ISO14044] standards provide the indispensable framework for LCA. This framework, however, leaves a range of choices, which can affect the legitimacy of the results of an LCA study [EC10]. When assessing data centers, the current state of LCA methodologies, the lack of applicable primary and secondary data for assessing data center components and systems, and the complexity of the data center create serious difficulties in performing a data center LCA. Currently, there is no LCA methodology developed specifically for data centers. There is a variety of software, database, and secondary data tools available with which to perform an LCA, and the methodology which best suits the study requirements is to be used [ABD12]. In the following chapters, the work focuses on gathering information to construct databases for inventories of data centers and their components, and to evaluate the current alternatives for End-of-Life and the technologies available for recovering of materials that help to improve the material and primary energy efficiency of the lifecycle.

2.6. Key aspects for LCA in data centers

This section summarizes a framework for identifying and describing the elements necessary to assess a data center’s complete life cycle. This focuses on defining applicable assessment boundaries and environmental concerns. By using a comprehensive approach that encompasses the data center’s supply chain, the impacts and the consequences of changes in the process can be assessed [ABD12].

Several organizations have published their methodologies for LCA applied to data centers. [SD13] and [ISO14067] focus on GHG but are not specific to data centers. [EC10a] and [ET11] consider a data center as part of an IT network. [Ha09] focuses on data centers but with emphasis on the energy management of the use phase and on metrics for sustainability. [IC13] focuses on a data center's energy management system with a consideration of life cycle impacts, focused on best practices for a "green" data center. [Wh12] provided a methodology based on screening of inventories. [Ma09] presented an LCA-based approach to estimate the sustainability impact of equipment in terms of its lifetime exergy (available energy) consumption. This approach divides the life cycle into two phases: embedded phase, involving impacts related to product design decisions (material extraction, manufacturing and supply chain impacts, and end-of-life); and operational phase, including impacts related to decisions during product use (operation and maintenance). Following is a summary of the LCA Framework applied to data centers, as per Section 2.5.

2.6.1. Goal definition

The goal of this dissertation is to evaluate the resource depletion and the primary energy demand for the lifecycle of a data center. Since the focus is on critical material depletion, the study is framed around the embedded phase and the EoL of a data center and its components. This study is to be presented as part of the ongoing research on material criticality and resource depletion, hence the target audience is policy makers and researchers within the area. This study advances the work done in resource depletion assessment and on potentials of urban mining from high grade electronics.

This study is categorized as a stand-alone LCA [BT04]. This is used to describe a specific product in an exploratory way to get acquainted with the product's environmental performance.

Results are to be peer-reviewed as part of the publication strategies for this dissertation. This includes workshops, conferences, and scientific journals. **Annex 2** presents a complete list of the related publications by the author. Additionally, databases developed are to be included as Life Cycle Inventories for replication. Complementary, an information system based on the information gathered, calculation methodologies applied for the obtainment of results, and on the evaluation and visualization of said results is to be developed as a tool for modelling and results data analysis.

2.6.2. Data center scope definition

When considering the scope of the assessment of a data center, the distinct phases on the lifecycle need to be considered. Additionally, for the establishment of a reference unit, the output of the data center, being it a service, computations, or the operation of the data center itself, can be considered for this quantification. **Figure 2-12** presents an extended view of the production system of an IT system, such as a data center. This also considers the software development portion. For the intended application, the study focuses on the development of hardware and its decommissioning. Considered stages on the lifecycle are:

- **Manufacturing and Construction:** manufacturing of IT and facilities equipment; construction of power, telecommunications, and transportation infrastructure for supporting the data center.
- **Transport:** to site and onsite transport of materials for data center equipment manufacturing; transportation of the equipment
- **Operation:** use and operation of the data center, equipment, and structure.
- **Equipment upgrade:** maintenance of equipment and structure, including upgrade and addition of equipment.
- **End-of-Life:** reprovisioning processes including decommissioning, reuse, redeployment, dismantling for parts, recycling, and final disposal.

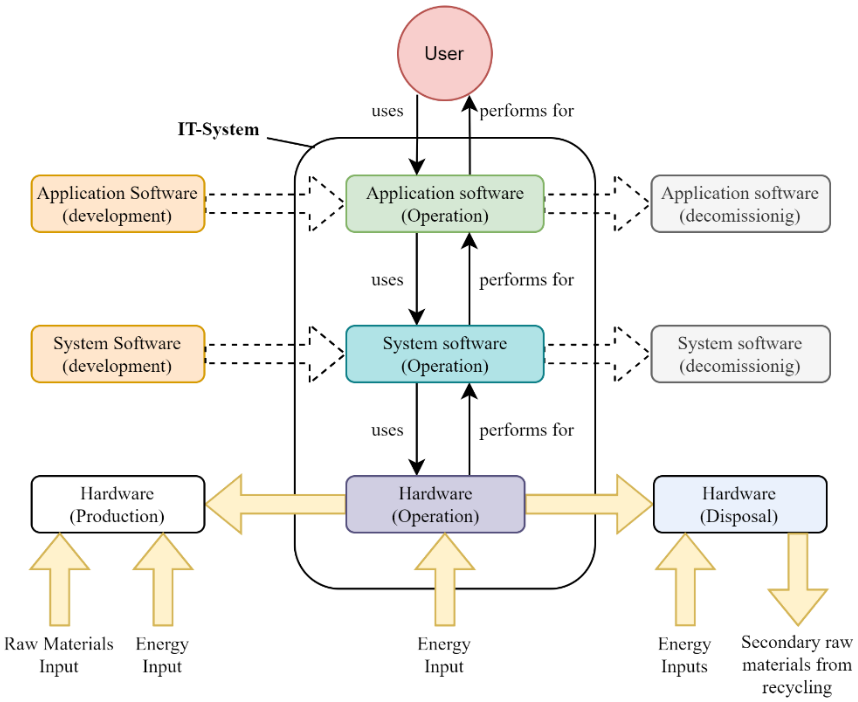


Figure 2-12: Simplified representation of an IT production system. Source: Modified from [HH18, Hil15].

Outside the boundaries of a data center are impacts caused by employee-related activities; impacts caused by non-data center usage of the building; grid-level electricity generation and distribution, IT commodity systems; telecommunication equipment and systems connecting the data center to the rest of the world, including satellites, submarine cables, etc. [ABD12].

The functional unit contributes by defining the scope of the system that will be evaluated by the LCA methodology and quantifying the service delivered by the data center system. All data (inputs and outputs of the system) should be linked to the functional unit that is defined in the scope of the data center LCA [ABD12]. An example of a functional unit can be the operation of a data center in a period of a year (in units of $kW_{IT} \cdot a$), or the whole lifecycle of the data center.

2.6.3. Data center Life Cycle Inventory

There is a limited quantity of primary or secondary data available on the equipment and systems used in a data center. An effective life cycle assessment is based on accurate data and considers the product category rules, which is a set of specific rules, requirements, and guidelines for developing environmental declarations [ABD12].

As part of a data center, all the facilities and infrastructures for power distribution and environmental control together with the necessary levels of resilience and security required to provide the desired service availability are considered. Power generation and delivery systems (UPS, transformers, switch gear, backup generators, power distribution units, batteries, power cables), IT equipment (servers, storage equipment, monitors, switches, routers, racks, network cables) and cooling system (chillers, air conditioning units, heat exchangers pumps, cooling towers) are to be included in the analysis. Equipment with impact contribution lower than 2% can be neglected in subsequent iterations.

Currently, there is no effective methodology by which equipment lifetimes can be factored or distributed across an LCA analysis, and current standards and assessment methodologies are silent on how to compare impacts and attributes with different periods. Although the benefits are not typically quantifiable, the use of more robust and upgradable equipment will reduce the overall impact of the data center [ABD12]. For IT components, the average lifetime lies between 3 to 5 years, with high end servers extending it to 8 years. Power supply equipment and air conditioning equipment have lifetimes of 20 years, with batteries needing replacement every 5 years.

The current state of LCA methodologies and the lack of reliable primary and secondary data for the complex equipment and systems used in a data center will require several iterations to introduce a significant degree of uncertainty and approximation into any final results [ABD12]. Data sources are limited, and the data must be extracted from various sources to construct a complete model of the data center. The preferred hierarchy of data is:

- **Primary data:** collected data that is directly measured or calculated.
- **Secondary data**: data derived from other sources such as literature or databases.
- **Proxy data:** primary or secondary data related to an input, process, or activity that is similar (but not representative) to the one in the inventory, which can be used in lieu of representative data if unavailable.

Most LCA of raw material gathering and metal production processes do not consider the mining and mineral processing stages in any detail, largely due to a lack of publicly available data [HN15]. Since this is the focus of this dissertation, this data needs to be updated or filled. This produces high uncertainties in the resulting impacts. As an example, studies on IT equipment have shown uncertainties of 20% to 30% in estimates of emissions impacts on a single, high-volume server system [ABD12]. Updating of the databases for raw material gathering and their results is shown in Chapter 7.

2.6.4. Life Cycle Impact Assessment

The environmental impacts under consideration must be clearly defined, in accordance with the goals of the study. The LCIA can be disaggregated into the data center life cycle stages. There is no standardized list of impact categories, so the choice of impacts needs to agree with the scope, in this case critical resource depletion [ABD12]. Midpoint indicators [Gu06] and endpoint indicators [Go99] are commonly used for reporting. Chapter 3 covers an analysis of the existing impact categories, with section 3.4 detailing the formulation of new categories suited for the evaluation of critical material depletion.

Impacts normally incorporated in the LCIA include energy consumption during operation, raw material depletion for construction of the data center structure, raw material depletion for manufacturing of IT and facility equipment, land use and environmental impacts of the facility, mix of energy-generating sources used to support operation, water consumption during operation; and reuse, recycling, and/or disposal of IT and facility equipment and materials. Secondary impacts can also include hazardous substance content of data center building and equipment, and air pollution during operation. Missing in these categories are impacts that include the socio-economic relevance of materials within the area of study, which is discussed further in Chapter 3.

The key areas of importance are energy consumption during the use phase (related to energy efficiency), the embodied impact of materials in the data center (including IT equipment manufacturing and maintenance) which show the importance of the energy sources for all phases [FTW17, Sh09, WAS15].

2.6.5. Interpretation and reporting

Organizations can use LCIA results to make more informed decisions regarding design and operational activities that contribute to reducing a data center’s environmental impact, including reducing material depletion and optimization of recovering strategies. Such activities include determining when to retire equipment versus re-deploy it and identifying opportunities for virtualization and consolidation of lower-performing systems onto a single platform to reduce overall energy use and improve system utilization.

To facilitate clear communications, a single number representing the global environmental impact may also be presented. The complexity of a data center and the lack of credible data and methodologies hinder the creation of a single aggregate number describing the environmental impact. [ABD12] recommends assessing metrics or use values for each of the impacts mentioned above and identifying system or operational approaches to optimize the metric or reduce the use of the resources.

As given by the general low quality of data, several iterations for improving data and refining the models are required. The uncertainty of the results and the further improvements in these is also to be reported. This dissertation serves also as a case study to evaluate the application of LCA use in a real-world data center scenario and determine what needs to be updated or added. Methodologies for evaluating data quality are presented in the next section, and results on data quality are presented in **Chapter 7**.

2.7. Methods for evaluation of data quality and uncertainty

Within the evaluation of Life Cycle Inventories, concerns arise regarding the quality and reliability data used for the study. Issues such as uncertainty of the measurements taken and of the appropriateness of the proxy data used and of the representativeness of the process analyzed must be considered when reporting. [ISO14044] lists under "data quality" aspects such as representativeness, uncertainty (precision), and other directly data quality related aspects, but also aspects such as methodological consistency, data sources used, and reproducibility. Data quality within LCA is a significant issue for the future support and development of LCA as a decision support tool and its wider adoption within industry [AW16].

2.7.1. Definition of data quality

[ISO14040] defines data quality as *"characteristics of data that relate to their ability to satisfy stated requirements".* Thus, the quality of a given LCI model, of datasets, or of a database, fully depends on the "stated requirements." For this reason, it is sometimes referred as "fitness for purpose" [Ci21]. The data quality goals should explicitly define needs for representativeness, including temporal, geographic and technological aspects, and completeness. [ISO14044] addresses the concept of data quality by two approaches. First, on data quality in the stricter sense, which refers to aspects that determine the quality of the inventory data and the related LCIA results. Second, to aspects that relate to data quality documentation and review and to efforts of basic consistency such as nomenclature and terminology [EC10].

Data quality is composed of accuracy (representativeness and methodological appropriateness and consistency), uncertainty (also called precision) and completeness of the inventory. All of these contribute to the overall quality and typically the weakest of them determines (lowers) the overall data quality. In general, in LCA, the lowest quality can be found regarding representativeness, methodological appropriateness and consistency (especially on system level), and completeness. Data quality of LCA starts from the quality of the single inventory data values [EC10]. Initial data quality requirements must also be specified in the goal and scope phase of an LCA study. Data must be used appropriately in relation to the goal of the study. A critical review needs to address data quality in LCA case studies [Ci21].

2.7.2. Data quality indicators

Collected data usually represents the system being modeled with an accuracy lower than 100%. Data quality indicators are used and structured to provide a qualitative analysis of data (using a semiquantitative system) to compare data collected against the intended goal and scope of the project. However, neither [ISO14040] nor [ISO14044] define how these areas are to be addressed. No specification on to which component or level a data quality analysis should be applied. [ISO14044] defines ten key categories required for addressing data quality:

a) **Time-related coverage:** age of data and the minimum length of time over which data should be collected.
b) **Geographical coverage:** geographical area from which data for unit processes should be collected to satisfy the goal of the study.
c) **Technology coverage:** specific technology or technology mix.
d) **Precision:** measure of the variability of the data values for each data expressed.
e) **Completeness:** percentage of flow that is measured or estimated.
f) **Representativeness:** qualitative assessment of the degree to which the data set reflects the true population of interest (geographical coverage, time, and technology coverage).
g) **Consistency:** qualitative assessment of whether the study methodology is applied uniformly to the various components of the analysis.
h) **Reproducibility:** qualitative assessment of the extent to which information about the methodology and data values would allow an independent practitioner to reproduce the results reported in the study.
i) **Sources** of the data.
j) **Uncertainty** of the information (e.g., data, models, and assumptions).

The qualitative and quantitative evaluations are done at the flow level. Data quality analysis at this flow level analysis permits a more detailed understanding of the data quality than can be provided at the process level, since the process level can be a combination of many different flows from many different sources [AW16]. Flow level indicators address source reliability, temporal, geographic, and technological correlation, and data sampling methods. A methodology to evaluate these qualities is built around establishing a matrix for data quality evaluation.

2.7.3. Pedigree matrix

The pedigree matrix was introduced to uncertainty analyses as a method to code qualitative expert judgement for a set of problem-specific criteria into a numerical scale [FR90]. [WW96] applied this methodology to LCA. This method evaluates five criteria with a rating scale from "1" to "5". Low ranking values (scores of "4" or "5") do not necessarily indicate "bad" data, nor do high ranking values (scores of "1" or "2") indicate "good" data. Rather they qualitatively describe how the data relate to the goal and scope, and highlight potential areas of improvement in the data quality [AW16].

The pedigree matrix is not designed to capture all areas of data quality, but to semi-quantitatively address certain key areas to improve communication of data quality results. Not all data quality areas are addressed using a pedigree matrix. Following criteria is evaluated for different flows in a process model:

- **Reliability**: This indicator refers to the reliability of the source to address that some information sources in LCA are more reliable than others. A more reliable source is always desirable, independent of the application. Independently peer-reviewed, empirical-based sources are seen as most reliable, unqualified estimates as least reliable [CA21, We13].
- **Completeness**: Completeness indicates the degree to which the included flows represent the actual system of interest and enable full impact characterization. It addresses whether and how to which extent a given information can represent a larger group.
- **Temporal Correlation**: Indicates the correlation between the time period the data was collected and the year the model represents [AW16]. A dataset represents a certain period. As time passes, input and output flows of a process can change. Changes in different areas (technological, geographical) occur at different speeds, hence distinct factors may be applied for different sectors.
- **Geographical Correlation:** Indicates the appropriateness of the sample region in representing the model region. The intended geographical data coverage is the geographical area from which data for a unit process should be collected to satisfy the goal of the study [AW16].
- **Technological Correlation:** Quantifies the differences that may be present between data source and technology scope [AW16]. Technology refers to the product and the production process, and it is the one data quality indicator that most determines the specific inventory of a process dataset. This indicator addresses differences that are omitted by the other indicators: time, location, and also other indicators may impact the technology used in the process [Ci21].

2.7.4. Uncertainty and probability distributions for LCIA data

[ISO14044] defines precision as the "measure of the variability of the data values for each data expressed". Uncertainty is used for expressing the quantitative degree of the lack of precision. It represents the degree to which further measurements or calculations done by different experts will produce the same results. The ISO definition relates to the statistical meaning of stochastic uncertainty. [Mu16] indicates that uncertainty in LCIA inventories can come from:

- Intrinsic variability and stochastic error of the parameters, due to measurement uncertainties. This uncertainty is captured in a basic uncertainty factor.
- Uncertainty due to the use of imperfect data, such as data resulting from estimates, lacking verification, or extrapolated from temporally, spatially and/or technologically different conditions. This is called additional uncertainty.

For uncertainty, the actual value of a quantity is unknown and described by a probability distribution. This distribution is based on the information or metadata about the value and can be reduced by improving the metadata. Mathematically, the uncertainty of a value is defined through probability distributions. This represents the values a parameter can take and uses information on the probability of this value taking place. Various probability distribution functions can be applied to LCIA data. One of the most used is the lognormal distribution. In this type of distribution, the logarithm of the variable is randomly distributed. It presents certain characteristics that make it appropriate to represent the uncertainty of the value of a flow within LCA. Negative values cannot be defined through a lognormal distribution. Since the flows which are scrutinized in LCA are physical quantities, they cannot be negative, so a lognormal approach is suitable. The function is also scalable, meaning that the mean can be increased, while holding the shape given by the geometric uncertainty factor. This is useful to adapt to LCI since the reference value of the flow can be altered while keeping the information on uncertainty unmodified.

The lognormal distribution (**Figure 2-13, Eq. 2.1**) is represented by two definition parameters: the geometric mean (μ_g) and the geometric standard deviation (σ_g). The geometric mean is the deterministic value, and the geometric standard deviation captures the information on the uncertainty. It is represented by :

$$f(x, \mu_g, \sigma_g) = \frac{1}{\sqrt{2\pi} \ln \sigma_g} exp\left(-\frac{(\ln x - \ln \mu_g)^2}{2 \ln^2 \sigma_g}\right) \qquad \text{(Eq. 2.1)}$$

Where x is the variable , μ_g is the geometric mean, and σ_g is the geometric standard deviation. The confidence intervals for the 5th and 95th percentiles are calculated as presented in **Eq. 2.2**:

$$CI_{68\%} = \left[\frac{\mu_g}{\sigma_g}, \mu_g \sigma_g\right], CI_{95\%} = \left[\frac{\mu_g}{{\sigma_g}^2}, \mu_g {\sigma_g}^2\right] \qquad \text{(Eq. 2.2)}$$

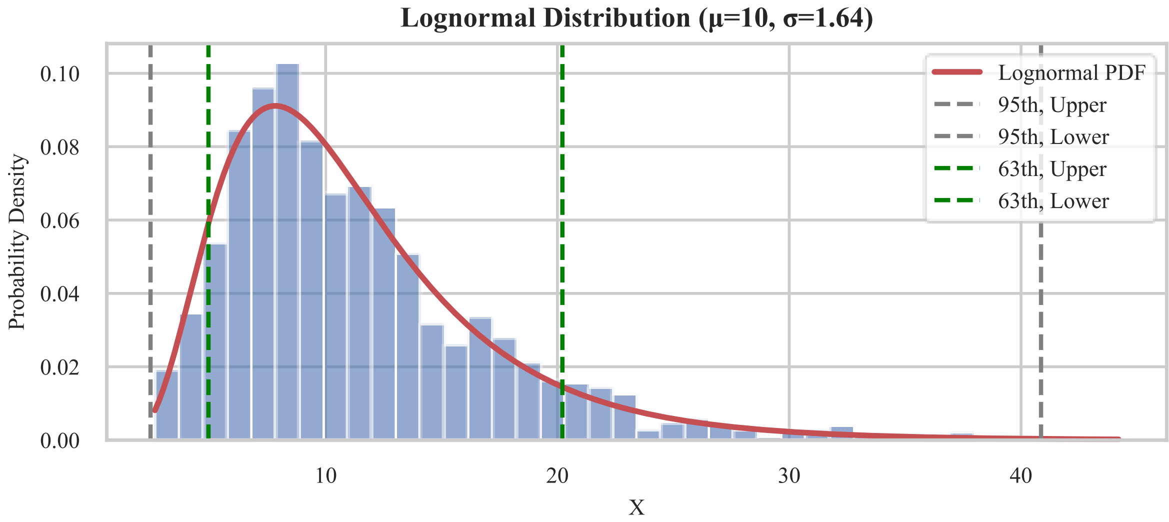


Figure 2-13: Example of a probability density function for a lognormal distributed variable.

The pedigree matrix is used to address qualitative uncertainty. Past pedigree matrices have used uncertainty as an indicator. The uncertainty of a measurement is composed then of a basic uncertainty factor and on the additional uncertainty due to data quality. Due to the properties of the lognormal function, the basic uncertainty of a measurement and the uncertainties derived from the pedigree matrix indicators can be then aggregated to estimate a total uncertainty for the flow value. **Eq. 2.3** shows the calculation of the geometric uncertainty based on the parameters of the pedigree matrix.

$$\ln\left({\sigma_g}^2\right) = \sqrt{\sum_{i=0}^{5}(\ln U_i)^2} \tag{Eq. 2.3}$$

Where the indexes of U_i relate to the source of uncertainty as follows:

U_0 : basic uncertainty factor
U_1 : uncertainty factor for reliability
U_2 : uncertainty factor for completeness
U_3 : uncertainty factor for temporal correlation
U_4 : uncertainty factor for geographic correlation
U_5 : uncertainty factor for technological correlation

2.7.4.1. Data quality factors and characterization

The databases for LCA may include information on data quality for background process and contain also detailed documentation for the sources of information and aspects such as geographical zone, time of data gathering, and process information. It also includes data quality information and uncertainty values.

A Pedigree Matrix is also included to assess the quality of data, and it is included in the calculation methodology to estimate results data quality. It can also be used to assign data quality and uncertainty values to specific process information within a custom build model. **Table 2-3** presents the information found in this table, which is used to quantify data quality.

Table 2-3: The ecoinvent pedigree matrix. Source: Modified from [We13].

Indicator score	1	2	3	4	5
Reliability	Verified data based on measurements	Partly assumed or non-verified measured data	Non-verified data based on qualified estimates	Qualified estimate (by industrial expert)	Non-qualified estimate
Completeness	Representative for the process over a proper period	Representative for >50% of the process considered	Representative for only part of the process (<<50%)	representative for only one part of the process	Unknown which part of the process is represented
Temporal correlation	Less than 3 years	Less than 6 years	Less than 10 years	Less than 15 years	More than 15 years
Geographic correlation	Data from area under study	Average data from larger area	Data from area with similar production	Data from area with slightly similar production	Data from unknown or different area
Further technical correlation	Data from process under study	Identical technology but different process	Data from processes under study but from different technology	Data on related processes or materials	Data on related processes on laboratory scale

Default basic and additional uncertainty factors are considered and a method to combine basic and additional uncertainty is applied only for the lognormal distribution. For calculating the additional uncertainty, the pedigree matrix results are not taken directly, but after a transformation producing an uncertainty value from the data quality scores (**Table 2-4**). The values in this transformation table never exceed 2.0 and are mostly below 1.5. [CMW12] established a set of empirical data quality factors. However, some indicators do not have a related uncertainty for the lowest of data qualities.

Table 2-4: The ecoinvent pedigree matrix data quality uncertainty values. Source: Adapted from [We16].

Indicator score	1	2	3	4	5
Reliability	1.00	1.05	1.10	1.20	1.50
Completeness	1.00	1.02	1.05	1.10	1.20
Temporal correlation	1.00	1.03	1.10	1.20	1.50
Geographic correlation	1.00	1.01	1.02	1.06	1.10
Further technical correlation	1.00	1.13	1.20	1.50	2.00

2.8. Conclusions

This section presented an overview on the current state of the art on the research on the topics of data center and LCA. The goal is to provide a foundation for the execution of LCA applied to data centers, with considerations of other life cycle phases outside of the operation phase.

As stated in different sources, most of the research and analysis is focused on the operational phase. The analysis and research on optimization of data centers is tied to minimizing energy consumption during the service phase of a data center. This has provided an extensive basis for evaluation of data center performance, and a wide range of indicators that cover many aspects of the operation of a data center. These indicators, however, do not consider other aspects such as embodied energy or material content. Additionally, categorization of data centers does not provide a sufficient basis for evaluation of life cycle impacts. Therefore, each data center must be evaluated individually, and thus inventorization of each facility is required for an assessment that provides results of high quality, so that the LCA models developed represent appropriately the inventory of a data center.

LCA as a scientific methodology has been implemented for some case studies for data centers. However, these studies still focus on the operational phase, and focus on evaluating electric energy use, which remains dependent on the local energy mixes. An extension of these studies is possible using the frameworks stated in this chapter, since many of the methodological aspects are given in literature, which serve as a guideline for conducting LCA on data centers and on their equipment. Despite this, few research regarding assessment of the demand of primary energy and raw (critical) materials for manufacturing data center equipment is available. This aspect is to be addressed in this work, with a key aspect being the building of new indicators focused on evaluating raw critical material depletion in Chapter 3.

The absence of published data on material composition and on manufacturing processes for data center equipment may result in poor data quality of the results. To evaluate this aspect, methods for a quantitative evaluation of data quality are to be implemented. These methods focus on assessing the appropriateness of the information used with regards to the objectives of the study, and may be understood as a technological, geographical, and temporal correlation to the system they represent. By means of direct inventorization of operating data centers from different institutions, quantification of BoM from decommissioned data center equipment, and of laboratory analysis of material content in data center WEEE, the quality of this information is to be improved, which is to be evaluated in Chapter 7.

3. Development of Methods for Criticality Assessment within LCA

This chapter summarizes the development of the methodologies for criticality assessment within LCA, developed to answer the main research question. The requirement for indicators to reflect depletion of resources comes from the goals of this study, since the indicators used for data center focus mostly on the operational phase, as reflected in Section 2.4. By aligning the goals of the study with the research questions from Section 1.3, the scope of the study can be refined to include indicators that reflect the problem of depletion with considerations of material criticality. This chapter presents existing methods (Section 3.3) and new developed methods (Section 3.4) developed within this work for use in the LCIA calculations in Chapter 7 (**Figure 3-1**). The information required and the results are saved in databases containing information on criticality and on the resulting characterization factors (Chapter 6).

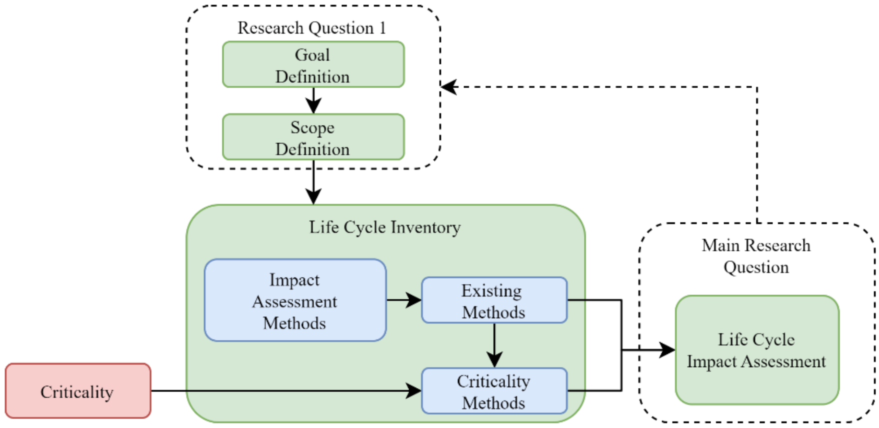


Figure 3-1: Development of criticality-based life cycle impact assessment methods.

3.1. Refinement of goal and scope

3.1.1. Refinement of goals

This LCA study has as general goal the investigation of the environmental performance associated to the raw material extraction and manufacturing processes of the data center equipment, and the environmental impacts involved during its use and end-of life phases. The scope then excludes the use phase because the energy consumed during the use phase is decoupled with the material flows. Another desirable achievement is to make available a suitable framework for evaluation of data center equipment, develop calculation methodologies to integrate inventories and automated calculation procedures for LCA, and to provide updated databases for similar of studies. To achieve the general goal, and following the Secondary Research Question 1, this study will aim to answer the following specific questions:

a) What are the specific resource depletion impacts associated to a data center life cycle, from cradle to grave, excluding of the operation phase?
b) Which set of indicators are suited for resource depletion evaluation?

c) What components are responsible for the greatest environmental impacts related to resource depletion?
d) What is the role of material recovery in improving resource efficiency and helping to alleviate issues such as material scarcity?

These questions are answered following the LCA methodology. To help with these questions, specific set of impact assessment methods are further developed in this chapter.

3.1.2. Refinement of scope

For this evaluation, LCA models representing the different components of data centers need to be developed. The goal is to evaluate the different production chains and manufacturing processes to quantify the total amounts of energy and material demand. The use of appropriate indicators allows evaluating these parameters. These need to represent the materials demands by their physical amount and by aspects such as criticality.

There are several impact assessment methods used for evaluation of resource depletion. However, these methods lack consideration of aspects such as material supply risks or relative economic importance. Section 3.3 gives an overview of existing indicators, and Section 3.4 details newly developed or updated indicators created for the purpose of this dissertation.

3.2. Raw materials in the economy

Raw materials are essential to produce a broad range of products and services, including IT equipment. Some raw materials are referred to as "critical raw materials" (CRM) due to their comparatively high economic importance and high risk of supply disruptions [EC20b]. Although geological scarcity is unlikely, supply risks lie in import dependence, the concentration of production in politically unstable countries, and the nationalization of mining companies [BST12].

The rapid technological innovation cycles and the growth of emerging economies has led to an increasing demand for these materials. Consumption of raw material resources implies a decrease in future availability and hence resource depletion. Because of continuous modifications of function and design of appliances, electrical and electronic equipment (EEE) contains a highly heterogeneous mix of materials. Essential constituents include metals such as precious metals (gold, silver, and palladium) and special metals (indium, selenium, tellurium, tantalum, bismuth, antimony) [CBR11]. In the 1980s, computer chips contained twelve elements. Today, as many as sixty different elements are used in fabricating integrated circuits [Ba14], with around 34 metals in the category of are earth, scarce, and scattered metals [Li22]

The manufacture of components and the use-phase energy consumption are often responsible for most of the environmental impacts of EEE. Metals can often have a significant environmental impact because of their toxicity, the use of energy and water in processing, their tailings, or related emissions [Gr12]. Based on weight, steel and plastics are the two dominant materials used in EEE. The weight distribution of the different substances differs from the value distribution and so does the distribution of related environmental pressures [Ba14]. Precious metals account for a significant part of the economic value of EEE, especially when recovery is considered.

Securing access to a stable supply of such materials is a major challenge for economies with limited natural resources, such as the EU, which is heavily dependent on imported supplies of many minerals and metals needed by industry. There is a risk of supply disruptions due to supply concentration and political instability of the producing countries. Environmental policies commonly address resource efficiency and scarcity [Ma15]. Resource security is a premise then for sustainable development [SBF15].

The term resource efficiency refers to maximizing the output of a system while minimizing its resource consumption and it is a key element in sustainable development and security supply. Methods are required to ensure the ecological and efficient use of resources [KSB14]. Scientific methods such as LCA make it possible to consider the impacts caused by distinct stages of the IT life cycles.

3.2.1. Material criticality

Raw materials are the base of all value chains, hence key enablers for all sectors of the economy. The life cycle of raw materials can give an overview on the environmental impacts of raw material gathering but says nothing about changes in supply or demand. Studies on material criticality addresses these aspects [Gr15]. Criticality assessments evaluate products, technologies, companies, or a country’s economy. They can also be done for different periods, e.g., according to the current resource data and reserves or as a long-term projection. For these reasons, criticality assessments can diverge, since they depend on the selected indicators, the underlying data, and the goal of the study. A review of recent approaches reveals a general consensus that criticality is comprised of two main dimensions: supply risk and economic importance of its uses [De16].

[EC10c] published a list of *‘‘Critical Raw Materials”*. [EC20b] updated this list, while maintaining the same approach. The methodology underpinning the identification of CRMs for the EU combines two main variables: economic importance (EI) and vulnerability to supply disruption due to poor governance (SR). High economic importance means that the raw material is of fundamental importance to industrial sectors that create added value, which could be lost in case of inadequate supply and if adequate substitutes cannot be found. Supply risk means that the supply is associated with a considerable risk of not being adequate to meet EU industry demand. Raw materials, which reach or exceed the thresholds determined by [EC20b] are listed as “critical”. The report does not rank materials in terms of criticality. This publication also calculates these values with data from the last five years and many different databases, including the official EU data, public data, and some information from other non-EU members (**Figure 3-2**). A new list of critical materials is expected to be published for 2023.

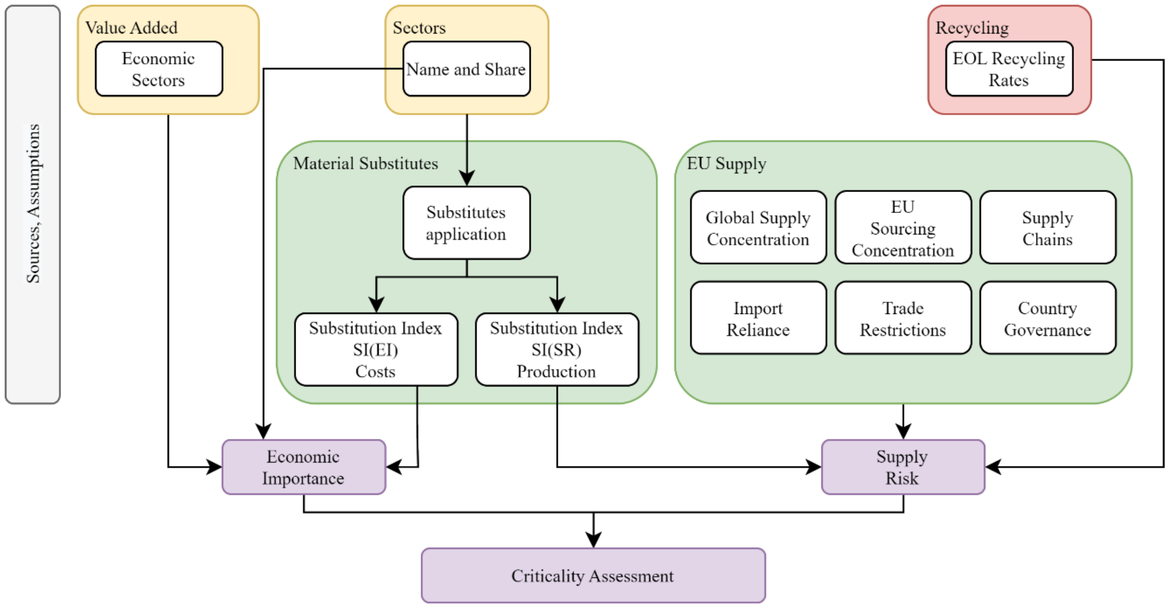


Figure 3-2: Procedure for development of criticality indicators. Source: Modified from [EC20b]

3.2.2. Economic importance

Economic importance gives insight on the relative relevance of a material in the context of the EU economy with respect to the end-use application and value added of corresponding EU manufacturing sectors. **Eq. 3.1** shows how the economic importance (EI) is calculated, where A_s is the share of end use of a raw material in an economic sector according to the European Classification of Economic Activities system [EC08], Q_s is the sector’s value added and s denotes the sector. A correction value for substitution is also included (SI_{EI}), which is related to technical and cost performance of the substitutes for individual applications.

$$EI = \sum_s (A_s Q_s) SI_{EI} \qquad \text{(Eq. 3.1)}$$

3.2.3. Supply risk

Supply risk is the risk of a disruption in the supply of the material to meet industry demands. It is calculated based on the concentration of primary supply from countries producing raw material and it considers their governance performance and trade characteristics. Supply risk is determined at the bottleneck stage of the material, which means at the point of extraction or processing, hence the highest risk point. Additionally, recycling and substitution reduce the risk. Following parameters are considering for calculation of supply risk [MBS18]:

a) Level of concentration of worldwide production of raw materials, using the Herfindahl-Hirschman Index (HHI).
b) Political and economic stability of the producing countries, using the Worldwide Governance Indicator (WGI).
c) Potential of substitution of raw materials (based on a substitutability index estimated through experts' opinion and aggregating the substitutability for the different uses)
d) Recycling rate, using estimates on end-of-life recycling rates [Gr11].

WGI is the most robust indicator to capture the level of governance in a country in the context of criticality assessment. Moreover, WGI is applicable to different life-cycle stages of a material (e.g., mining and refining). However, WGI does not capture risks due to export restrictions. [EC20b] incorporates novel methodological elements for trade, import dependency, and the actual supply mix to the EU, in parallel to substantial improvements for substitution and recycling as risk reducing measures. **Eq 3.2** shows how the supply risk (SR) is calculated, where IR is the import reliance, GS is the global supply, EU sourcing is the actual sourcing of the supply to the EU, HHI is the Herfindahl-Hirschman Index, WGI is the scaled world governance index, t is the trade parameter, EoL_{RIR} is the end-of-life recycling input rate and SI_{SR} is also the substitution index for Supply Risk.

$$SR = \left[HHI_{WGI,GS,t}\frac{IR}{2} + HHI_{WGI,EU,t}\left(1 - \frac{IR}{2}\right)\right](1 - EoL_{RIR})SI_{SR} \qquad \text{(Eq. 3.2)}$$

3.2.4. Results on material criticality

Representation of the criticality concept uses the described indicators. [EC20b] considers a material as critical when both a high potential impact of a shortage (economic importance) and a comparatively high probability of such a shortage (supply risk) are present. Thus, criticality is a matter of degree and comparison, and thresholds are defined in both dimensions to distinguish between those raw materials considered critical and those that are not.

This produces a shortlist (**Table 3-1**) of "Critical Raw Materials" that highlight the underlying issues accounted for in the respective methodologies and serve as a focus point for concrete actions of policy makers. **Figure 3-3** presents the overall results of the 2020 criticality assessment. Critical Raw Materials are located within the criticality zone ($SR \geq 1$ and $EI \geq 2.8$) of the graph.

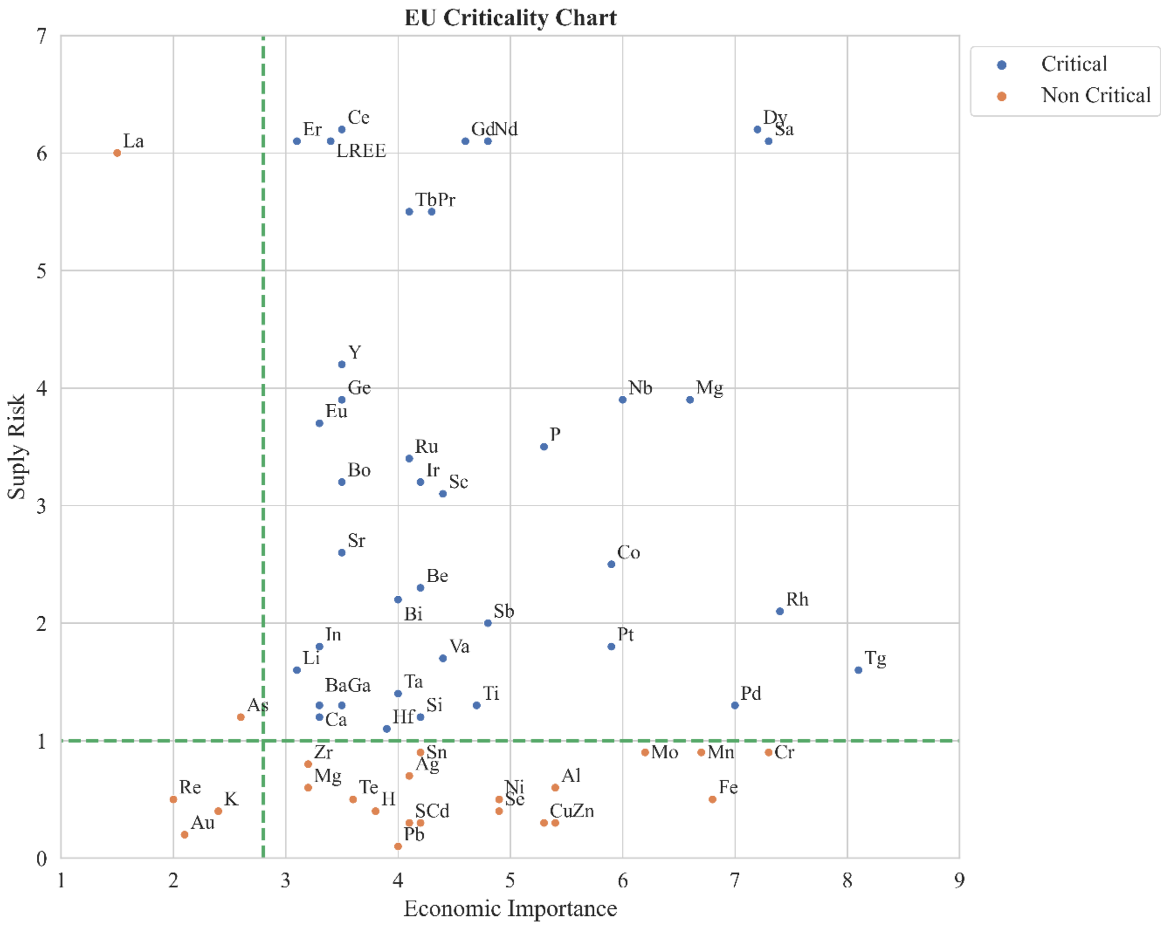


Figure 3-3: Critical Raw Materials. Source: Data from [EC20b].

Table 3-1: Critical Raw Materials. Source: Data from [EC20b].

Antimony	Fluorspar	Magnesium	Silicon Metal
Baryte	Gallium	Natural Graphite	Tantalum
Bauxite	Germanium	Natural Rubber	Titanium
Beryllium	Hafnium	Niobium	Vanadium
Bismuth	HREEs	PGMs	Tungsten
Borates	Indium	Phosphate rock	Strontium
Cobalt	Lithium	Phosphorus	
Coking Coal	LREEs	Scandium	

3.2.5. Comments on criticality

In the previous decade there has been interest in criticality of raw materials, enough to warrant the development of rigorous and quantitative methodologies for assessing criticality [EG11]. [Gr12] uses a similar approach that considers vulnerability to supply restriction and supply risk. It also extended the approach to addressing an additional dimension: environmental implications. This is an attempt to include cradle-to-grave environmental impacts as a separate dimension. It focuses on the impacts of mineral use, rather than on the supply risks.

Examining the shortlists of critical raw materials, [BST12] points that there is a bias towards so-called technology metals and minerals, which are only used in small quantities for very specific applications.

These “technology” minerals are often only mined in small volumes, which makes price volatility and producer dominance much more likely. New sources of demand arising from newly developed applications can cause demand to outstrip supply in the short term. Most criticality approaches have the intention to account for substitution and recycling but the implementation into the calculations diverge. Moreover, data on recycling is difficult to assess properly, especially for scarce metals such as rare earths [De16].

The indicators are developed using data with temporal boundaries. Hence, some of the materials identified as critical might only pose a temporary problem, and these studies may not be able to reflect other problems in longer scope. The usefulness of short lists of critical raw materials as a policy instrument, therefore, depends not only on the degree to which a particular methodology reflects the underlying issues but also on the timeframe chosen for the analysis [BST12]. Combining these indicators with parameters that consider depletion of available reserves can provide an understanding of the resource consumption problematics with a long-term horizon. This combination of factors is formulated in Section 3.4.

3.3. Existing indicators for assessment of material and energy depletion

The approach of LCA to resource depletion is characterized by a lack of consensus on methodology and on the relative ranking of resource depletion impacts. This can be seen from a comparison of characterization factors. Different approaches yield vastly different characteristics of the impacts from resource depletion and show gaps in the number and types of resources covered [KSB14]. The existing methods currently focus on aspects such as material depletion or global warming potential, without consideration of criticality, potential for replacement, or material efficiency. The indicators omit the temporal variations of material stocks. This section provides an overview on the existing methods and their indicators for assessing raw materials consumption and highlights their limitations when it comes to evaluating the total impacts of modern technologies.

3.3.1. Evaluation of resource depletion within LCA

LCA modelling of processes and products uses databases and models of processes that contain information about raw material mining, product manufacturing, and the physical properties of a system’s input and output flows to assess a product’s physical and economic impacts. The raw material data on mining and processing found in these databases varies due to different data sources. These consider the economic value of the materials used, the resource stock, and the energy required to obtain an additional unit of raw material.

Individual indicators related to elementary flows are not always used to produce results. Instead, several flows are aggregated, weighted, and added using midpoint and endpoint methods. This leads to a joint assessment that reflects all the life cycle impacts on nature, humans, and the atmosphere. The results of mass balances and life cycle inventories are weighted and added to the midpoint indicators, which then are then weighted and added to the endpoint indicators, whose aggregation results in a single LCA score (**Figure 2-11**).

Existing methods for the assessment of resource consumption in LCA relate to the energy and mass of the resource used, exergy or entropy impacts, future consequences of resource extraction (e.g., surplus energy, marginal cost), and diminishing geological deposits. Other methods also evaluate the environmental damages caused by raw materials extraction [Sc14]. Quantification of mineral resource consumption in LCA has been heavily discussed in the literature. There is a multiplicity of approaches for quantifying the effects in the raw materials impact category, as there are several impact category indicators in LCIA [Ye09].

Three approaches are currently used to quantify resource consumption: mass-based accounting (material and energy flow analysis); impact assessments using material flow analysis (MFA) and inventories in LCA; and criticality assessments [MBS15, Bl17]. Material flow analysis can show hot spots for raw material consumption and waste flows. LCIA can show which areas of protection are most affected during a product's life cycle. A criticality assessment identifies materials that are critical and might become scarce in the future (**Figure 3-4**).

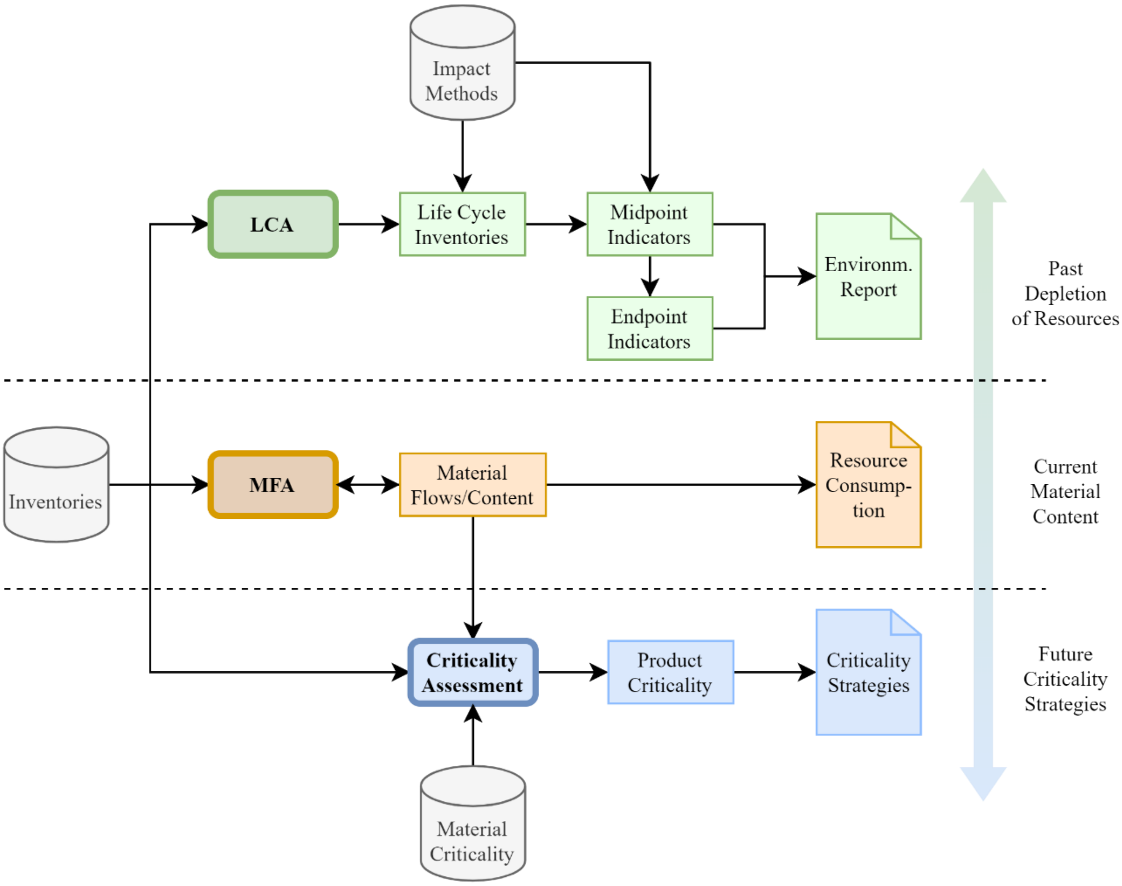


Figure 3-4: Current methodologies for assessing resource depletion and their impacts.

3.3.2. Resource accounting methods (RAM)

Resource accounting methods are used to measure the material and energy throughputs between natural and anthropogenic systems for the purposes of conducting a material flow analysis or developing life cycle inventories. These focus on calculating the specific mass of materials or energy inputs and outputs of a product [AOA16, KSB14]. Resource accounting methods that are suitable for LCA include:

- **Cumulated Material Demand (CMD)** includes all the extracted raw materials in weight units, without differentiation regarding criteria such as scarcity, availability, and exhaustibility [Gi12].
- **Environmental Development of Industrial Products (EDIP)** – *Non-Renewable Resources* considers the total mass input of distinct natural mineral resources and aggregates them equally regardless of their origin (country or specific deposit) or any scarcity-related parameter [BBC12].
- **Cumulated Energy Demand (CED)** accounts for resources with energy or heating value such as oil and natural gas, but also renewable sources such as solar energy and biomass [AOA16]. This approach takes into consideration all the energy consumed during the extraction, manufacturing, and disposal of a product. It represents a product's total energy demand [Me11, Hu10].
- **The Cumulative Exergy Demand (CExD)** uses the CED as a baseline but uses exergy as indicator. Exergy of a resource is the maximum amount of useful work that can be obtained from it [Bö07, De08]. By using exergy, the CExD can account for several types of resources including those with no heating value. This method does not have spatial differentiation.
- **Cumulative Exergy Extraction from the Natural Environment (CEENE)** considers several elementary flows, with a higher number of characterization factors than other than CExD. One of the differences between CEENE and CExD is the approach used to account for the exergy of metals and minerals. CEENE enables to account for very different natural resource intakes, from renewable resources, nonrenewable resources, water and atmospheric resources, and land use [De07].

3.3.3. Midpoint methods

The impact-based methods use LCIA methodologies from the life cycle assessment framework. The amount of inventoried material and energy resources is multiplied by characterization factors that represent specific resource-related impacts. These factors are developed based on the properties being studied, such as resource stock depletion, or the economic impacts of depletion, or damage to the environment [AOA16]. These methods include:

- **CML** focuses on environmental impact categories expressed as resource use or emissions released into the environment [MBS18, Hu02]. Following impact categories are relevant:
  a) **Abiotic Depletion Potential (ADP),** which is multiplied by the extracted amount of a given resource, and compared with the depletion of 1 kg of antimony (Sb) as a reference [KSB14, Hu02]. The ADP characterization factors for minerals and fossil fuels are calculated by comparing the resource's extraction rate to its ultimate available reserve [BK16, SBF15, SR17]. The characterization factors are developed using data on ultimate stock reserves, referring to the quantity of resources that is ultimately available. The separation of minerals and fossil fuels into distinct categories provides a better representation of the different reserves [Sa16, vG16]. [EC10] adopted a version of the Abiotic Depletion Potential that is calculated using the reserve base instead of the ultimate reserve estimations.
  b) **The Global Warming Potential (GWP)** represents a system's equivalent carbon dioxide (CO_2) emissions that contribute to anthropogenic climate change. To quantify the effect of different greenhouse gases and express them CO_2-equivalent emissions, the emission quantities are multiplied by characterization factors [My13]. Although not a method for evaluating resource consumption, GWP is the most well-known LCA indicator, and thus worth including for communication purposes.
- The **Anthropogenic Stock Extended Abiotic Depletion Potential (AADP)** may be considered a complementary method for the ADP, by including the depletion assessment resources that have already been extracted from their deposits and are now available in the anthroposphere. However, due to the difficulty of obtaining consistent data, it has characterization factors for a reduced number of metals [SBF11, SBF15].
- The **Eco-Indicator 99 midpoint method** considers the decrease in resource quality based on current extraction rates. The metal depletion category considers all mineral resources as of equal importance and omits substitution possibilities. It uses a lognormal distribution of concentrations of mineral resources to quantify extracted amounts against grade and use this relationship to calculate marginal effects of present extractions. The concept of surplus energy allows quantifying the required increase of efforts [Go01].
- The **ReCiPe midpoint method** was developed with characterization factors for fossil fuels, metals, and minerals, and a different approach is used for each resource. The *Mineral Resource Depletion* (MRD) impact category uses data about deposits and evaluates the depletion of metals and minerals. This method also considers decreases in the concentration of minerals found in ores due to their extraction, normalized to kilograms of iron [AOA16]. This is achieved by using the monetization of surplus energy demand to characterize future efforts for resource extraction. Marginal increases in a resource's extraction cost per kilogram forms the basis of the model [Go09, KSB14].

3.3.4. Endpoint methods

Endpoint methods are based on midpoint methods. They are developed to consider the overall environmental burdens associated with resource extraction and use, rather than the most immediate impacts such as the diminishing of stocks or deposits [KSB14, AOA16]. The results are assigned to protected areas, weighted in a common unit (e.g. points), and aggregated in order to present the total impacts in a single equivalent score [SR17]. This shows the relative importance of resource depletion in comparison to the other categories and the total environmental impacts of a process.

The calculation of single-point Eco-Indicator scores is intended to aid day-to-day decision making, and also serves as a general-purpose impact assessment method in LCA [EC10]. Endpoint methods are based on various midpoint indicator methods and include:

- The **Eco-Indicator 99 endpoint** evaluates the total impact of using resources by considering the increased workload involved in the extraction of more inaccessible reserves. Categories aggregated include damage to ecosystem quality, damage to human health, total resource consumption, and total impacts [Go01, AOA16, SR17].
- The **ReCiPe endpoint** differentiates between fossil depletion and mineral depletion in the resource category [AOA16, EC10, Go09].

3.3.5. Selection of indicators for evaluation

The answer to the question “what is the right indicator or method?” is: “there isn’t one.” There are always a variety of indicators, and the method is selected based on the overall question under investigation. **Table 3-2** presents a summary of the discussed methods related to raw material usage during the life cycle. The EU recommends using CED to evaluate the impacts related to total resource consumption and identify potential direct savings in primary resource use, and to improve process efficiency [EC10]. EDIP is used to evaluate total resource consumption for each distinct metal. For the midpoint assessment, [EC10] recommends that the ADP be presented together with GWP for company reports and other communication. The ReCiPe endpoint method is the recommended endpoint LCIA method, as it differentiates between fossil and metal depletion in the resource category [AOA16].

3.3.6. Gaps on indicators for material depletion assessment

There is a lack of consensus across impact assessment methods for mineral resource consumption in LCA [KSB14], as the different methods were developed using different approaches for the evaluation of impacts. Most methods acknowledge the depletion of natural resources from a functional point of view. This neglects the intrinsic value of minerals [Hu02]. Expanding the analysis of the impacts of material usage requires an evaluation of socio-political, economic, and environmental dimensions. These need to be developed in addition to the existing analysis of LCA.

Table 3-2: Methods for assessing the impacts of material resource consumption.

Category	Method	Indicator	Unit	References
Resource Account Methods	CED	Cumulated Energy Demand	MJ_{eq}	[Hu10]
	CExD	Cumulated Exergy Demand	MJ_{eq}	[Bö07] [De08]
	CEENE	Cumulative Exergy Extraction from the Natural Environment	MJ_{eq}	[De07]
	CMD	Cumulated Material Demand	kg	[Gi12]
	EDIP2003	Material Depletion	kg	[HP05]
Midpoint	ADP GWP	Abiotic Depletion Potential Global Warming Potential	$kg_{Sb\text{-}eq}$ $kg_{CO2\text{-}eq}$	[SBF15], [Gu06], [vG16]
	AADP	Anthropogenic Abiotic Depletion	$kg_{Sb\text{-}eq}$	[SBF11], [SBF15]
	ME	Eco-Indicator 99 - Mineral Extraction	points	[Go01]
	MRD	ReCiPe - Mineral Resource Depletion	$kg_{Fe\text{-}eq}$	[KSB14], [Go09]
Endpoint	Eco-Indicator 99	Resources - Total	points	[Go01]
	ReCiPe	Total Resource Depletion	points	[Go09]

Cumulated Energy Demand (CED) and Cumulated Material Demand (CMD) are considered in Germany's national sustainability strategy [Gi12]. These two indicators lack information on distinct raw material consumption. The EDIP indicator on the other hand, presents non-renewable resource depletion results based on the total mass of each separated resource [WW17]. However, the EDIP categories for each raw material (such as aluminum) leave aside information such as material origin or production processes.

CED, CExD and CEENE remain influenced by fossil resources. The same can be said about endpoint, single score indicators [AOA16], where the weighting of midpoint indicators related to fossil fuel usage overwhelms the impact of mineral depletion. Reporting mineral depletion separately is therefore preferred.

Abiotic resource depletion is one of the most debated impact categories. There is no scientifically accurate method for deriving the weighting factors that are used to calculate abiotic depletion based on the input and output flows. Diverse ways to characterize these weighting factors do exist, such as a decrease in the resource itself, a decrease in international reserves of useful energy, or an incremental change in the environmental impact of extraction processes at some point in the future. Therefore, an assessment of only one indicator can provide insufficient information, which could lead to incorrect conclusions [vG16, Dr16]. Additionally, the development of different methods has resulted in different characterization factors for distinct materials, and some materials were not considered during the development of the methods. For example, neodymium, palladium, and silver are not included in the Eco-Indicator 99 midpoint and endpoint methods for calculating the depletion of metals.

Changes in economic data caused by fluctuating demand, exploration and supply cycles, politics and socio-economic trends make the inclusion of a temporal dimension inescapable [Dr16, Sa16]. The consequences of further exploitation of these metals need to be analyzed. Furthermore, the materials considered “critical” vary according to market conditions, as seen on the evolving list of critical raw materials [BST12]. Criticality indicators are calculated for minerals and metals, so that economic and geopolitical factors can be included in LCA. However these criticality indicators are not used when researchers evaluate the material demands of products [KSB14]. The following subsection presents a set of indicators developed and updated within this dissertation to include criticality in LCA. These indicators are to be used to evaluate resource depletion with considerations of criticality in Chapter 7.

3.4. Formulation and development of criticality-based indicators for LCA

This section provides an overview of the development of indicators for LCA that include the discussed aspects of criticality. The goal is to develop a novel set of characterization factors that include the information on criticality as per the definition of the EU. These indicators are to be applied and their usefulness also evaluated by using the results of the impact assessment of data center equipment presented in Chapter 7.

3.4.1. Critical materials and their relationship to the material demands of IT hardware

Increased usage of IT hardware has raised awareness among different stakeholders that this development also relates to increasing demand for critical metals. IT devices contain critical materials, and their development is vulnerable to supply disturbances. Criticality assessments might be a suitable method for policy makers to understand and regulate the market. Although data is often sparse, the available information about the material demands of IT suggests that current practices are likely to lead to scarcity for some metals in the not-too-distant future [GE12]. Thus, raw material productivity could be increased by minimizing material inputs and reusing production waste, which would result in lower environmental impacts and less consumption of scarce resources [Gi12]. [EC10] recommends methods for LCIA to cover some scarcity-related issues, such as depletion from mines. Similarly, life cycle data for critical raw materials can provide valuable insights into the options for managing these materials at the end-of-their-life stage, particularly when evaluated using a material flow analysis [Ma15].

There is no ideal indicator or method available in LCA to assess impacts caused by raw materials and criticality, or the potential benefits of recycling to alleviate supply chains. Mass and unit-based metrics provide insufficient information about the benefits of the recycling rates of critical materials. Most of the commonly used approaches in LCA are still incapable of predicting the physical scarcity of raw materials in the future and the consequences for sustainable material use. As resource efficiency is considered a key element for sustainable development, there is an increasing need for suitable methods to address the sustainability of resource use [KSB14].

Due to the dependence on raw materials and their availability in new technologies, recent literature proposed the integration of resource criticality assessments in the life cycle sustainability assessment framework [MBS18, KPP19]. Resource criticality has so far received more attention outside the LCA community and is gaining importance in policy making. It is therefore desirable to use a resource depletion indicator that reflects the supply criticality of a given resource, subject to economic, political and strategic influences, in addition to mere availability in the natural environment [KSB14].

3.4.2. Criticality-weighted abiotic depletion potential

Recent works proposed the integration of resource criticality assessment within LCA [Ge16, ScB14, So15, MBS18]. The **Criticality Weighted Abiotic Depletion Potential (CWADP)** here proposed is a set of indicators that merge the concepts of ADP and criticality. The ADP characterization factors are modified using the criticality values of raw materials. This addresses a missing link in LCA and the impact of resources with a focus on their criticality. It reaches a high degree of abstraction in terms of economic values as it is related to and normalized to kg of antimony equivalent. Normalization allows comparing results between different products and provides a baseline for assessment.

It is based on ADP of natural resources and uses the two main parameters defined by the EU to determine the criticality of a material (economic importance and supply risk) to build the indicators for each parameter. Comparing the CWADPs to the corresponding EU criticality values and its thresholds show the equivalent criticality of the assessed product. This information reflects the impacts of criticality on LCA and assesses the total resource consumption of critical materials in a system. Criticality values are taken from EU criticality reports [EC20b]. The dynamic nature of the results allows investigating the impact of criticality over time.

Eq. 3.3 describes the calculation abiotic depletion, which is the result of the sum of each resource ADP multiplied by its mass:

$$AD_{total} = \sum_i ADP_i * m_i \qquad \text{(Eq. 3.3)}$$

With the calculation of the individual characterization factor ADP_i described in **Eq. 3.4**:

$$ADP_i = \frac{\frac{DR_i}{R_i^2}}{\frac{DR_{ref}}{R_{ref}^2}} \qquad \text{(Eq. 3.4)}$$

where:

ADP_i is the abiotic depletion potential of resource i (kg_{Sb} /kg_i);

m_i is the quantity of resource i extracted (kg);

R_i is the ultimate reserve of resource i (kg);

DR_i is the extraction rate of resource i (kg/year) (regeneration is assumed to be zero);

R_{ref} is the ultimate reserve of the reference resource, antimony (kg);

DR_{ref} is the extraction rate of the reference resource, R_{ref} (kg/year).

Moving from the abiotic depletion to the criticality weighted abiotic depletion is achieved by multiplying the ADP_i of a resource with the normalized criticality factor c_{ix} of a resource to build the $CWADP_{ix}$ of this resource, as presented in **Eq. 3.5**:

$$CWADP_{ix} = c_{ix} \cdot ADP_i \qquad \text{(Eq. 3.5)}$$

where:

$CWADP_{ix}$ is the criticality weighted abiotic depletion potential of resource i based on the criticality parameter x;

c_{ix} is the normalized criticality factor of resource i based on the criticality parameter x;

To exclude a decreasing impact of the criticality parameter on the CWADP its value is normalized to avoid values below 1.0 (**Eq. 3.6**). Therefore, both parameters, the economic importance and the supply risk of a resource are be divided by the lowest respective value of all critical resources in the report:

$$c_{ix} = \frac{c_{x_i}}{c_{x_{min}}} \qquad \text{(Eq. 3.6)}$$

where:

c_{x_i} criticality parameter x of resource i;

$c_{x_{min}}$ minimal criticality parameter of resource i in the data base.

Since the criticality, values are being updated in perennial cycles these CWADPs will change with any new report released. So, the CWADPs will need to be indexed with the corresponding report and the chosen criticality parameter to guarantee a unique assignment, e.g., "$\text{CWADP}_{\text{EI-EC2022}}$" for the CWADP using the economic importance parameter (EI) based on the report by the European Commission (EC) published in 2022. This indexing method allows the unique designation and the use of any criticality parameter of any database in general.

By including the normalized criticality parameter into the equation of the abiotic depletion above, **Eq. 3.7** allows obtaining a life cycle impact:

$$\text{CWAD}_x = \sum_i \underbrace{c_{ix} * ADP_i}_{CWADP_{ix}} * m_i \qquad \text{(Eq. 3.7)}$$

where x is the criticality parameter used.

Creating a quotient of the criticality weighted abiotic depletion and the abiotic depletion defines the criticality factor which shows the impact of a given criticality parameter x within the LCA. **Eq. 3.8** describes the calculation of such equivalences:

$$SR_{eq} = \frac{\mathrm{CWAD}_{SR}}{AD}, EI_{eq} = \frac{\mathrm{CWAD}_{EI}}{AD} \qquad \text{(Eq. 3.8)}$$

here SR_{eq} and EI_{eq} are the equivalent criticality indicators for the analyzed product.

3.4.3. Geo-Political Supply Risk

The Geo-Political Supply Risk (GPSR) involves developing characterization factors for each elementary flow, based on the individual Supply Risk of the material and on the global production of this, thus integrating Supply Risk directly into the LCA methodology. This method, first proposed by [MBS18], aims to quantify the risk of short-run supply disruptions in commodity trading between countries as a function of production concentration, supply chain composition, and political stability of producing countries. This indicator divides the Supply Risk indicator by the total amount of produced raw material. This allows highlighting the materials that are used in lesser amounts over the bulk materials. The Supply Risk relates to the market, using data on mine production [Ob16]. The formulation given in **Eq. 3.9** states that:

$$GPSR_i = \frac{SR_i}{P_i} \qquad \text{(Eq. 3.9)}$$

where:

$GPSR_i$ is the Geo-Political Supply Risk of the material i (1/kg);
SR_i is the Supply Risk of the material i (1);
P_i is the global production of the material i (kg).

Like other impacts, the total $GPSR$ of a product is obtained via the elementary mass flows of the LCI and the characterization factors of **Eq. 3.9**, as described by **Eq. 3.10**:

$$GPSR = \sum_i GPSR_i \cdot m_i \qquad \text{(Eq. 3.10)}$$

where:

$GPSR$ is the total Geo-Political Risk of the system (1);
m_i is the individual mass flow (1).

[MBS18] developed these indicators and evaluated different combinations of Supply Risk and exponentials. The use of the Supply Risk combined with the global production better reflects CRM importance and therefore could be used in LCA for an assessment of resource security impact for the

EU. This dissertation expanded on the characterization factors and updated inventories and databases to update the indicators.

3.4.4. Results on proposed methods

Including criticality into LCA has been challenging to achieve but desirable to accomplish. Innovative approaches for the evaluation of resource consumption of products by building comparison values based on LCIA combined with weighted criticality values to show the direct impacts of criticality on LCA results. **Figure 3-5** presents the characterization factors for the developed indicators.

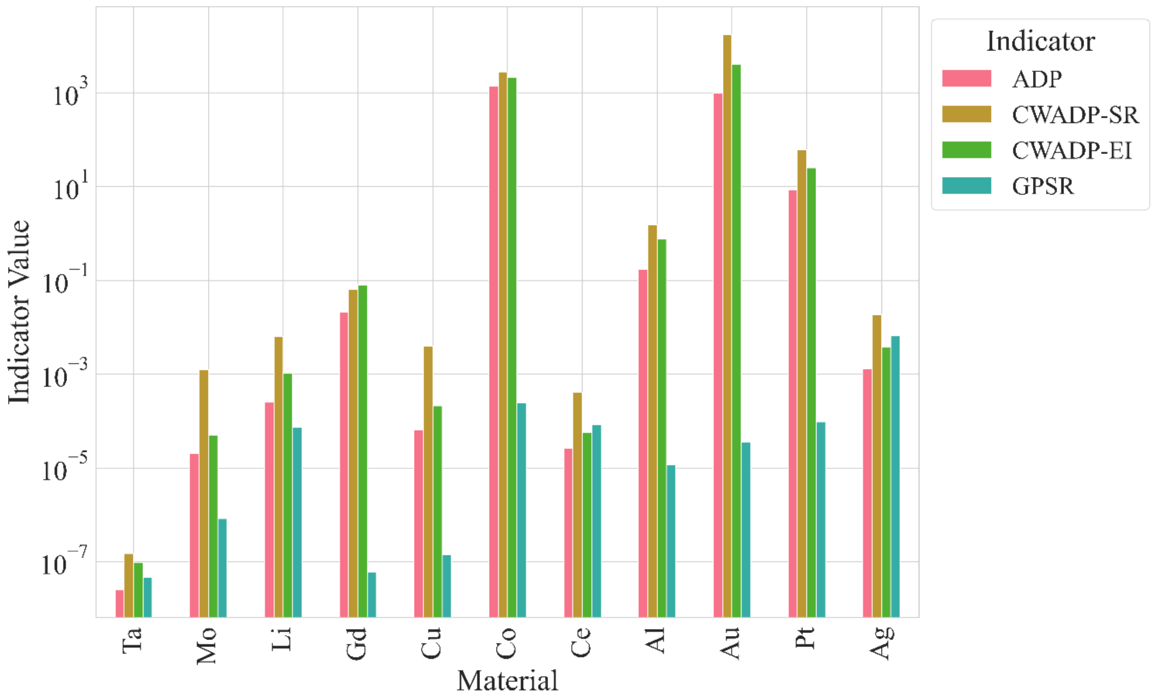


Figure 3-5: Comparative values of the developed indicators. Logarithmic scale.

As mentioned above, numbers and values that could be compared to ecologic values should be avoided and there is no uniform opinion about the “ideal” indicator assessing and reflecting the criticality of resources. Therefore, this indicator should reflect the impact as an additional factor to be added to existing and recognized methods used in LCA.

The proposed indicators are applied in several case studies in the following chapters using inventories of products used in data centers. Using these characterization factors, the results on the different impact categories can be calculated. The process considers the gathered information on parts composition of the different devices to construct product systems based on the inventory information.

3.4.5. Outlook on the developed indicators.

Indicators such as the Criticality Weighted Abiotic Depletion Potential represent initial attempts to merge the concepts of criticality with resource depletion. There is a lack of fully dynamic criticality analysis, although some authors have conducted static assessments of different time periods, or analyzed stock and flows of materials over time [Gr12, DG11]. Thus, novel approaches are required to incorporate the dynamic aspect of criticality. The indicators here developed and expanded can be understood as an extension of the well-known abiotic depletion potential (ADP). This could be a straightforward and universal method to include the impact of a criticality parameter into LCA and thus could be closer to the Sustainable Development Goals to secure raw materials. The criticality factors resulting from the quotient of the criticality-weighted abiotic depletion and the abiotic depletion of a product is a direct indicator for this impact and the underlying method is independent of the choice of the database and the criticality parameter used. These methods can serve to assess resource security in LCA when there is the need to enhance strategic and socio-economic considerations.

The normalized criticality factor of a resource is the key factor in the interpretation of the results. This factor depends on the database for criticality parameters of a given report. Depending on the database and its underlying calculations used for the criticality parameter, the normalized criticality factor might have non-linear amplitudes. Even effects of feedback due to correlations to the abiotic depletion potential are possible. An interpretation of the criticality factor should then always be done based on the database used.

Focusing on the socio-economic and geopolitical perspectives, [MBS18] identified the GPSR as an alternative for the characterization of resource security and criticality concerns for adoption within in LCA. This has the capability to include socio-economic and geopolitical considerations related to the use of material resources. Of the options, the supply risk related to the annual mine production gives more importance to specialty metals and reflects more closely the results on criticality of [EC20b]. However, the problematic of focusing on scarce materials used mostly in technology manufacturing persists and may be unsuited for use in other applications.

Data and data sets of comparable quality are not always available for all raw materials included in the LCA, as seen in indicators such as the abiotic depletion potential and in the list of critical raw materials. A common database for the comparison of different raw materials would increase the quality of information on relevant issues [BST12]. Today, there is still great uncertainty when comparing different LCIA related to raw material and criticality impacts, but there are already projects underway that take this issue seriously into account, such as the “Sustainable Management of Critical Raw Materials” project [EI17]. In addition to the assessment of primary resource availability, future studies need to consider differentiating between primary and secondary resources [Sc14].

Addressing dependencies between indicators can also show the effects of reducing material use in other impact categories. Studies on the impacts of the effects of recovery technologies and omit effects such as ‘rebound’ or ‘leap frogging,’ which could disrupt the supply of raw materials to manufacturers. Including a dynamic analysis in these methodologies could provide information for policy development. These dependencies between indicators are evaluated statistically in Chapter 7.

4. Development of Life Cycle Inventories of Data Center Equipment for Cradle-To-Grave Analysis

This section presents an overview on the information gathering process and on the data for evaluation of critical material and energy depletion impacts of data centers. This is based on clusterization of devices in different layers, and on the establishment of databases for the information collected. First starting with a screening of case studies of data centers in northern Germany, selected devices are disassembled for this research, and their most relevant constituents, namely printed circuit boards, are analyzed in laboratory to characterize the material composition of reference components. Results on material composition are compared to the values found in databases and in literature, systematized in new databases, and are later incorporated in the inventories. This contributes to improving data quality, which is used in Chapter 7 to compare results quality. Models for the different components are built based on previous literature, existing databases, and by development of new processes, with the updated information being incorporated accordingly into the model building structure proposed in Chapter 6. This led to databases with updated information based on inventories of the data centers under study, the information on composition of data center devices, their constituent parts, and the updated material content information. These inventories are later used for life cycle impact assessment calculation and an assessment of the potentials of material recycling (**Figure 4-1**). Cradle-to-Gate models can be calculated, or later incorporated with End-of-Life models.

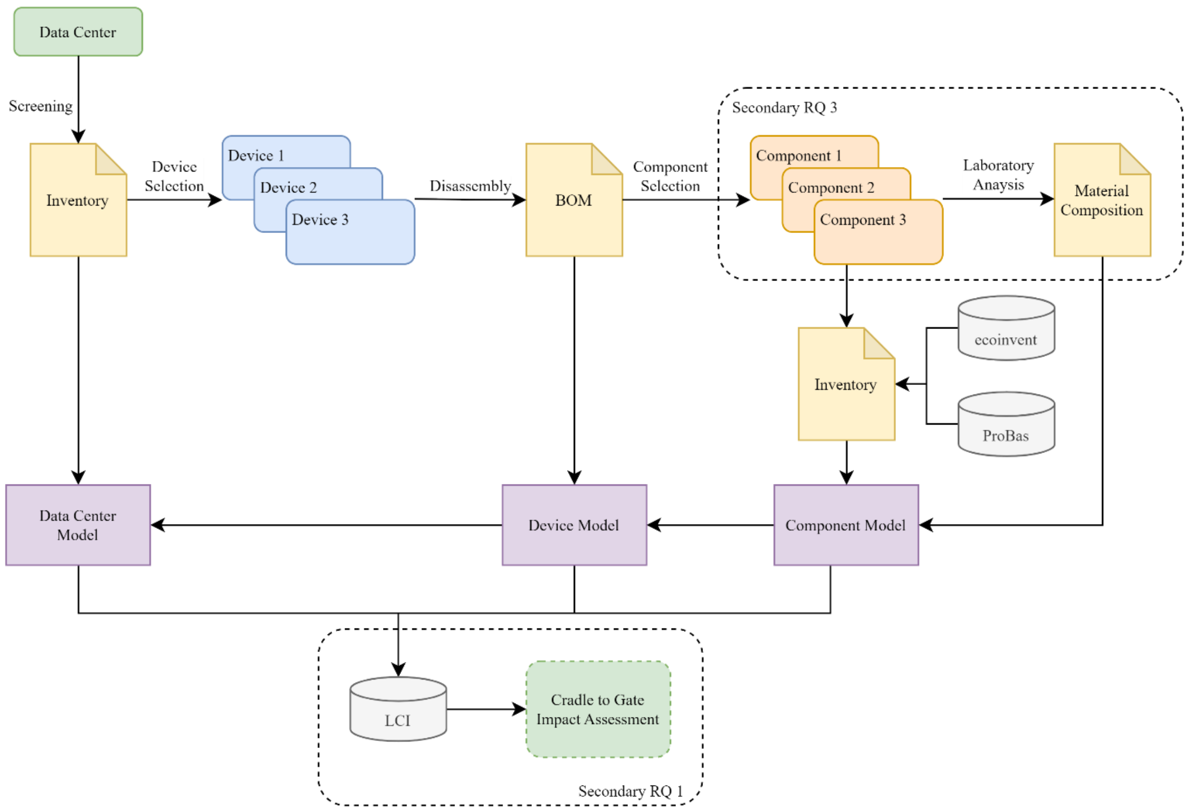


Figure 4-1: Information flow for development of databases with Life Cycle Inventories for data center components.

4.1. Methodology

For the preparation of life cycle inventories for life cycle impact assessment, different methodologies were applied:

a) **Proxy research:** As part of the proxy research (related literature and values) an analysis of existing databases containing information on data center equipment or similar components was conducted. This with the goal of analyzing which information on these components exists, and which is the quality of this information for this research. This identifies research gaps and data gaps.
b) **Development of case studies:** Different case studies were conducted to analyze the bill-of-materials (BoM) of components at the End-Of-Life from data centers. Disassembly and weighting of the individual parts are registered here. Information on data center inventories is gathered to conduct case studies in whole facilities.
c) **Preliminary modelling and simulation:** Based on the first inventory analysis and on the proxy research, preliminary models of the components are executed. This with the goal of identifying hot spots and inventories with low data quality, which will need to be further improved. This step is further developed in Chapter 7.
d) **Laboratory analysis:** Given the requirements on information and the preliminary identification of components with the highest critical and valuable material concentration, several components are analyzed in laboratory to evaluate material composition and improve the data quality of the models. This information is systematized in databases containing updated information.
e) **Inventory data base actualization:** With the research gaps identified, and the identification of missing elements and outdated values in the database, the outdated information in the raw material gathering process databases is updated with the laboratory results, which is then validated against similar studies by comparing the trends and values obtained.
f) **Results improvement assessment:** With the information gathered on material composition and on raw material gathering processes, updated calculations on the models are executed using the architecture of Chapter 6 and evaluated in Chapter 7. This is to analyze the changes in the results and on the quality of results obtained, which are evaluated via uncertainty analysis. Changes to data on material content are presented in this chapter, whereas the improvement on results quality is evaluated quantitatively in Chapter 7.

This chapter describes the process of developing LCI for data centers based firstly on proxy research for developing an approach to data center hierarchical structure. Case studies are developed based on the inventory information. A description of the laboratory analysis is included when describing relevant components. Finally, a description of the different life cycle models for the most relevant components of data centers is provided.

4.2. Clusters for data centers and their components

The guidelines produced by The Green Grid [ABD12], provide a framework for identifying and describing the elements necessary to assess a data center's complete life cycle, taking all relevant environmental impacts into consideration. These guidelines do not delve into all the economic and social aspects of sustainable data center operations, such as the use of "critical materials" and does not attempt to determine the level of accuracy that can be achieved in assessing the life cycle impacts of a data center. Both aspects are of importance for the evaluation of critical material depletion and evaluation of accuracy and completeness of the analysis, which are objectives of this dissertation. Hence, improved data and additional methodologies are to be used.

4.2.1. Identification of clusters for material analysis

This subsection identifies devices that require a deeper analysis, based on the information presented in Section 2.2. The most relevant devices for the purposes of this research here are identified for further analysis. For the other clusters, categorization options and the corresponding raw material-relevant components are described.

Figure 4-2 shows the scheme of the clusters of the inventory. It displays the delimitation of the cluster levels and the cluster groups that fall below them, down to their breakdown according to the raw materials. The levels lead from the system-level of data center via the application-related first level of the system groups, the levels of the individual devices, their components, their modules, to the last level of raw materials. Following levels are portrayed:

- The system size defines five size categories of the data center system, according with Section 2.3.1: server racks with an average of 5 servers, server rooms with 19, small data centers with 150, medium-sized data centers with 600, and large data centers with 6 000 servers.
- At the system category level, the data center system is subdivided into the application-related categories: the IT devices, power supply, air conditioning, and other support infrastructure.
- At the devices level, the systems are divided into modular components. The IT equipment cluster is divided into high-performance clusters, such as servers, storage clusters, and network technology. The UPS, generators, batteries, and related components are assigned to the cluster of power supply. Air conditioning and cooling devices are assigned to the climatization cluster. The other infrastructure cluster includes fire protection, security technology, and small consumers such as lighting and screens.
- At the components groups level, the system devices of the IT system are divided into their separable components: printed circuit boards, molded parts, heat sinks, copper cables, fiber optic cables, (semiconductor, magnetic and optical) storage, power supplies, fans, batteries,

amongst others. Before the raw material breakdown, the components need to be considered in more detail.

- In the modules level, the components of the different parts are further divided into individual manufactured parts, such as capacitors, resistors, printed wired boards, cable terminals, magnets, terminals, etc. This relates to existing or newly developed databases that provide a direct indication of the raw material composition.
- At the end of the breakdown, the components are linked to the raw material content. Raw materials are also categorized based on their application group, such as base metals, precious metals, platinum group metals, and rare earth elements. The material content of the different devices is assessed with the use of proxy databases and of laboratory analysis performed with the purpose of improving the information available. The databases for life cycle of material impacts are also here linked with the material demands.

4.2.2. Methodology for screening inventories for LCA of data centers

[Wh12] introduced the screening methodology for LCA in data centers. This method makes use of LCA data from previous studies held in databases. Where data is missing or is non-existent this method approximates components to the nearest comparable option. Such an LCA allows for the identification of hot spots in a comparatively short period of time. This may later be embellished by improving the databases and the inventory information.

4.2.3. Description of case studies

Information from existing data centers in northern Germany is used as case studies for the applied methodology. These operating data centers were screened to provide a complete inventory list of their infrastructure and hardware. These belong to different types of organizations extending from communal oriented data processing facilities, commercial business applications, and data centers for researching of IT optimization (**Table 4-1**). All IT equipment is within racks arranged in cold aisle containments, and for the purpose of modelling it is assumed there is no free-standing kit.

Table 4-1: Summary description of the considered case studies. These correspond for existing and operating data centers.

Label	Rack density (kW/Rack)	IT load (kW)	No. of server units	Size category	Tier
DC1	4.4	122	485	Medium	II
DC2	6.4	64	180	Small	III
DC3	3.4	3	5	IT Cabinet	I
DC4	3.1	15	135	Small	III
DC5	3.3	99	444	Small	III

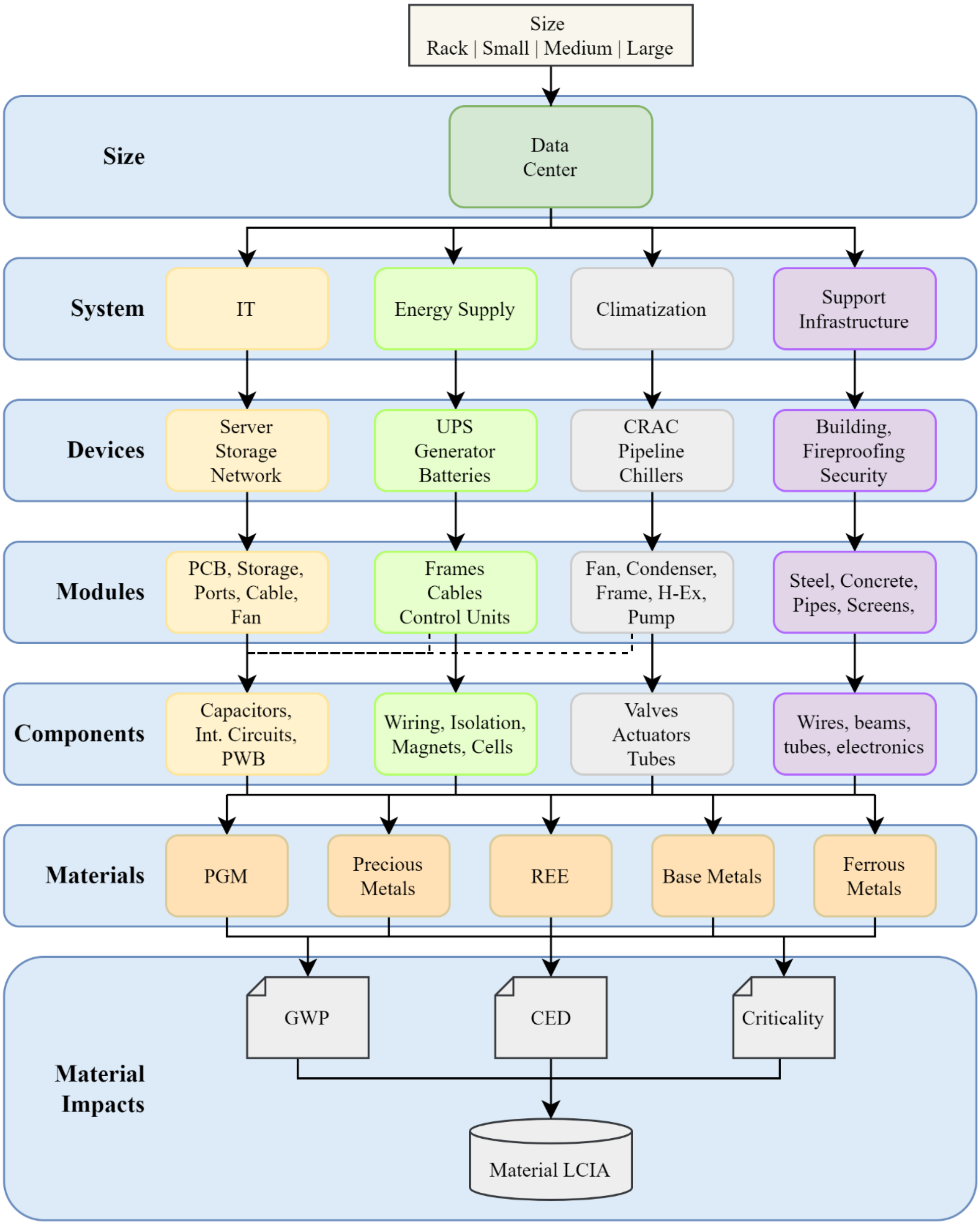


Figure 4-2: Cluster for analysis of materials in a Data Center.

- DC1 operates with water cooled down by a compression chiller system and has a free cooling system to extract heat from the IT halls, and PDU and UPS rooms. This system is backed up by a redundant chilled water system. Due to its commercial oriented use, it presents peak loads during the month of December.
- DC2 is part of a bigger research institution, and its power supply and cooling energy supply are part of bigger institutional facilities.

- DC3 is a small IT cabinet of a private organization.
- DC4 is an experimental facility with the purpose of researching IT performance and energy use in data centers, with a cooling system of variable capacity based on chilled water.
- DC5 is a communal oriented organization that provides data processing services, uses redundant chilled water system, and operates under IT redundancy.

4.2.4. Functional unit

The general function of a data center is to provide computing. This calls for an assessment based on a unit of computing output. However, due to the heterogeneity of data centers and their purpose, referencing the results to a general computing unit is still complex. Different stages of the research call for different functional units that adjust to the objectives of the stage of the research. For the first portion, where individual components are assessed to identify hot spots and requirements on improvement of data, whole devices are considered as a unit. [Wh12] applies a per-kW of computing per-year basis for the complete assessment of a data center ($kW \cdot a$). This last approach also allows a sophisticated model where material flows of data centers can be incorporated based on their lifetime.

4.2.5. System boundaries

Section 3.1.2 defined the boundaries of the study. The study is a cradle-to-grave investigation with exclusion of the operational phase and considers the life cycle of a data center and its components from the extraction of raw materials (cradle) to the eventual end-of-life of the facility (grave). For the first screenings and assessment of results quality, the boundaries are set up to the production phase (cradle to gate). This is because without proper information on material content, an analysis of EoL and recycling strategies will result in inaccuracies. Stages included are then refined to:

a) **Manufacturing***:* This stage includes the material and energy inputs in the extraction of raw materials, their transport to the manufacturing plant, manufacturing of each material and component, and final assembly.
b) **Transport:** No specific data was available on the transport used to transfer final products to site. Assumptions for transport and values given in other sources were included. As an example, 200 km average transport from plant to plant for server components to assembly plant was included. This assumption may also be used for End-of-Life transport to disassembly and recycling facilities.
c) **Use*****:*** Since this study focuses on impacts of raw materials, only material flows are considered during the use phase. This includes component exchange and use of consumable materials, such as cooling refrigerant. IT would undergo exchange every 2 to 5 years, batteries every 5 to 10 years, and facilities every 20 years. General maintenance is excluded.

d) **End-of-Life:** Broadly speaking, this stage includes transport of the components to disassembly facilities, disassembly processes, crushing and/or manual or automatic separation, and recycling of materials using different technologies. The recovery of materials is modelled as "avoided mining". This means that the generated ores are considered to generate negative impacts of the same specific absolute value as the raw ore. A more detailed specification of these processes is given in Chapter 5. This stage is included after a first evaluation of material composition data accuracy.

4.3. Data collection and databases

4.3.1. Data collection

The first stage encompassed exhaustive data collection. Information was gathered on the inventories of the data center, with lists of IT devices, cooling equipment, and energy supply infrastructure. Additional data, such as power and data cable length were extrapolated based on the number of devices. All IT equipment is considered as WEEE for the EoL, with different scenarios for disposal and treatment. Equipment such as cables and metal frameworks were considered as scrap metal for recycling. Here, reference values for the composition of the devices were considered, and proxy databases were first included. These serve to identify components with hotspots on material usage and embedded energy.

A second step of the research included disassembly of EoL components of the data centers under study, which provided decommissioned equipment for their analysis. This led to an inventory database on parts of the devices. The lifecycle databases of the different components and subcomponents were first modelled using proxy information from existing databases, and updated information for the inventories.

Inventory information for gathering of raw materials in its commercial form varies by source and quality. Information on the product life cycle of some common materials such as aluminum, copper and iron is already included in the ecoinvent 3.4 database [We16]. The database on raw material gathering processes was analyzed to evaluate accuracy and representativeness. One of the gaps found was the absence of some critical materials on the database, such as individual rare earth elements. Moreover, the ecoinvent database presents some products as byproducts of other mining activities or represent them completely as other materials due to the multiple outputs that come from the same mine. E.g., platinum was represented using gold flows, which lead to errors in the assessment of the impacts of critical material use. This substitution required a modification of the databases to include materials originally omitted, and to separate properly processes with multiple outputs. This update is also presented as a key contribution of the research and described in Chapter 7.

Individual material assessments were conducted using the research outputs of a previous update in the life cycle assessment of metals, presented in [NE14], as a starting point, and updated sources on global mining output were gathered from sources such as the US Geological Survey [Ob16]. The updated materials database is later used for impact assessment calculations.

LCI information is gathered from specific studies to create models for the various processes required to mine and process the different raw material. In cases where mining and refining activities generate multiple materials, economic allocation of environmental impacts and resource use provides a method for attribution of the total impacts of those materials. Economic allocation factors are derived from information about the economic value of the manufactured goods and combined with the mass fraction of each product.

4.3.2. Databases for LCA

Databases for LCIA exist for various products and processes. After a screening of available databases, some of the relevant databases for this study are:

- **Ecoinvent 3.x:** The ecoinvent database provides updated information on energy mixes and industrial production processes for IT and electronic components, although not focusing on data center components. In addition, it offers a collection of methods for assessing environmental impacts. These methods also serve as a starting point for the development of criticality-based impact assessment methods, but the characterization factors are updated and modified according to the methodology presented in Section 3.4. The current of this database version is 3.8 [We16].
- **GaBi v2002.2:** This database, attached also to the software of the same name, contains worldwide industry data from primary sources with background data sets. It contains extensions for specific industrial activities.
- **ProBas+,** a refined version of the ProBas dataset of the German Federal Environment Agency, includes information on energy, materials, products, transport, and waste. It contains information on processes centered around Germany and has information on the manufacturing of electronic components such as computer chips. However, the process of wafer manufacturing has no backup information.

Of the databases currently used in the scientific community, the best known are the GaBi and ecoinvent databases. Since the ecoinvent database has attributed geographic location information and a list of electronic components, is used as a starting point. Software restrictions make it preferable, as the GaBi software is not open source. The information of the ProBas database on integrated circuit manufacturing is used later for comparison. Other databases were deemed incomplete, are discontinued, or focus on other types of products.

4.4. Modelling methodology

Given the wide variety of products included in data centers, and the multiple system configurations, it becomes difficult to develop exact models of each component in the case studies. [FHS10] and later [Sz18], [Sc18] and [Pe20] proposed an approach based on the definition of "*Reference Products*" and "*Reference Units*" to construct models of devices which are representatives of the devices and components present in the data centers under study.

Reference devices are established from the inventory list of devices used in the data centers, which consideration of the technical aspects and their functionality within the system. Reference components are gathered from a technical characterization of the Bill-of-Materials of the selected device. The material data for the reference components is collected from literature sources, existing databases, and from specific laboratory analyses.

Figure 4-3 gives an example of this construction for the case of IT devices. Reference modules are included as a disaggregation of components.

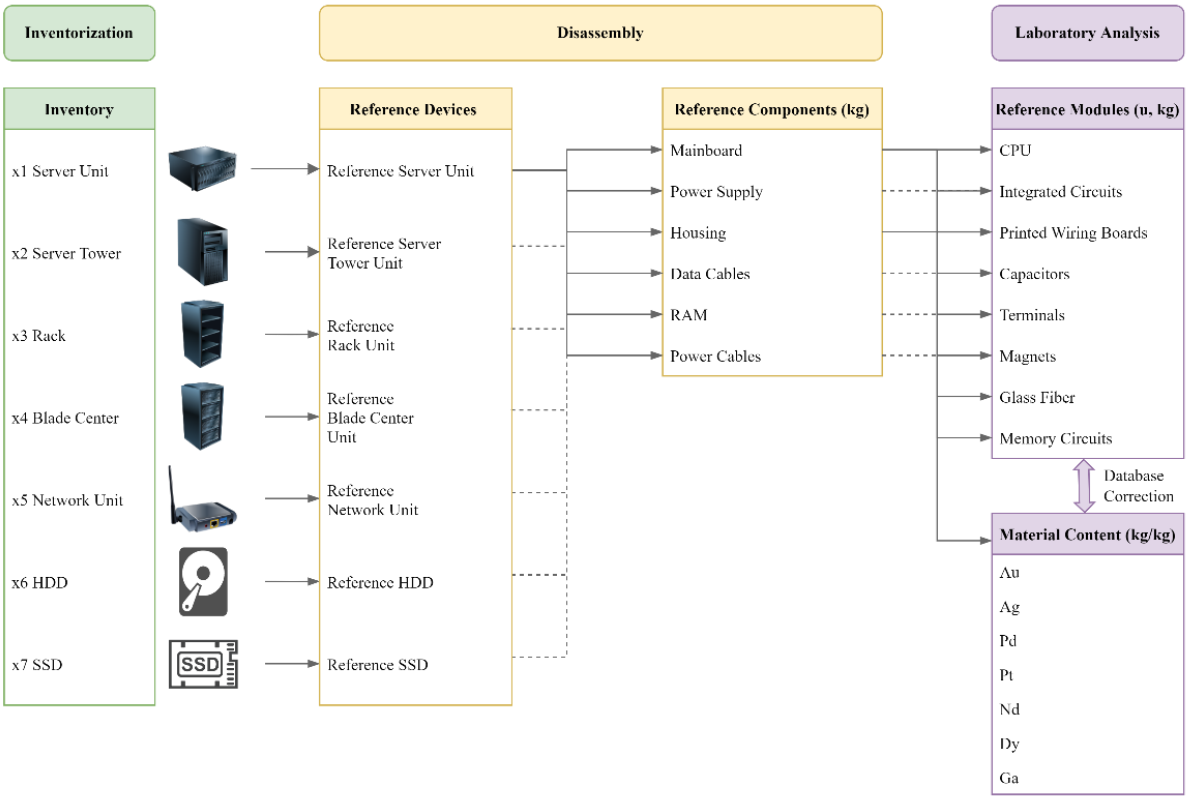


Figure 4-3: Procedure for creating databases for modelling of components of data centers.

4.4.1. Reference devices

Reference devices are meant to represent a variety of similar components. [FHS10] established a set of products based on market information. However, for the application of this study, the reference products must be in accordance with the inventory lists of devices available for analysis. This results in a reduced number of devices, focusing on IT devices, and is based on typical server classifications. These classifications include different reference devices for servers, network devices, and storage components. As an example, servers are categorized in stand-alone (mainframe) servers, tower servers, server blades, rack servers, Unix servers. Hard disks are categorized according to their technology and size (SSD, HHD 3.5" and 2.5").

Each reference device has different technical specifications and performance. These differ from each other in key characteristics, such as type and number of installed processors, memory capacity, network interfaces and thus also the design of power supply, cooling, and housing. Therefore, models for each of these components can be used to build up the model of each reference device.

Devices of other subsystems are determined by their size and their composition. The first approach to develop models for these devices is to use inventory data and literature data for the bulk of their materials and identify hot spots in the impact assessment phase. An example of these is the transformer for energy supply, whose size depends on its nominal power. These support devices also include electronic components, such as PCBs for the control devices, which can also be modelled to build up the model of the device.

4.4.2. Reference components

For a characterization of the reference devices, the weight contribution of their characteristic components is analyzed to develop a BoM. This is the basis for the inventories of data center devices and their components. Components are separable elements that are obtained during disassembly. Each of the components is then modelled after a proxy product of a database to reach a first iteration of the model. These serves as a bridge for a preliminary assessment of the material composition of the devices. Components include printed circuit boards, power supply units, cooling units, storage components, cables, amongst others.

4.4.3. Reference modules

In a deeper category, each of the components is comprised then of modules, which represent the constituting elements of the components. This refer to, for example, CPUs, integrated circuits, capacitors, RAM memory, etc. [FHS10] and [PHS19] (a preliminary study for this dissertation) identify these as hotspots for material depletion impacts, hence the importance of assessing them in detail.

4.4.4. Disassembly analysis

This part of the research is based on the dismantling of data center devices conducted in collaboration with Mairec Edelmetallgesellschaft GmbH, one of the project partners of the project TEMPRO. Further sampling and analyzes were also carried out by the Technische Universität Hamburg (TUHH) [Pe20].

Twenty-eight different types of servers were obtained for disassembly. The servers were dismantled, and the inventories of the parts were collected, with the weight of the individual components registered for development of BoM with an emphasis on the printed circuit boards. With the dismantling of the test material provided, the individual parts of the IT devices were separated, dismantled, and the weight of the individual components was measured.

Identified components include mainboards, expansion cards, memory modules, and CPUs attached to the motherboards. Servers also contain storage units (HDD, SSD), CD/DVD drives, power supply units, and cooling units. **Table 4-2** presents an example of the inventoried composition of the servers.

Table 4-2: Overview of the component fractions of a decommissioned server. Results come from disassembly of servers conducted in this study.

Material	Weight Percentage (%)
Motherboard	4.65
Expansion Cards	1.20
HDD/SSD	0.73
RAM and CPU	0.51
Back panels	1.35
Power Supply Boards	6.99
Aluminum	5.74
Fan	3.87
Hard Drive Magnets	1.33
Iron	69.78
Plug Cable	1.03
Heatsink (Copper	0.92
Others	1.90

4.4.5. Laboratory analysis of material composition

After obtaining different samples of the PCBs, the amount of different valuable and critical materials in the main components of servers was analyzed, since these are the components with the highest critical and precious material concentration. The devices were categorized and sorted into categories by application:

- Motherboards
- Expansion boards
- HDD printed circuit boards
- RAM (memory boards)
- CPUs (separable from motherboards)
- Power supply boards
- Network boards

For the analysis of material composition, samples of the above components were cut into long strips and then into smaller pieces. Then these pieces were crushed to 4 mm, then 2 mm, and then 0.2 mm to obtain a homogenized fraction. Mairec conducted analysis to evaluate the fractions of copper and precious metals. These crushed samples were later sent to the TUHH for further laboratory analysis for other metals, such as REE. The samples were treated with acids for further atomization and analysis in the ICP-OES equipment (Inductively coupled plasma - optical emission spectrometry). To identify the metal content, microwave digestion was carried out with acid (aqua regia). The microwave acid digestion process followed the analysis process described in DIN-EN 16174.

The results of this analysis allow a new characterization of the material content in the mentioned devices. There are some key differences between the laboratory data and the assumed literature values. The content of aluminum and iron is lower than initially reported. The content of gold, silver, and precious metals is up to one order of magnitude higher, indicating higher material concentration than previously reported. Another novelty of this analysis is the reporting of critical material content, such as dysprosium und neodymium. **Figure 4-4** and **Figure 4-5** display some of these values compared to previous assumed information.

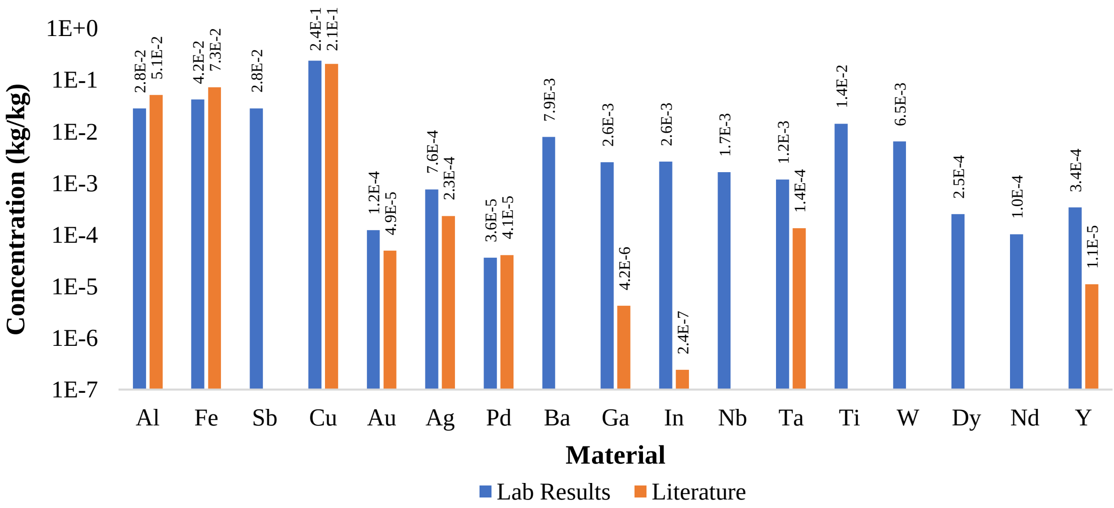


Figure 4-4: Difference of data between the results from the laboratory analysis and the existing data from literature for server motherboards.

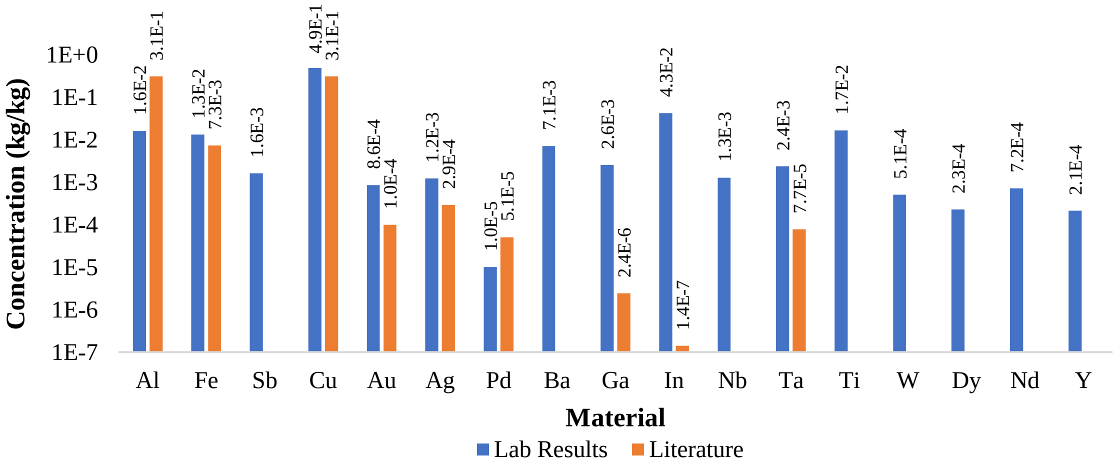


Figure 4-5: Difference of data between the results from the laboratory analysis and the existing data from literature for RAM.

4.5. Life Cycle Inventories of data center elements

4.5.1. Description of inventories for modules

This section describes a summary of the LCI for modelling of the modules that have the highest impacts on material depletion and on primary energy demand. As there is a vast number of electronic components, only a small selection is described here. The developed LCI databases include a description of components of lesser relevance.

4.5.1.1. Processors

[Pr16] presented information on production of CPUs. [Sc18] developed models based in a differentiation according to front-end back-end manufacturing processes. The frontend process includes the structuring, coating, and doping of silicon wafers. The backend processes include building connections and assembling into CPUs. These models are also incorporated in the ecoinvent 3.4 database, and are based on the production of silicon wafers, with a requirement of 180 cm^2 of wafer surface per kilogram of CPU. Average die density is taken as 629 g/m^2. Transport from is specified as 2 500 km via freight train and on lorry, representing transport from frontend to backend manufacturing plants, and similar values for transport to assembly plants. Modelling includes mix from electricity sources representing production, mainly from China and the United States. Further intercontinental transport includes transoceanic freight (10 000 km). The production of wafer is given in square meters, whereas the integrated circuit is given in weight units. **Figure 4-6** presents a schema of the model for this process.

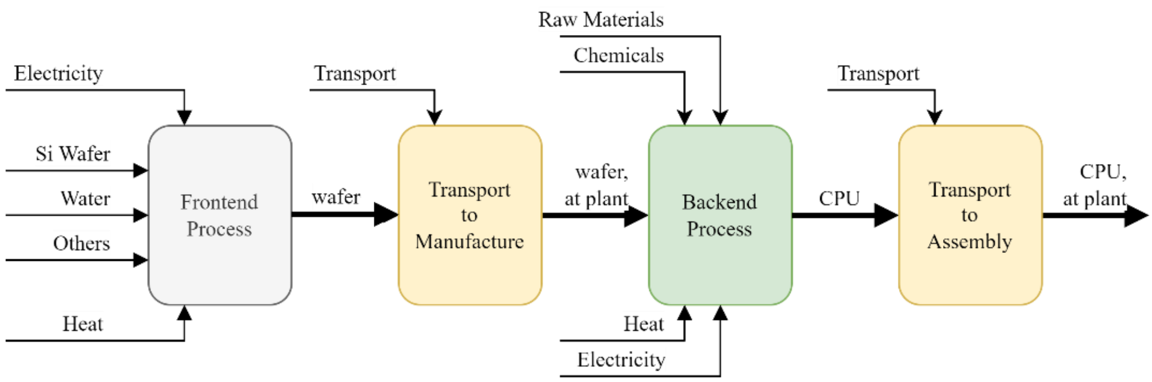


Figure 4-6: Description of process chains for life cycle inventories for CPUs.

4.5.1.2. Integrated circuits

Integrated circuit production is based also on the processes for manufacturing silicon wafers. Integrated circuits include frontend and backend processes. This is modelled as memory integrated circuits, in accordance to the approach of [Pr13]. Electricity mixes are represented as a mixture of country specific mixes. Integrated circuits are used to populate printed wiring boards to compose printed circuit boards. A die area of 44.4 mm^2/kg is considered in the ecoinvent database. [Sc18] also includes integrated circuits directly on mainboards, without differentiation of products. Transport activities include transport from wafer factory to frontend process plant, from frontend to backend process, and to the final assembly plant. The process is like the one in **Figure 4-6**.

4.5.1.3. Capacitors

Manufacturing of capacitors includes using critical metals such as tantalum and precious metals such as silver. There are different types of capacitors considered for the fabrication of printed circuit boards, and their use depends on the type of application intended. Electrolytic capacitors are widely used in ICT, whereas the tantalum capacitors are used in surface-mounted devices where small areas and high-capacity density are required. For a general model, tantalum, silver, manganese, palladium, and titanium presence is dependent on the specific capacitor type. Tantalum is given as powder manufactured for capacitors, whose process is linked to the ecoinvent background process. Data is normalized at 1 kg of capacitor. **Figure 4-7** represents this process, where the optional components are marked in dashed lines since their input depends on the type of capacitor manufactured.

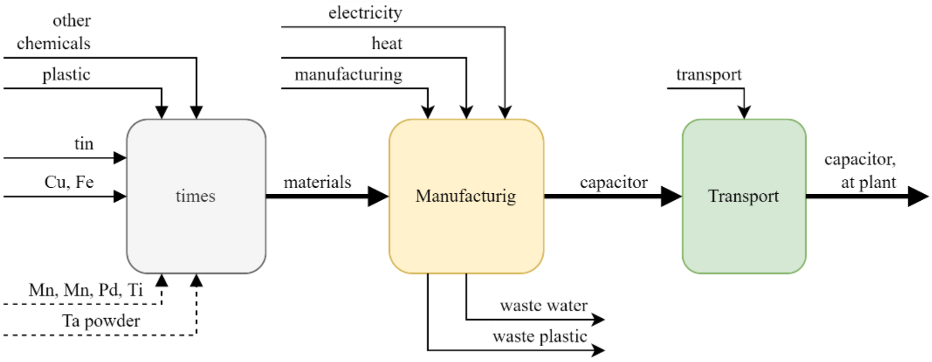


Figure 4-7: Model for life cycle inventory of capacitors.

4.5.1.4. Printed wiring board

Printed wiring boards are the basis for mounting the different modules, such as integrated circuits, resistors, capacitors, transistors, and other electronic components. The ecoinvent database has a variety of models for printed wiring boards, albeit the applications are oriented towards personal computers. Several differentiation characteristics are for surface, or through-hole mounting, the lead content, and the type of soldering used. Lead-free PWBs include metals such as gold, silver, and nickel. Transport includes land transport from manufacturing plant to assembly plant. Data from [Hi07] was extrapolated to 2017. The data corresponds to a six-layer FR4 multilayer printed circuit board, which simplified the information on backend processes. This is a similar process as the one in [Pr16]. The flow information is referenced to 1 m^2 of printed wiring board. Similar assumptions on transport as for the integrated circuits were made. **Figure 4-8** represents a generalization of this process, where the inclusion of precious metals is dependent on the type of board.

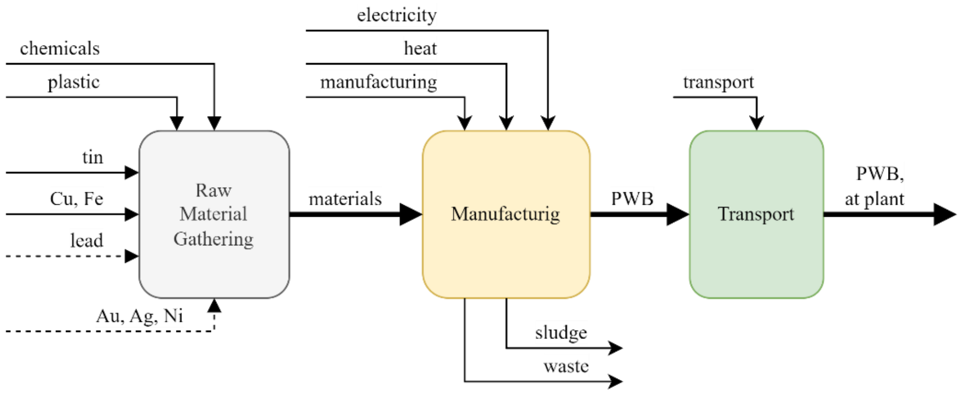


Figure 4-8: LCI for the manufacturing of printed wiring boards.

4.5.1.5. Magnets

Neodymium is used for strong permanent magnets. Magnetic storage devices, such as HDD, can contain powerful magnets based on neodymium. Another material that can meet the needs of magnets in HDDs is samarium cobalt. According to DIN-EN 60404-8-1, neodymium magnets contain 28% to 35% neodymium (mass fraction) and 0% to 10% other light rare earths such as dysprosium, terbium, and praseodymium. [Sz18] established the content of Nd between 20.8% and 28.8% for magnets used in 2.5" und 3.5" HDDs. For NdFeB magnets, a typical composition of 65% iron, 1% boron, 2% cobalt, 24.8% neodymium, 6.2% praseodymium and 1% dysprosium are estimated. These magnets are manufactured by melting the mixture, consisting of neodymium, iron, and boron; followed by casting of this mixture into ingots. The ingots are subsequently pulverized to powder, which, in turn, is sintered and magnetized to form the permanent magnet [TMK21]. **Figure 4-9** details the model used, which is based on a proxy for aluminum technology and considers an estimation on transport of 20km from production to HDD assembly plant.

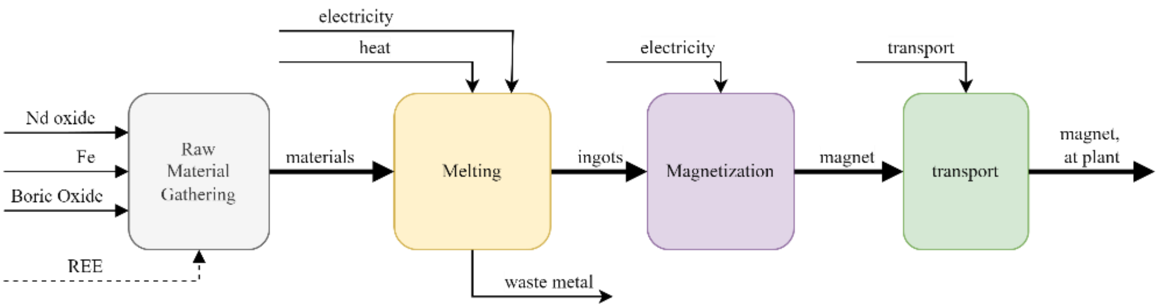


Figure 4-9: LCI for the manufacturing of magnets for HDDs.

4.5.2. LCI for components

At the component level, most of the material depletion impact embodied energy depletion impacts are focused on electronic devices, such as printed circuit boards, RAM memories, storage technologies, and cables with their connectors. Their manufacturing processes are modelled after the modules described in the sections above.

4.5.2.1. Printed circuit boards

Printed circuit boards are fundamentally characterized by a very high variety of materials. This depends on their subcomponents and on the functionality of the board. PCBs for an UPS have different composition than that of a server, and within server there may be different categories of PCBs. The material composition of the server boards is determined by the number of processors (CPU), memory, and network connections (ports) fitted. Mainboards make up most of the PCBs in IT equipment, with a share of around 80%. Adapter boards with various applications are connected to the main boards (also called Printed Wiring Boards, PWB). Memory modules and CPU (chips) are usually attached to the motherboards of the servers. Hard drives, CD-ROM drives, and power supplies also contain circuit boards. Network technology devices such as switches are also equipped with motherboards. **Figure 4-10** represents the inventory for manufacturing a PCB.

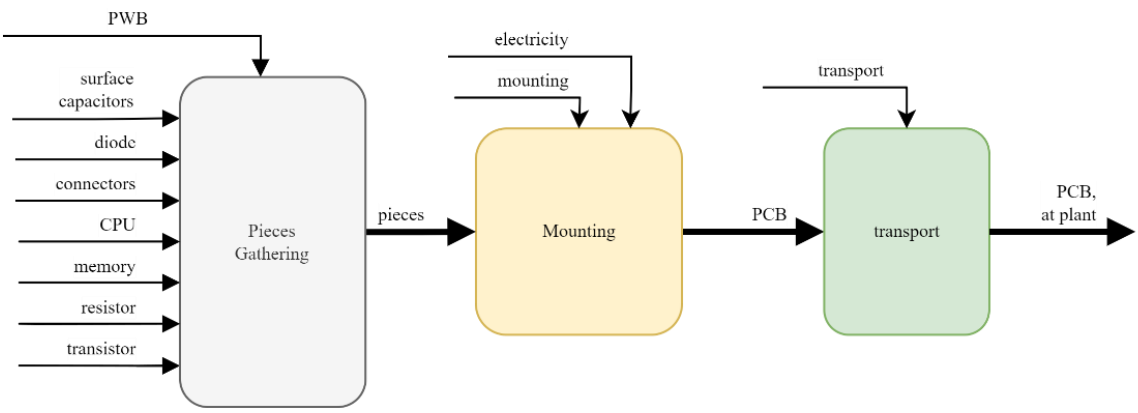


Figure 4-10: General schema for the LCI of a printed circuit board, with example of a mainboard.

Most of the valuable materials are found in PCBs, which leads to a broad classification of them into low, medium, and high-grade PCBs, based on the value of the metals that can be recovered. **Table 4-3** presents a classification based on gold content, which is generally used when discussing recycling of PCBs [Sz14]. This classification is however insufficient for this dissertation, and a deeper analysis is required. However, to keep a relation with current literature, these denominations are also later employed. [FHS10] differentiates the various PCBs existing in servers according to the value of the material content as well.

Table 4-3: Categorization of PCBs by Gold content. Source: Data from [FHS10].

Category (Grade)	Gold (ppm)
Low	<100
Medium	100-400
High	>400-

Within the disassembly analysis, several types of PCBs were identified, each with a particular purpose and material composition. Material content information is firstly gathered from a reference data based on past studies [Sz18, FHS10, Ha06], which allows a first evaluation of material content (**Table 4-4**). Based on this information, reference PCBs from data center components obtained during the disassembly were evaluated to assess the material content. The LCI databases are later modified accordingly to reflect the material content and the related material depletion of each component. Following elements are considered:

a) **Mainboards** are modelled as populated printed wiring boards, with a memory component included. This is built upon the "printed circuit board - mounted memory" process in ecoinvent. Mainboards include a CPU (represented as a logic type chip) and a memory (memory type integrated circuit). Additional components of relevance include surface capacitors, connectors, and diodes.

b) **Expansion cards** serve as accessories to add functionalities or to extend capacities. These are also modelled with a similar composition as mainboards.

c) **Memory cards** are considered as RAM Modules and are modeled as an aggregate of integrated circuits, which are based on the memory type integrated circuit model in ecoinvent. [Pr13] considers a RAM memory of 1 GB as a reference product, with a die surface area of 43 mm^2. A reference RAM module is equipped with nine memory chips mounted in a circuit board, with an extra chip for parity. Efforts for the assembly of the circuit board must be considered in the modelling of the RAM. Memory cards contain gold contacts that compose most of the valuable metals found. Transport activities include transport from wafer factory to frontend process plant, from frontend to backend process, and to the final assembly plant.

d) **HDD boards** can be present in servers as part of the storage devices, or as separate components. The composition of PCBs for HDDS are represented as PCBs with lower valuable material composition. These are modelled as a mixture of different PCBs to adjust to the material composition presented, which represent an average of the mixture found in data centers.

e) **Network boards** are also present on servers as part of the communication components (LAN terminals). These are found to have valuable material composition, mostly because of gold contacts. Network boards are modelled analogously as adapter boards.

f) **Power adapter boards** have a smaller circuit board which are small in relation to the outstandingly large electrical components (e.g., electrolytic capacitors, coils, transformers, resistors, heat sinks). The proportion of non-ferrous metals and iron is assumed to be relatively high. This reduces the material content and thus are modelled as a printed circuit board with low material content (Pb mounted surface PCB).

Table 4-4: Literature values for material composition of Printed Circuit Boards according to their application. Source: Data from [Sz18, FHS10, Ha06]. Content given in is in mg/kg.

Material	Mainboard	Expansion Cards	Memory	HDD-Board	CPU	Network Board
Ag	232.35	232.35	348.53	248.87	290.44	23.24
Al	51430	51430	39320	25720	308590	128580
Au	49.38	60.96	198.38	132.31	99.89	3.62
Be	0.24	0.24	0.18	0.26	0.14	0.1
Co	24.77	24.77	18.94	26.53	14.18	10.5
Cu	205730	205720	308590	220350	308590	411450
Fe	73030	73030	7300	36520	7300	175280
Ga	4.21	4.21	3.22	4.51	2.41	1.79
In	0.24	0.24	0.18	0.26	0.14	0.1
Nd	0	0	0	0	0	0
Ni	13370	13370	10220	14320	7660	5670
Pb	15430	15430	0	16530	0	6540
Pd	40.72	40.72	61.08	43.62	50.9	4.07
Si	436140	436130	333430	467150	249740	184950
Ta	1440	1440	1100	1540	820	610
Y	135	135	103.21	144.6	77.3	57.25
Zn	11.01	11.01	0	11.79	0	4.67

4.5.2.2. Cooling units for electronics

Cooling units are mostly modelled as aluminum, brass and iron bodies shaped as a heat exhaustion device. These can also include fans (from plastic), with small PCBs (modelled after a power adapter board) for control.

4.5.2.3. Power transmission cables

Power transmission cables are mostly comprised of copper and plastic. Wire drawing process for wire manufacturing and plastic extrusion is considered in the models, as well as transport. Data is modelled after a 1 meter of low voltage transmission cable with a weight of 1.04 kg/m.

4.5.2.4. Network cables

Network cables for communication devices are modelled after data for UNINET cables, with a weight of 360 g/m [We16]. These consist of plastic and copper, and the model includes the manufacturing efforts for wiring and molding process. Plugs are modelled separately as copper and plastic pieces. Data cables in servers can contain gold in their pins, which are modelled separately (**Figure 4-11**). Data cables for servers with gold in their terminals can contain precious metal concentrations as high as 100 ppm.

4.5.2.5. Optic fiber cables

Optic fiber cables are modelled directly with data from ecoinvent, and modified to include the presence of rare earths, since these were absent in the original database. These present traces of germanium in the form of germanium oxide. Optic fiber cables are used in network devices [FHS10, Sz18].

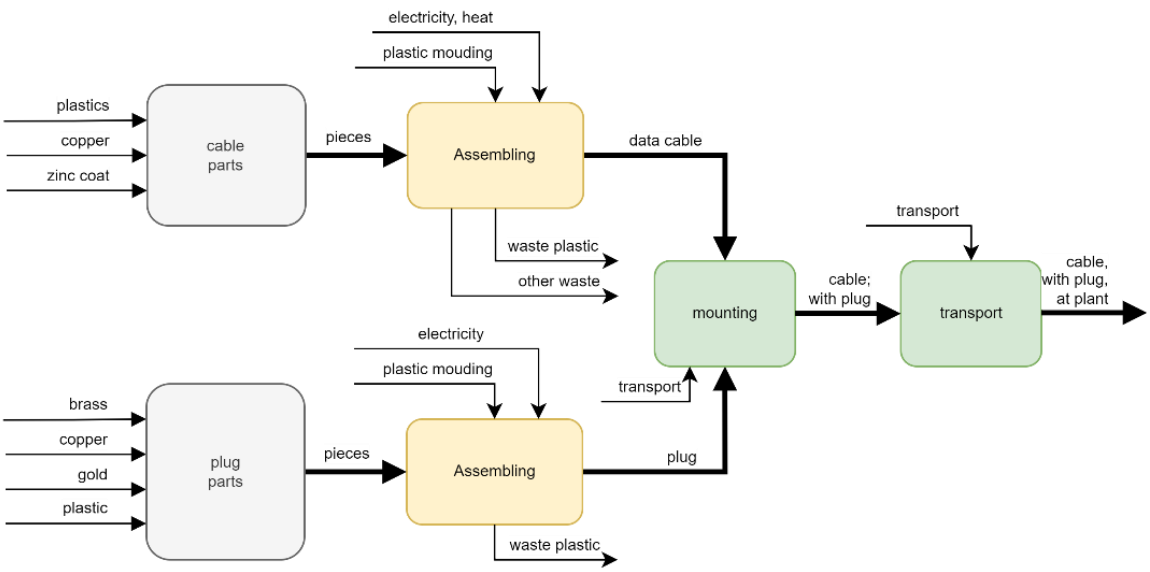


Figure 4-11: Manufacturing process for a data cable with connection terminals.

4.5.3. LCI for reference devices

4.5.3.1. Servers

There are different categories of servers. [bi13] details a categorization of servers by type, which include tower server, rack servers, blade serves, and microservers. Due to the different configuration of servers, different models of these components were developed. The first approach follows the establishment of average units proposed by [FHS10]. Selected reference products are established here. After that, specific units were selected from data center decommissioned devices and were analyzed for their composition. These vary in size, and a reference unit of 1U is selected for scaling purposes. From this, tower servers and rack servers are the most used in data centers. The following items were then selected as reference devices.

- **Server 1U** is modelled after a server with one height unit. The model of a PowerEdge 1950 excludes storage, which is later inventoried separately. It consists of main memory with 8 memory modules. Added storage devices also include two 3.5" HDDs and one 2.5" HDD.
- **Server 2U** is defined based on a HP ProLiant DL360 G3 server, excluding external storage. Added storage includes four 3.5" HDDs and two 2.5" HDDs.
- **Sandwich servers** are servers 1U unit but half the depth. This is modelled after a Pyramid-Supermicro server. It is equipped with a CPU, mainboard, and two memory modules. The examined server is modelled with four memory modules.
- **Server (1+N)U** are scaled up from Server 1U without storage, with half of the housing content for every additional unit. External storage is modelled separated.
- **Half-Blade servers:** The model is based on a PowerEdge M620, divided into mainboard, processors, and adapter boards.

- **Blade server** model is based on a PowerEdge M710. This model includes storage devices of 3,5", which are modelled separately. Its main component consists of 18 memory modules.
- **Blade center** model is based on the disassembly of a Dell PowerEdgeM1000e. It is comprised of external housing, 9 fans, 6 power supplies, a mainboard, and 6 switches.
- **Server housing,** the enclosure of a server, consists primarily of steel chassis. A PCB is included for connection of the plugged module, modelled as a small mainboard unit. The steel structure is around 80% by mass. The remainder is considered as data cables and plastic parts.

Table 4-5 shows an example of the disassembly analysis, which serves as a first iteration for the modelling. The components are assigned to the models discussed in the previous section. A proxy for assembling in a manufacturing plant is based on the existing database for energy and manufacturing efforts existing in the ecoinvent database, plus shipping (mixture of sea and freight).

Table 4-5: Example of components list for a Server 2U, based on a model HP ProLiant DL380.

Component	Weight (kg9	Count	Model
Power Adapter	1.696	2	Network PCB
Main Memory	0.024	6	RAM PCB
Housing	14.832	1	Fe
Plastic	0.304	1	Moulded Plastic
Hard Disk	1.001	6	HDD 3.5 in
Fan	0.165	8	Fan
Network Card	0.121	2	Expansion Cards
Active Riser Card	0.169	1	Expansion Cards
DVD Drive	0.256	1	DVD Drive
Battery	0.002	1	Li battery
Motherboard	1.060	1	Mainboard
Processor	0.022	2	CPUs
Processor Cooler	0.433	2	Cooling Unit
Voltage Regulator	0.062	2	Expansion Card
Rectifier Module	0.602	1	Expansion Card
Circuit Board	0.018	1	Expansion Card
Server Cable	0.089	5	Data Cable
Main Circuit Board	0.294	1	Expansion Card
Connection Board	0.028	1	Expansion Card
Cable(Motherboard)	0.013	1	Data Cable
Power Cable	0.009	1	Power Cable

4.5.3.2. Storage devices

Storage devices within data centers can be categorized in SSD and HDD, the latter being subdivided in HDD of 2.5" and 3.5".

a) **HDD:** [Pr16] provides a first dataset for a 1TB, 3.5" in HDD. Disassembly data for an HDD is then obtained after a WIDE ULTAR320 3.5" HDD , and a DELL Savvio provides data for the HDD 2.5". The data for the components of these devices is modelled after the LCI of PCBs, magnets, cables, and similar components from the previous section, plus additional upstream components when required. 2.5" and 3.5" drives are similar in components but differ in size and weight. [Pr16] assumes that the size of the integrated circuit in the printed circuit board is the same. Energy for production is scaled accordingly.

b) **SSD:** Solid State Drives are modelled after information from the disassembly from an SSD included in a Brocade Bladecenter. These consist mostly of printed wiring boards with integrated memory circuits, plus a socket from a 2.5" HDD. In these memory modules, gold contacts can account for a relatively large proportion of the board. The configuration of memory populated integrated circuits is assumed for SSD circuit boards and SD cards.

Table 4-6: Material composition for an HDD 2,5 in, 1TB.

Component	Weight (kg)	Count	Model
Housing (Fe)	0.086	1	Iron Housing
Housing (AI)	0.158	1	Al housing
PCB	0.014	1	HDD PCB
Magnets	0.003	2	Magnet
Magnetic Tape	0.002	1	Magnet
E-Motor Housing	0.006	1	Iron Casting
Plate Disks	0.007	2	Al, casted

4.5.3.3. Network hardware

[FHS10] made the initial assumption that the Network composition is equivalent to 10% of the amount of materials in servers. Inventories on network devices are here gathered to improve this assumption. Network components are modelled as a collection of Network-PCB and metal (iron housing) components. **Table 4-7** presents an example of the list of the inventory of a network unit.

Table 4-7: Material composition for a network unit.

Part	Mass (kg)	Count	Modell
Iron Housing	0.571	1	Iron Housing
Network PCB 1	0.102	1	Network PCB
Network PCB 2	0.122	1	Network PCB
PCB, low content	0.002	2	Power Adapetr PCB
Case	0.008	1	Plastic

4.5.3.4. Racks

Racks are used to hold servers, storage units and network devices. Most of the material of racks consists of iron, plastic, glass, and aluminum. The amount of material present in racks is dependent on the number and type of servers and devices, and extrapolations can be made to estimate the amount of material present in a data center IT room. [FHS10] indicates an average of 5 server units per rack, with an estimated 87% iron content.

4.5.3.5. UPS

UPS as devices are here simplified as battery-backed up power supply devices. Two types of UPS are considered: single-phase UPSs, mostly used in smaller locations (server rooms), and three-phase UPS, used in bigger datacenters. The size of an UPS and the material content are scaled up to its nominal power, with average outputs between 3 kVA and 60kV as studied units. These consist of batteries (mostly Lead-Acid), iron, aluminum, copper, and low-grade electronic components. Models for manufacturing and forming parts, and for transport are included. The size of the UPS capacity depends on the redundancy of the data center (tier category) and on the required IT power.

4.5.3.6. Electric storage system for UPS

The electric storage (battery) system for UPS devices consists of the electric storage units, power converters, electronic control and regulation, and network connections. Most of the batteries are of the lead-acid type, which has the advantage of its high recycling capabilities. The batteries are connected to the control board by cables. The power converter and the control consist of a larger transformer and of additional power electronics (switching transistors, microcontroller, etc.). A model for a battery is established separately and based on the ecoinvent database. Control units and power converters are modelled after the PCBs presented in previous sections. **Figure 4-12** represents the process for manufacturing and assembly of a UPS unit with batteries.

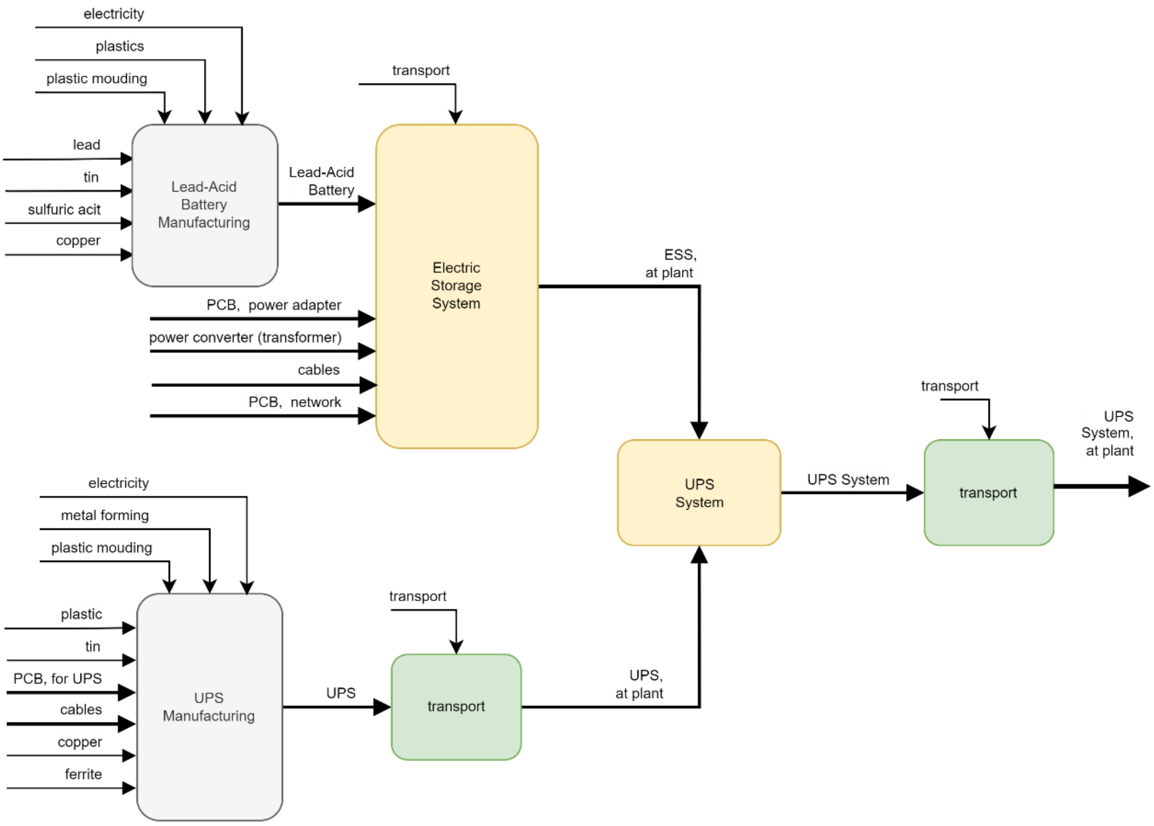


Figure 4-12: Schema for the LCI of a UPS System for data centers.

4.5.3.7. Other electrical supply systems

Generators are modelled using mostly data on their material composition, which is present in the ecoinvent database. Generators consist mostly of copper and iron, with smaller, low grade printed circuit boards. A reference product of 200 kW and 850 kg of weight is considered and escalated by size.

Transformers for data centers are mostly of the low voltage type. These include mostly bulk materials, such as iron, ferrite, copper, plus plastic components. Similarly, low grade PCBs can be found in these devices as control units. A reference unit of 500 kW weighing 3 tons is used as reference product and scaled accordingly.

Lithium batteries are gaining ground as secondary batteries for backup power supply. There are several types of composition of Li-Ion batteries, some of them using cobalt (15 -20% of weight per pack). Recovery of lithium (2-3% of weight per pack) is of current interest, however no procedure for recovery is already established at an industrial scale that can provide data for recycling. Other components are iron supporters and copper cables.

The amount of power cables, of the 3-phase type, are extrapolated using a factor of 1.1 kg/kW of installed electric capacity. These consist mostly of copper and plastic.

4.5.3.8. Climatization units

For medium data centers and above, most of the cooling is done via air conditioning. Air conditioner inside the IT room can be of the split-air type (used in server rooms) or an air-cooling system (for small data centers and above. Air cooling inside the IT rooms is done via heat exchangers that use chilled water (or a mix of water and glycol). Chilled water is obtained via compressed chilled devices.

a) **Air conditioning units:** [Ol12] developed a model with a complete inventory for an air conditioning unit within a data center. This model consists mostly of a radiator, fans, condensation pumps, and a small control unit, with additional hydraulic components for chiller fluid control (**Table 4-8**). A small control unit is also included and modelled as low-grade PCB.

   Radiators consist mostly of copper and aluminum. Fans are manufactured from steel, aluminum, and copper. Pumps are manufactured from cast iron and aluminum. Most of the hydraulic components consist of copper tubes, iron tubes, cast iron, copper (for heat exchangers), and bronze. The encasement is mostly steel. An average reference unit size of 10 kg/kW is extrapolated, based on the results of [FHS10].

b) **Water cooling devices:** Most of the cooling in data centers is done through compressed chilled water devices, with free-cooling devices taking a considerable portion in recent years. Components include fans, pumps, compressors, copper tubes, and others. The sizing of the cooling system is dependent on the heat removal requirements of the IT system, and the material composition of these is escalated accordingly. A reference value of 9.1 kg/kW of installed cooling system is used to calculate the inputs of components and material flows. Nominally, the cooling capacity must match the IT capacity, with requirements of redundancy being specific to each case study, following the n+1 schema.

Chillers are comprised mostly of copper, steel, iron, plastics, and a small portion of low-grade electronics. Similarly, pumps are mostly cast iron, steel, and copper. R134a is considered as the standard refrigerant used in compression chilling devices, with a specific value of 0.31 kg/kW required, and a loss of around 0.5% per year during the use phase.

Table 4-8: Breakdown of components for an air-cooling system with a power of 350 kW. Source: Based on [Ol12].

Component name	Amount	Weight (kg)/unit	Total Weight (kg)
Radiator	1	155.8	155.8
External Encasement	1	206.7	206.7
Fan	3	6.2	18.6
Condensation Pump	1	1.1	1.1
Control Unit	1	0.5	0.5

4.5.3.9. Transport

General assumptions for transporting elements, components, and devices include the terrestrial shipping of goods, such as IT components, to port (400 km), from plant to plant (200 km), intercontinental shipping of goods (sea shipping, 10 000 km), and the intracontinental transport by lorry (1100 km) to site.

4.6. Data center equipment inventories

The different equipment of data centers is grouped according to the systems presented in Section 4.5. This allows grouping the components and developing inventories based on the devices installed on the data center facilities. Given the heterogeneity of the devices found, these were paired with reference devices and counted as unites.

Within the development of this research, different project partners with operating data centers made their inventories available for this research. Inventories on their devices were developed that accounted for the number and type of devices installed and for the technical characteristics of these devices. This data is compiled and paired with reference devices to facilitate the development of models that represent the complex structure of a data center.

The key aspect of these case studies is the information regarding the IT systems. These are disaggregated into 3 subsystems: servers, storage, and network. **Figure 4-13**, **Figure 4-14**, and **Figure 4-15** display an overview of the inventories gathered for the case studies analyzed. Information gathered included, in a broad sense:

- Size of the data center
- Inventory of IT equipment
- Power supply system sizing inventory
- Climatization equipment sizing and inventory.

One of the limitations of this research is that for some cases, the power supply of the data center is part of the power supply of the infrastructure of the organization. This was approached by stating that the size of the power supply and cooling systems scales according to the power of the IT devices. While this is a firstly simplified approach, the impact of these broad assumptions on the material depletion is to be further analyzed, as these systems do not contain important amounts of critical metals whose extrapolation can impact the results of this analysis.

When not available, information on cooling facility size and on electrical supply system size was extrapolated using reference values based on the IT power installed.

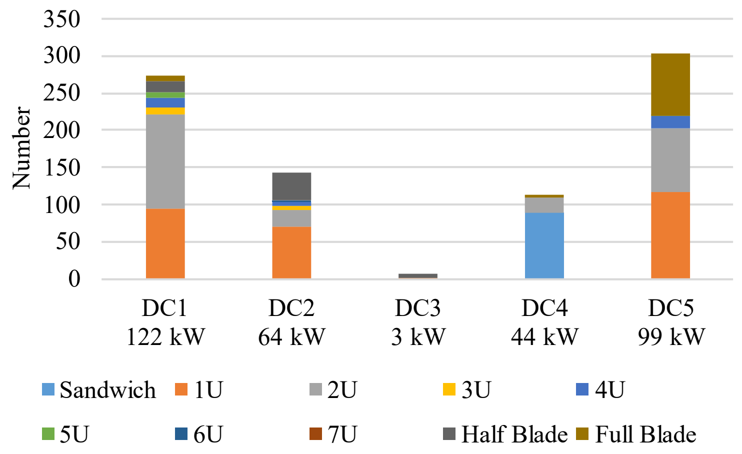


Figure 4-13: Number of servers installed in each facility under study.

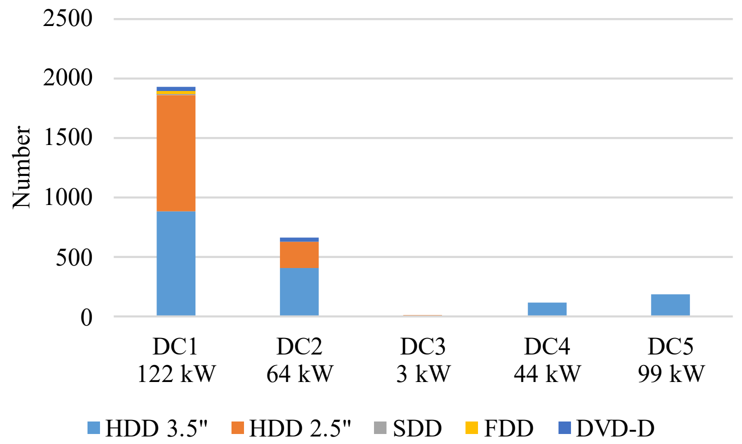


Figure 4-14: Number of storage units installed in each facility under study.

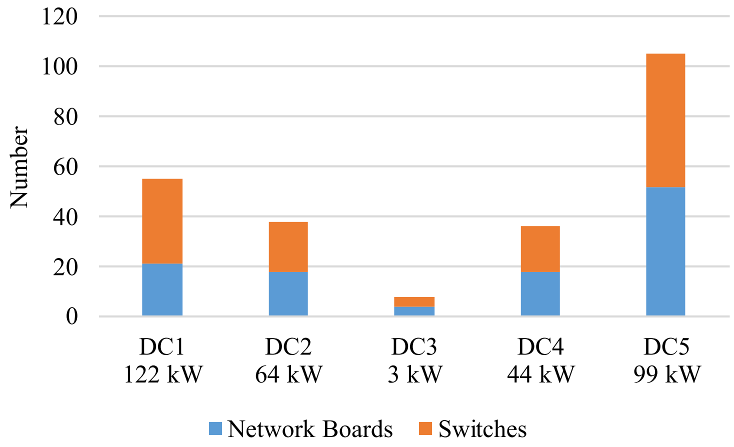


Figure 4-15: Number of network devices installed in each facility under study.

4.7. Conclusions on life cycle inventories for data centers

This section presents an overview on the development of life cycle inventories for posterior evaluation of resource depletion impacts. Several case studies are presented as an approach to obtain inventory information on data centers as a base to develop life cycle inventories. Different equipment, namely servers, network devices, and storage devices, were disassembled to analyze their composition and to obtain information on their components. Specific components, such as printed circuit boards of different categories, were then evaluated in laboratory analysis to obtain data on material content of specific critical material components of data centers. This without disregarding the material composition of other components with bulk materials in the inventories. Newly gathered information on material composition shows that literature values originally assumed are outdated. Results on material composition indicate a higher concentration of precious metals as previously reported, which is expected to have direct influence on the results of material depletion impacts in later calculations. As an example, the content of gold is 2.4 times higher than initially assumed for mainboards, and around 3 times higher for silver. It is notorious that the content of rare earth elements, such as dysprosium, neodymium, and yttrium, is here also for the first time reported as part of the information on material content.

Previous work on assessment of data center inventories, such as [Wh12], and later work focused on Germany, such as [Sc18] and [FHS10], already included extrapolated inventory of data centers. The present study approach includes for the first-time firsthand information on material composition, improving the quality of the data by performing direct analysis instead of assuming proxy values from similar components or technologies.

This part of the research is however limited by the availability of devices that were obtained for disassembly, and on the developments in IT that result in constantly changing material compositions. Extrapolation of the results is to be conducted carefully, with a proper assessment of the reduced quality of extrapolations.

With improved information on material content, better models on material recycling can be constructed, with the procedure for model building being detailed in Chapter 6. This requires then modelling of recycling technologies and assessment of the potential of material recovery from electronic components of data centers. The next chapter details models for recycling of data center components based on current technologies. With the inventories presented and the improved information on material content, and the inclusion of recovery, complete life cycle models can later be developed to estimate resource depletion and research the potential benefits of different recycling strategies. The results, presented in Chapter 7, require a deep analysis to assess the validity of this study and of the methodologies here employed.

5. Circular Economy Approach for Data Center Components

This chapter focuses on the development of life cycle inventories for strategies for the EoL of data center components. Due to the variety of materials present on data centers and the focus on critical materials of this dissertation, the attention lies on the recovery of critical and valuable materials. An overview of the recycling directives and the general recycling of electrical and electronic equipment serves as a starting point for the analysis of EoL processes. Due to the particularities of recycling modelling in LCA, such as the multiple outputs obtained or the substitutability of the final product, modelling methodologies and evaluation indicators for recycling must be defined. An analysis of the process chain of recycling follows, with consideration of the various EoL chains and metal recovery technologies applied in the industry based on literature reviews and industry data, which is gathered as recovery factors and as inventory databases. The development of inventories is executed by combining the information on these processes with the available information on material composition of inventories presented in Chapter 4, particularly from printed circuit boards, based on units of weight of product recovered, and on specific energy and material inputs and outputs for different recycling chains (**Figure 5-1**). This serves to answer questions on benefits and impacts of EoL processes on critical material sustainability of data center components.

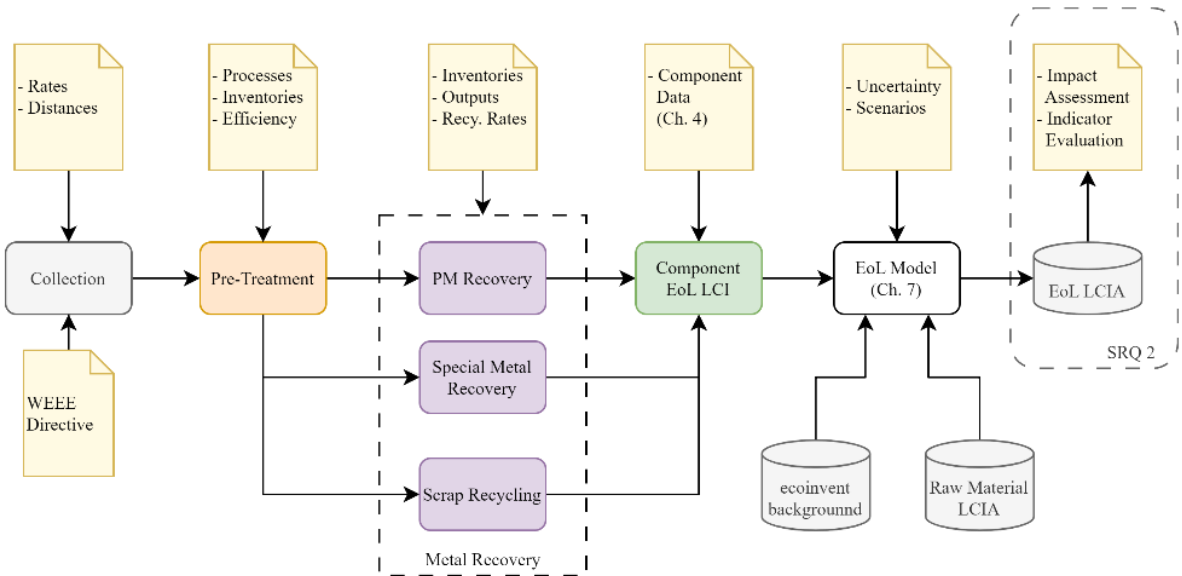


Figure 5-1: Process for development of EoL models for data center components.

5.1. Recycling of electrical and electronical equipment

Electrical and electronic equipment (EEE) has a highly heterogeneous mix of materials. The EoL treatment is especially important because of increasing concerns that waste electrical and electronic equipment (WEEE), containing hazardous constituents, may negatively impact the ecological environment and affect human health if unproperly managed [An16]. Disposal in landfills or traditional incineration produces harmful effects to the environment. Additionally, up to 95% of mining energy is saved when recycling metals, with corresponding savings in GHG emissions [Iş18]. This being noted, it is the value of the metallic fraction, mostly of gold, which is the main driver for industrial WEEE recycling.

PCBs concentrate the most valuable materials in in WEEE. In data centers, they stand for 5-10% of overall WEEE weight but hold a high part of valuable material. However, more than 70% of PCB scraps cannot be efficiently recycled and recovered and are thus incinerated or landfilled [Li04]. Issues with collection within the EU show that the collection rate is insufficient, too much WEEE is exported (legally and illegally) from the EU, and finally, the recovery rate from end-processing of WEEE is insufficient for specific metals, since the recycling process focuses on extracting bulk materials. This is partly because thermodynamics limit the technical recyclability of certain metals if they are alloyed [Ba14].

The economic driving force for WEEE recycling is the recovery of material value, 95% of which is attributed to precious metals and copper, 80% attributed to gold [Ch17]. From the technological point of view, current WEEE recycling approaches demand high energy and are environmentally dangerous. These can recover about 30–35% of the metals present in PCBs, with purity levels going between 85% and 95% depending on the element. Some materials, such as rare earth elements, cannot yet be economically recycled [Cu15]. However, recovering metals from scrap is much less energy-intensive than from ore. When considering the whole recycling chain, most recycling recovery rates fall to 28% of the total weight. For example, recovery of silver is only 11.5%, for gold is 25.6% and for palladium is 25.6%. For copper, iron and aluminum, the estimated recovery is about 60%, 95.6% and 75% respectively [DFF15].

5.1.1. European legislations on management of WEEE

Three main regulations exist at EU level for the treatment of WEEE: 1) the WEEE directive, 2) the RoHS directive (Restriction on Hazardous Substances), and 3) the REACH regulations (Registration, Evaluation, Authorization and Restriction of Chemicals). The most important for the development of the goals of this thesis is the WEEE Directive. When considering circularity of EEE products, proposed regulations of relevance include the “Eco-design Requirements for Sustainable Products”, the “Framework for Ensuring a Secure and Sustainable Supply of Critical Raw Materials,” and the “Proposal for Promoting the Repair of Goods” (known as “Right to Repair”).

5.1.1.1. WEEE Directive

The WEEE Directive (Directive 2012/19/EU) looks to prevent and minimize WEEE by reuse, recycling, and recovery. A chief role is given to manufacturers and distributors being required to cover the costs of collection, treatment, recycling, and recovery of WEEE. Producers must set up individual or collective schemes for the collection and treatment of WEEE. The directive aims to solve the problems associated with improper management of WEEE, which alongside the RoHS Directive (2002/95/EC) complements the measures on preventing landfilling and incineration of hazardous waste. It also introduced the a "take-back system" assigning the responsibility of WEEE collection on producers [EC12].

This directive defines WEEE as *"Electrical or electronic equipment which is waste… including all components, sub-assemblies and consumables, which are part of the product at the time of discarding."* WEEE is grouped into ten primary categories. WEEE from data centers falls under the category of "IT and telecommunications equipment," although components from other categories are also present. It includes the requirement not to dispose of WEEE as unsorted municipal waste and to collect such WEEE separately [EC12].

The revised WEEE Directive has a variety of improvements on the earlier iterations. Critical raw materials are included in the purpose; a new minimum collection rate of 45 % must be achieved within 4 years and 65 % after 7 to 9 years. The rate is calculated as a percentage of the average weight of EEE placed on the market in the three preceding years. European standards for the collection, storage, transport, treatment, recycling, and repair of WEEE and its preparation for reuse are also included, although no technical definitions on processes are given. The recycling rates defined are solely weight based, making the recycling of all materials equally important. Thus, to achieve the quota, usually it becomes most important to recover plastics, iron, aluminum, and copper. This neglects the incentivization of recovering valuable or critical metals.

5.1.1.2. Eco-design Requirements for Sustainable Products

The European Green Deal [EC19] Europe's sustainable growth strategy that aims to transform the Union into a fair and prosperous society, with a modern, competitive, climate-neutral and circular economy. It sets the ambitious objective of ensuring that the Union becomes the first climate neutral continent by 2050.

The *"Proposal for Setting Eco-design Requirements for Sustainable Products"* [EC22] has as main objectives to reduce the negative life cycle environmental impacts of products. It therefore lays down a framework for setting eco-design requirements based on the sustainability and circularity aspects listed in the *"Circular Economy Action Plan"* [EC20a], including critical material content, resource efficiency, and for reducing products' carbon and environmental footprints. It aims to make products last for longer and to boost the use of recycled content in products, decoupling the economic development from natural resource use and aiming at the reduction of material dependencies. The framework will allow for the setting of a wide range of requirements, including product durability, reusability, upgradability, reparability, and recyclability.

5.1.1.3. Framework for a Secure and Sustainable Supply of Critical Raw Materials

The proposal for a *"Secure and Sustainable Supply of Critical Raw Materials"* [EC23a] aims to strengthen the different stages of the European critical raw materials value chain, to diversify the EU's imports of critical raw materials to reduce strategic dependencies, and to ensure the free movement of critical raw materials on the single market while ensuring a high level of environmental protection, by improving their circularity and sustainability.

This framework goes in hand with the EU's waste framework on the collection, reduction, recycling, and treatment of waste, including of waste streams containing critical raw materials. Operators and governments must then analyze the critical raw materials recovery potential in extractive waste. It encourages Member States to take measures to prevent the generation of waste, targeting products containing critical raw materials.

Recycling should become increasingly important and reduce the need for primary extraction and its associated impacts. This framework gives special relevance to permanent magnet recycling, which contain critical raw materials, such as neodymium, praseodymium, dysprosium and terbium, boron, samarium, nickel, or cobalt. Permanent magnets should therefore be a priority product for increasing circularity.

To address the current lack of information on the critical raw materials potential of closed extractive waste facilities, Member States should draw up a database containing all information relevant to promote the recovery, notably the quantities and concentrations of critical raw materials.

To limit such damage and incentivize the production of more sustainable critical raw materials, the Commission should be empowered to develop a system for the calculation of the environmental footprint of critical raw materials.

5.1.1.4. Right to repair

The proposal on *"Common Rules Promoting the Repair of Goods"* [EC23] aims at products which are discarded prematurely, even though they could be repaired and used for longer. Major causes for the decreased lifespan of goods purchased by consumers included the difficulty for consumers to repair products themselves, the inconvenience, inflated costs, or non-availability of repair services for consumers.

This framework aims at prioritizing repair whenever it is cheaper than replacement within the legal guaranteed framework, producing additional environmental benefits due to lower manufacturing demands. It helps to reduce greenhouse gas emissions, waste, and use of additional resources by increasing repairs and thereby extending the lifetime of goods. Member States shall ensure that at least one online platform exists for their territory that allows consumers to find repairers.

5.1.2. Databases for WEEE recycling

Several information sources can be assessed to evaluate the status of WEEE recycling. Some databases supply information on the collection of WEEE, while other databases refer to the life cycle inventories of some WEEE products and their downstream processes.

According to the WEEE Directive, member States shall collect annual information, including estimates, on the quantities and categories of EEE placed on their markets, collected through all routes, prepared for re-use, recycled and recovered within the Member State, and on separately WEEE exported, by weight [EC12]. Already in [PR19], the author identified the necessity of a common database schema at European level with participation of different actors involved in the supply chain recovery of critical metals, with the aim of supplying standardized information for management and research. Moreover, the lack of a common database for the comparison of different material contents and recycling processes limits the extent to which recycling potentials or cradle-to-grave environmental impacts can be evaluated at a European level. This is because data of comparable quality is often unavailable. Building up such a database is additionally complicated by different national interpretations of the WEEE Directive.

Commonly, the databases on recovery and quantities of WEEE are unlinked to databases with information on recyclability, recovery ratios of processes, recycling processes inputs and outputs, or impact assessment of WEEE recovery by process. For these purposes, either specific process information is needed, or databases holding life cycle inventories of industrial recycling processes must be developed. These LCI databases, such as the ecoinvent, have information on energy and material uses for recovery of specific case studies, such as laptops. These databases also offer the possibility of creating models of specific processes, which is the approach executed in this dissertation. The lack of unified data and the unavailability of many of the studied source's results in the requirement for creation of models for recycling to evaluate the potential benefits within a holistic energy and material saving strategy. These models are based on diverse sources for individual industrial and experimental recycling processes, and on firsthand data on material composition. This harmonized framework will contribute to evaluate the environmental impacts of critical material recovery from WEEE and provide a common database for evaluation of such processes.

Additionally, LCI data on raw material production of a wide variety of materials is also needed. This was already developed, updated, presented in Chapter 4, and serves as a basis for quantification of the savings obtained by recovering metals from WEEE. This comprises the foundations for performing Life Cycle Impact Assessment on recycling of data center components.

5.2. Recycling in Life Cycle Assessment

Modelling of recycling in LCA aims to study the environmental impacts of recycling of products and to study the benefits of recovering materials and energy from waste streams when these are used in new processes or are reincorporated to the original material streams. A comparison of savings with the products these recycled materials are replacing is thus necessary to evaluate potential gains. The sustainability of different recycling strategies can then be analyzed using the proper indicators. **Figure 5-2** shows a simplified recycling process for EEE and their WEEE outputs.

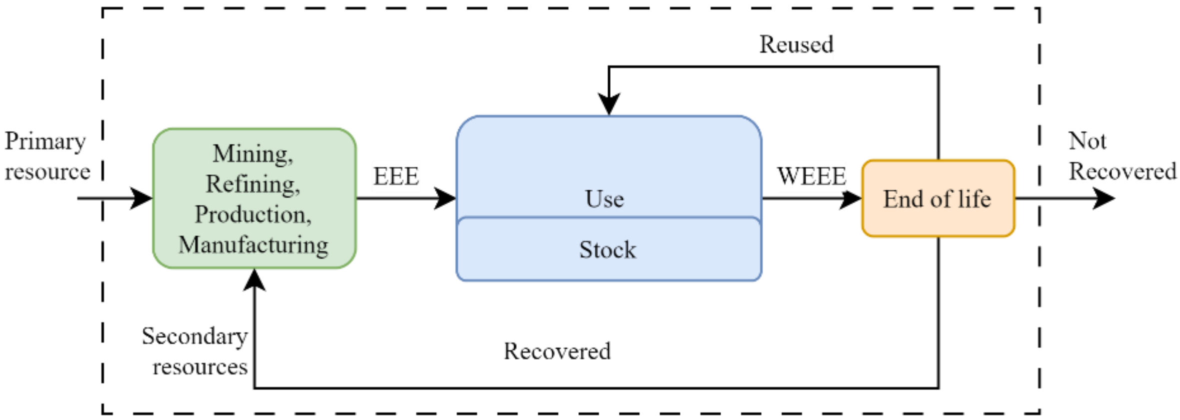


Figure 5-2: Life Cycle of EEE and their WEEE streams. Source: Modified from [Al14].

5.2.1. Modelling of recycling

Through the processing of EoL products secondary materials, energy resources, and parts are regained in a form, which allows to use them in later products. They can replace primary production of the same or another material, energy form, part, or product. This always involves some form of processing. Methodologically, the outputs can be considered as replacement of equivalent uses, such as energy, or direct replacement of materials of the same quality, such as minerals.

The approach normally is a consequential LCA, since the goals are to reflect the consequences of recycling when using secondary goods (i.e., substituting high value primary production). The superseded mix of processes is to be determined and their avoided production is credited. For this, a true joint process needs to be found, which studies the replacement of recycled materials in the production of raw materials. This approach is usually combined with Material Flow Analysis (MFA), and in the case of recovery of metals, it is useful to study the different material flows during the EoL processes. The avoided inventory of primary production of a good is credited to the EoL product or waste according to the degree that it is recyclable. Only the amount of goods that cannot be obtained back from the secondary good (e.g., losses due to incomplete collection, recycling losses, etc.) is modelled as primary production [EC10b].

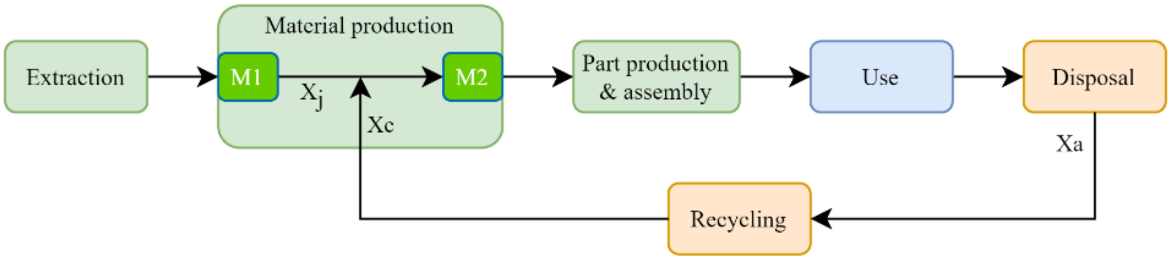


Figure 5-3: True joint process obtained from recycling of an EoL product under consequential modelling. Source: Modified from [EC10b].

Whereas other modelling approaches exist, such as open loop recycling, for the purposes of evaluating the direct benefits of recycling of metals, a closed-loop approach is preferred, since it is a requirement that the materials obtained from recycling have qualities that allow them to replace materials on the market, and thus no degradation of material is desired or expected.

5.2.2. Allocation of recycling products

The impacts of recycling are often assigned depending on the scope of LCA. If only the recycling process is being evaluated, then it considers the input of waste material without any initial burden. In consequential LCA, the impacts of substituted processes are calculated using data on material or energy production being replaced for the original production. As a result, the recycling process avoids the impact of the primary production. For this reason, the approach is also known as “avoided burden” .

Given the different outputs of recycling (e.g., a mix of metals), multiple products can result from one process. This multifunctionality can be solved by applying an allocation procedure. Several allocation procedures exist to assign the impacts to various products. As revenue generation is the driving force in the market, the first and most common alternative is economic allocation. The impacts of recovery are distributed based on the economic value of the final products of each metal, which then can be divided by the quantity produced to obtain a normalized impact by unit.

To evaluate different technologies, prospective consequential LCA and comparative consequential LCA are conducted. Some technologies considered as alternatives are scaled-up for comparison with existing technologies. Environmental impact performance comparison of the different recycling scenarios and technologies is then executed. The goal is to evaluate the available technologies and recycling routes.

5.2.3. Scope of EoL in LCA

Usually, the EoL includes the reuse and recycling process. For reuse, transportation and potential remanufacturing activities are included. For recycling, transport, preprocessing, and metal recovery processes are considered.

When discussing data center components, most of the IT devices have an average life time of between 5-8 years for high-end servers, and 3-5 years for other equipment [ABD12]. Data center devices lifetime can also be modelled using a Weibull distribution, which can be applied using the corresponding shape and scale parameters for the specific product type [Ho20]. Most of the reuse takes part within the organization, and discarded devices are disposed for recovery. In agreement with the WEEE directive, data center operators use provider schemes to dispose of the devices. Other devices, such as infrastructure, cooling units, and back-up generators have lifetimes between 10 and 20 years.

5.2.4. Functional unit

Several ways of approaching the functional unit in recycling include considering recycling of a whole device, recycling of distinct parts that are first grouped together from several dismantled devices (i.e., recycling of 1 kg PCB), and recovery of one unit of "recovered good" (e.g., "recycling of 1 g of gold"). Some more complex functional units can include "recovery of mix of metals" to bypass multifunctionality [BBC12].

[Li19] defines the functional based as "recovery of 1 kg of gold" from WEEE assuming that the recovery efficiency of gold is the same for all recycling processes, which excludes experimental processes but can serve as a starting point for establishing a comparison basis. For the purposes of this work, metal recovery processes are first evaluated based on inventoried data for recovery of valuable metals, and then scaled to 1 kg of discarded product. This allows connecting the functional unit of disposal (in kg) with the inputs for recycling.

5.2.5. Indicators for evaluation of recycling

Direct evaluation of recycling is based on either global indicators or specific indicators. [EU12] measures the overall WEEE recycling efficiency at three levels:

1. Collection rate, which is the ratio between generated WEEE and WEEE collected for recycling.
2. Recycling process efficiency rate, which is the quotient of a recycled material and that material collected with WEEE for recycling.
3. (Element-specific) recycling rate, which refers to functional recycling and is defined by the ratio of recycled material (or element) and the total amount of this material (or element) in generated WEEE.

Data center specific recycling metrics are mostly mass based. The most representative is the Material Reclamation Ratio (MRR), defined as the sum of the amount of recycled/reclaimed/repurposed material over the inbound material. This can be specific for EEE equipment, resulting in the MRR-EEE. The inverse of this value is known as Material Reuse Effectiveness (MRE). Additionally, reporting of the volume and composition of materials disposed of as solid waste sent to recycling centers; and volumes repurposed or reclaimed, either inside or outside the organization is encouraged [Em11].

The [ISO14021] calculates the recycled content as the mass of recycled material divided by the total input mass. Within LCA, the environmental impacts from recycling come mostly from energy use within the recycling process and direct emissions from it. Midpoint and endpoint methods are used to quantify these benefits. These benefits are calculated as negative impacts from savings resulting in substitution by the output products.

Criticality of materials is commonly overlooked, but the application of the indicators developed in Chapter 3 can provide an overview on the circularity of the recycling processes and stablish how beneficial is the recycling to encourage critical material sustainable use. This in accordance with the proposed *"European Regulation for Critical Raw Materials"* [EC23a]. Criticality weighted-based recycling rate, proposed in this study, aims at assessing the total fraction of critical resources recovered from a recycling process. This set of indicators is used to evaluate different strategies in Chapter 7.

5.3. Process chains for data center components EoL

The components of a data center have distinctive characteristics, thus requiring different recycling processes (**Figure 5-4**). Bulk metals and plastics can be sent to be recovered directly as scraps. Cables need to be separated into plastic and copper. Batteries have special recycling processes. If existing, hazardous substances need to be managed separately for disposal. Most of the critical materials are concentrated on PCBs. Recycling of PCB has its own specific processes. Emphasis in these processes is given since 97% of the critical material content is concentrated in PCBs.

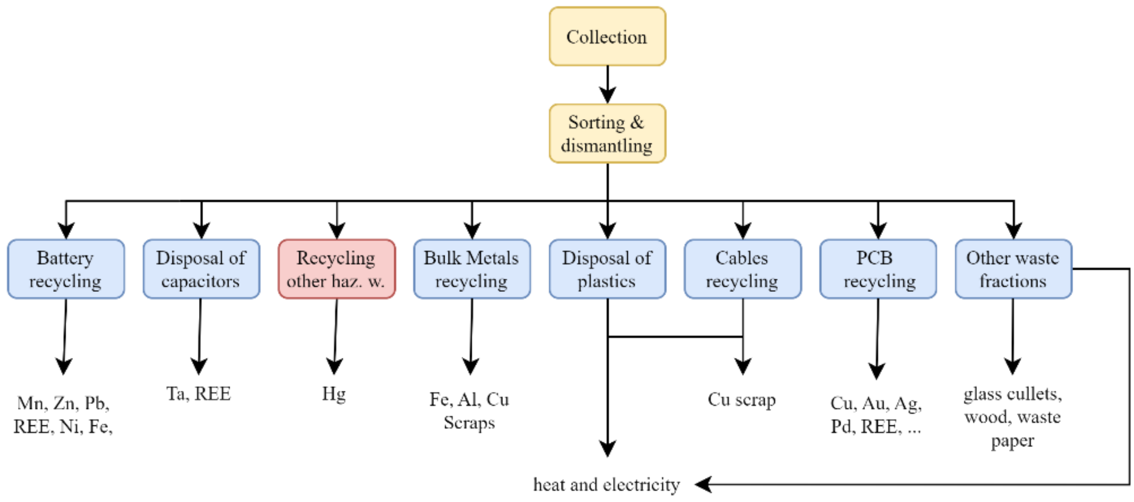


Figure 5-4: Different recycling routes for data center components.

Recycling of PCBs can be further divided into further steps 1) disassembly: targeting on singling out hazardous or valuable components for special treatment; 2) upgrading or pre-treatment: using mechanical processing and metallurgical processing to upgrade the materials content; 3) refining or metal recovery: where materials are purified by using chemical or metallurgical processing so as to be acceptable for their original using [CZ08].

5.3.1. Collection, transport, and pre-sorting

In the first step, the discarded electrical and electronic devices are collected to be sorted. The presorting (also called triage) is recommended to feed the WEEE in treatment processes adequate to their composition, thus enhancing process efficiency. Pre-sorting can be done based on material content. Although collection rates of 40% are normally reported for WEEE, in the case of data center equipment a collection rate of 100% can be estimated, since data center operators need to guarantee disposal and destruction of decommissioned devices.

Transport from operation site to pre-sorting facilities is modelled by broad estimates. The use of freight lorry and 250 km distance are assumed. Usually, the traveled distance plays a minor role in the contributions to environmental impacts of the whole recycling scheme. Presorting is done manually and therefore excluded as energy input.

5.3.2. Pre-treatment

Treatment means any activity after the WEEE has been handed over to a facility for depollution, disassembly, shredding, recovery, or preparation for disposal [EU12]. Before metal recovery, the various metals and materials contained in WEEE must be liberated first. The liberation usually is done by a size reduction process (such as shredding or crushing), supported by prior manual dismantling of certain components. These smaller particles are then sorted into defined output fractions, making use of their specific physical and optical characteristics. Typical sorting processes used are magnetic separation of ferrous parts, eddy current separation, and gravity separation [Ha06] (**Figure 5-5**). Finally, metallurgical processes are used to recover select materials from the scraps to obtain almost pure secondary resources.

5.3.2.1. Manual sorting and dismantling

Many metals are concentrated on certain parts of the WEEE components, and manual separation is often needed. Disassembly of these parts is the most time-consuming operation. Automatic, semiautomatic, and manual disassembly systems have been developed, the latter being the most adopted technique. The recovery efficiency by manual treatment is a lot higher than that of automatic systems. Manual sorting and dismantling are economically unfeasible in developed economies.

Without a manual dismantling precious metals are often either sent to further mechanical pre-processing or sent with the plastic mix and lost. Manual dismantling allows the recovery up to 92% of silver, 97%

of gold and 99% of palladium, whereas mechanical processes only recover 44%, 51% and 28%, respectively [Ba14]. Reasons for these losses are related to the mechanical treatments that smash most contacts and ceramics and are dispersed in the dust and in other shredding residues. Similar losses occur also for other electronic components embodying other CRMs [AM13]. The manually sorted fraction is further separated and 40% of this fraction is sent to special treatment, the remaining 60% are bigger metallic parts which are recycled [BBC12].

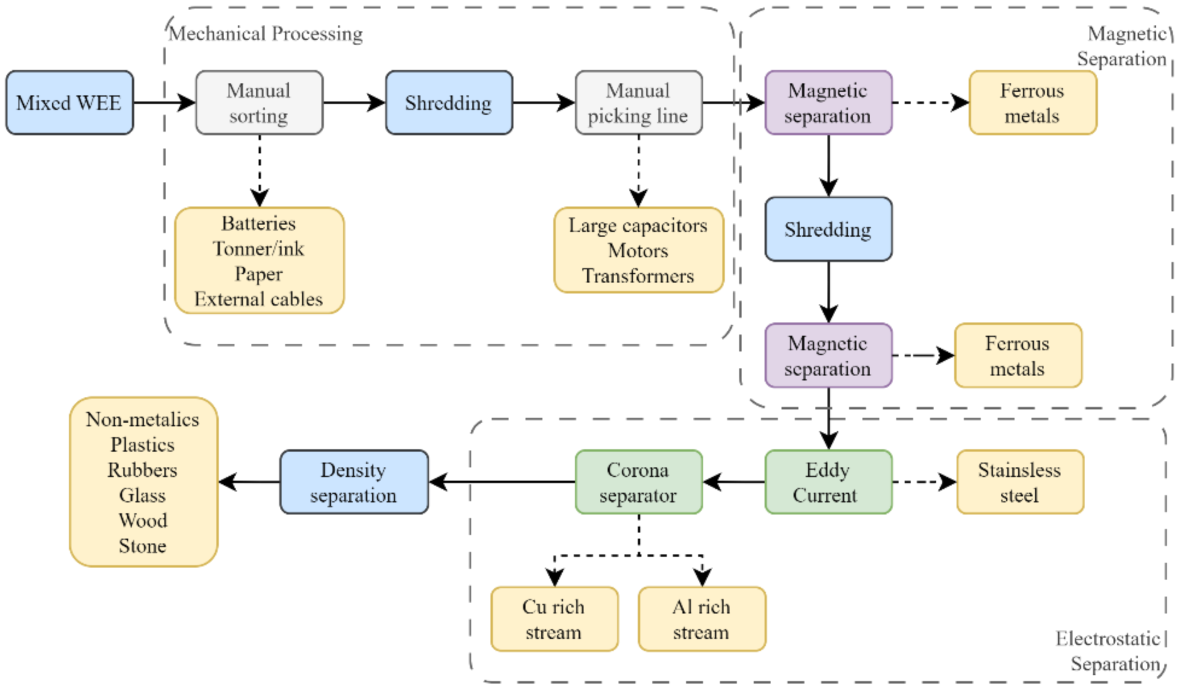


Figure 5-5: Schematic for preprocessing of WEEE. Source: Adapted from [DFF15, Kh14],

5.3.2.2. Size reduction

Manual sorting and dismantling are typically followed by a size reduction step. Size reduction is made via mechanical cutting and shredding to reduce the size of the metal-containing fractions. Size fraction is relevant to reduce the possibility of particles having several types of metals. Waste PCBs are comminuted by multiple crushing systems to liberate metals and nonmetals.

5.3.2.3. Magnetic separation

Magnetic separators are used for the extraction of ferromagnetic metals (iron and nickel) from non-ferrous metals and other nonmagnetic wastes. Nonferrous materials are crushed in a non-magnetic fraction by gravity. Efficiencies of the recovery of this method can be up to 99% for the ferrous fractions. The magnetic fraction of crushed PCB ranges between 4.5% and 11% of the total weight [Ja16].

5.3.2.4. Electrostatic separation

The non-magnetic fraction is then transported to an electrostatic separator. Materials are separated based on their electrical conductivity difference. Copper- and aluminum-holding streams are produced. The electrostatic separating capability depends on the difference in polarity and the amount of charge obtained by particles to be separated. There are two typical electric conductivity-based separation techniques [Ya11]:

- Corona electrostatic separation can successfully separate the mixed particles that have significant difference in conductivities. The electrostatic separator can remove non-ferrous metals from non-metallic materials.
- Eddy current separation uses the principle that in the separation zone gravitational, centrifugal, and frictional forces influence the falling particles, but only magnetic force deflects the ferrous particles to a higher degree [Ka16]. Eddy currents can be induced in an electrically conductive particle by a time-dependent magnetic field.

5.3.2.5. Gravity separation

Gravity is used to separate materials of different specific gravity by their relative movement in response to the force of gravity and resistance to motion offered by a fluid, such as water or air. In practice, close size control of feeds to gravity processes is required to reduce the effect on the size [CJ11]. This is applied for the separation of metals from non-metals.

5.3.2.6. Automated optical sorting

With the fast development of the Charge-Coupled Device sensor, computing, and software technology, optical sorting processes have been developed in both recycling and mineral processing industry. Data gathering and analysis improves the separation performance of automated sorting equipment. The measuring of particle properties such as color, texture, morphology, conductivity, and others allows high-quality sorting of mixed materials into almost pure fractions. Systems involving the use of multiple sensors have been developed over the past few years [CJ11].

5.3.2.7. Recovery rates of pre-processing

Mechanical treatments are characterized by low capital operating costs. However, the main drawback is represented by the losses of valuable and critical metals and significant dust generation [MCB19]. [HPW15] reports complete losses of REEs contained in NdFeB magnets of hard disk drives. Mechanical processes are well designed to recover mass relevant metals (iron, copper, aluminum) with yields up to 80% [MCB19].

Empirical studies show that the overall pre-processing efficiency of dismantling procedure for ICT WEEE is 80% for Au, 49% for Ag, and 66% for Pd. The highest pre-processing efficiencies (97% Au, 92% Ag, 99% Pd) can be achieved by multi-level deep manual dismantling, which means that subcomponents such as HDDs, SDDs, memories, or CPUs are further separated manually. This leads to a higher concentration of critical metals in the material for end-processing. A combination of mechanical and manual processes leads to gold recovery rates of 70%, which is the dominant method used in the industry (**Table 5-1**). The components are first separated by smashing, which is followed by handpicking of valuable components. Hazardous components are either removed manually before smashing (manual depollution) or afterwards by handpicking. The components are then reduced to small pieces by shredding or hammer milling and the output material is finally automatically sorted [Ba14].

Table 5-1: Recovery rates for several metals under manual and mechanical separation processes. Source: [Ba14].

	Manual	**Deep Manual**	**Mechanical**	**Manual + Mechanical**	
Distribution in the EU-27	24%	0%	0%	76%	**Overall**
Ag	49%	92%	11%	75%	69%
Co	100%	100%	100%	100%	100%
In	100%	100%	100%	100%	100%
Li	100%	100%	100%	100%	100%
Ta	80%	97%	0%	0%	19%
Te	80%	97%	0%	0%	19%
W	80%	97%	0%	0%	19%
Au	80%	97%	26%	70%	72%
Be	80%	97%	0%	0%	19%
Ga	80%	97%	0%	0%	19%
Ge	80%	97%	0%	0%	19%
Pd	66%	99%	26%	41%	47%
Ru	0%	97%	26%	70%	53%

5.3.3. Life Cycle Inventories (LCI) for pre-treatment

There is difficulty in establishing a LCI for each individual process, since all of the separation normally happens in the same facility. [BBC12] established a LCI for the whole pretreatment of PCBs, which included manual sorting, separation, and mechanical separation of elements for further refinement (**Table 5-2**). The reference unit is 1 kg of processed PCB, and the iron and aluminum rich outputs are sent to the scrap market. The copper fraction is sent for refining. Residual waste and plastic are sent to incineration (**Figure 5-6**). The specific fractions are dependent on the material content of PCBs.

Table 5-2: Life Cycle Inventory of the pre-treatment process.

Description	**Value**	**Unit**
electricity	6.60E-02	kWh
Emissions to air		
aluminum	1.00E-06	kg
antimony	1.00E-07	kg
bromine	2.00E-07	kg
cadmium	2.00E-08	kg
chlorine	3.00E-07	kg
chromium	5.00E-08	kg
copper	4.00E-07	kg
iron	5.00E-06	kg
lead	4.00E-07	kg
nickel	2.00E-07	kg
phosphorus	1.00E-08	kg
polychlorinated biphenyls	2.00E-09	kg
tin	3.00E-07	kg
zinc	1.00E-06	kg

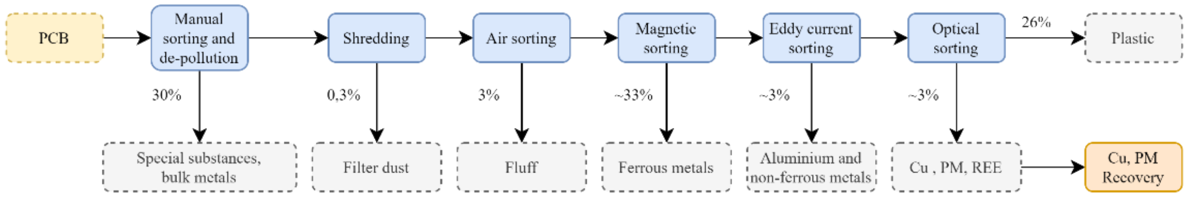


Figure 5-6: Life Cycle Model for the pre-treatment facility process. Source: Adapted from [BBC12].

5.4. Metal recycling for printed circuit boards

The final recovery process takes output fractions produced in preprocessing to recover metals. This is achieved through treatments based on physical, chemical and biological processes [MCB19]. Three main material streams are created during pre-processing: 1) ferrous fractions go to steel plants to be recovered as slag, 2) aluminum fractions to aluminum refiners, and 3) copper, lead, zinc, and other precious metal fractions are treated in integrated nonferrous metal smelters [GEE09]. During end-processing the final metal recovery and thus value recovery takes place. The most common include pyrometallurgical and hydrometallurgical processes. Modern pyrometallurgical and hydrometallurgical refineries achieve 95% recovery of Au and can recover several metals in addition to precious metals and copper. Experimental procedures, such as electrochemical and bioleaching processes have shown promising results and are here incorporated for evaluation.

5.4.1. Pyrometallurgical recycling

Pyrometallurgical processes involve the use of elevated temperature processes to extract metals. They have been successfully implemented to recover valuable metals from WEEE by firms such as Umicore in Belgium and Outotec in South Korea [Re17b]. These methods can recover various metals like Cu, Ag, Au, Pd, Ni, Se, Zn, and Pb. Pyrometallurgical routes are used initially for the segregation and upgrading of precious metals (Au and Ag) embedded into base metals (Cu, Pb, and Ni), followed by hydrometallurgical and electrometallurgical processing for the recovery of other valuable metals and REE.

Integrated smelters combining pyrometallurgical and hydrometallurgical processes can recover precious metals, copper, and other non-ferrous metals, including certain critical metals, while isolating hazardous substances. Precious and special metals (Pd, Au, Ag, Pt, Ru, Co, In, and Te) are extracted with a collector metal (Cu) while other metals such as Li, Be, Ta, and REEs end up in the slag. The processes have high recovery rates for some metals: >95% for Ag, Au, Pd, and Ru, 90% for Co and Te, and 50% of Indium. The rest of materials, such as Ta, Ge, end up in slags [Ba14].

[Li19] studied a process for refining of WEEE in a black copper smelter. The process can be described in four consecutive steps (**Figure 5-7**): 1) a reduction furnace where the polymers present are used as reducing agent to obtain the Cu scrap; 2) an oxidation furnace for separation of metal impurities as oxide slag; 3) fire refining to remove the oxygen in the molten Cu and produce Cu anode; and 4) the electro refining processes, which include Cu and precious metals electro-refining. Due to the heterogeneity of material content, individual energy and material requirements are escalated for each reference component developed in Chapter 4. **Table 5-3** presents an example inventory for pyrometallurgical recovery in an integrated smelter for 1 kg of PCB representing a mainboard. The differences in reduced material content are due to losses in the recycling process. Material losses during pretreatment can here be added as a factor for the recovery of materials.

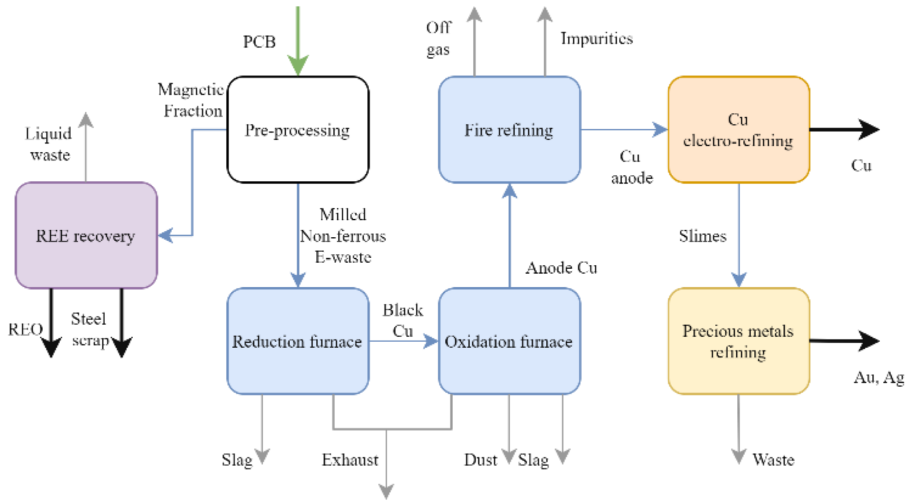


Figure 5-7: System Boundary for pyrometallurgical processing. Source: Adapted from [BBC12].

Table 5-3: Life Cycle Inventory for the recovery of metals from 1 kg of WEEE using the pyrometallurgical route.

Process inputs		
electricity, medium voltage	1.80E+00	MJ
sulfuric acid	2.20E-04	kg
water, completely softened,	9.60E-02	kg
activated silica	6.10E-03	kg
air flow, for pyrolysis	2.40E-01	kg
calcium carbonate, precipitated	7.20E-03	kg
charcoal	4.70E-02	kg
compressed air, for pyrolysis	3.20E-01	kg
input copper scrap, sorted, pressed	1.60E-02	kg
hydrochloric acid	3.20E-03	kg
input iron ore, beneficiated, 65% fe	8.70E-03	kg
limestone, crushed, washed	4.40E-03	kg
natural gas, high pressure	2.40E-02	kg
sodium hydroxide	2.50E-04	kg
sodium sulfate, anhydrite	1.00E-03	kg

Recovered metals		
palladium	2.50E-05	kg
silver	5.20E-04	kg
gold	8.50E-05	kg
alluminium scrap	1.60E-02	kg
copper scrap	2.30E-01	kg
iron scrap	2.90E-02	kg
Process outputs		
exhaust gases, from pyrolysis	6.20E-01	kg
carbon dioxide emissions	6.80E-01	kg
municipal solid waste	1.70E-01	kg

5.4.2. Hydrometallurgical recycling

Hydrometallurgical techniques involve leaching metals into solutions during reactions with leachant and oxidants. Separation and purification are then performed to obtain primary products for refining (**Figure 5-8**). After extraction, the respective leaching solutions go through a purification step, or directly to metal recovery through chemical reduction or electro-refining [Li19]. Hydrometallurgical techniques offer the advantages of lower gas emission and slag generation, but consume substantial amounts of strongly corrosive chemicals, such as nitric acid, sulfuric acid, and aqua regia.

Low investment and the high recovery rate are the primary advantages. Hydrometallurgy is more predictable and controllable than pyrometallurgy, allowing selective material outputs. No gaseous emissions are generated but large amounts of liquid effluents are produced as a result of the extraction procedure [MCB19]. REEs can also be recovered. WEEE treatment solely by hydrometallurgical processes exists but it has not been implemented on an industrial scale yet [Ba14]. For this reason, prospective LCIs are created based on the material flows and the recovery rates. Most of the studies present normalized information with a functional unit of 1 kg of Au recovered. A process for each type of reference component is created to adapt the process demands to the material content information (**Table 5-4**).

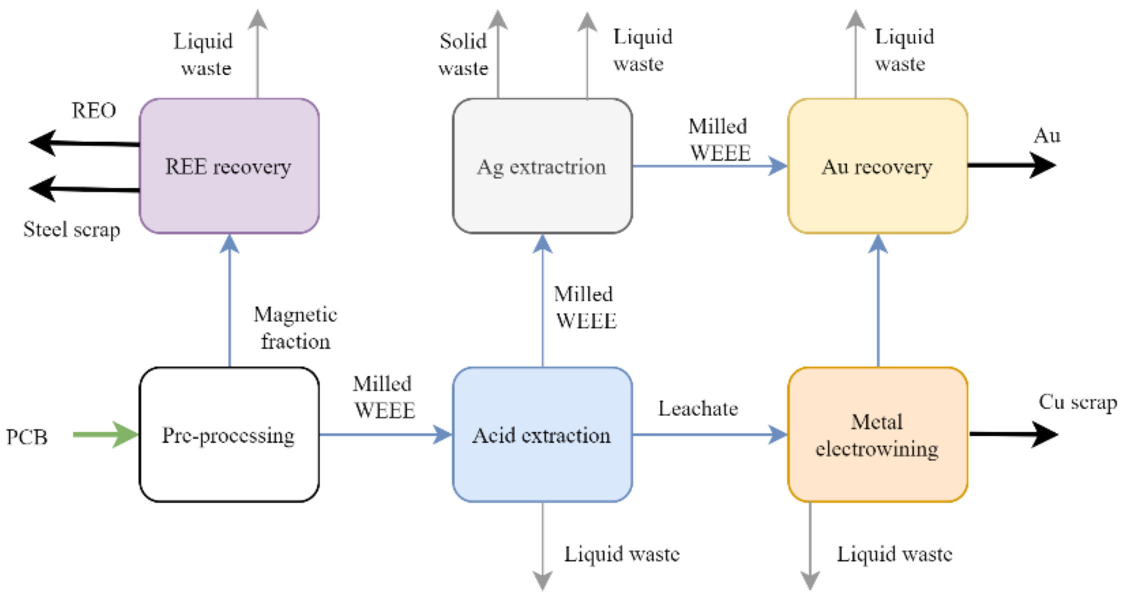


Figure 5-8: Schematic of hydrometallurgical recovery processes for WEEE. Source: Adapted from [Li19].

Table 5-4: LCI for hydrometallurgical recovery of 1 kg of WEEE. Source: Adapted from [Li19].

Inputs		
zinc	1.60E-03	kg
electricity, medium voltage	5.96E+00	MJ
sulfuric acid	4.29E+00	kg
hydrochloric acid	3.19E-02	kg
limestone	3.86E+00	kg
sodium hydroxide	1.67E-03	kg
sodium sulfate, anhydrite	6.85E-03	kg
hydrogen peroxide	5.89E+00	kg
iron (III) chloride	1.14E-03	kg
sodium persulfate	7.22E-04	kg
sodium persulfate	4.37E-03	kg

Recovered Metals		
palladium	6.75E-06	kg
silver	7.12E-04	kg
gold	5.77E-04	kg
aluminum scrap	8.85E-03	kg
copper scrap	3.28E-01	kg
iron scrap	8.86E-03	kg
Outputs		
municipal solid waste	1.32E-01	kg
wastewater	3.03E+01	kg

5.4.3. Electrochemical recovery

Electrochemical recovery is a novel alternative process. An electrochemical recovery of base metals liberates PM-containing fractions (**Figure 5-9**). This has lower chemical consumption, enhanced control, and reduced energy demand compared to the pyrometallurgical and the hydrometallurgical processes. [Li19] presents an inventory of an experimental process, which is presented for 1 kg of gold recovered. These values are normalized to 1 kg of WEEE and adjusted to the material content of each reference component (**Table 5-5**).

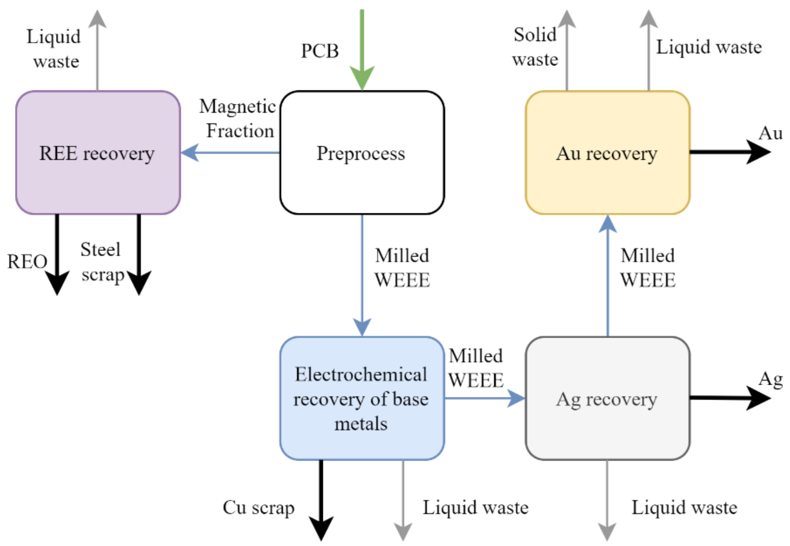


Figure 5-9: Schematic of electrochemical recovery for WEEE. Source: Adapted from [Li19]:

Table 5-5: LCI for recovery of metals using electrochemical recovery for 1 kg of PCB from a control unit.

Inputs		
zinc	4.68E-05	kg
electricity, medium voltage	1.74E-01	MJ
sulfuric acid	1.26E-01	kg
hydrochloric acid	9.34E-04	kg
limestone	1.13E-01	kg
sodium hydroxide	4.88E-05	kg
sodium sulfate	2.00E-04	kg
hydrogen peroxide	1.72E-01	kg
iron (iii) chloride	3.34E-05	kg
sodium persulfate	2.11E-05	kg
sodium persulfate	1.28E-04	kg

Recovered Metals		
palladium	2.70E-06	kg
silver	3.11E-04	kg
gold	1.69E-05	kg
aluminum scrap	8.68E-02	kg
copper scrap	1.74E-01	kg
iron scrap	1.11E-01	kg
Outputs		
wastewater	8.85E-01	kg
municipal solid waste	3.87E-03	kg

5.4.4. Biometallurgy

Biometallurgical processes have been researched to recover metals from WEEE. These use microbes for metal extraction, and encompass two related microbial processes: bioleaching and bio-oxidation [Er13]. It targets valuable metal fraction from WEEE, focusing on gold and copper. Under optimized conditions, 92.2% and 99.2% of Cu and Au, respectively, can be removed [Is17]. It provides benefits in terms of treating and disposing of strong inorganic acid waste compared to the weaker and more readily treatable organic acids generated by microorganism cultures. Recovery of other metals is also under research due to low investment cost, less environmental impact, lower energy consumption and better control than pyrometallurgy or hydrometallurgy routes [Ka16]. [Iş16] presented an analysis where the combination of biometallurgy and hydrometallurgy yielded the best results in terms of material recovery (**Figure 5-10**).

The extraction of metals such as Co, Mo, Ni, Pb, and Zn from sulfidic ores by bioleaching is technically possible. However, currently only Cu and Au are the metals recovered in significant proportions by this way. Most of the applications are still at laboratory scale, especially with reference to REEs [MCB19]. **Table 5-6** presents an inventory for the recovery of metals from WEEE for 1 kg of PCB.

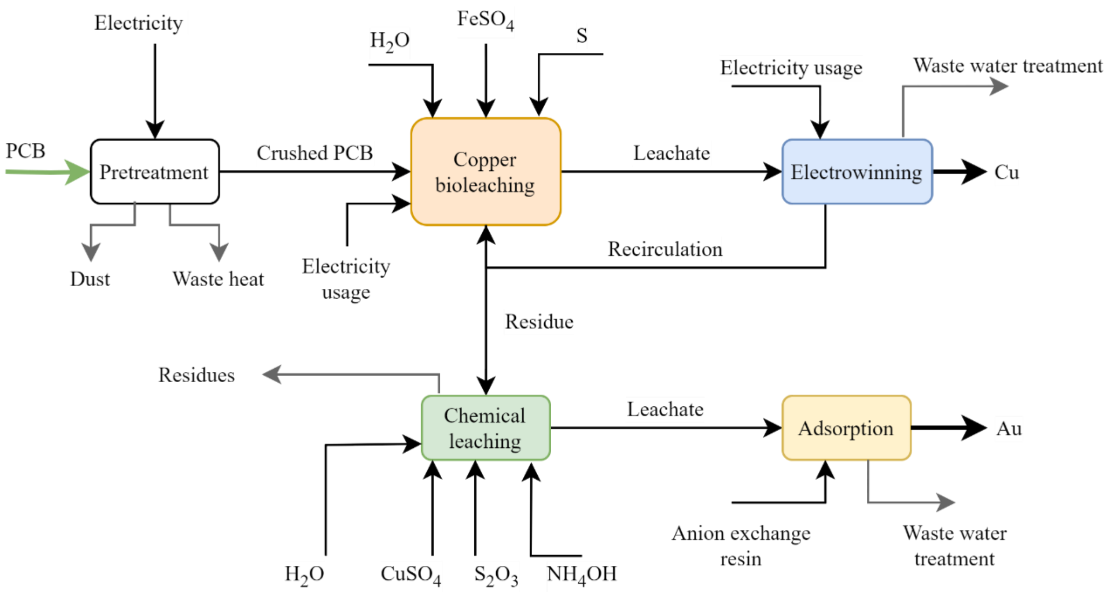


Figure 5-10: Schematic for biometallurgy hybrid process. Source: Adapted from [Iş16].

Table 5-6: Life Cycle Inventory for recovery of 1 kg of PCB with mainboard. Source: [Iş16].

Inputs		
electricity, medium voltage	1.45E+00	MJ
sodium sulfate, anhydrite	2.68E-02	kg
ammonium nitrite	5.91E-03	kg
copper sulfate	5.29E-03	kg
activated carbon, granular	3.73E-03	kg
iron sulfate	2.71E-02	kg
sulfur	3.11E-03	kg

Recovered Metals		
gold	6.97E-05	kg
copper scrap	0.224749	kg
iron scrap	0.028058	kg

5.5. Special processes

High recycling costs and low economic and regulatory incentives tend to discourage the recycling of certain materials [Ho20]. The recovery of specific metals is modelled separately as these can be separated in preliminary stages of pretreatment. Such is the case of tantalum in capacitors, or neodymium in magnets. Magnets are special focus for recycling in the newly proposed "*Framework for Critical Raw Materials*" [EC23a]. Some others are results of the final product and are present in slags, such as REE, that may still be recovered, although the processes are in early stages.

5.5.1. Tantalum recovery

Tantalum is a critical metal whose main application is the production of capacitors. These contain metallic Ta and tantalum oxide (Ta_2O_5), surrounded by layers of MnO, C and Ag [Ch18]. They also contain Al, Fe, Ni, Ti, and Zi at fractions lower than 1%. Ta capacitors must be removed from PCBs manually. [Ba20] presents a process for treatment of tantalum capacitors which includes treatment by pyrolysis to isolate metallic components, which are then leached to obtain 92% pure Ta_2O_5 (**Figure 5-11**). A model for recovery of these components considers the content of 1 kg of Ta capacitors, which is modelled separately from the other recycling processes (**Table 5-7**). The recovered material in this case is tantalum oxide, which can be reused directly for manufacturing of capacitors.

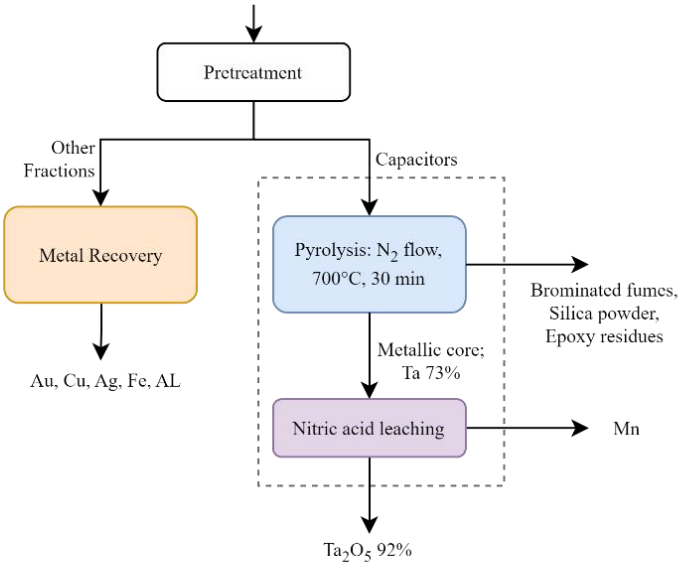


Figure 5-11: Process route for recovery of Ta from capacitors. Source: Adapted from [Ba20].

Table 5-7: LCI for the recovery of tantalum oxide from capacitors. Source: [Ba20].

Inputs		
heat, natural gas	3.1E+01	MJ
nitric acid	3.1E+00	kg
nitrogen, liquid	6.2E+01	kg
phosphoric acid	3.1E+00	kg
Outputs		
bromine, for tantal recycling	4.4E-03	kg

Recovered Material		
tantalum, powder, capacitor-grade	1.6E-01	kg

5.5.2. Neodymium and REE recovery

Magnet-to-magnet recycling of NdFeB magnets is a preferred alternative to direct metal recycling, since it avoids the production processes of magnets, and uses mechanical rather than chemical processes. [Ji18] compared the environmental impacts of virgin magnet production and magnet-to-magnet recycling, with direct use of the recycling outputs as material inputs. As the recycling route uses most of the waste materials, only 0.5 g to 1.0 g of new materials are needed to produce 1 kg of NdFeB. The process of recovery includes transport, demagnetization, blasting, acid cleaning, hydrogen mixing, pulverization, sintering, and magnetization, compression, and cutting, and electroplating (**Figure 5-12**). Material losses within the process are collected and reused as raw material feedstock (**Table 5-8**)

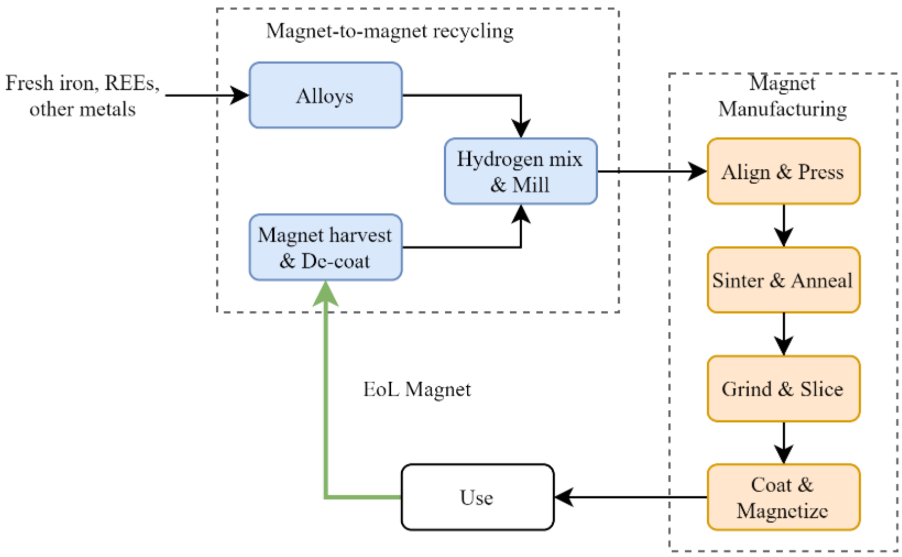


Figure 5-12: Schematic of process for magnet-to-magnet recycling. Source: Adapted from [Ji18].

Table 5-8: LCI for magnet-to-magnet recycling for 1 kg of product. Source: [Ji18].

Inputs		
Materials/fuels		
transport, lorry >32 mt	7.36e-02	tkm
transport, freight train	2.11e+00	tkm
transport, lorry 16-32 mt	1.49e-01	tkm
Electricity/heat		
electricity, for collection	3.44e-02	kwh
electricity, for sintering	4.62e+00	kwh
electricity, for grinding	1.24e+01	kwh
Materials/fuels		
collected NdFeB magnets	1.23e+00	kg
neodymium	8.78e-05	kg
dysprosium	3.53e-04	kg
iron pellet	5.56e-06	kg
copper	1.78e-05	kg
cobalt	1.17e-04	kg
hydrogen, liquid	4.78e-03	kg
chemical, organic	1.63e-04	kg
sulfuric acid	1.25e-03	kg
sodium hydroxide	3.40e-04	kg
soda ash, dense	6.80e-05	kg
nickel, 99.5%	1.07e-01	kg
sodium phosphate	1.36e-04	kg
water, unspecified	1.93e-03	m3

Outputs		
Waste to treatment		
nickel smelter slag	1.49e-01	kg
sludge, pig iron production	1.82e-01	kg
Emissions to air		
nickel (emissions to air)	4.49e-06	kg
Emissions to water		
borate (emissions to water)	2.04e-04	kg
nickel, ion (emissions to water)	1.43e-06	kg
nickel sub-sulfide	6.80e-05	kg
wastewater	7.14e-04	m3
sodium saccharin	3.40e-05	kg
Recovered material		
NdFeB magnet	1.00e+00	kg

5.5.3. NiMH batteries

Nickel metal hydride batteries contain REEs such as La, Ce, Pr, and Nd. Until recently, the industrial recycling of NiMH batteries consisted of the smelting of whole battery focusing on the extraction of nickel for use in stainless steel production. REEs were lost in the smelter slags. Recently research has led to the development of metallurgical methods for the recovery of Ni, Co and REE from NiMH batteries [TC14]. [Si20] developed inventories for recycling of NiMH batteries that recovered nickel, steel and REE oxides mixture (**Table 5-9**). Recycling of NiMH batteries involves deactivation, mechanical processes, and the recovering of metals. After deactivation by thermal treatment, manual dismantling and the separation of electrodes is needed. Cells are processed in a crushing mill and in a disintegrator. Hydrometallurgical leaching leads to the recovering of metals, including sulfuric acid leaching and solvent extraction. Recovery rates for Fe, mischmetal (mixture of metals) and Ni are 95%, 85%, and 70%, respectively.

Table 5-9: LCI for recovery of metals from 1kg of NiMH batteries. Source: [Si20].

Inputs		
Hydrometallurgical leaching		
n-methyl-2-pyrrolidone	1.40e-04	kg
citric acid	9.52e-01	kg
H2O2	1.74e-01	kg
water	1.20e+00	kg
electricity	1.26e+00	mj
heat	5.35e+00	mj
Energy for recycling		
electricity - crushing	1.21e+00	mj
electricity - drying	1.09e+01	mj
electricity - sieving	3.32e+00	mj
Transport		
rail transport	5.16e-01	tkm
truck transport	5.97e-01	tkm

Outputs		
Recovered metals		
chromium steel	8.00E-02	kg
mischmetal (REE)	5.06E-02	kg
nickel 99.5	2.39E-01	kg
Emissions to air		
arsenic	2.25E-03	g
cadmium	6.08E-01	mg
carbon dioxide	1.03E+00	kg
lead	8.38E-03	g
methane	2.57E-02	g
nitrogen dioxide	2.50E-02	g
sulfur dioxide	2.93E-02	kg
sulfur oxides	1.00E-05	g
vanadium	1.72E-02	g
zinc	2.61E-02	g
Emissions to water		
acenaphthene	3.00E-05	mg
barium	2.93E-01	g
copper	3.13E-01	g
nickel	5.40E-04	kg
phosphorus pentachloride	4.07E-01	ug
selenium	2.35E-02	g

5.5.4. Recycling of bulk components

Most of the rest of the material content of interest for recycling is composed of steel frames and steel components, cables, aluminum frames, and plastics. It is assumed that a travel distance to a treatment plant of 250 km (75% by lorry, 25% by train) to recycling facilities takes place [HWG05]. Fe and Al are modelled as scraps for treatment at plants. Cables are separated into plastics and Cu, the latter modelled as scrap. Plastics, when no further information is supplied, are sent for incineration.

5.6. Uncertainty of data

For the EU to increase the recycling of critical and valuable metals in WEEE, it is necessary to access improved data on quantities of critical metals contained in the different products in the EU [EC23a, EC12]. This dissertation tries to close the gap for the case of data centers, and the methods can be replicated to other products.

Uncertainty in the developed inventories comes from lack of knowledge on where the metals are in various components, lack of information on the composition of collected WEEE, and from the maturity of the recycling processes considered. If scaling of the results presented here is further developed, increased uncertainties are bound to appear, so extrapolation to regional potential for recyclability can lead to results with low quality. This leads to problems when assessing the potential of urban mining. Better data can lead to better understanding of flows of critical materials used in technological applications and better foundations for policy development [Ch15].

Uncertainty around the environmental data can also be a product of methodological assumptions in LCA. The choice of allocation, the ex-ante method applied to some experimental methods, and the multiple outputs bound to the same process may lead to further uncertainties. When mapping uncertainties, [Ch10] applied general percentual uncertainties regarding characterization (5-20%), WEEE generation (30%), and collection (10%). Some uncertainties have been improved in this analysis due to the high collection rates of data center equipment, and on the experimental nature for characterization of WEEE material content from PCBs. Uncertainties of recycling procedures vary depending on how mature and established the process is. The influence of the procedure with the attached uncertainty will produce results of different quality, which is further analyzed in Chapter 7.

5.7. Conclusions

This chapter developed Life Cycle Inventories for the EoL of data center components. Starting with collection of EoL equipment, inventories on pre-treatment and metal refining for WEEE are here studied. Inventories for recycling of bulk materials are also presented. Since processes such as incineration and landfilling mean a complete loss of critical materials contained in WEEE, for the purposes of this work only processes where recovery of metals is possible are considered.

The developed inventories are based on industrial and experimental data on the different steps of the recycling chain. While most of the values for transport are assumed from estimates, information on pretreatment and metal recycling process inputs and outputs, and process efficiencies are gathered from multiple reports and scientific studies, particularly from existing recycling facilities in the European Union. Data on transport estimations, collection rates, material loss during pretreatment, and material recovery for each output metal during metal recycling processes is needed. Models for special processes for the recovery of REEs and Ta are also developed. Although still in an early stage, these processes have potential to alleviate the criticality of some key metals used in technological applications.

For the final recovery stages, different processes are considered for recovery of metals. Each process has its own maturity stage and presents different material and energy demands. To assess the benefits and drawbacks of these recycling strategies, proper allocation methods and indicators need to be included. This can allow a choice of recycling routes which improve circularity of critical materials, while also considering other environmental impacts. The modelling method assumes that the output fractions can replace directly the metal produced from mines, this resulting in a reduction on the impacts associated with material use.

The developed inventories are also coupled with the diverse types of reference components developed in Chapter 4. Since these have different material compositions, the amounts of recovered material and the related inputs need to be also considered. This attempts to close one of the biggest gaps in assessments of metal recycling, since usually the material content is taken from average values or from literature, or from a particular sample. This process provides high quality information for the recovery of metals from data center components. The information gathered is also used to build models, which is described in detail in Chapter 6. Moreover, the nature of the disposal of data center devices also improves the quality of data on key aspects such as collection rates. The impact of the different processes on improving circularity of critical materials is to be evaluated in Chapter 7.

Further improvement of these inventories can include the inclusion of novel processes (such as pyrolysis), an assessment of reuse as an alternate strategy, and a direct comparison with traditional methods such as landfill or direct incineration. These inventories can serve as a tool evaluation of recovery strategies, and evaluation of hotspots for material loss.

6. Development of a Software Architecture for Calculation of Life Cycle Impacts of Data Centers

This section details the development of an information system built for Life Cycle Impact Assessment of data centers. **Figure 6-1** describes the process for this development applied in this chapter. Motivations for this development include the data-intensive nature of LCA and the number of models needed to be created to answer the research questions. The development is based on the software development cycle. Requirements are specified based on the dissertation objectives and research questions. Similar existing solutions are researched within the LCA domain, so that existing work is also considered. The software design includes development of a technical solution at both the software system level and on the subsystem and component level. A multi-tier architecture and its subcomponents and their interactions are specified. The implementation section describes the different components and artifacts developed in detail. The developed system is evaluated locally and with consideration of the requirements and objectives established. Future development possibilities are formulated based on the potential applicability of the software solution. This system is used to produce the results for evaluation in the next chapter.

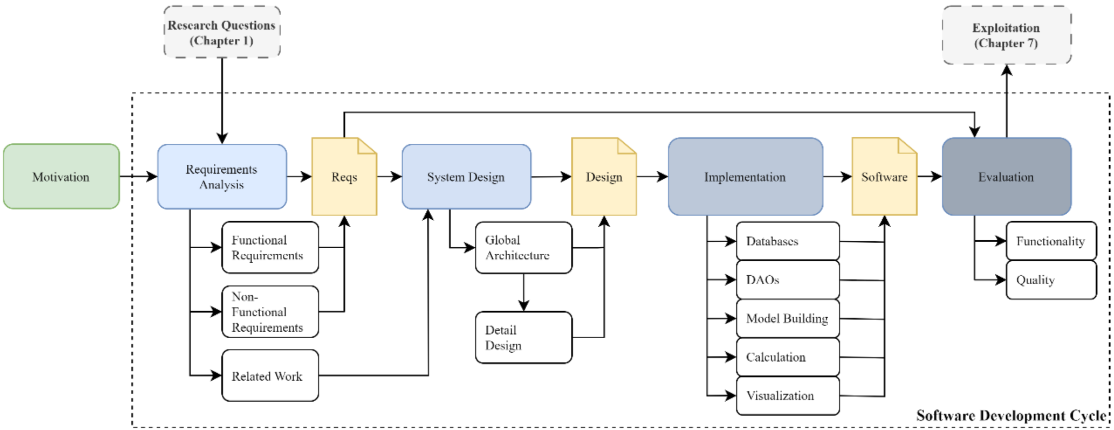


Figure 6-1: General software development process applied in this chapter.

6.1. Motivation for development

The creation of models for LCA is a data intensive procedure. The LCI process is usually the most time consuming and resource intensive section of the study and requires several iterations to achieve results of desired quality. Model building must be done carefully in LCA software interfaces. LCIA results are often too complex for stakeholders unfamiliar with environmental assessments and must be heavily processed before presentation. Given the vast number of values resulting from LCIA, their evaluation can be overwhelming for non-domain stakeholders.

Within the LCA process, there is a strong need for data exchanges between actors, especially between process designers (or process responsible) and LCA experts to ease information flows. [Ra17] indicates a lack of approaches for gathering and synthesizing information flows from downstream lifecycle stages to support system evaluation, design, and optimization. This added to the difficulty of getting proprietary industrial data, especially in the domain of data centers. Current LCA tools are not well integrated into knowledge management systems such as external databases. There are challenges in integrating product data into LCA databases. Many issues arise from data sources, coupling of formats, and selection of proxy or representative process [Ki12]. [Ra17] discusses these issues by pointing the difficulties on incorporating information gathered from architectural projects into LCA for decision making. A separation of specific process knowledge management systems, LCA software, and scripting or visualization tools used for analyzing LCA results is usually found (**Figure 6-2**). There is a lack of interoperability between the different software systems used for LCA [AD14].

There are opportunities to improve the LCA process and to ease the flows of information by improving inventorization and using tools that enable systematization of the inventories and of the resulting impacts. This can allow to translate „big data" into „big insight". This requires tools that can combine automated, data-driven approaches for life cycle data inventorization, model creation, calculation, and analysis with functionalities that enable domain experts to generate novel insights [Ra17]. Most of the effort is oriented to gathering and creating the inventories list and then finding the correct datasets in the LCA process database. As a result, LCA studies are commonly conducted at the end of the design process, when the necessary information is available, but it is too late to affect the decision-making [HGH20]. This hinders the development of including LCA in the decision-making process.

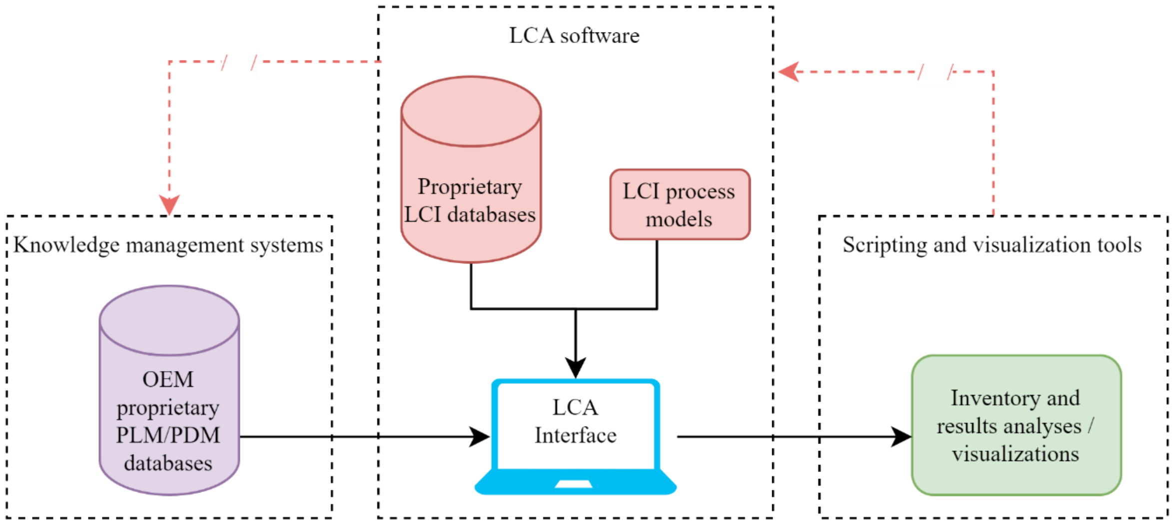


Figure 6-2: Status of the connection between product inventories, LCI databases, and result evaluation tools. Source: Adapted from [Ra17].

These challenges are also present in the current study. Issues about inventories, such as the diversity of the products in the studied data centers and the complexity of the reference components and devices selected, resulted in extensive data that required to be organized. Similarly, the update and creation of a materials database affected the structure of many processes in the LCI databases used. Finally, the use of time-dependent parameters such as criticality indicators and reference prices for allocations means also that the data needs to be updated and that the resulting indicators and results from allocation need to be periodically modified. Given these challenges, several alternatives are studied to attempt to close the gaps between the different information found. Addressing these challenges can improve the quality and quantity of the results, perform evaluations which can otherwise take considerable amount of time, and present a framework that can be replicated and could significantly aid sustainability-focused decision-making throughout the product lifecycle by helping actors to make use of the results here found.

6.1.1. Structure of the development

The structure of the development follows broadly the general software development cycle, with emphasis on its application for this study. Steps include [Ba11]:

1. **General analysis and requirements specification:** This step includes the establishment of the requirements of the software, with focus on the desired functionalities applied for this dissertation. This is evaluated in Section 6.2.
2. **Software design:** The focus is to develop a technical software solution in the sense of a software architecture from the given requirements of a software system. The design process often takes place in two steps: 1) Global design, where the software architecture is defined, and 2) Detailed Design, where the individual subsystems and components are then specified. This is detailed in Section 6.3.
3. **Implementation:** This process includes implementation of the stablished architecture in different code artifacts. This also includes testing for detection of problems and issues in the artifacts. An overview of the different artifacts developed is given in section 6.3.
4. **Evaluation:** This step is focused on evaluating the interoperability between components, the fulfillment of the requirements and the outputs produced. Evaluation of the software is done in section 6.4, while the produced results are evaluated in Chapter 7.

Since the aim of the developed information system is strongly tied to the obtention of the dissertation goals, publishing and deployment are not included in the development.

6.2. General analysis and requirements specifications

This section serves as a foundation for the development of the required artifacts for the obtainment of the results of this dissertation. The general requirements for the developed information system arise from the research objectives and thus must be developed from there.

6.2.1. Functional requirements

[RJ14] presents a general structure for the definition of system requirements (**Figure 6-3**). These are developed on the desired capabilities of the system and arise from the general workflow of an LCA oriented towards the competition of the thesis objectives described in Chapter 1. **Figure 6-4** details the link between these functionalities and the obtainments of the research goals. These requirements are:

FR1. Automation: The system must be able to automatically build LCA models based on inventories from screening and Bill-of-Materials and create product systems connected with background process.

FR2. Granularity: The system must be able to build models of different granularity levels considering parts, components, devices, systems, and whole data centers.

FR3. Indicators: The system must allow the creation of custom indicators for impact assessment.

FR4. Data Quality: The system must incorporate data quality information in the input and output data and include data quality calculations.

FR5. Scope: The system must be able to build recycling models based on inventory, recovery factors, and product composition.

FR6. Results Evaluation: The system must perform LCIA calculations and store the impact assessment results in an accessible format. Results are to be postprocessed for evaluation.

FR7. Experimentation: The system must allow parametrization, sensitivity analysis, and uncertainty modelling.

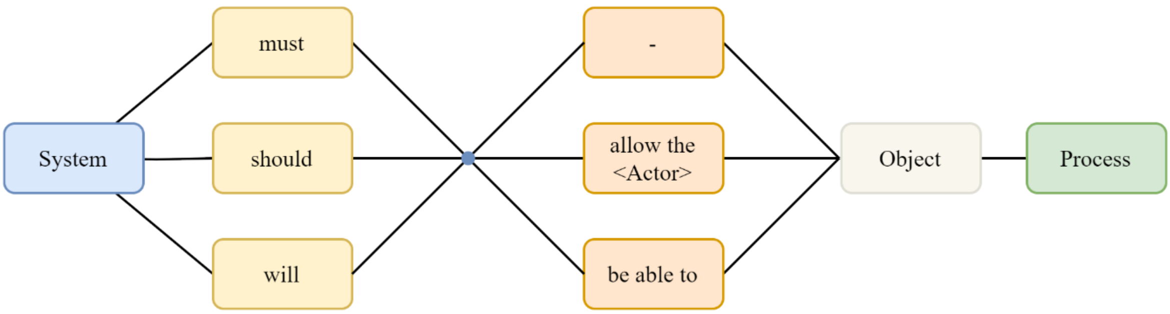


Figure 6-3: Template for functional requirements. Source: [RJ14]

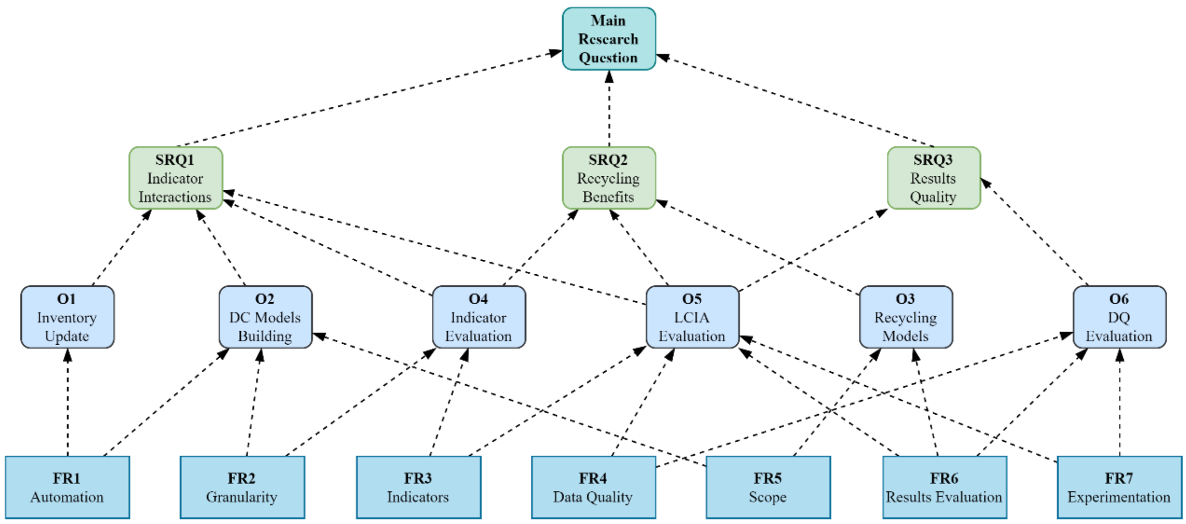


Figure 6-4: Dependencies between the functional requirements, thesis objectives, and research questions.

6.2.2. Non-functional requirements:

Non-Functional requirements are bound to the qualities, to the attributes, and to the limitations of the designed system. These are mostly derived from the constraints of this research. Such desired requirements are:

- **Scalability:** The system should be able to build and model data center configurations regardless of size. Databases must be able to hold information on multiple processes and products.
- **Updateability:** The system must allow an update of indicators based on criticality parameters and on allocation factors.
- **Privacy:** The data inventoried must be anonymized, and the resulting inventories must be stored without description of the process chains representing data center configuration or architecture.
- **Performance:** Given the complexity of the models and the number of calculations needed, a reasonable computation time is to be expected. Monte Carlo simulations, for example, which last longer than 24h are undesired.
- **Usability:** When possible, non-commercial tools are to be used. This with the goal of maximizing usability and replicability.

6.2.3. Related work

This subsection provides an overview of some software solutions developed to close similar gaps. LCA software and tools that include LCA software as part of an evaluation of products are reviewed. The goal is to find similar tools and study their limitations and contributions to further the development of the system.

6.2.3.1. Software for LCA

There are different commercial applications for conducting LCA. The basic function of these software tools is to determine energy and mass balances on a model representing a product process and allocate energy and mass flows to calculate inventories and environmental impacts. These software packages have as their main components the databases used and the internal applications for model building and for impact calculations. Software tools may work with one or more databases. Some software solutions are offered with proprietary databases. [OJP14] conducted an evaluation of available software for LCA, and focused on three tools that were chosen due to their widespread application: GaBi, SimaPro, and openLCA.

Table 6-1 presents a summary of the characteristics evaluated. Based on this analysis, openLCA is chosen as the tool for modelling in this dissertation. The main advantage is the openness of its source code, which is key for automation of model building and creation of inventories.

Table 6-1: Features of the most used software for LCA.

Features	GaBi	SimaPro	openLCA
LCI Database	Gabi, ecoinvent	Ecoinvent, US LCI, Dutch LCI	Not included
Uncertainty analysis	Monte Carlo	Monte Carlo	Monte Carlo
Data quality	No	No	Yes
Reporting	Self-editor, excel export	Graphical, excel export	Graphical, excel export
Results	Multiple Indicators	Multiple Indicators	Multiple Indicators
License	Commercial	Commercial	Open
Parametrization	Dynamic	As factor	As factor

6.2.3.2. BIM and LCA

Within construction projects, Building Information Modeling (BIM) is a digital tool that involves creating and managing a 3D virtual model of a building. This model includes geometrical and physical properties of the building. The digitization of the design process through the use of BIM, and the need for the inclusion of environmental considerations, called for the creation of tools that allow exchange of information between BIM software and LCA software [WD19]. This takes the advantage that BIM models provide structured data on material composition [AD14]. Current commercial LCA tools are limited in that they do not offer many possibilities of integrating inventorization with external information systems. For these reasons, several solutions for exchanging inventory information have been built.

There are several approaches to integrating these tools. In one of the most common approaches, a Bill-of-Materials (BoM) is exported from a BIM tool as a spreadsheet. The BoM is then imported into the LCA software, where the model environmental assessment is conducted. A disadvantage is that the LCA practitioner must manually link the different components (with their quantities) to predefined LCA profiles available in the LCA database or create new LCA profiles. Calculation and visualization are done within the LCA software. Another disadvantage is that any change in the BIM model usually means restarting the process, so parametrization is usually difficult (**Figure 6-5**).

In a second approach, the BIM model is imported "as such" in a dedicated LCA software. Usually, a specific open exchange format is needed. The imported data includes, for example, geometric parameters, so that material quantities (surfaces, volumes, mass) can be determined. It may include material specifications as well. Based on these imported data, the LCA practitioner must link the building components not already specified to predefined LCA profiles. Calculations and results analysis are performed within the LCA software.

Another novel approach is including impacts of specific profiles within a BIM software. This includes specific values of embodied impacts for varied materials, which can be directly assigned while constructing the BIM model. The results are summed up under consideration of the reference service life of the individual components, and can be summed directly in the BIM application [HGH20]. This solution is present in packages such as SolidWorks Sustainability.

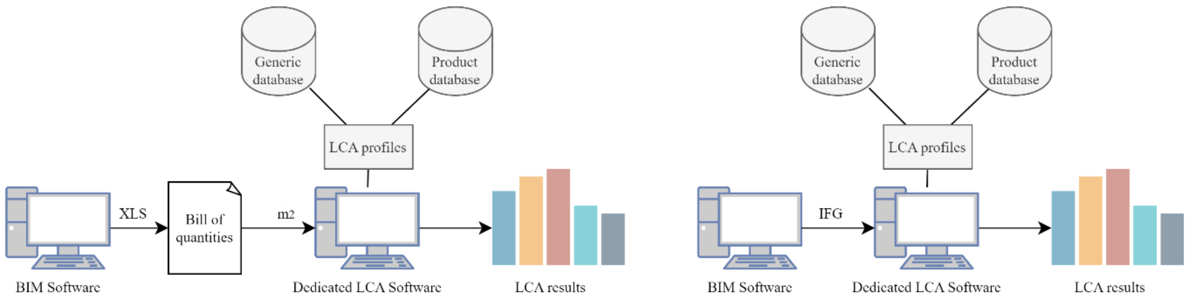


Figure 6-5: BIM strategies for LCIA. Source: Modified from [WD19].

Limitations of these methodologies come from the limited databases that exist for representing a particular product, and on the need of linking a concrete material to a specific product. Thus, a lack of structure on the data is always present. Moreover, the impacts of aspects such as transportation are often neglected or must be manually included. If only the building stage is considered, use phase is then omitted, thus decoupling the environmental performance of buildings as an aspect of sustainability. Lastly, EoL strategies are completely overlooked.

Key advantages of these processes are a reduction of time needed on tasks such as inventorization, and on manual entry of data. When including embodied impacts of materials on the BIM software, a quick first assessment of impacts, such as emissions, can be easily obtained.

Further potential for development of the integration of LCA in BIM suggested in literature are:

- Organization of the BIM inventory according to standards (e.g., ISO 12006, classification schemes, reference products)
- Structuring elements and sub-components hierarchically with specified levels of granularity.
- Linking of BIM elements and quantities with respective LCA datasets and scenarios for EoL (replacement, disposal, recycling)
- A parametric approach for setting up the LCIA based on both BIM and LCA model to facilitate changes.

6.2.3.3. Web-based tools

Web based tools present an interface that allows connecting users with large scale databases and hosted software applications for conducting LCA. These tools present also visualization of results. These tools can be used with relative ease and are based on inventories that need to be coupled with specific product databases. Software packages such as Antelope allow publishing and analysis of life cycle models [BS15]. Brightway2 is an open-source framework for LCA written in python that allows users to apply open-source graphing libraries to create visualizations [Mu17]. SimaPro Collect is a web-based platform for sharing and uploading LCA models and performing scenario analysis [PR23].

While these tools have the advantages of being widely available, they offer poor customization and are limited on the capacities required for this study. However, visual representation are useful tools that will be implemented for data analysis.

6.2.3.4. Databases for LCA

Since the goal is working with an open-source calculation engine, the databases are selected in a format compatible with openLCA. This software uses a specific format for its databases, which converts various LCA data formats (such as ecospold) and allows to access the database through the openLCA API. This allows creating and saving flows, process, and product systems that represent the data center and its components. Through the product input/output structure, it is then possible to build products and process chains while keeping granularity, thus enabling the identification of hot spots through the analysis of contribution trees. Additionally, databases of impact indicators and characterization factors can be exported, edited, and imported. This allows creating and updating indicator values for impact assessment calculations.

The benefit of having an API to create product systems is that the models can be created, updated, and interconnected using data from separate databases. Databases containing BoMs, material criticality, recycling ratios, recycling inventories, and other information required for the evaluation of data center components can be separately stored. Additionally, the results can be fetched, and the values stored in databases or in separate files (such as CSV). This makes possible the automation of creation and update of models, and of saving and postprocessing of results as well.

6.3. System design

This section details the design of the components of the system and their interaction. The global system design defines the software architecture , and the detail design specifies individual subsystem within the architecture.

6.3.1. Global software architecture design

The software architecture describes the structures of the software system using architectural building blocks and their relationships and interactions with one another, and their physical distribution [Ba11].

Various reference architectures patterns exist that align with different requirements to satisfy functional and quality attributes. The decision on this pattern is mate to satisfy these qualities [Ka18].

Several aspects drive the choice of an architecture for the information system for this work. [Ka18] conducted a study where different architectures were surveyed within software developers. Functionality, technology constraints, and quality are key aspects for selecting an architecture, with functionality at the forefront. Moreover, within the Academic and Education sector, [Ka18] found that usability and modifiability are key factors on deciding for an architectural pattern. From the architectural patterns analyzed, the multi-tier pattern was found to align better with the objectives of this work. This is due to its simplicity, modularity, the interoperability of the components, and the possibility of having separated databases that keep their integrity and limit their access. It is a scalable solution, and it is highly maintainable since the applications, databases, and visualization components are separated.

Each tier of this architecture pattern has a specific role and responsibility within the application. A feature of a multi-tier architecture pattern is the *separation of concerns* among components. While closed tiers ease isolation and help modular changes, there are times when it makes sense for certain tiers to be open, for example, if content of a database wants to be directly shown (**Figure 6-7**). Some reported disadvantages are that the system may be difficult to build, separated entities for databases and applications need to be built (usually separated servers), and good knowledge of object-oriented concepts is needed for the development.

Several versions of this architecture exist, with the easiest one presenting three tiers. One tier deals with the presentation part of the system (user and system interfaces), another handles the business logic, being the core of the system, and the last tier takes on the data storage. [Fe08]. This structure can be further split to gain granularity and better structuring of the system. Since a User Interface is out of scope, the system is presented in five different subsystems, explained in the sections below (**Figure 6-6**).

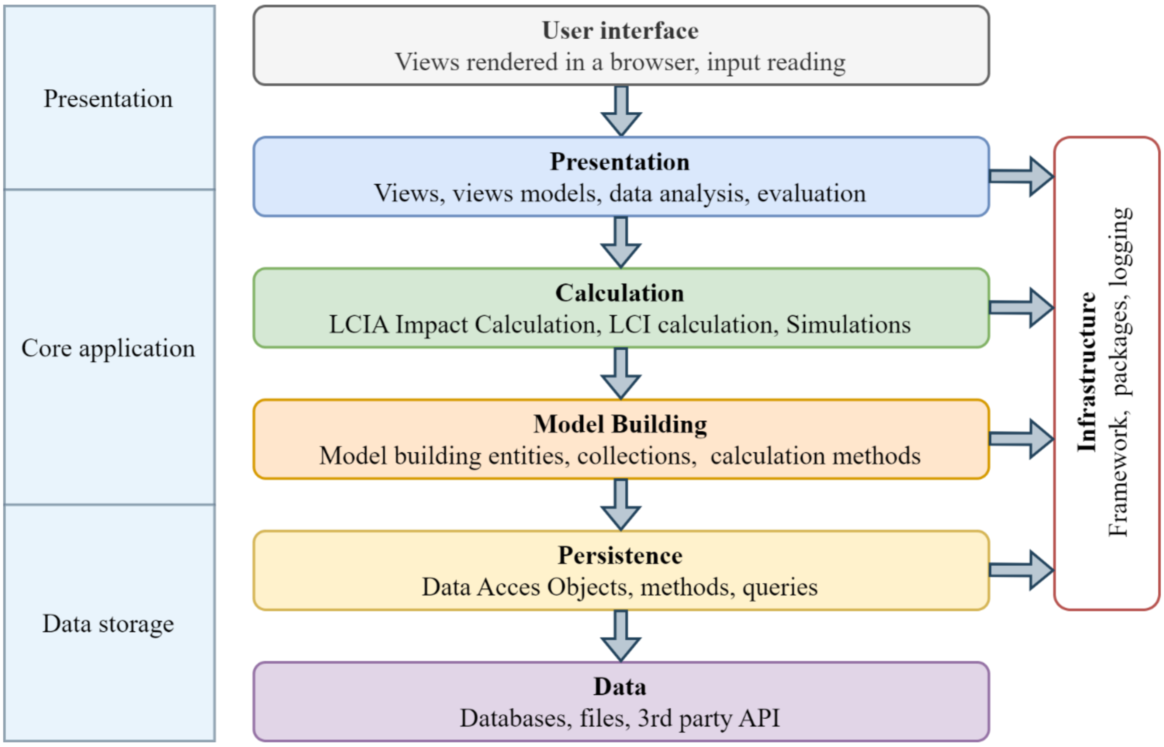


Figure 6-6: Multi-tier architecture with its components.

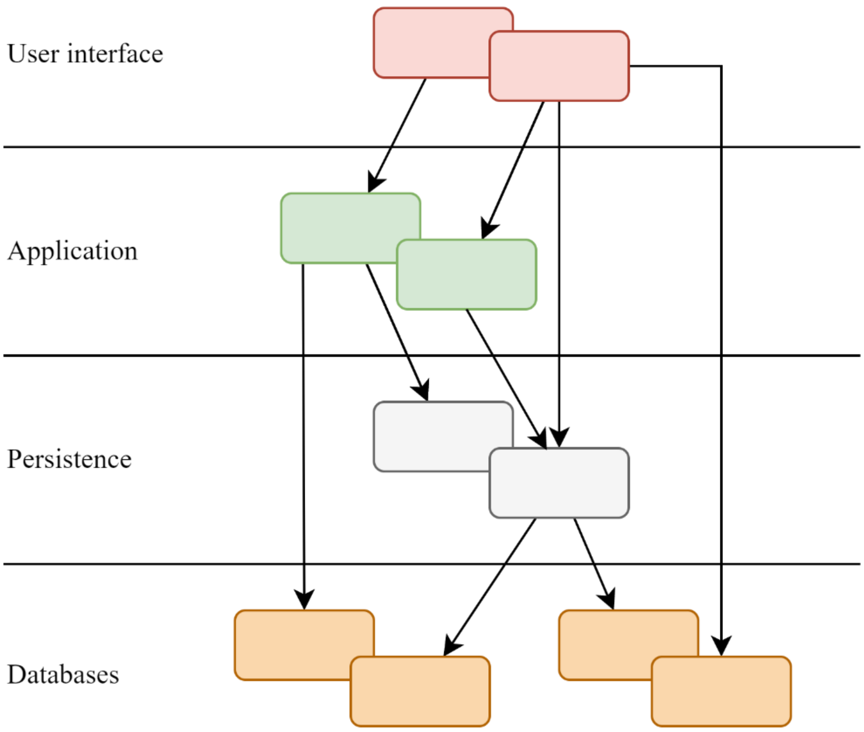


Figure 6-7: Concept of the open tier architecture.

6.3.1.1. Database tier

This tier handles storing and managing the data used by the other tiers. This includes collected data, generated data, models, and downstream LCA process. Included in this tier must be:

- Relational databases handling products inventories and BoM.
- Databases for material criticality.
- Databases for recycling process data (rates, inputs, outputs).
- LCA Databases.
- Results databases.
- LCIA Databases (simplified versions of inputs/outputs) with anonymized data.

The database tier structure ensures that data is properly split and is available to other tiers. It will also ensure that the data is secure and available to the other tiers when needed.

6.3.1.2. Persistence tier

This tier handles collecting, processing, and managing data related to the life cycle of a product. It is used to connect the application tier to the databases or data source. It has methods which are used to perform operations on database like insert, delete, update, and similar. This tier has stored procedures which are used to query databases. Hence this layer sets up a connection with the database and performs functions on the database. It can also create data (such as CSV files) to store other modelling results.

6.3.1.3. Domain model tier

This tier has as its main function to build specific flows, process, and product systems associated with LCA using the openLCA API. It has several applications to collect data from exchanges (inputs and outputs), reference processes, and inventories. This data is used to build LCA models which contain the required input, outputs, reference process, process providers, data quality schemes, uncertainty values, parameter factors, and other data required for calculations. It uses the persistence tier to access information on different models, can store these models, and the results of the calculations as LCI models.

6.3.1.4. Calculation tier

This tier handles performing the LCIA calculations based on the data and models created by the data management and model creation tier, and on the impact calculations methods specified (predefined or created). This involves using the openLCA calculation engine to calculate direct impact assessments to perform environmental impact calculations for assessing material and energy resource needs and performing experiments on models such as sensitivity analysis and Monte Carlo simulations of specific products and processes. Existing data centers of varied sizes can thus be mapped more easily via the modular structure The possibility of scripting these modeling processes in openLCA enables the various steps to be automated, so that the entire inventory of a data center can be analyzed for each part, component, device, or system without manual intervention.

Additionally, to gather information on components content, total flow requirements of components and of material flows can be assessed, so total results and total contents available for recovery can also be indicated. This is useful to assess urban mining potential.

6.3.1.5. Results analysis tier

This tier handles analyzing the results of the LCA calculations and presenting them to be interpreted accordingly. The visualizations are to be developed using common data analytics methods and open-source packages. The goal of the visualizations is to answer the research questions, so the results presented must be oriented towards giving insight on these points. This requires creating customizable reports, graphs, or charts to display the results of the LCA calculations. This also involves statistical analysis of results and obtaining insights on the results of the experiments conducted.

6.3.2. Detail design and component structure

This section details the components of each tier and specifies the interaction between them.

6.3.2.1. Databases

The first step for creating databases is to systematize the information obtained during this dissertation. The data is cleaned and stored in SQL databases, which provide the required structure so that it can be easily accessed, created, or modified via queries. Following databases must then be created:

- Material process data is gathered on raw materials, mining processes, material costs, and EU criticality values. This data is stored in a Materials Database.
- Data on data center inventories is stored is SQL tables. This data holds information on parts composition, pieces composition, devices BoM, data center system inventories. The structure of this data also allows for space for saving results of impact assessment resulting for calculations, since the results can be linked to the corresponding product system modelled.
- Data on material recovery, recovery fractions, recovery process inventories, and on different collection and recovery ratios are also stored.
- The ecoinvent 3.4 database is stored separately since it needs first to be imported by openLCA and decompressed. This database has been altered and updated to include several mining processes for raw materials that were absent in the original version of the database. Considerable changes were made to include critical materials and their mining processes. This database serves as base for creating the different flows, products, processes, and product systems needed to build the models required of this dissertation (**Figure 6-8**).

- Impact Assessment Methods in XML format must be imported to the LCIA Database. This XML database holds information on characterization factors and is built using information on material criticality and factors on material depletion potential.
- CSV databases holding results of Monte Carlo simulations and of sensitivity studies are stored in this tier. These are saved in separated plain files to avoid overloading the SQL databases and to allow multiple iterations to save results on the same indicator.

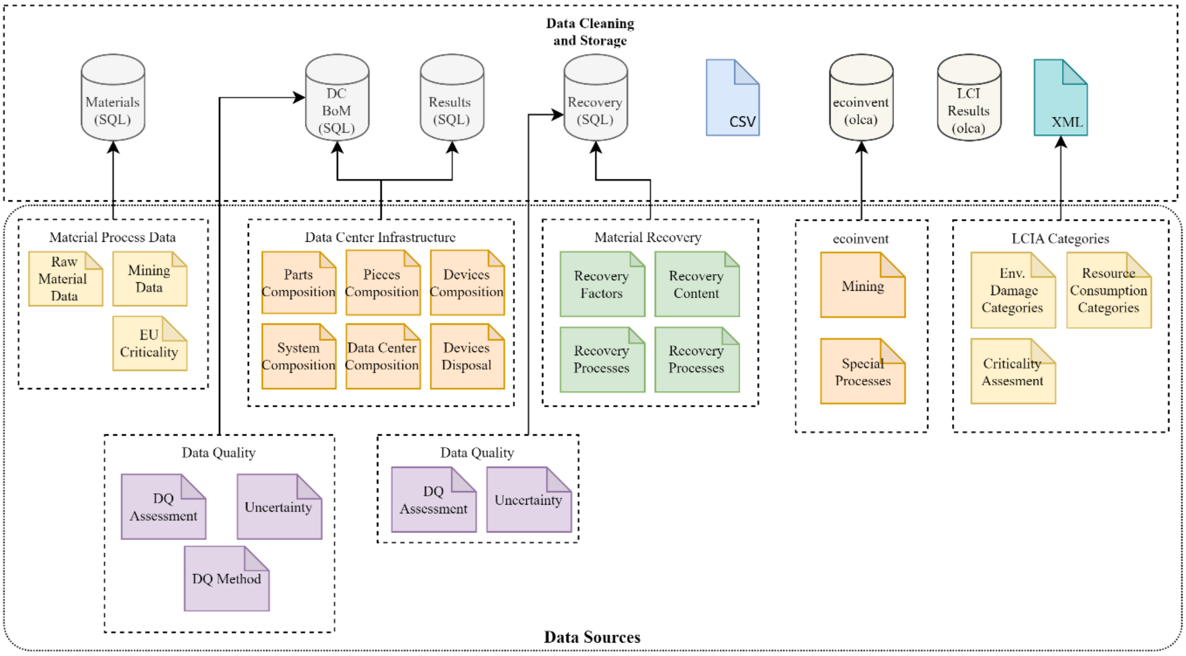


Figure 6-8: Elements of the database tier and flow of data for creating the databases. SQL databases can be merged into a single database.

6.3.2.2. Persistence tier objects

This tier has as objective to access the databases and separate them from the rest of applications. These consist of SQL Data Access Objects (DAO) for SQL and for the environmental databases (**Figure 6-9**).

- For SQL databases, SQLite extensions are used to connect and close databases.
- For environmental databases, the openLCA API is used to connect and close the databases specified by name.
- For XML data, python packages to read and write XML are used.
- For CSV data, python, and java packages to read, write, create, or overwrite files are used.

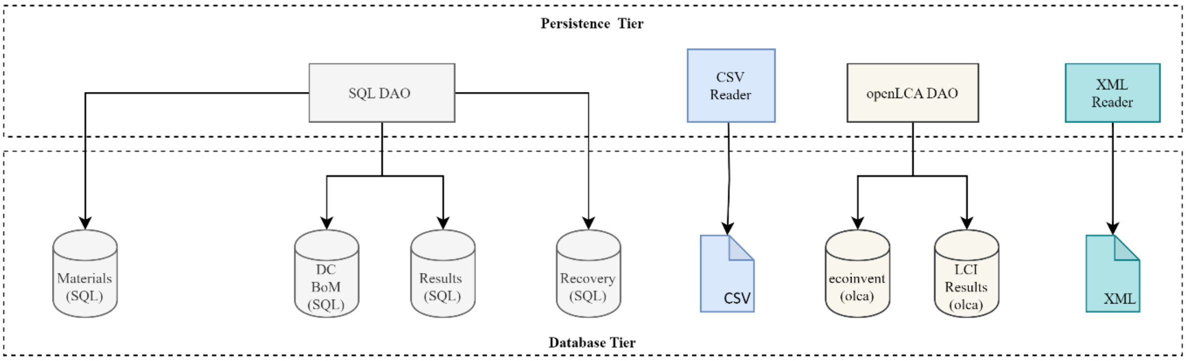


Figure 6-9: Persistence tier components.

6.3.2.3. Model building Components

Several classes and methods are required to perform specific tasks regarding model building. Following items are then contained in this tier:

- **Category building:** using the distinct levels of disaggregation for data center components (data center, systems, devices, components, parts, materials, and EoL)
- **Flow building:** For each product, a reference flow with proper units must be first built. This uses information such as category and reference unit.
- **Process building:** Using information on reference products and input/outputs for each process from the BoM databases. Information on data quality, uncertainty, and data quality method is also given here.
- **Product system building:** Using information on process, a model for the product system is built and interconnected with the corresponding providers to create product process chains.
- **Impact category:** Using information on existing indicators, material criticality, and allocation factors.

Scripts for creating all the required categories, flows, process, and product systems are also included for automation of the construction of the model database. Utility functions to access information in the databases are also included. These are, e.g., wipe database, create all products in a category, fetch process list, fetch exchanges list, amongst others (**Figure 6-10**).

Extra classes to temporarily store the information are also developed. These serve as a bridge between the information obtained from the SQL databases with inventory info and the environmental databases.

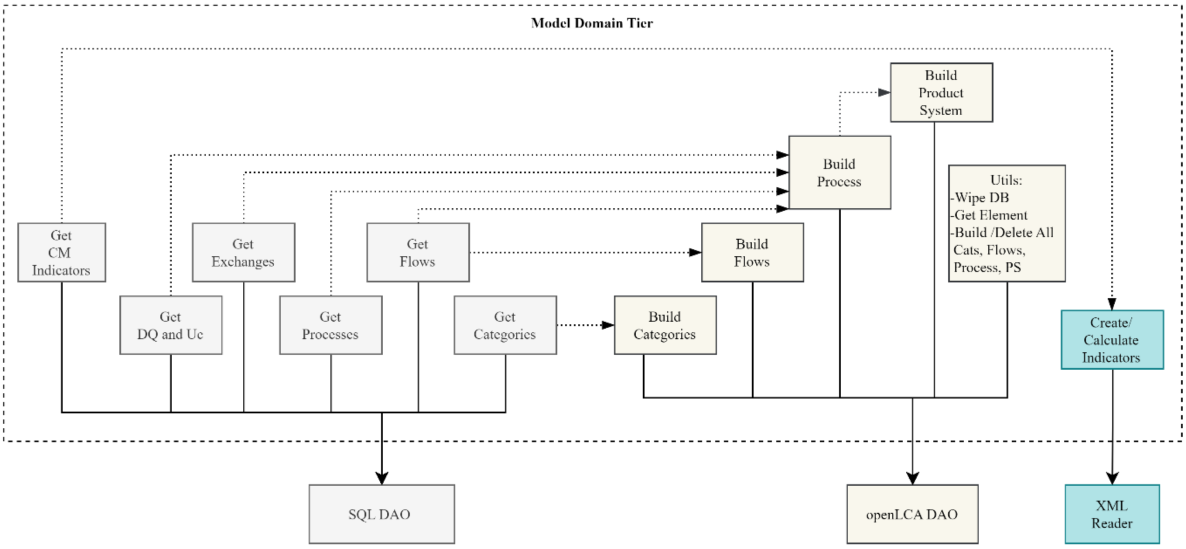


Figure 6-10: Model building tier components.

6.3.2.4. Calculation tier

This tier is built around calculating the impacts of a specific product, which can be called by its name or by its identification (**Figure 6-11**). The system needs to firstly get information on the existing product systems, select the specific product system from the environmental database, select a calculation method (a detailed calculation is selected), impact categories, perform calculation on impacts, and save the results in a database. For the calculation, the openLCA calculation engine is used.

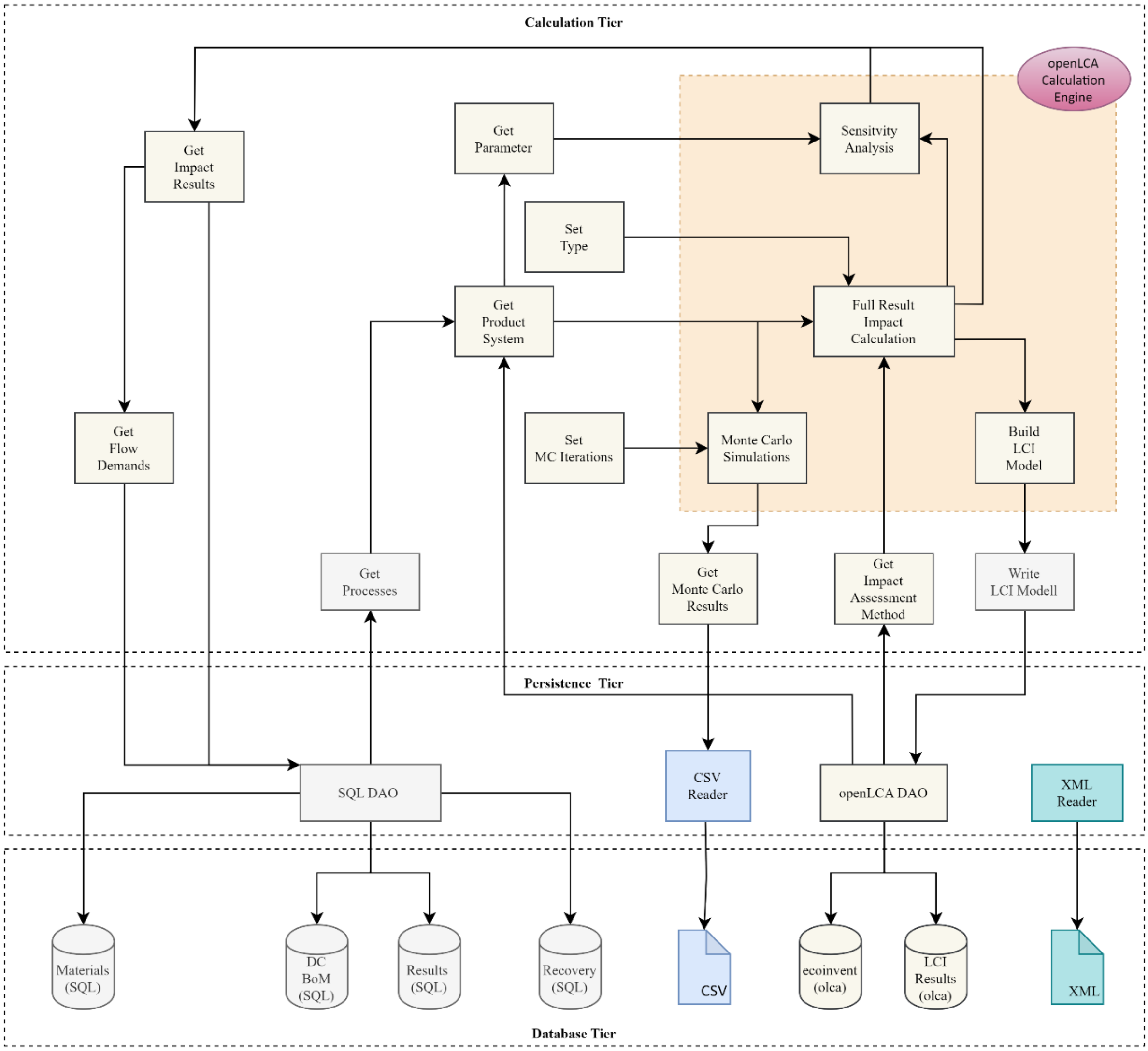


Figure 6-11: Model calculation tier components.

A simplified inventory (without a process product chain) is also calculated and is stored. This anonymized version contains only elementary inputs and outputs and can be used later for quick evaluation of environmental impacts. These inventories are saved in the environmental database.

Results saved include total impact by category, total material flow required, and total flow of reference products, such as mainboards or CPUs. This allows an inventory of different granularity at higher levels, which then can be evaluated for recycling evaluation. If all the products or a list of products are to be calculated, a list is obtained from the SQL databases.

Additionally, for selected processes, sensitivity studies need to be conducted by varying one or more parameters. Monte Carlo simulations must be conducted for products. Due to time constraints, only selected products with the highest impacts on material and energy demand are considered. This requires a specified number of runs and writing of the results in separated CSV files.

Since the calculation of recycling potential needs first evaluation on content of components for recycling, the EoL models are built after the calculations on data center components and systems take place. The recovery models are built then as an intermediate step. Recovery potential using different material recovery strategies is evaluated for components, devices, and data centers. This also allows various levels of detail within the urban mining potential. Results are written in the databases using the persistence layer to get data models.

6.3.2.5. Results analysis tier

This section is composed of scripts and methods that automate the evaluation of results based on the research questions (**Figure 6-12**). Results required include:

- Indicators characterization factors.
- Evaluation of impacts associated with each material, per kg of ore produced. This to supply a basis of comparison for recovery savings.
- Environmental impacts on resource depletion (energy and materials) for product systems at different granularity levels, including whole data centers.
- Fractional contribution of metal mining to total impacts of products.
- Environmental impacts of EoL strategies, including metal recycling, considering the savings from metal recovery.
- Material flows during product lifecycle, including recovery.
- Sensitivity analysis results evaluation.
- Result on correlation between indicators
- Data quality and statistical analysis of Monte Carlo simulations for uncertainty analysis.

Since the results are calculated and stored in SQL databases and in CSV files, the analysis is done using the persistence layer to access the previously mentioned data. Results are saved either as tables or visual representations of the data. Data is analyzed using open-source analysis tools or custom-made applications. **Figure 6-12** details the application of these analysis to achieve the research goals.

6.4. Implementation

This section provides a summary of the different objects developed specifically for the construction of the system. The goal is to present an overview of the internal structure of the different components developed during the implementation of this system.

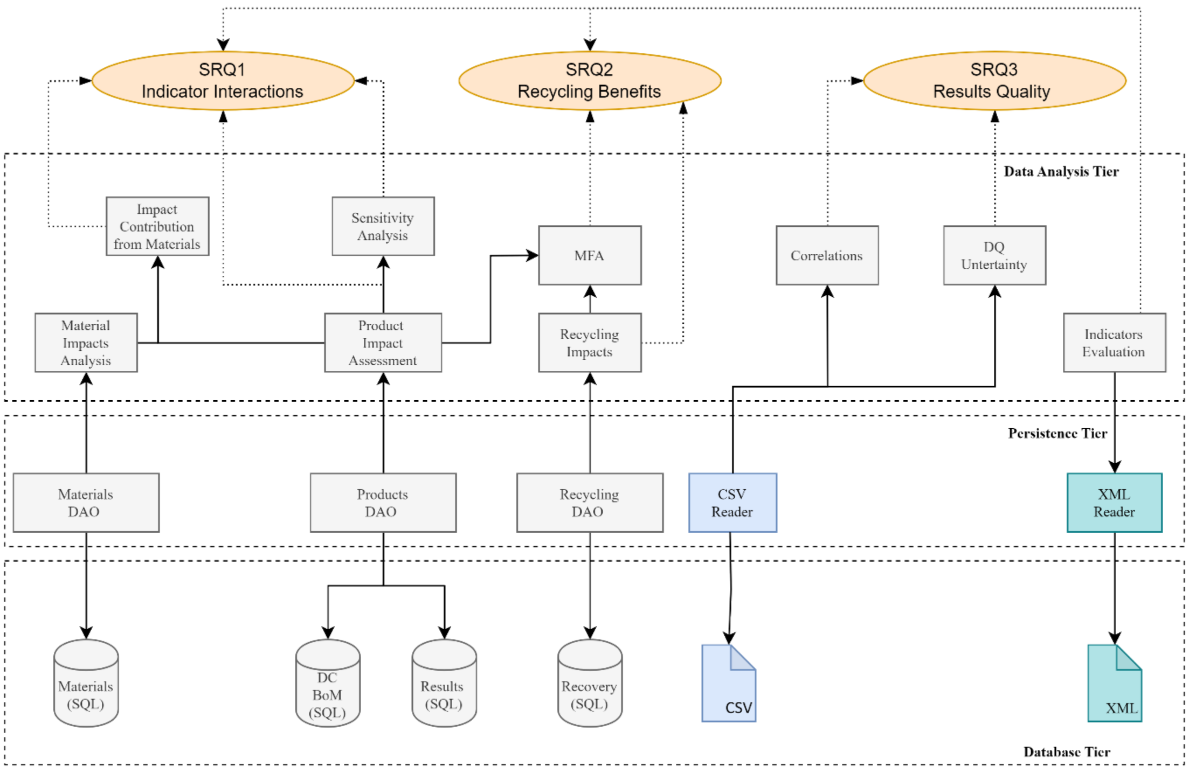


Figure 6-12: Data evaluation tier components and links to the research objectives.

6.4.1. Databases

SQL was chosen to store information on materials, data center inventories, recovery processes information, and results. SQL offers key advantages such as speed in queries, stability, and integrity of the databases. The use of structured queries makes it possible to save results in an organized way for posterior analysis.

Figure 6-13 shows one example for the Materials Database. This contains the necessary information on materials which serve as input in the LCIA for said materials. Information on embodied impacts of these materials is also included. This allows structuring the information so it can be used for posterior analysis. Data such as material symbol (for indexing), physical and economic allocation (for mining processes with multiple outputs), material category (such as precious metals, base metals, ferrous metals), and criticality factors are here stored.

The inventory data of data center components is also stored in the databases. As an example, the inventories for the devices are stored by saving the obtained BoM in structured tables (**Figure 6-14**). A device can then contain specific quantities of reference modules, reference components, and specific inputs from the ecoinvent database (specified by name).

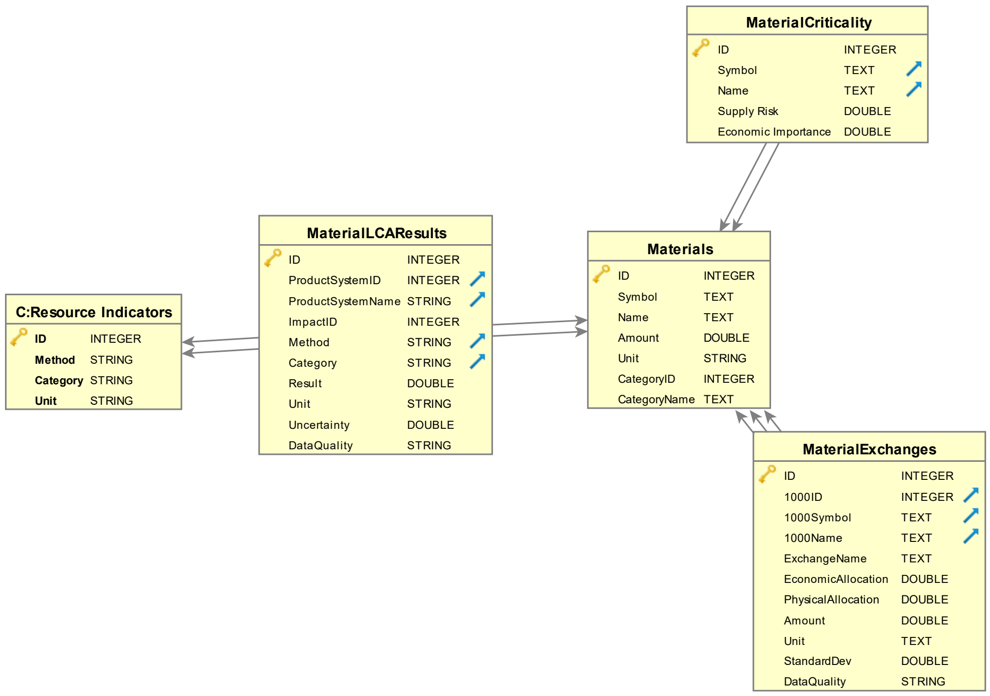


Figure 6-13: Materials database Entity Relation Diagram (ERD).

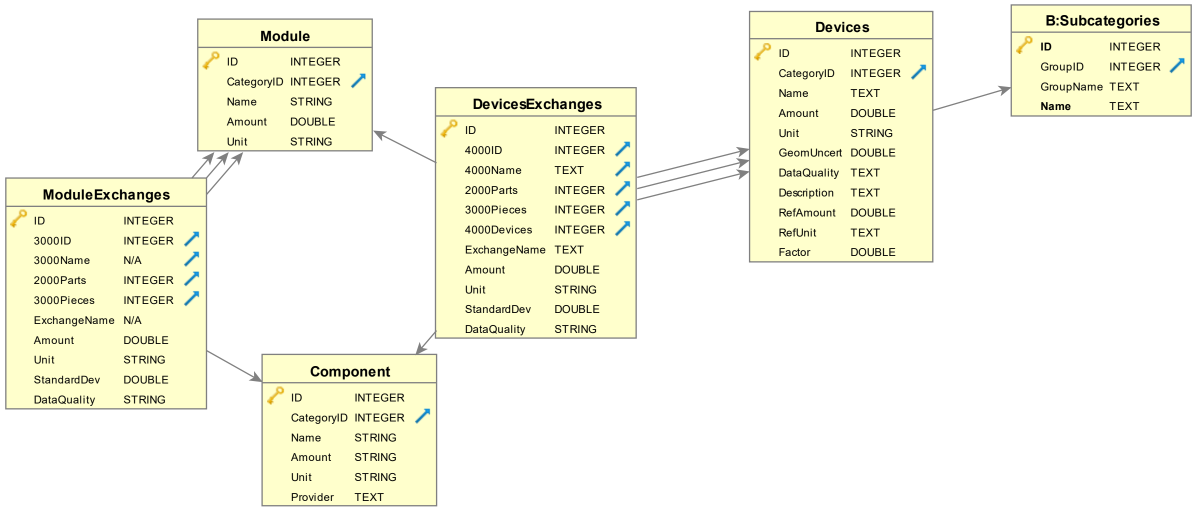


Figure 6-14: Devices BoM database ERD.

The inventories of data centers are also saved using structured tables (**Figure 6-15**). The subdivision in systems, devices, modules, and components allows retaining the required granularity in the analysis.

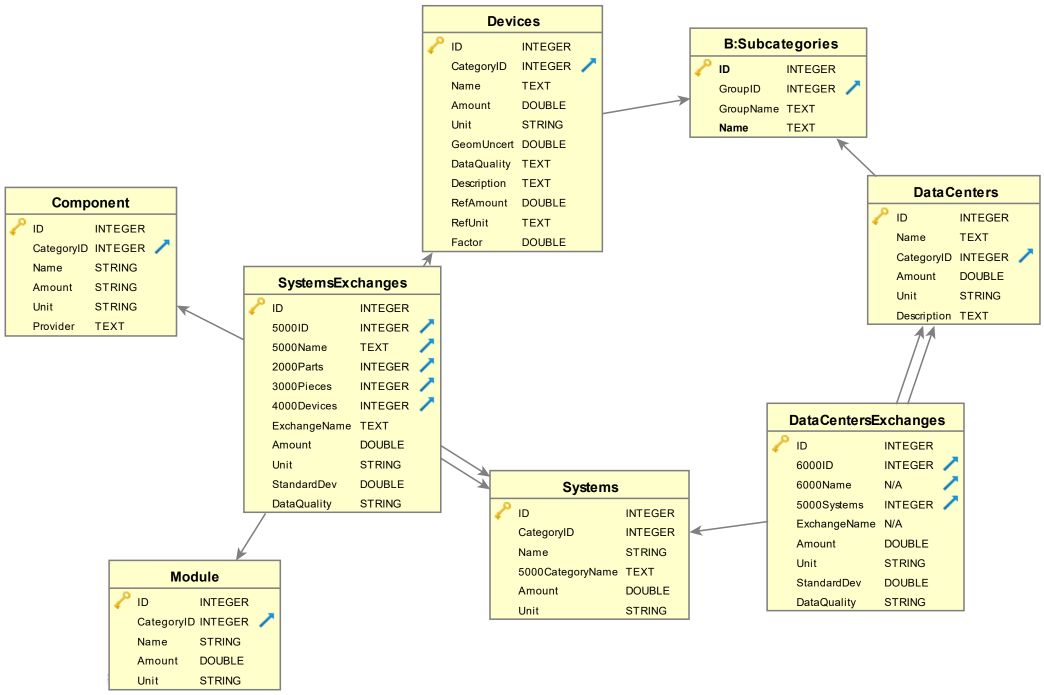


Figure 6-15: Data center inventories ERD.

Recycling and recovery information is stored using a similar approach (**Figure 6-16**). The information on recycling models contains data on inputs and outputs of recycling processes (exchanges), materials content on components and modules, recovery rates.

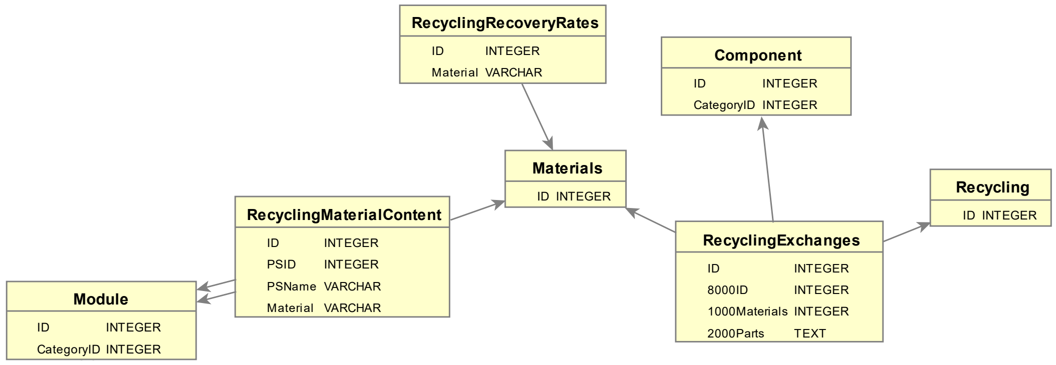


Figure 6-16: Recycling database ERD.

The results database is developed with the help of the tables with list of the different levels of components of a datacenter, from materials, components, modules, devices, systems, data centers, and recycling of different products (**Figure 6-17**). This uses a list with the required indicators that are selected for evaluation.

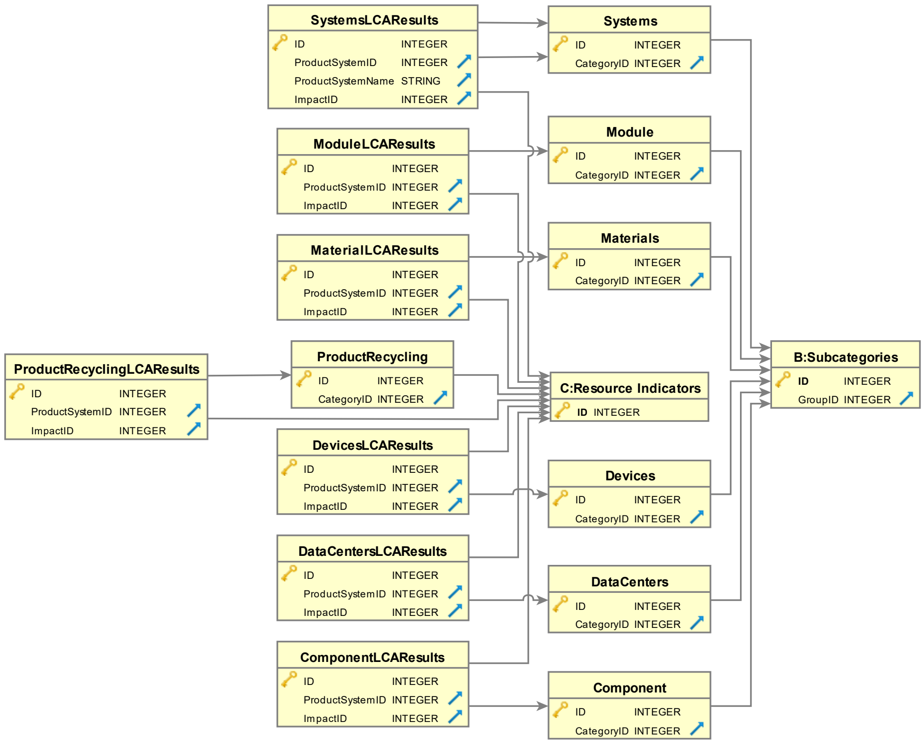


Figure 6-17: Results database ERD.

The ecoinvent database is directly imported using the openLCA interface and saved separately. This database needs modification for inclusion of several processes which are initially absent from the database, which needed to be created first manually.

6.4.2. Persistence layer

Since the native development of openLCA is done in Java, this was chosen as the language to develop the persistence layers to access the SQLite databases and environmental databases for creation of product systems and for writing and saving of results from the calculations of environmental impacts. The openLCA modules can be imported directly from the .jar packages downloaded from their website [Gr21].

DAO objects for the SQLite databases are created using the `Sqlite-jdbc.3.36.0.3` plugin. CSV databases are created and accessed through the `opencsv5.6` plugin. The ecoinvent database is accessed through the `org.openlca.core` package.

Figure 6-18 shows an example of the SQL DAO class (`ConnectSQL`) with some utility functions created for querying the SQL databases. The database is accessed by its filename name. A connection object (`sql.Connection`) is created by the DAO and can be used by the util functions to perform queries for reading, writing, deleting, and updating information.

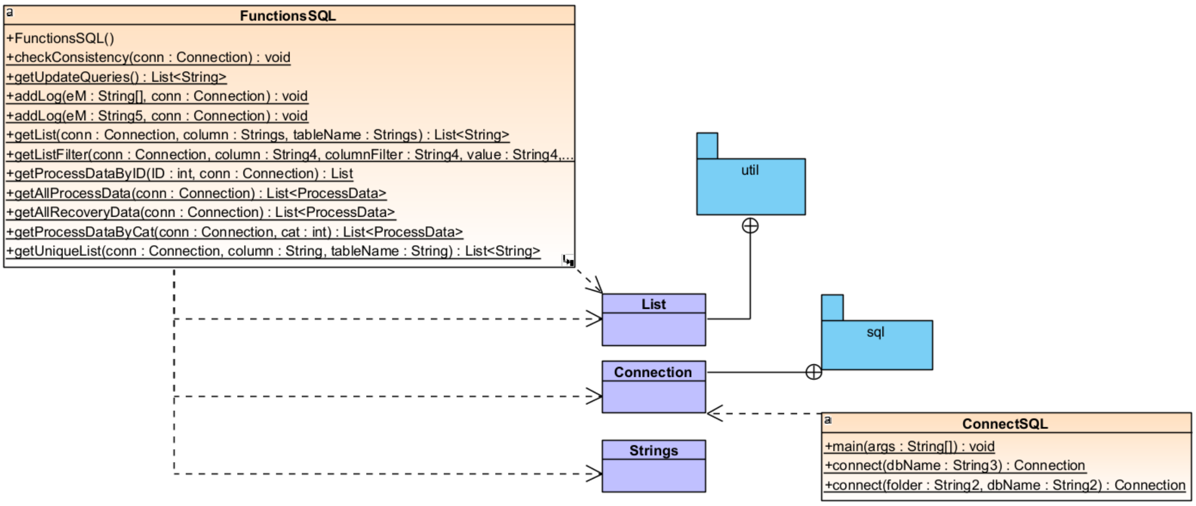


Figure 6-18: Class structure for reading SQL databases.

Figure 6-19 shows the connection with the environmental database. The connection is achieved using the database name as a string, which is passed to create a database object using the `olca.core.database` package. Several helper functions are also built, which can find specific objects such categories or model types using information obtained by reading the SQL database. This achieves a connection between the information on the SQL databases and the environmental processes database.

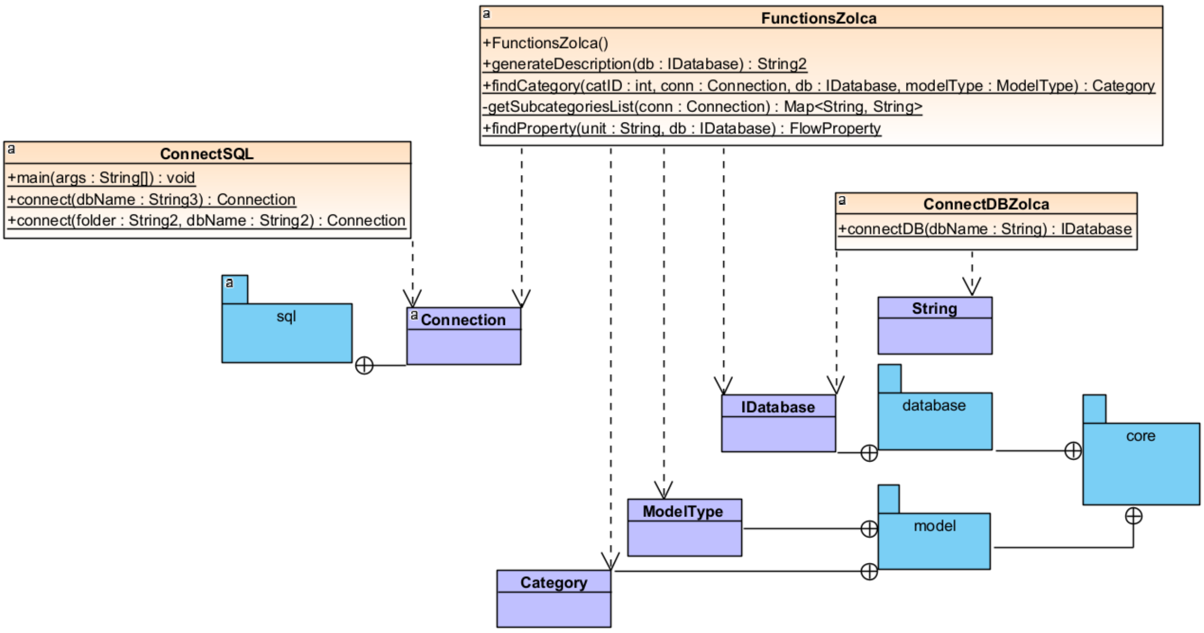


Figure 6-19: Class structure for connecting to the environmental database.

6.4.3. Model building layer

This layer is constructed to build specific flows, processes, and product systems using the information stored in the SQL databases and linking that information to the environmental database. **Figure 6-20** presents a schematic for the creation of flows. For each product specified, a flow needs to be created, so it can be used as reference for process exchanges. The basic information of the flow (ID, name, unit, reference amount) is first stored in a data class (`Classes.ProcessData`) built with information read from the BoM database obtained through the SQL DAO class (`sql.Connection`). This information is sent for building a flow object (`core.model.Flow`) within the environmental database (accessed through the openLCA DAO class (`core.database.IDatabase`). The flow object is stored in the environmental database within the proper category.

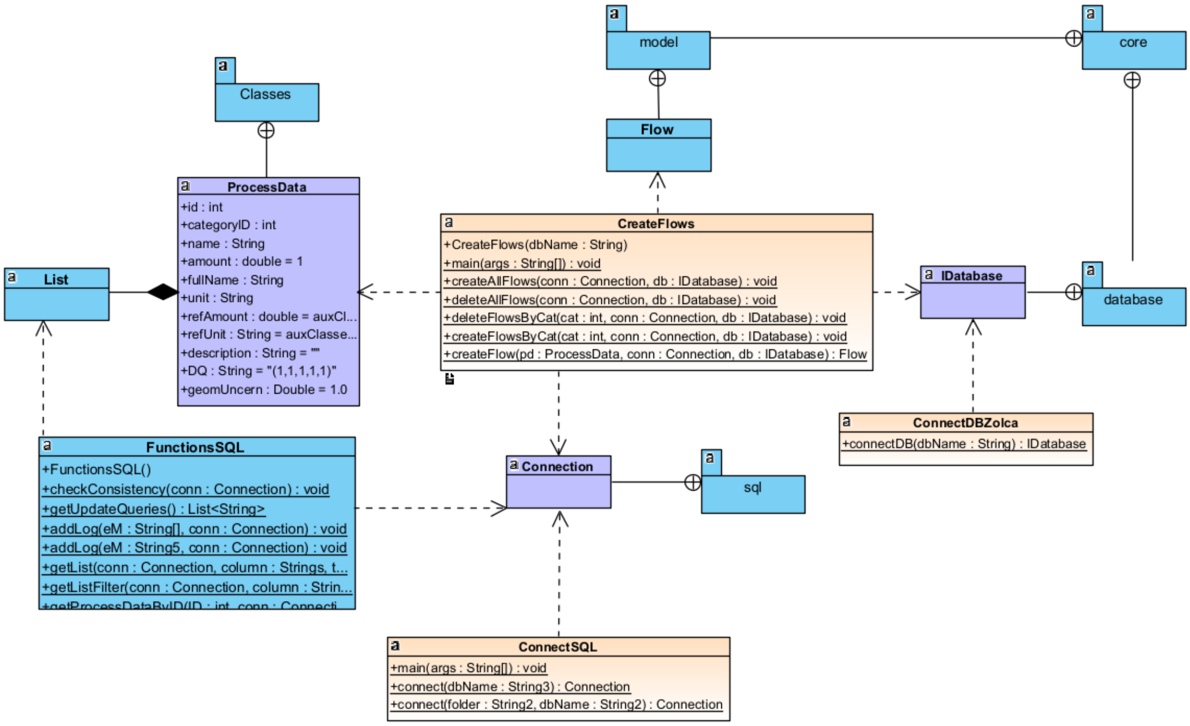


Figure 6-20: Class structure for the creation of flows in the environmental database.

Figure 6-21 details the class structure for creating a process. For each process, there is a reference flow, created as specified in **Figure 6-20**. With use of a SQL DAO (`sql.Connection`), data on the reference quantities and on the exchanges (`Classes.Process`) is used to create a Process object (`core.model.Process`) to be inserted in the environmental database (`core.database.IDatabase`). These processes are used later to create a chain of processes as product systems, which are later autocompleted and stored for posterior calculation of environmental impacts.

6.4.4. Calculation tier

This tier contains several classes for calculation of environmental impacts. At its core is the openLCA calculation engine (`core.math.SystemCalculator.calculateFull`). This package is used with different setup configurations to obtain the contribution results as an object containing the data on the calculation outputs. (`core.results.ContributionResult`).

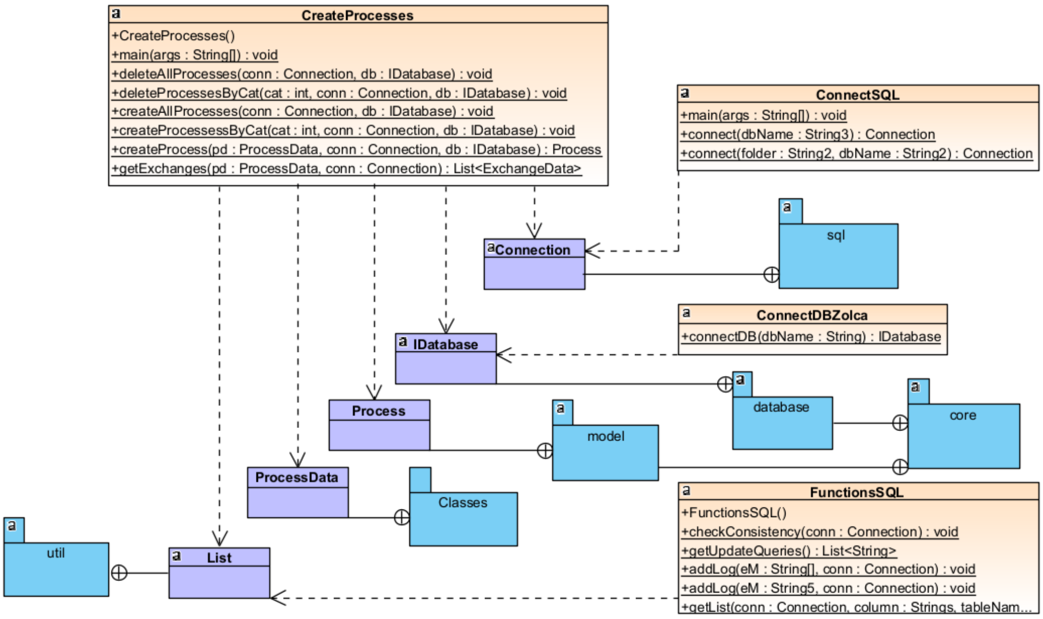


Figure 6-21: Class structure for the creation of Processes in the environmental database.

A SQL DAO (`sql.Connection`) is used to read information on a specific product and store it in a custom data class (`Classes.ProcessData`). This information is used to search for an existing product system in the environmental database (`olca.core.IDatabase`). Once the product system has been selected, an impact assessment method (`olca.core.model.ImpactMethod`) is selected from the environmental database based on the name specified on the impacts database. This is used to set up and execute the calculation of the environmental impacts. The information on the results is written in the contribution results object. Specific information is gathered from this last object, saved in a data structure object (`util.HashMap`) for intermediate storage of results, and later written in the results database using a SQL DAO (`sql.Connection`).

Multithreading is implemented for this process to allow parallel calculation of multiple product systems using a multi-thread object (`Runnable`) and a List (`util.List`) of product systems. This same object is implemented in the Monte Carlo simulation for reduction of calculation time (**Figure 6-22**).

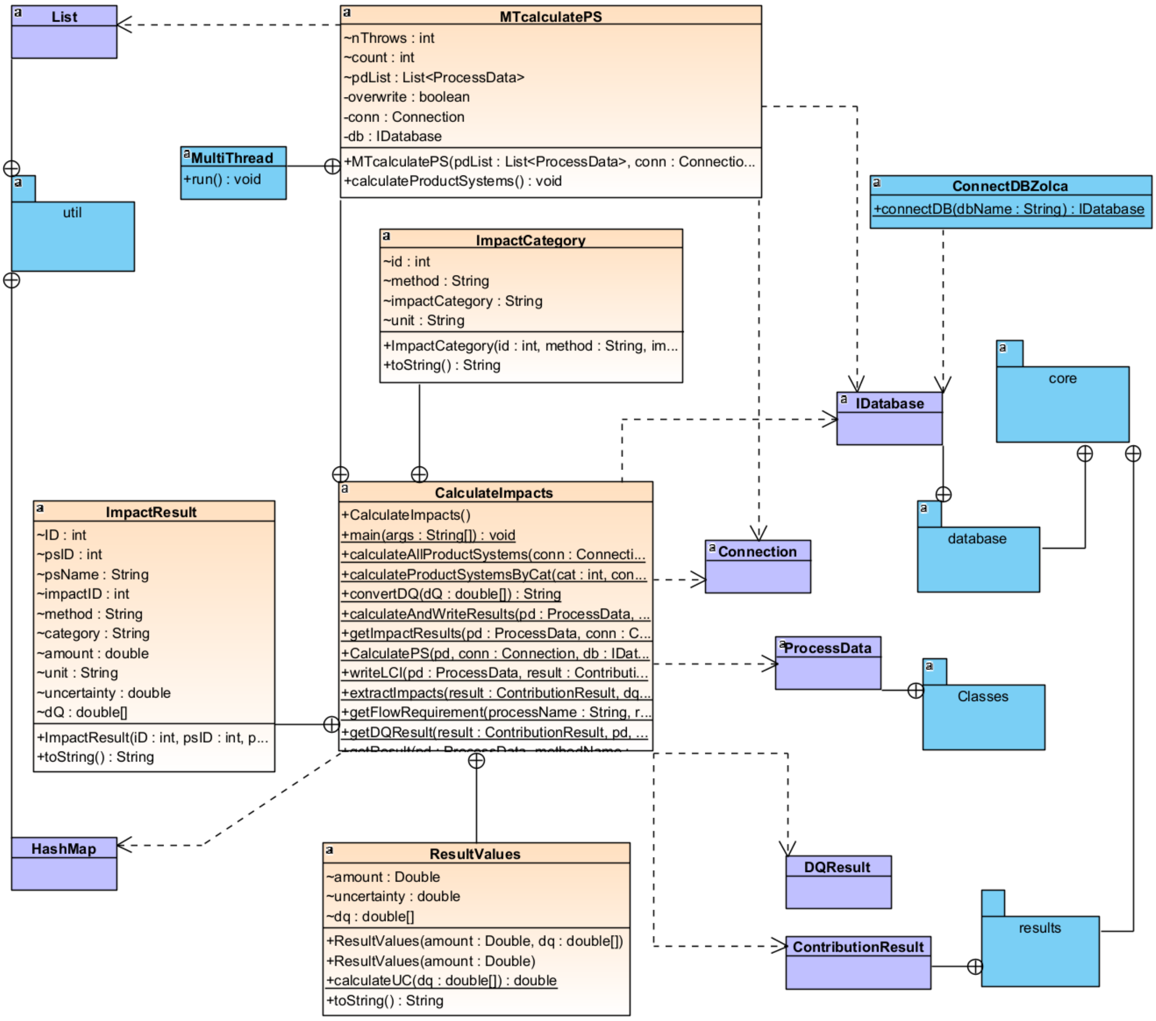


Figure 6-22: Class diagram for calculation of environmental impacts

6.4.5. Results evaluation tier

This tier is focused on the evaluation of data obtained after the calculations have taken place. Due to the wide availability of tools for data analysis and plotting existing in python, this programming language and its environment are used for evaluating calculation results and preparation of reports.

As such, this tier is based on accessing the data stored in the SQL Results Database and evaluating the impact assessment results data. Given the number of results, these processes are scripted for faster evaluation.

As an example, the evaluation of indicators of material use is done by directly analyzing the impact assessment results by selecting relevant categories and grouping the material indicators by material category. **Figure 6-23** represents this process. A list of products and the desired impacts for evaluation are first given by the user in a Notebook interface. A DAO (`sqlite3.connect`) is used to access the information present in the database on material data, process data, and results of LCIA. This information is read using Dataframes (`pandas.DataFrame`), whose internal methods are used to filter the results by environmental impacts, group results by material category, and normalize results. Plots are built and saved using Figure objects (`matplotlib.pyplot.subplots`). The process is repeated for all the product systems specified at the beginning.

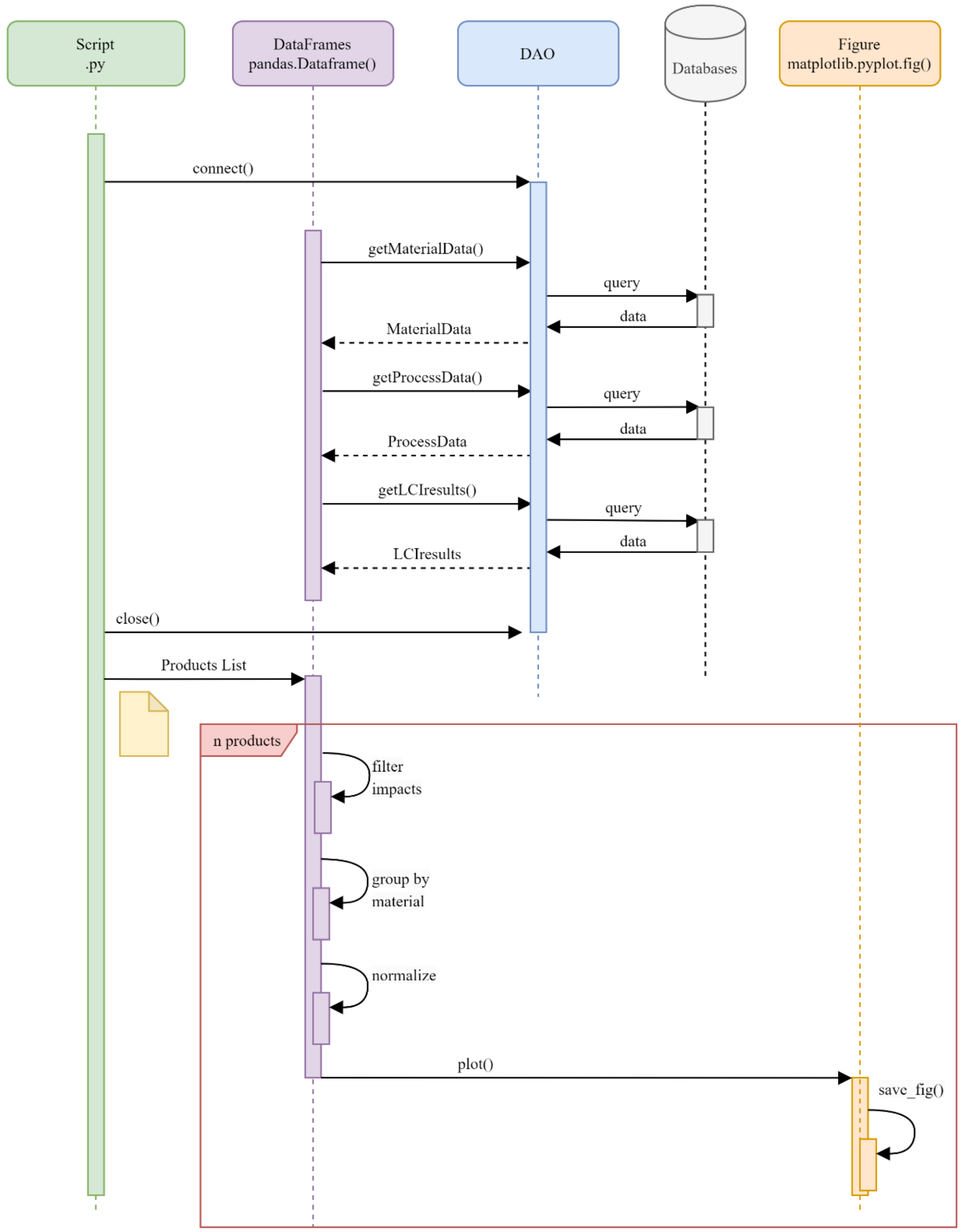


Figure 6-23: Sequence diagram for evaluation and reporting of data on environmental impacts of products.

A similar process is done for evaluation of correlations between the different indicators. This is achieved by studying the results of the Monte Carlo simulations (**Figure 6-24**). The products analyzed and the environmental impacts to be studied are first given as lists. Dataframes (`pandas.DataFrame`), are used to directly read the CSV files resulting from the Monte Carlo simulations. Data is then filtered by impacts and cleaned. A PairGrid (`seaborn.PairGrid`) is created and used to evaluate the dataframe holding the results. Scatter plots, histograms, and kernel density estimate (KDE) distributions plots are created using the PairGrid package. The correlations between each pair of indicators are evaluated using a statistical calculations package (`scipy.stats`). A Heatmap with the correlation results is also created. The process is repeated for all the product systems selected.

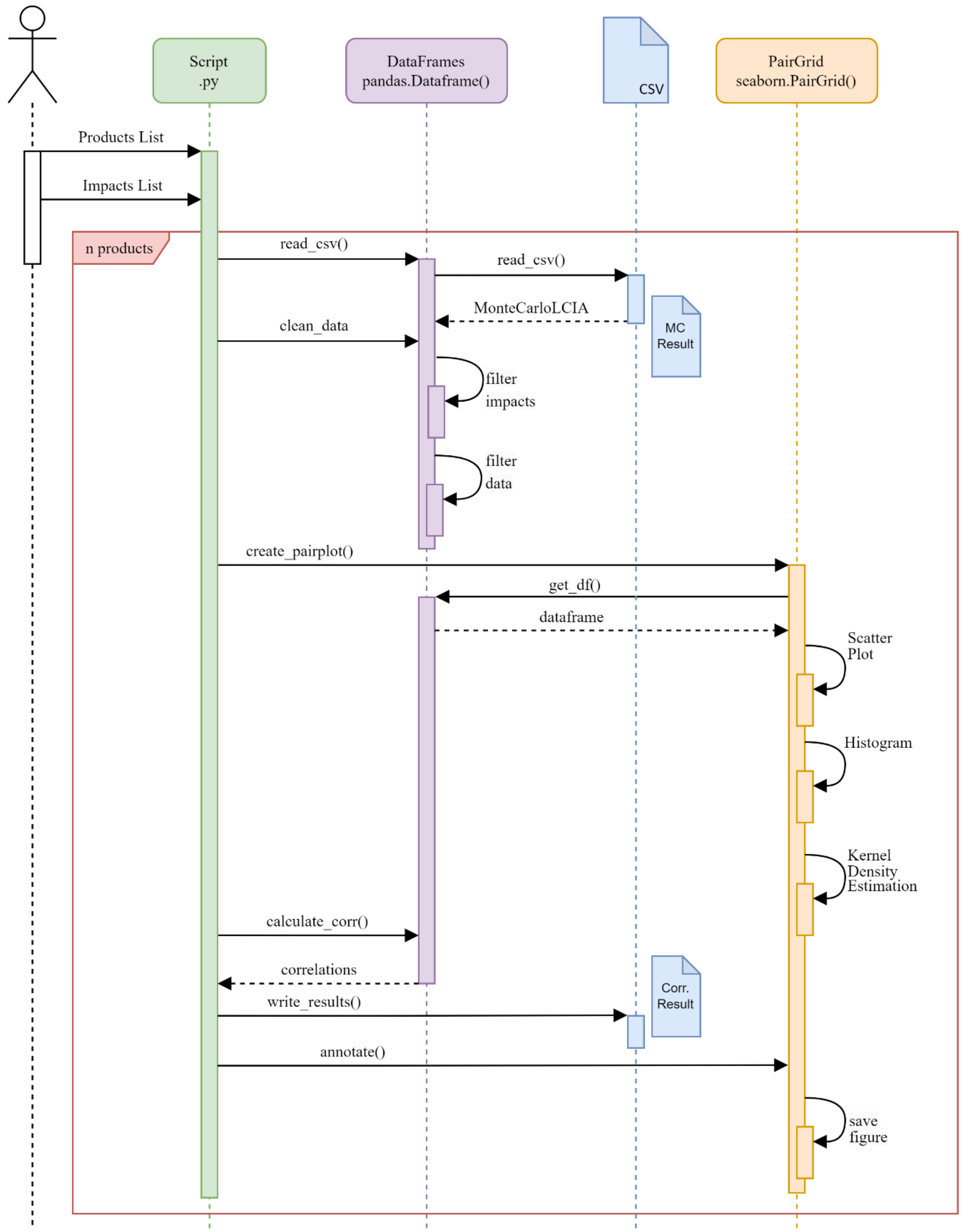


Figure 6-24: Evaluation of results dependencies.

6.5. Evaluation

The evaluation methodology for the developed software is done in accordance with the requirements established at the beginning of the development process. Additionally, qualities such as scalability, usability, and performance are also evaluated. The main goal of the development was to establish a tool that connects the material and inventorial information of datacenter components with the LCA modelling and calculation software. Evaluation is made regarding the functionality and usability of the information system, which are the key concerns in tools developed in the research sector.

For evaluating the functionalities of the system, inventories of data centers of varied sizes are built based on reference inventory data and on collected inventory data regarding size, IT load and equipment, and configuration of power supply and air conditioning. This with the goal of testing if different configurations are possible and if the models keep the granularity levels desired.

FR1. **Automation:** The inventory must be first collected from a table, and this must then be transferred to the inventory tables in the database. The different data center systems (IT, Power Supply, Air Conditioning, Infrastructure) are linked there directly with reference devices. Once the inventory is set up, the software can build a product system representing the data center and create links between the different processes. Key aspects to improve here are the necessity of inputting the inventories manually on tables through an SQL GUI or through a DAO which reads the information from an excel table and writes it on the SQL database (**Figure 6-25**).

FR2. **Granularity:** The build systems are based on product systems of different granularity levels that can be evaluated separately and are also kept in the product chain information found in the models. LCIA can also be conducted for products of various levels of granularity.

FR3. **Indicators:** New indicators were developed that align with the goals of this study. This is achieved separately of the model process and takes as input data that must be first cleaned.

FR4. **Data Quality:** Data quality is given as an input value (string, e.g., "`(1,2,1,3,2)`") when preparing the inventories for the different components, modules, and devices. To consider data quality on the calculations, the ecoinvent data quality schema is also included in the environmental database, which is first assigned when building the processes and the product systems.

FR5. **Scope:** The system can build recycling models based on inventory, recovery factors, and product composition. To achieve this goal, it was first necessary to evaluate the contents of products to be collected (e.g., total among of structural steel, or total amount of PCBs with mainboards), so a first run of the data center models was needed. With the information of products present in the data center models and using the same process for creation of product systems (based on reading inventories), models for recycling and End-of-Life are developed. These models assume first a "perfect" collection, so that factors such as collection rates can be later be changed for parameterization during the results evaluation. The models for recycling are based on a collection of models for individual recycling of separate components based on different parameters such as mass and method for recycling.

FR6. **Results evaluation:** Calculation for product systems is done using the openLCA calculation engine, and the results are evaluated using python packages. Simple scripts allow for looping through all the selected product systems for quick evaluation.

FR7. **Experimentation:** Studies such as Monte Carlo simulations and sensitivity analyses are conducted. The Monte Carlo calculation method found in openLCA also allows performing a set number of iterations. The use of parameters within the definition of the process allows modifying its value to perform several sensitivity studies during the calculation. Due to the amount of data resulting as output, these were saved in separate CSV files.

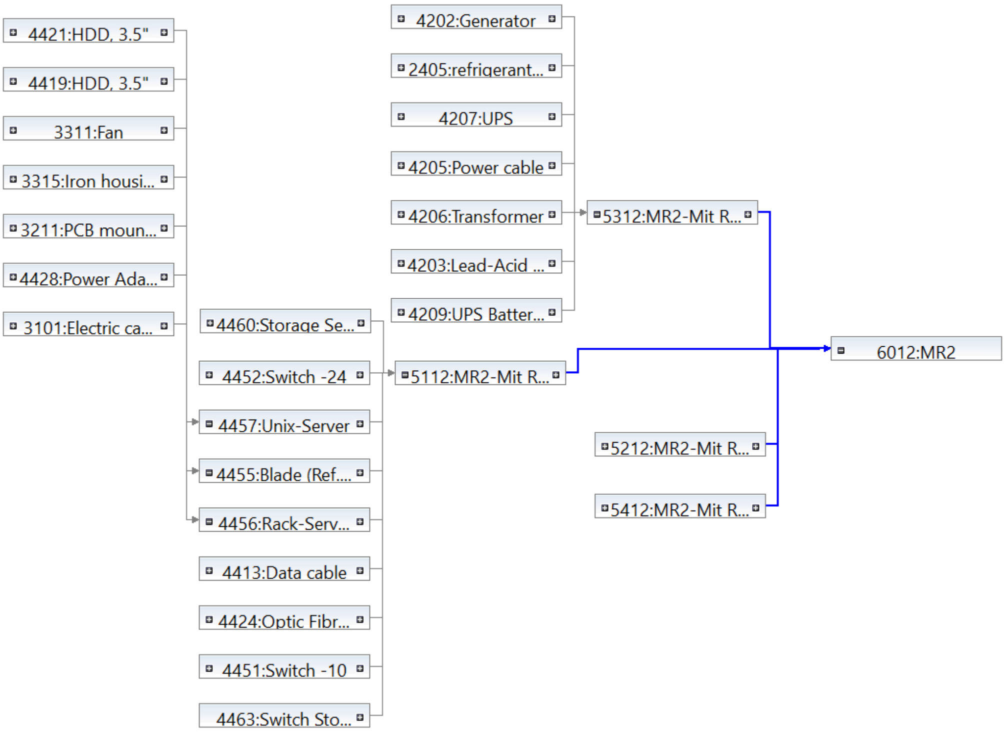


Figure 6-25: Example of a test use case as presented by the openLCA user interface.

Regarding the non-functional requirements, following aspects were found during the development:

NFR1. **Scalability:** The process of model building did not show any constraints regarding the model size or the size of the inventory for the tested case studies.

An issue regarding scalability is found in the results databases. Results are stored in vertical tables due to the required flexibility on the calculated environmental impacts. This resulted in extensive vertical tables with several rows for the same product system. Extending the databases or restructuring the format may be required.

NFR2. **Updateability:** To update aspects like indicator characterization factors, the scripts for updating must be separately executed and imported. This puts a limitation on the automation of the process since the updated values on indicators or economical allocation factors must be firstly manually gathered and cleaned from external reports (such as EU Criticality Reports).

For updating the inventories, the update of material quantities is done by reading and modifying the values of existing exchanges. However, deleting one or several exchanges was not allowed by the environmental database DAO due to the interconnection between different models, and in some cases deleting and rebuilding the process is required.

NFR3. **Privacy:** The inventoried data is anonymized, and the databases containing this information are not made accessible.

NFR4. **Performance:** Performance is evaluated in a local device using JDE 17 for the model building and calculation under Windows 10 OS (i7@ Intel Core i7 @ 2.50GHz). Under the current schema the process of building and autocompleting product systems is done in less than 30s. Calculation of environmental impacts of individual product systems takes around 60s. Parallelization allows reducing calculation times to a quarter by using 4 cores simultaneously. Monte Carlo simulations are set up for 2500 runs and take around 12h when using multithreading. This limited the number of product systems that were considered for this kind of analysis, which had first to be selected by finding hot spots of material related impacts.

NFR5. **Usability:** Only non-commercial tools were used for development of the system. Java was used to build classes, packages such as the openLCA libraries are open-source, and commonly known python packages are used for data evaluation and analysis. The goal is to provide a framework and make it reusable, and to provide a basis for future expansion. An important aspect is the documentation available on the used packages, which allows a clearer understanding of the used software.

A key limitation in usability is in the form of data input. No user interface was developed, so the system is not yet adequate to reach general usage.

6.5.1. Potential for future development

Future development of this tool may include aspects such as:

- Automation of economic allocation factors for materials, by linking to specific public price information.
- Development of several dynamic indicators to study the evolution of criticality and the influence of these factors on the resulting impacts over different periods. Indicators must be indexed by date (e.g., criticality factors for 2017 and 2020).

- Development of a User Interface which allows building a data center model based on inventories linked automatically with reference devices. This may allow performing quick assessments of material content and embodied impacts by using the information stored as LCI models.
- Deployment as a portable tool which holds LCI black box models with the impacts of devices. This, combined with a UI to enter data center configurations, may serve to get a first evaluation of material content, and provide a basis for assessment of urban mining potential.
- Deployment as web-service to perform quick environmental assessment. The structure developed is appropriate to be offered as a web tool to evaluate data centers embodied impacts. This requires a web-based interface, and a server to host the front-end. The input data can be saved in a separate database, and results can be sent directly for visualization. However, issues regarding storage and protection of data need to be considered before, as the databases such as ecoinvent are proprietary and subject to an end-user license agreement preventing those without a license to use them [Pe21].

6.6. Conclusions

This chapter described in detail the process of building an information system for managing the data collected during this research, performing LCA calculations, and analyzing the resulting outputs. Conceptualization, requirements specification, global architecture description, detailed design, implementation, and evaluation are part of the development of the tool here presented.

Requirements were specified based on the objectives defined at the beginning of this dissertation. Upon searching for similar software tools, specifically in the BIM domain, general concepts for data exchanges and BoM applied in LCA are considered for formulating a solution. From the existing architectural patterns, the multi-tier pattern is chosen for implementation.

The system developed for analysis is built upon this architecture, where the databases are created to store information on BoM, impact methods characterization factors, and impact assessment results. Model building and calculation is built around the openLCA software. Visualization and reporting are built using open-source python tools. This allowed automation of the various stages of the LCA process: LCI data management, model building, impact assessment, and reporting.

The current system has as a benefit the integration of structured databases holding inventory information with environmental databases, and to allow calculation and experimentation. For software developers, one of the greatest challenges is to improve the interoperability between different frameworks tools. Although the general principle has been developed for other applications, such a system needed to be built to satisfy the requirements of this dissertation. The development aligns with current efforts to create open source LCA tools, public inventories, nonproprietary data exchange standards, and the use of open-source software in research.

Compared to a traditional process, such as building the models directly in the LCA software interface, this system allows much faster creation of product systems while maintaining aspects such as granularity and background process information. Other existing solutions require the input of information directly in python scripts, which reduces usability. The complexity of associating each material and component with specific background process with the unit processes during the life cycle of a device (e.g., transport, manufacturing energy) is detected as a major difficulty.

As the evaluation is based on specific case studies, the effectiveness in evaluating other types of products is to be evaluated. The system is developed with a data center infrastructure under consideration, which has a characteristic hierarchical structure. However, the general principle of linking the different frameworks for automation of LCA is valid. Moreover, the repurposing and reproducibility of the different objects developed (such as databases, calculation tools, visualization tools) and of the assessment models is of advantage for the scientific community.

Further development may include deployment of the tool as a portable solution for quick evaluation of embodied impacts by local actors such as data center planners for reporting of GHG emissions, or the development of a web-based interface that can serve for assessment of urban mine potential of critical materials within a region. Such efforts need to consider that a reduction in complexity for end users when entering data in a user interface and privacy and protection of said data are of high relevance.

7. Results and Discussion

This section presents a summary of the results obtained from the calculation of Life Cycle Impacts for the models developed from Chapter 4. As a basis for calculations, impact indicators, first discussed and developed in Chapter 3, are selected for evaluation of impacts of the product systems constructed, which represent data centers and their devices and modules. Results on environmental impacts of raw material gathering are first presented, which constitute the basis for future evaluations. The different impacts of data center and its components, at different disaggregation levels, are then evaluated. This includes analysis of material flows for specific raw materials. The inclusion of End-of-Life models allows evaluating the benefits of recycling from a recovery and impact avoidance perspective. The models developed are used to study the effects that different pretreatment and metal recycling strategies have on material flows and on avoidance of environmental impacts. Results data quality is evaluated through the results of Monte Carlo simulations using the corresponding uncertainties, where the effects of input data quality are evaluated. Improvements on data are also analyzed by a study on the effects of the incorporation of laboratory data on the quality of the results. Through this chapter, the correlations and dependencies between the indicators selected are also evaluated, which allows to analyze where dependencies exists and to evaluate the benefit of use of the indicators created in Section 3.4 for the evaluation of material and energy use. **Figure 7-1** represents the structure of this chapter for the evaluation of results.

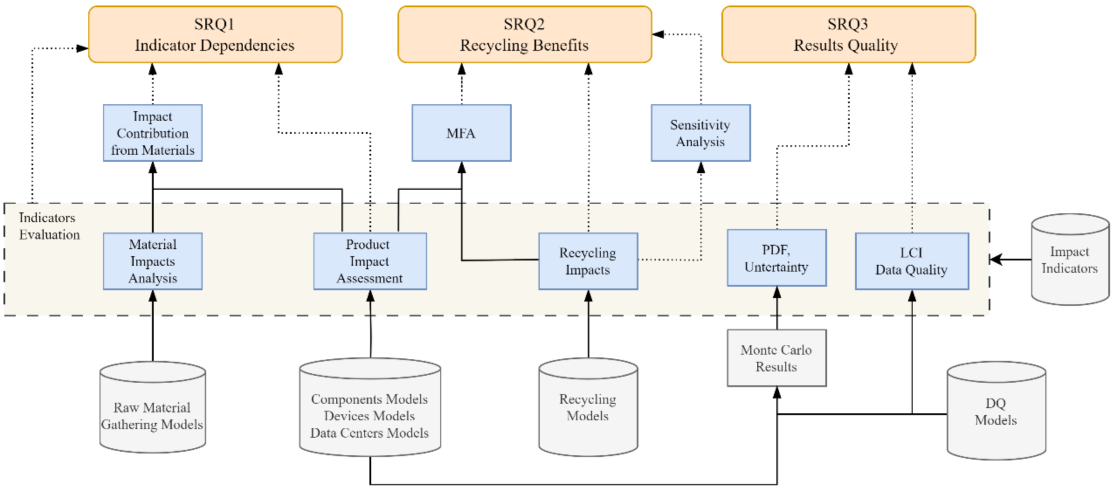


Figure 7-1: Structure for the evaluation of results according to the research questions.

7.1. Indicators selected for evaluation

The selection of indicators is done according to the goal and scope sections. Section 3.3 presented a list of existing indicators for material and energy depletion. The focus of this work is on material and energy resource demands and their interaction. Indicators are then selected based on their area of evaluation, aggregation level, and on the usefulness to communicate results. **Table 7-1** summarizes the selected indicators for further reporting:

Table 7-1: Selected indicators for LCIA evaluation

Area of Evaluation	Resource Accounting Methods	Midpoint Methods	Endpoint Methods
Material Resources	Cumulated Material Demand :CMD	Abiotic Depletion Potential - Minerals :ADP-M	
	Resource Depletion :kg_{Au}, kg_{Ag},	Economic Importance ADP :EI-ADP	
		Supply Risk ADP :SR-ADP	
		Geo-Political Supply Risk :GPSR	
		ReCiPe V1.13 - Metal depletion :MDP	ReCiPe V1.13 - Metals
Energy Resources	Cumulated Energy Demand :CED	Eco-Indicator 99- Fossil Fuels :E99-FF	
	Cumulative Exergy Demand :CExD	ReCiPe V1.13 - Fossil fuel depletion :FDP	ReCiPe V1.13 -Fossil Fuels
Environmental Affectation		Global Warming Potential :GWP	Eco-Indicator 99 -Total
		Abiotic Depletion Potential :ADP	ReCiPe V1.13 - Resources
			ReCiPe V1.13 -Total

Cumulated Material Demand and Cumulated Energy Demand have been recommended to study depletion of natural resources [Gi12]. Cumulative Exergy Demand offers a link between material and energy contained in ores [Bö07]. EDIP 2003- Non-Renewable Resource Depletion offers an insight on de total depletion of mineral ores containing elementary flows, and it is separated by material [BBC12]. Abiotic Depletion Potential (and its subdivision in minerals) is the current standard for evaluating depletion of material resources [EC10]. The variations developed in Chapter 3 (ADP-SR, ADP-EI, GPR) include criticality and reflect aspects such as economic relevance and supply risk. Eco-Indicator 99 is useful since it considers the increased effort in material mining, thus providing a link between material an energy [Go01]. ReCiPe V1.13 includes marginal extraction costs information and offers a link with economic activities [KSB14]. Global Warming Potential is a standard in LCA communication and is included for clarity and for validation of results [My13].

Figure 7-2 shows the values for criticality of different materials. It is noticeable that outside rare earth elements (REEs), there is no visible cluster for these materials. REEs have a heavily concentrated regional source, and the different REEs metals are usually produced from the same mineral ore (known as mischmetal). Other metal groups do not show such heavy clustering. The application of the criticality indicators to the Abiotic Depletion Potential characterization factors produces the Criticality Weighted ADP. Since both dimensions for these factors are derived from ADP, a correlation between these two is observed. This does not immediately mean that results on impacts based on these indicators are correlated, since material composition varies. Clusters here can be first observed for REEs, platinum group metals (PGM), and precious metals.

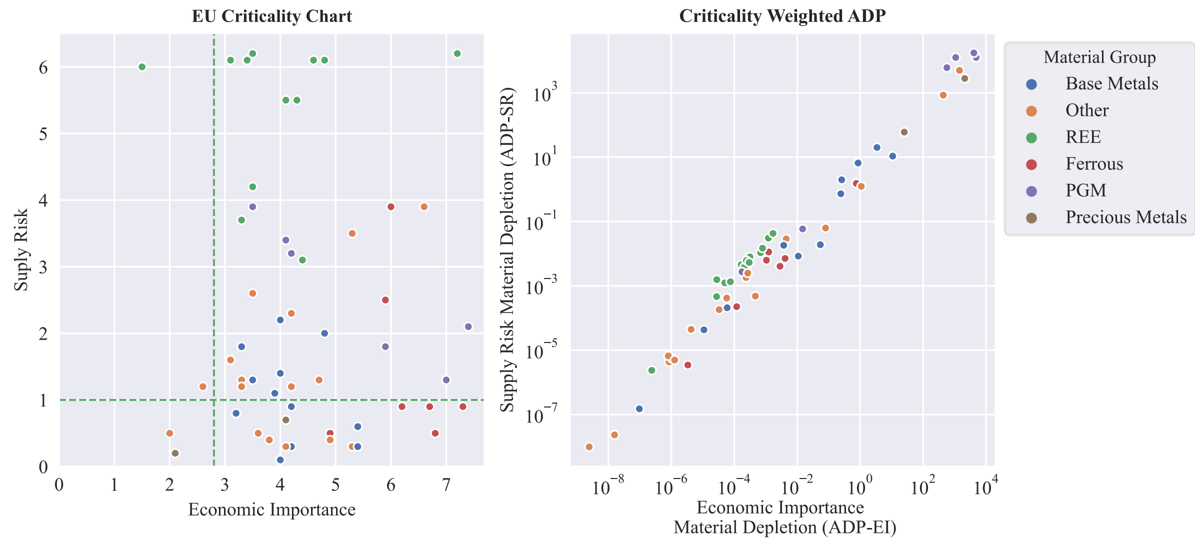


Figure 7-2: Criticality factors for different materials and conversion to criticality weighted ADP.

Figure 7-3 show the results of applying material production data to create the Geo-Political Supply Risk characterization factors. There is no correlation observed between factors. This is due to the incorporation of production data, which due to being in the denominator, scales the importance of certain materials such as scandium, indium, and tellurium. When evaluating the indicators for metal depletion for the ReCiPe V1.13 and from the Eco-Indicator 99 methods, it is noticeable that fewer minerals have characterization factors present in these methods. Most of them are base metals and ferrous metals. This limits the application of these indicators for evaluating products whose impacts of consumption of critical metals is being evaluated. At a logarithmic scale, these indicators do not show a clusterization either. An outlier in this method is tin, which shows a characteristic higher impact in both dimensions.

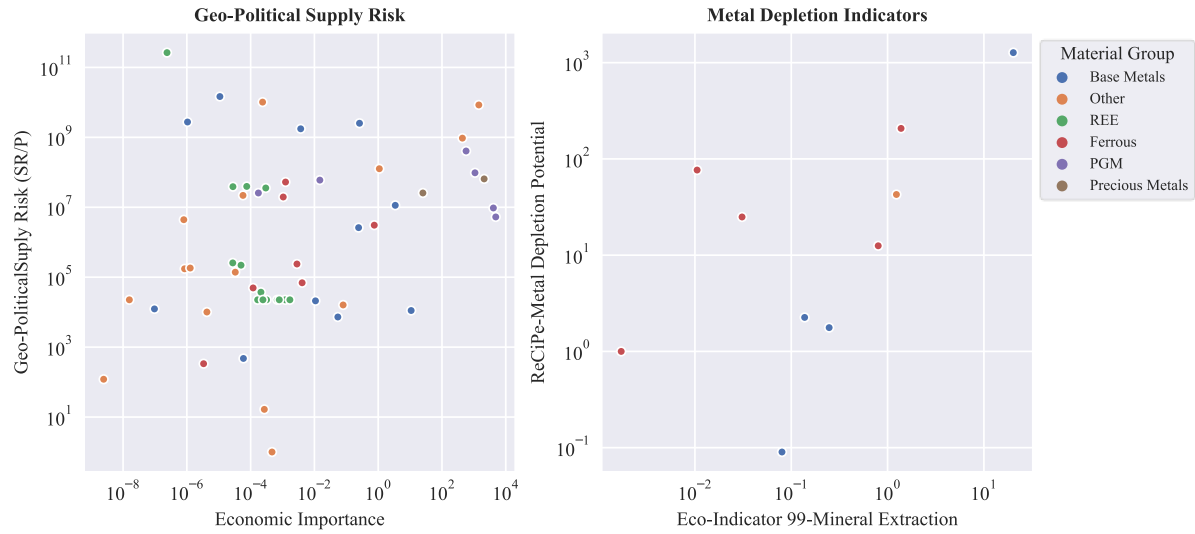


Figure 7-3: Geo-Political Supply Risk and Metal Depletion characterization factors.

Figure 7-4 shows the exergy demand for different materials and their relation to resource depletion. There is no direct correlation between exergy depleted from mineral ores and the depletion from materials from mineral reserves. This may indicate an uncoupling between material and energy demands for mineral consumption. When evaluating the dependencies of these energy-related characterization factors to other depletion methodologies, the lack of characterization factors for materials such as REEs still presents difficulties for a complete evaluation.

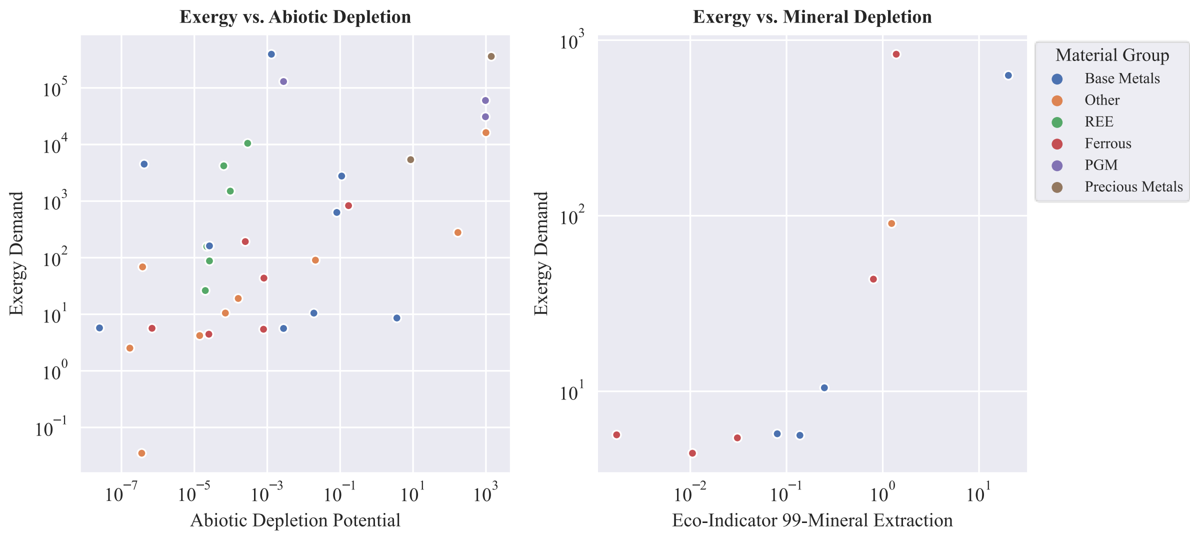


Figure 7-4: Exergy demand vs. metal depletion characterization factors.

Figure 7-5 shows correlations between indicators for material and energy. It is worth nothing the high correlations between EcoIndicator99 and ReCiPe methods. This due to the few data points and on the presence on the outlier found in **Figure 7-3**. As expected, the criticality weighted ADP indicators still present a high correlation (0.86-0.88). The rest of the indicators present lower correlations. Specifically, the exergy indicators present low correlations across the board. This points at the usefulness of using various categories of indicators to study different areas of environmental damage and resource use.

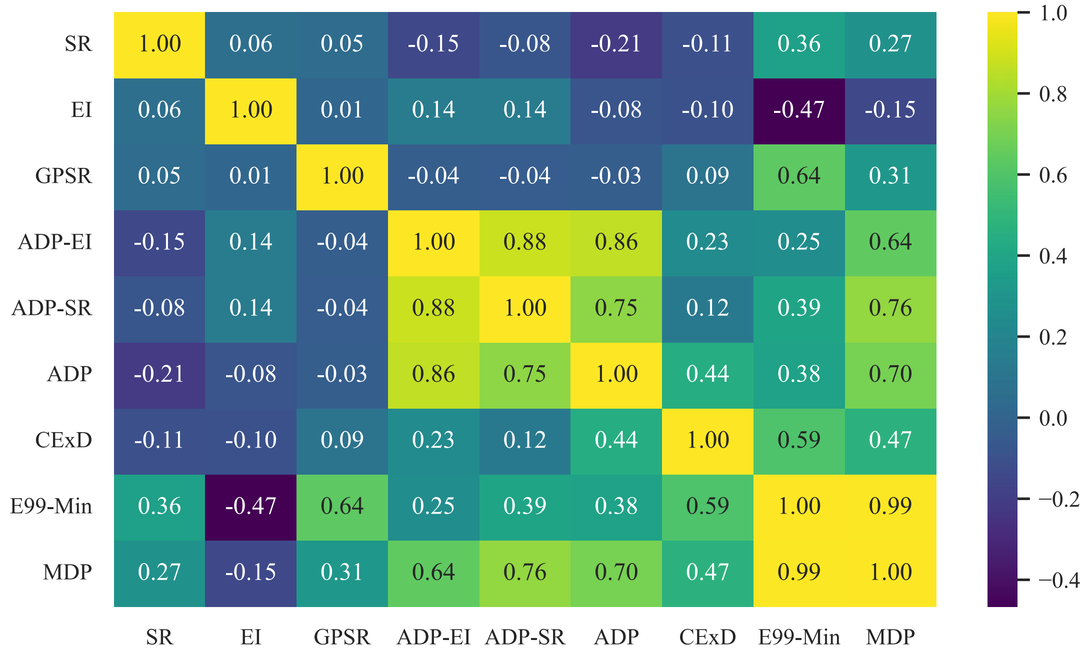


Figure 7-5: Correlations between characterization factors.

7.2. Impact assessment of raw material gathering

This section provides an overview of the evaluation of impact assessment performed for the material gathering processes for different ores. The process of updating inventories included creating models for processes that were originally absent from the environmental database. Other processes were originally replaced by other related processes (such as Ag being modeled as Au). This last assumption from the developers of the environmental database originally produced incorrect results when assessing elementary flow depletion and thus also incorrect results on the impact assessments.

Figure 7-6 details the results on the impact assessment for varied materials as their final market product, per kg of material. It is noticeable how precious metals, especially Au, have high impacts across indicators such as CED, ADP, and GWP. REEs have lower specific impacts for GHG emissions. Ferrous and base metals present lower impacts overall. When considering Geopolitical supply risk, the analysis of the criticality factors is reflecting on metals such as REEs, Ta, Nb, and Ga. In the LCA models, the economic allocation approach was adopted for the processes where multiple products occurred. Price information was compiled for 2022.

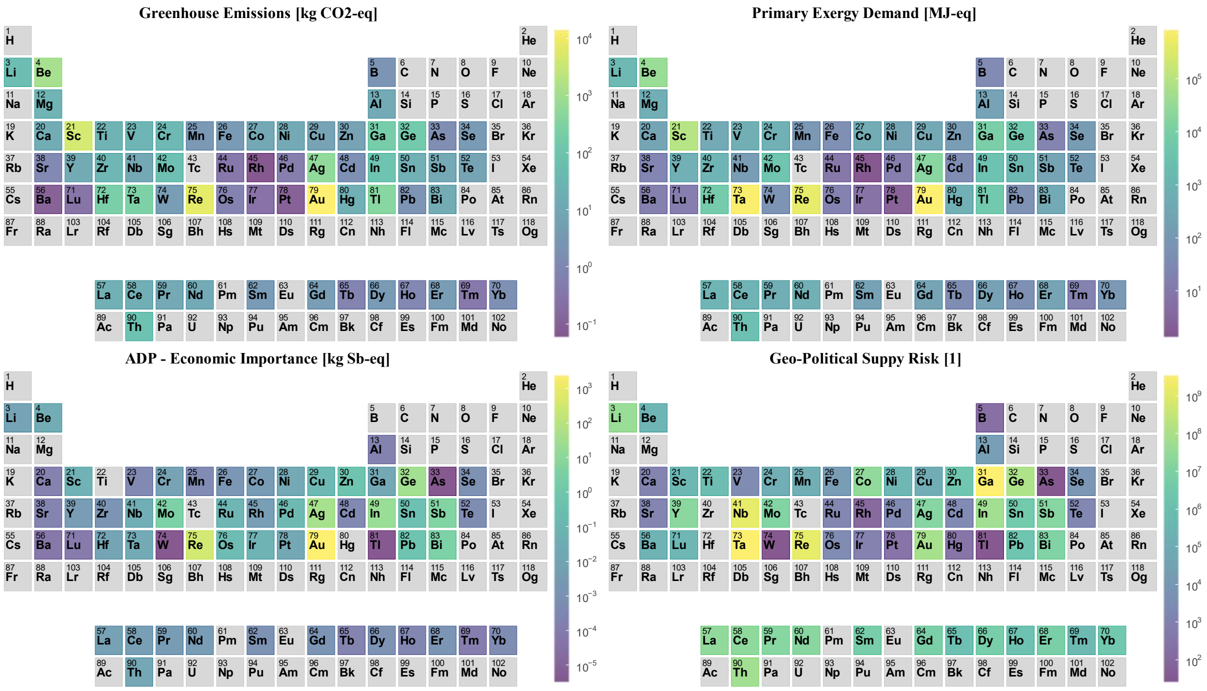


Figure 7-6: Direct impacts for gathering of raw material per kg produced as product.

Figure 7-7 directly compares the indicators selected to analyze the correlations between them. The criticality-based indicators do not hold a strong correlation, but clusters of materials categories can be observed presenting a partial correlation. This can be traced down to the allocation procedure as groups of metals them come for the same mining process (such as REEs, PMs and PGMs). CED and ADP present on the contrary a strong correlation. This is due to CED being calculated mostly from the energy required for mining efforts, which is a large fraction of the traditional ADP methodology (as it includes fossil fuels as part of the flows). Relating CExD and MDP is expected to provide a correlation since

CExD is a representative in the degradation of the energy quality (represented as exergy) and MDP is related to the increased marginal efforts of mining. Finally, GWP and the Total Impacts form the ReCiPe method also show a correlation, this due to the GWP being an important contributor for the total impacts on the ReCiPe method.

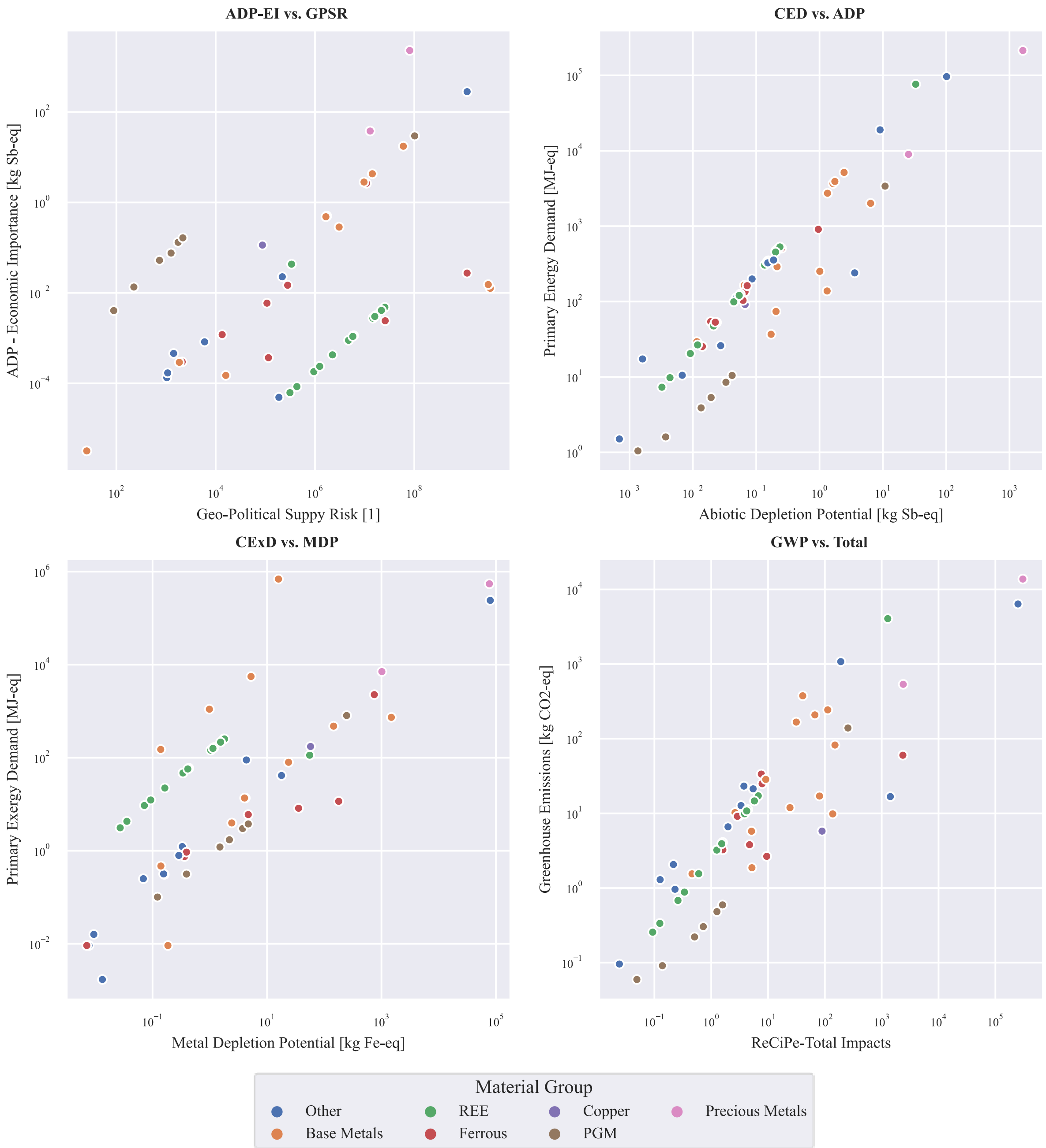


Figure 7-7: Direct comparison between different impacts for mining and production of different metal categories.

Figure 7-8 shows a full evaluation of correlations of the resulting impact assessment for the different process of mining metals analyzed. Lower correlations are observed for the supply risk indicators and for the CExD. GWP shows strong correlations with MDP, ADP, and the Total Impacts (ReCiPe). The economic importance ADP shows low correlations with the supply risk and CExD indicators, and high correlations with the rest of the indicators.

Figure 7-8: Heatmap of correlations between the specific environmental impacts for mining of materials

Figure 7-8 display correlations that help identify indicators with strong interdependencies and determine the independent impacts under evaluation. These correlations also assess whether the selected indicators capture different aspects of environmental impacts from data center component manufacturing. For instance, the high correlation between CED and GPW stems from their calculation methodologies, as both primarily rely on the impacts caused by consumption of fossil fuel resources. Similarly, traditional ADP and GWP exhibit a strong correlation due to the inclusion of fossil fuels as abiotic resources, considered alongside mineral resources. Indicators such as GPSR and CExD present lower correlations since both represent different aspects of resource depletion.

7.3. Impact assessment of data centers and their components

Figure 7-9 describes the results on impact assessment for critical material depletion categories. The analysis was conducted for various levels of product systems to study individual impacts and to provide a basis for a granular analysis. Products are presented in different groupings according to their application in a data center or its systems. At the module level, the products related to electronics present the highest specific impacts, with integrated circuits and memory devices having exponentially higher specific impacts. This is due to their highly concentrated critical material content. Their cumulated energy demand is also significantly higher due to the energy-intensive manufacturing processes.

At the component level, electronic components such as printed circuit boards and memory units present the highest specific impacts, pointing at the significantly higher critical material concentration for these devices. CED for these products also has important contributions from the energy for manufacturing.

For the devices analyzed, the IT devices present the highest material depletion impacts, again showing a higher critical material content. Since these results are presented for unit of device and not by specific unit (such as weight), components such as climatization devices (such as chillers) and energy supply devices (such as transformers and UPS) present high CED impacts due to the amount of material required for the manufacturing of a whole reference unit.

For the evaluated data centers, the correspondence of impacts correlates with the size of the data center. There is a positive correlation between the different impacts presented here, although the correlation factors are not similar.

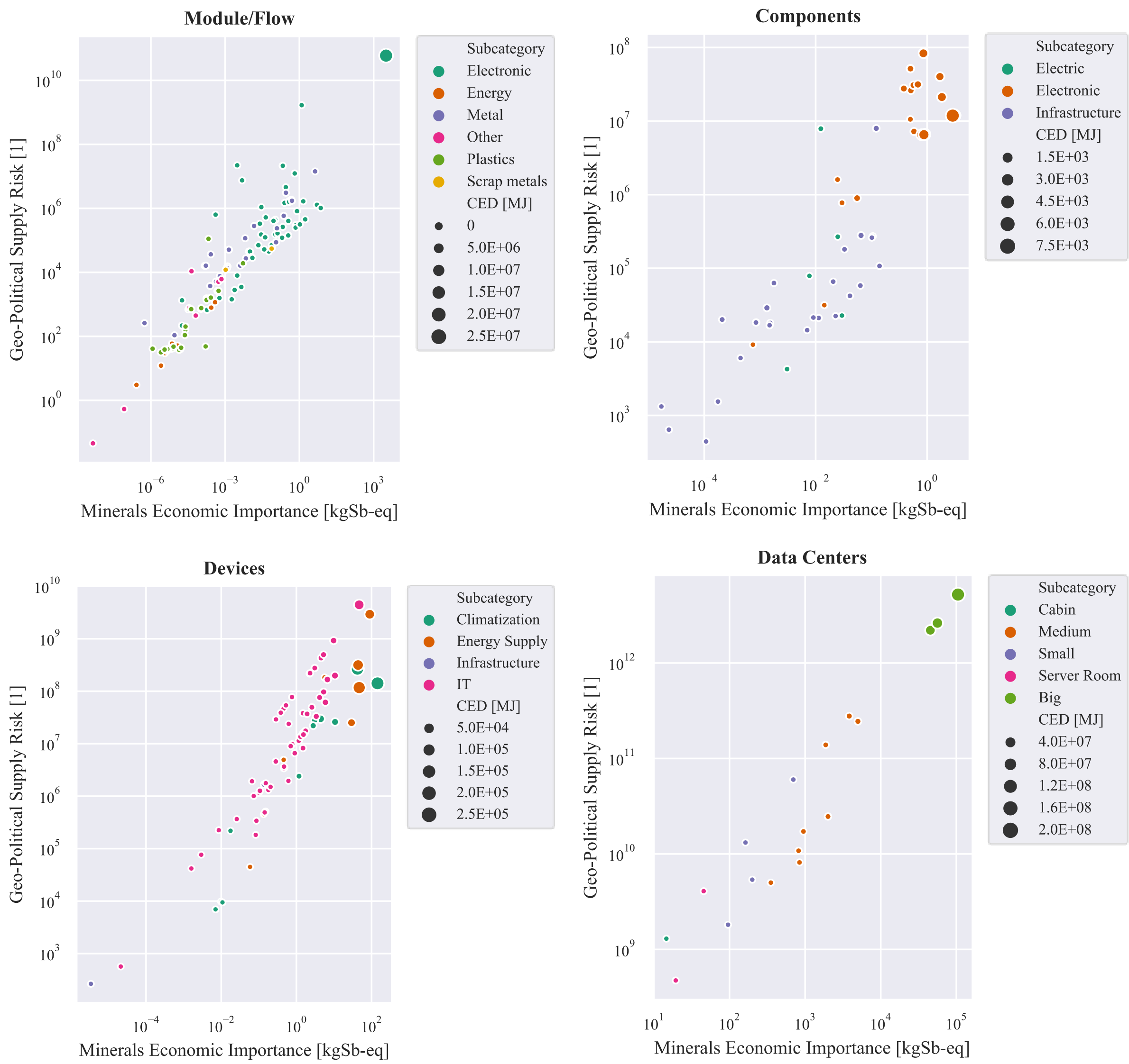


Figure 7-9: Life Cycle Impact Assessment at various levels for data centers and its components.

Figure 7-10 presents a selection of product systems with a disaggregation of the material related impacts and grouping by material category. These diagrams present an overview of which materials are contributing the most to the different impacts. A simple mass accounting shows information on material content of the different processes. As an example, for a mainboard unit, material content corresponds mostly to ferrous metals (Fe, Nd) and other materials (such as plastics). When evaluating indicators for critical material depletion, most of the impacts come from precious metals (Au, Pt) and PGMs (Pt).

Indicators related to supply risk and production (GPSR) come mostly from Ta in capacitors and Nd from ferrous alloys.

For a whole device such as a server, the bulk of the mass comes in from Fe for the frames. The distribution of impacts for minerals with economic importance (ADP-EI) comes mostly from precious metals and PGMs, whereas GPSR impacts are related to the depletion mostly of Ta. Ta shows important contributions across the whole products analyzed.

At a higher level of data centers, the bulk of materials corresponds to Fe and Cu. Impacts for depletion of minerals come from base metals (Zn for the UPS, Pb for batteries), Cu (cables and connectors), and precious metals and PGMs in electronics. GPSR depletion comes from Ta and Nd use.

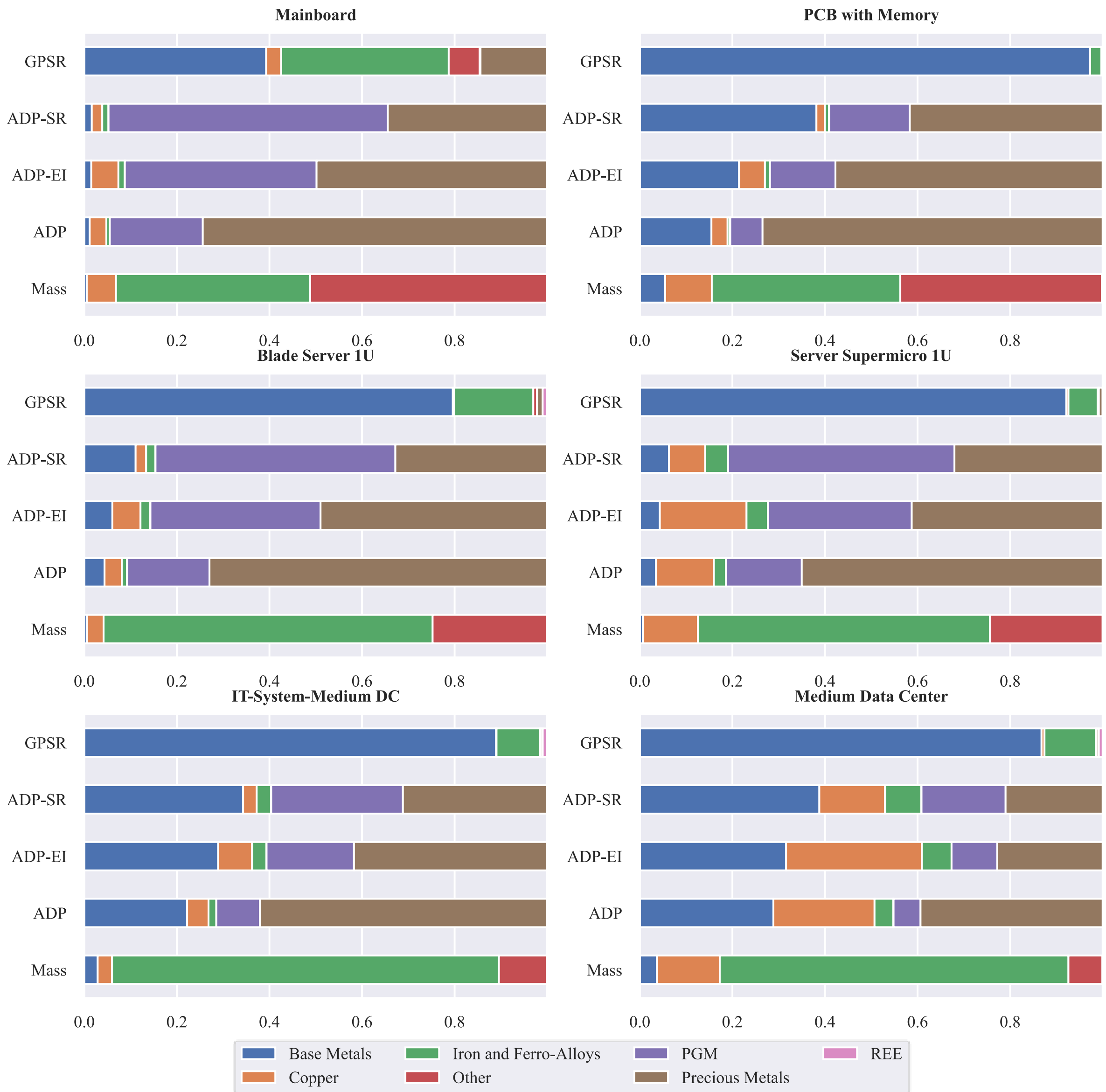


Figure 7-10: Contribution analysis to material impacts for selected products.

Establishing correlations between the impacts can be done for all the impact categories considered. **Figure 7-11** shows the correlations between the impacts obtained at the levels of components and devices. Higher levels were avoided since not enough data points are present to evaluate correlations satisfactorily. The heatmaps presented offer an overview of the dependencies of the indicators. For indicators heavily related to material depletion and quality of minerals, such as GPSR and CExD, low correlations with other indicators can be observed across the board. CED still has high correlations with traditional methods such as GWP, ADP, and Total Impacts (ReCiPe). This is due to the methodology of establishing these impacts, which assign high characterization factors to fossil fuel consumption, and on the relevance of fossil fuels to the local energy mix. Indicators relating to depletion of minerals and related economic efforts (such as ADP-EI and MDP) present medium correlations with all the other factors. This indicates a decoupling of these indicators with traditional impact assessment methods and reflects on the importance of presenting them separately.

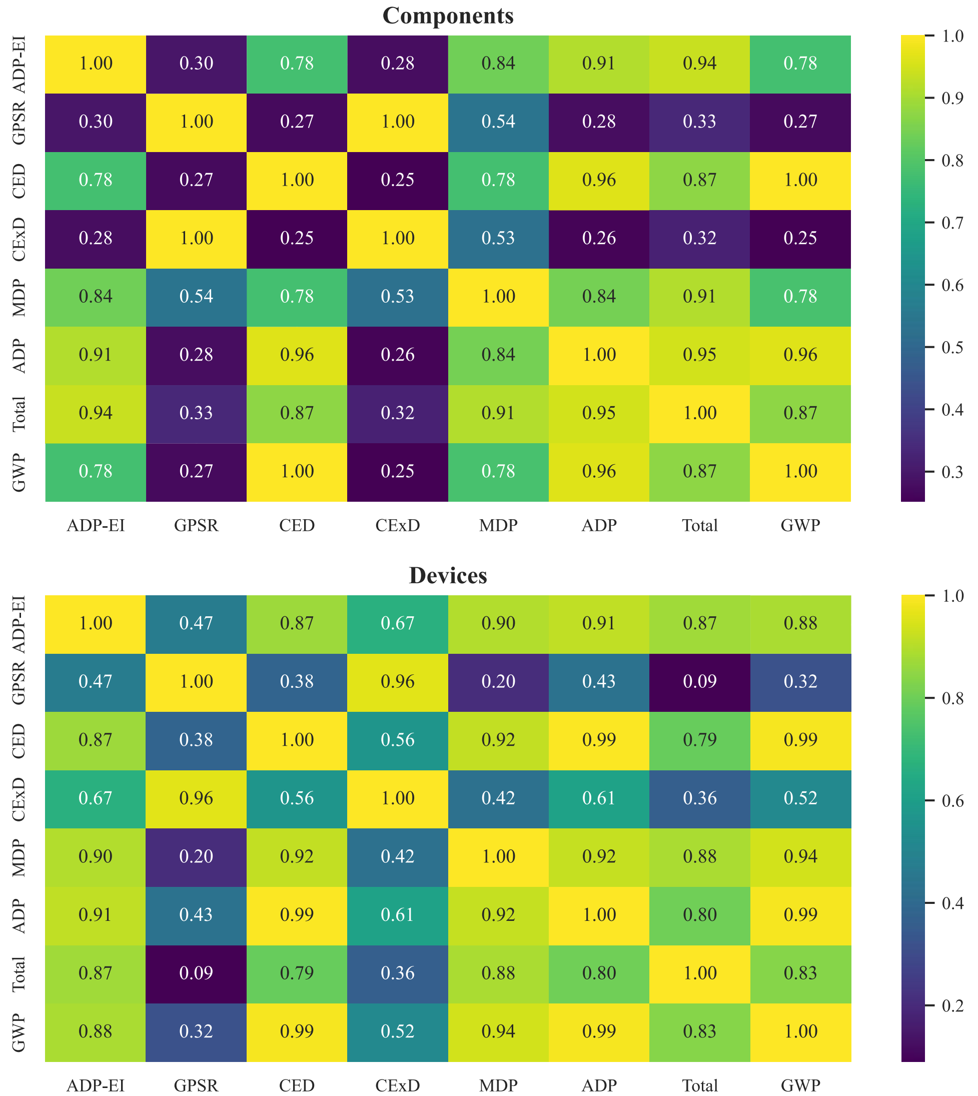


Figure 7-11: Correlation heat map for indicators for the evaluated products at various levels.

One of the aspects important for evaluation of impacts contribution is on the lifetime of the devices considered. Devices with high impacts of material depletion are in the category of IT, which have shorter life spans. Annualizing (by simple division by the expected lifetime) is a fast evaluation method to better show the intensity of material depletion related impacts from IT devices. **Figure 7-12** shows a comparison between the results of the impact assessment for a medium size data center and the results after an annualization has been estimated. As noted, the contributions of IT devices grow when considering their lifetime, taking more than 95% of the annualized impacts related to material use. This is an indicator of the high relevance of material recovery strategies for the materials present on these components.

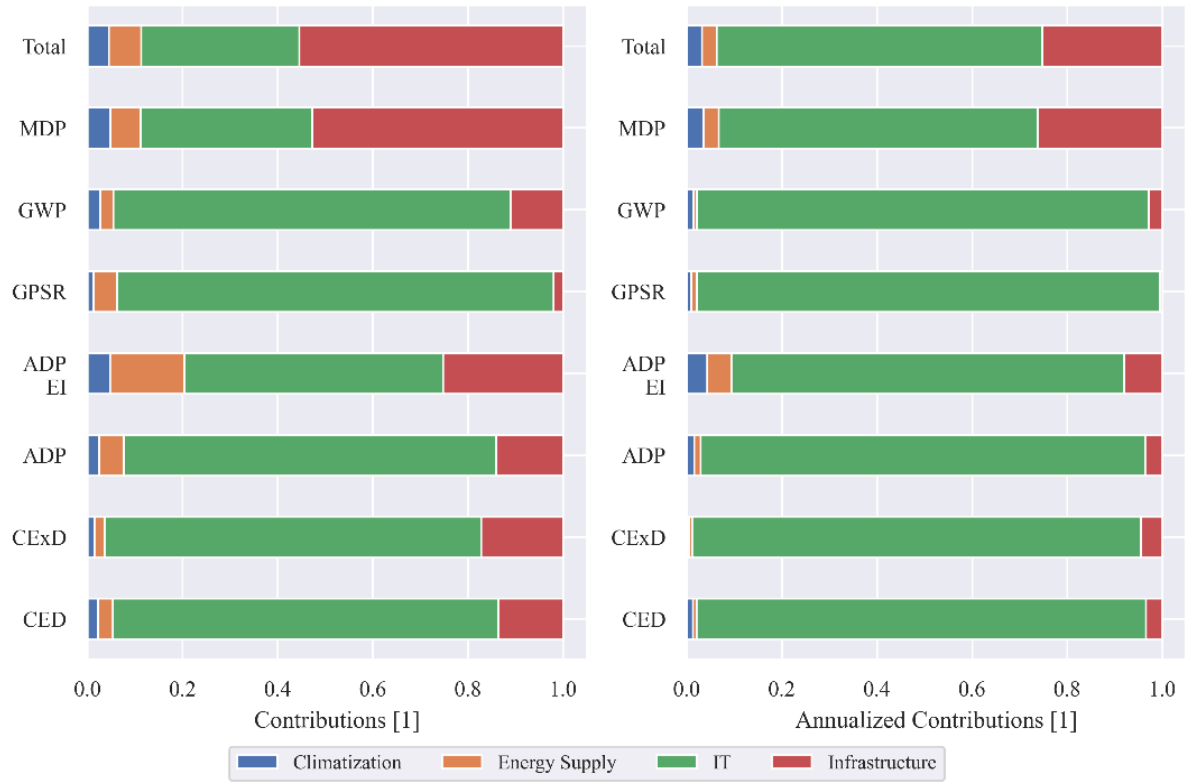


Figure 7-12: Comparison of LCIA before and after annualization by using lifetime expectations for product systems.

Different models of data centers were built as part of the evaluation of the information system and to validate the modeling methodology. Models of data centers based on inventories described in Chapter 4 are also built and evaluated together. As a reference unit, the service of a data center in units of $kW_{IT}{\cdot}h$ is considered, which is related to the size and operation type of a data center. This unit has also a relation to the energy consumption of the data center since it can be related to the hourly consumption of the IT. **Figure 7-13** presents the results of this evaluation. Correspondence in the log-log scale can be observed, although for impacts related to material energy quality (CExD) and material supply concentration (GPRS) a direct correlation cannot be seen, finding more dispersion at the lower size of data centers, where real case studies were built. Impacts across the categories present a linear correlation in this scale. This indicates that, when discussing data centers and their resource use, bigger facilities do not necessarily mean more resource- efficient infrastructures.

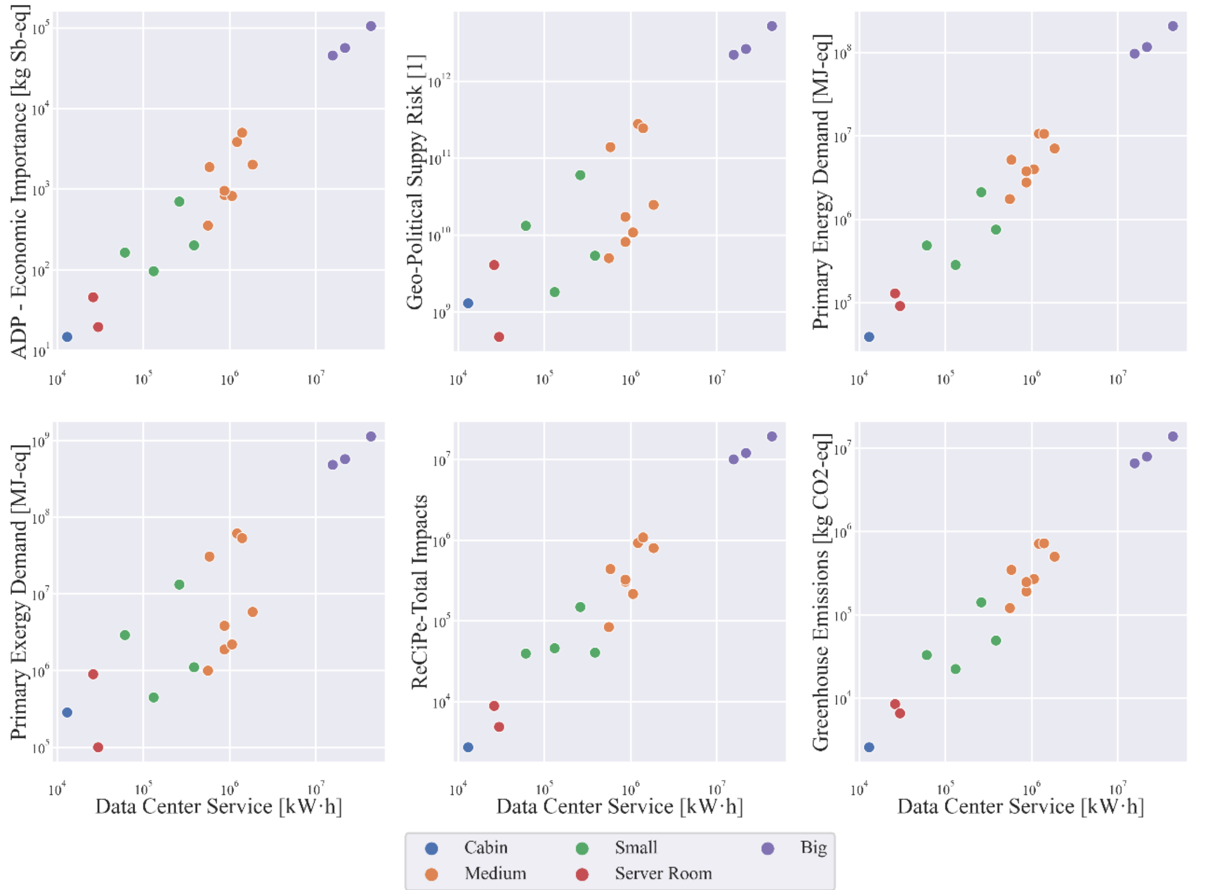


Figure 7-13: Correlations of Impact Assessment Results with the service unit (kW_{IT}·h) of Data Center operation for the created models.

For evaluation of the benefits of recycling, it is helpful to know how much of the initial impacts are due to raw material extraction and processing. **Figure 7-14** presents a summary of the CED for the different devices analyzed and the contribution of material extraction to the CED. In most cases, material extraction is responsible for around 25% of the impacts. When focusing on other material related impacts, such as CExD, raw material extraction accounts for 50-85% of the impacts (**Figure 7-15**). For impacts related to criticality, such as supply risk (**Figure 7-16**), raw material extraction contributes to almost 100% the impacts.

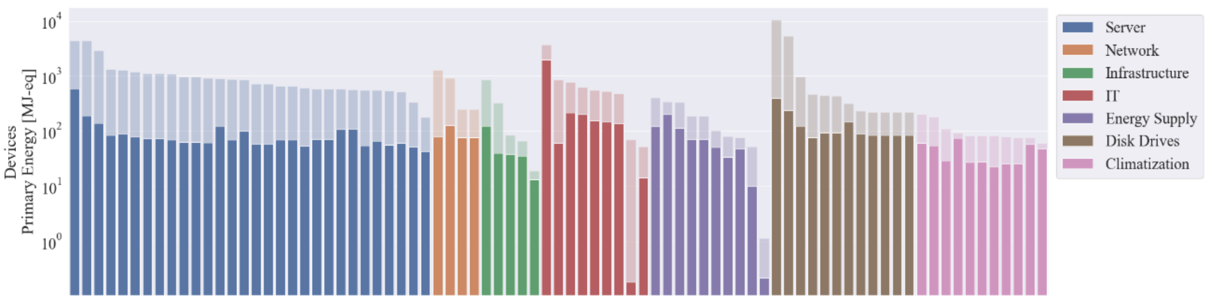


Figure 7-14: Total CED and contribution of raw material gathering to the total impacts for selected devices. The darker portion of the bar represents the contribution of raw material gathering to the total impact. Each bar represents a reference device evaluated.

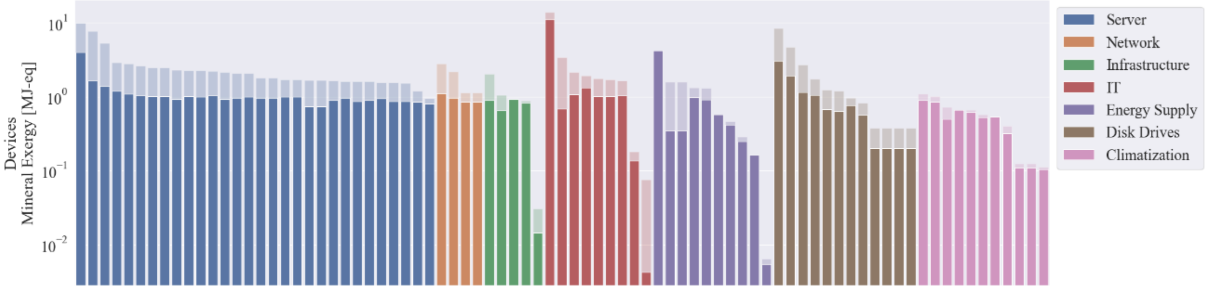


Figure 7-15: Total CExD and contribution of raw material gathering to the total impacts for selected devices.

Figure 7-16: Total depletion of materials by supply risk and contribution of raw material gathering to the total impacts for selected devices.

When discussing whole data centers, these contributions rise for 20-25% of CED (**Figure 7-17**) and 70-90% of ADP-EI (**Figure 7-18**), and similarly, all of the GPSR impacts comes from raw material gathering (**Figure 7-19**).

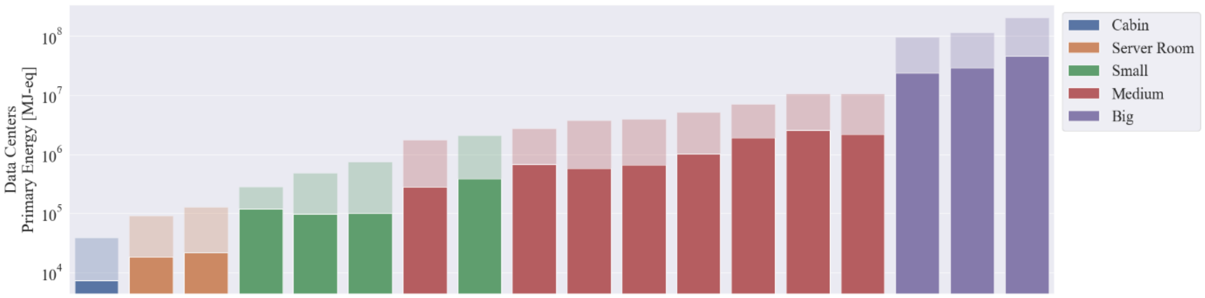


Figure 7-17: Total CED and contribution of raw material gathering to the total impacts for the Data Centers modelled.

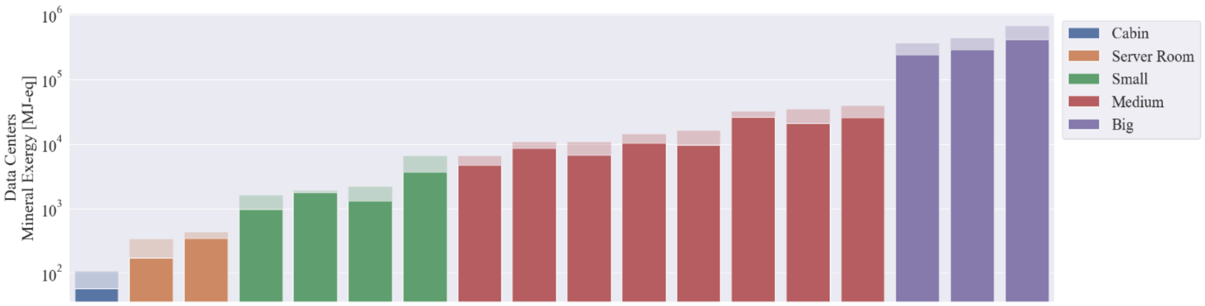


Figure 7-18: Total CExD and contribution of raw material gathering to the impacts for the Data Centers modelled.

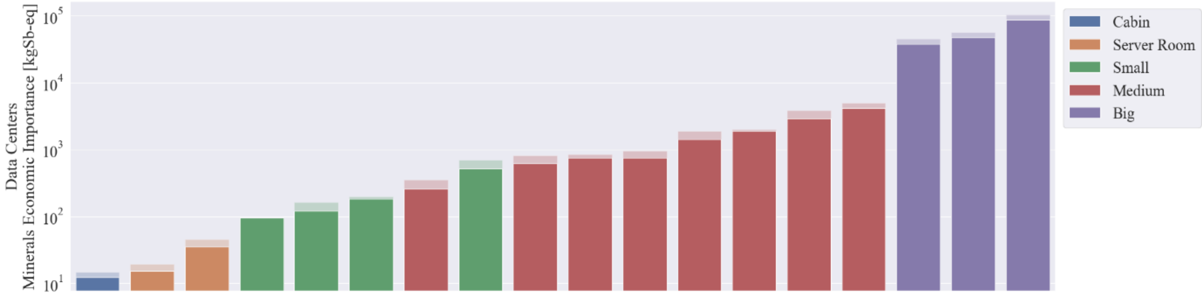


Figure 7-19: Total Depletion of Minerals by Economic Importance and contribution of raw material gathering to the impacts for the Data Centers modelled.

The contributions to the impacts of the data center can be understood via flow charts to map contributions to different impact indicators from systems, devices, and components, and to evaluate specific material flows, so the location of metals and the structure of impact contributions within a data center can be better understood. **Figure 7-20** shows the inputs of Au (as product metal) for the various levels of a data center. Higher concentrations are found in integrated circuits and printed wiring boards, all of it on IT devices. This is normally the focus of recovery and thus of high importance to be addressed.

The contributions of CED are completely distinct. **Figure 7-21** shows the contributions from various levels to the total of a data center embodied energy from manufacturing devices and systems. Whereas IT remains at the forefront of the contributions, important amounts come from infrastructure and climatization devices. This is due to the bulk of the materials required for manufacturing these components.

Depletion of minerals with high supply risk has a different structure, where the impacts come from manufacturing of capacitors and PWB related parts (**Figure 7-22**). Manufacturing losses are not displayed.

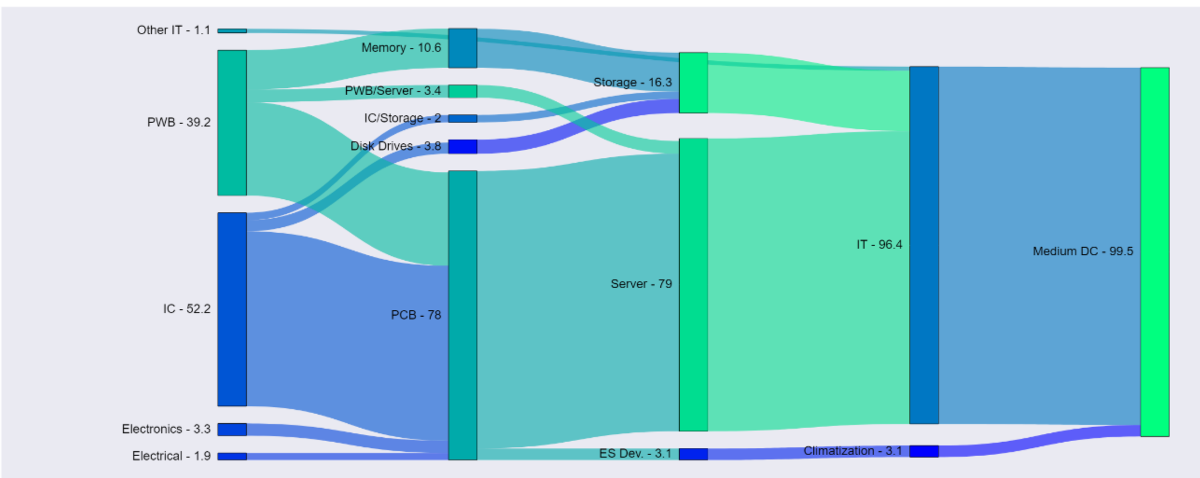


Figure 7-20: Flowchart for percentual input of Au for a Medium Data Center

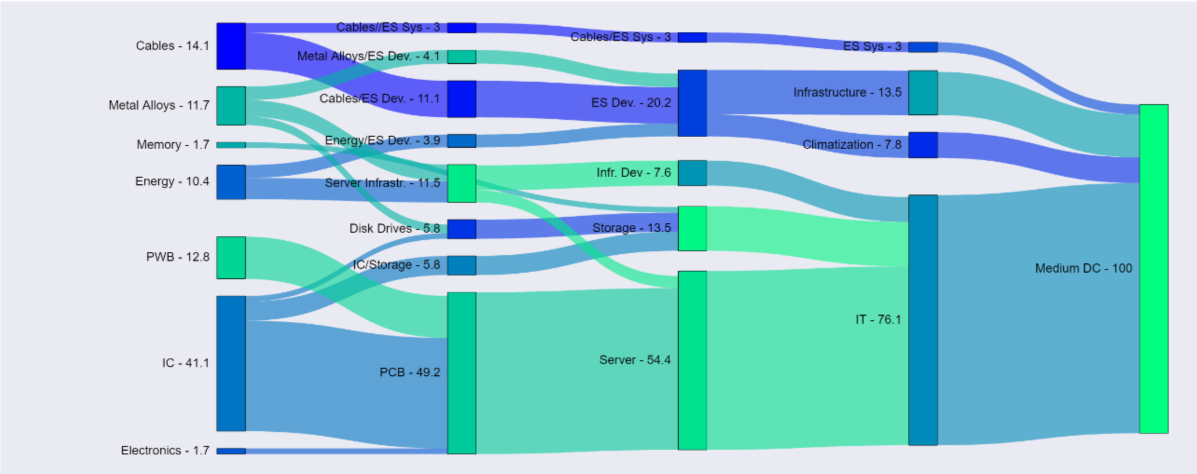


Figure 7-21: Flowchart for percentual contributions to CED impacts for a Medium Data Center

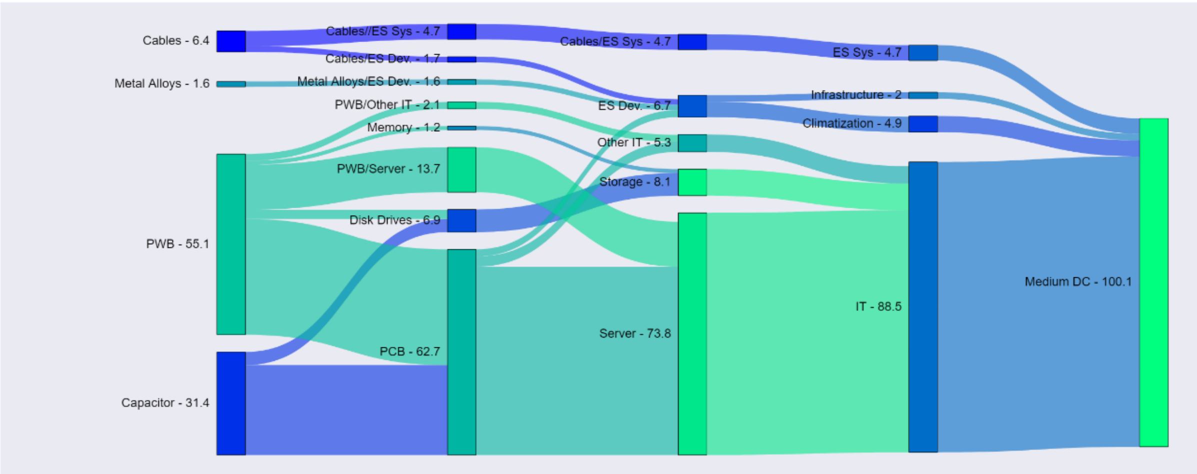


Figure 7-22: Flowchart contributions to Depletion of Supply Risk Minerals for a Medium DC

7.4. End-of-life for data centers and their components

The different possibilities for EoL described in Chapter 3 allow for creation of different scenarios and of parametrization of different variables that allow evaluation of strategies for material recovery. **Figure 7-23** shows an overview of the different flows for material under the different conditions evaluated. Two stages are important: a) the separation (pretreatment) which gives the amount of material sent for recovery, represented by a parameter that factors the relation between material inputs and outputs, and b) the metal recovery process, which provides the final material recovery outputs and is dependent on the technology used.

Figure 7-24 shows the LCIA for different recovery processes for a high-grade PCB. This process shows as positive impacts the energy and material consumption for the recycling processes, and as negative impacts the equivalent avoided impacts from substitution of primary raw material production. Two main differences between the processes are 1) the specific impacts for the processes themselves (represented by the blue bar) and 2) the different outputs and outputs fractions. Pyrometallurgical processes are the current industry standard and offer benefits from recycling precious metals and avoiding their primary production. Hydrometallurgical processes are energy and material intensive, and they also produce high amount of GHG emissions (related to the production of chemicals for the process). This even produces a negative balance for hydrometallurgical recovery process in categories such as GHG emissions (meaning positive GHG emissions). Bioleaching has limited benefits due to the materials obtained (only Au and Cu). Tantalum recycling is modelled as a separate process and therefore is recovered in all the scenarios with the same amount. There are light advantages for electrochemical recovery, mostly coming from the reduced specific energy consumption when compared to pyrometallurgical processes.

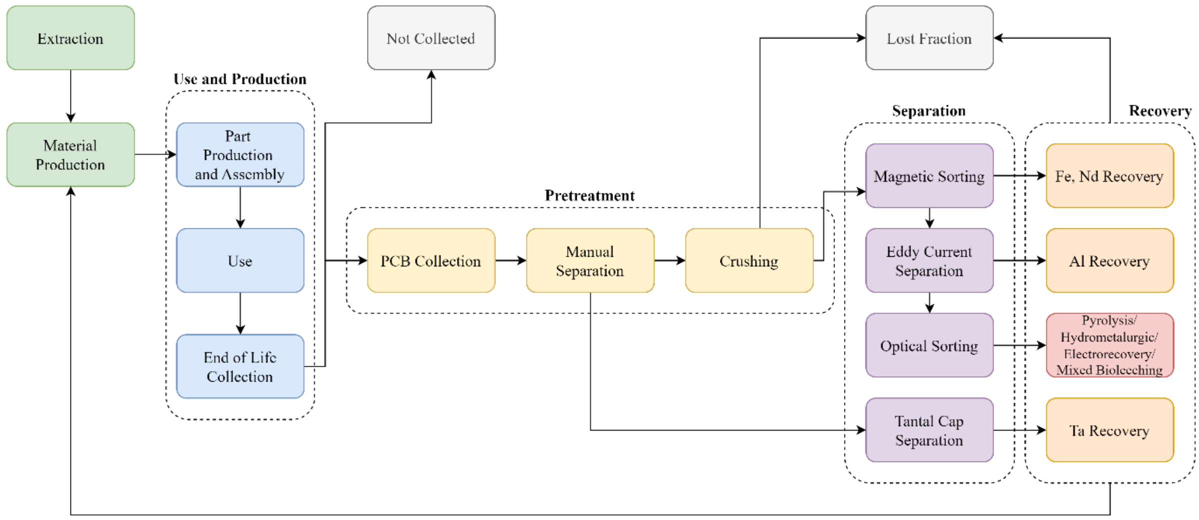


Figure 7-23: Schematic for the evaluation of recycling scenarios.

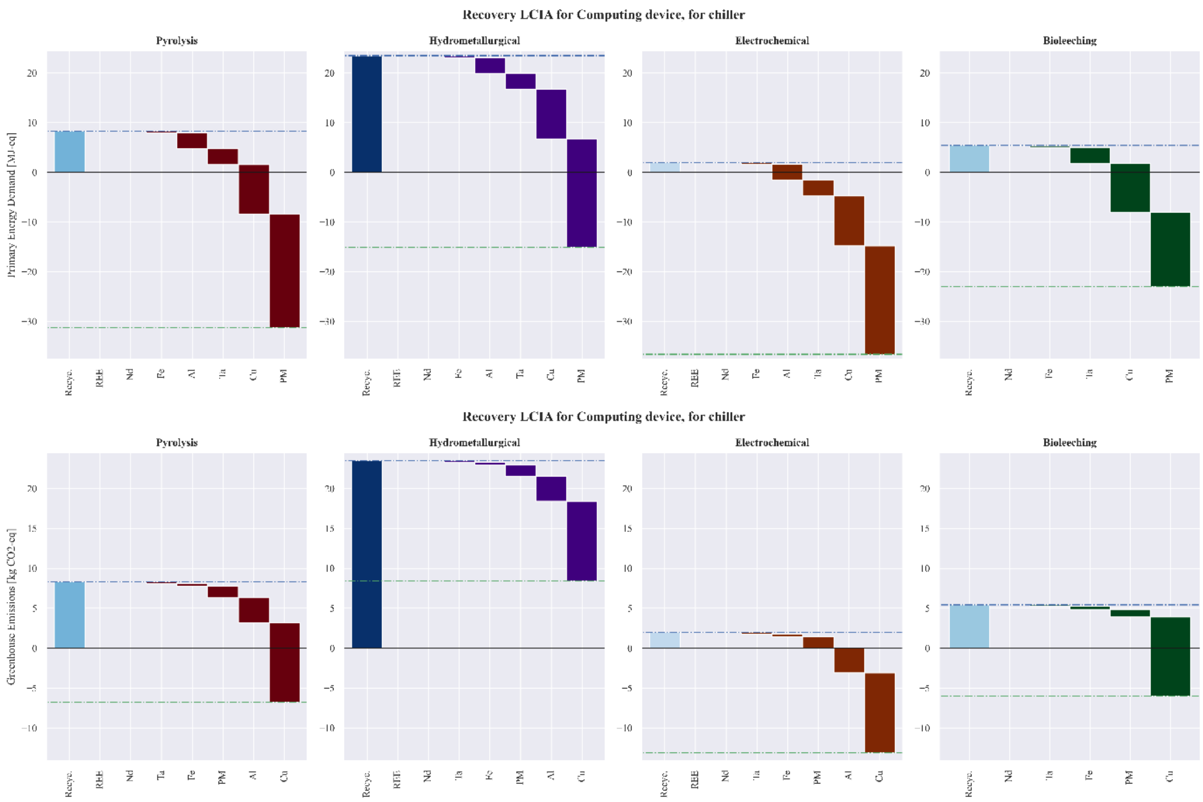


Figure 7-24: LCIA of recovery of metals from a mainboard per kg of module processed. The top line represents direct impacts of the recycling process. Bottom line represents net impacts after material gains are included.

Figure 7-25 shows the process for another PCB, per kg, with a wider variety of metal products recovered. Nd and Al also contribute to the balance of impacts. This positively affects the avoidance of primary energy use and the avoidance of metal depletion.

Figure 7-26 depicts the specific impacts associated with production of secondary metals from the recycling processes specified for a low-grade PCB. **Figure 7-27** presents the results for a high-grade PCB. It is notorious that impacts from secondary production are normally 1 or 2 orders of magnitude below the impacts associated with primary material production. Due to the allocation method selected and the different recovery rates from metals, there is not one single value resulting from the recovery process. This is still dependent on the material content of the inputs and on the process selected. Given that gold and copper are normally at the focus of evaluations, electrochemical processes can offer a considerable reduction on impacts of these two keys metals. The highest reduction is seen in iron, with impacts being 3 to 4 orders of magnitude lower than raw ore production. Tantalum offers comparable results for all strategies since it is modelled as a separate process.

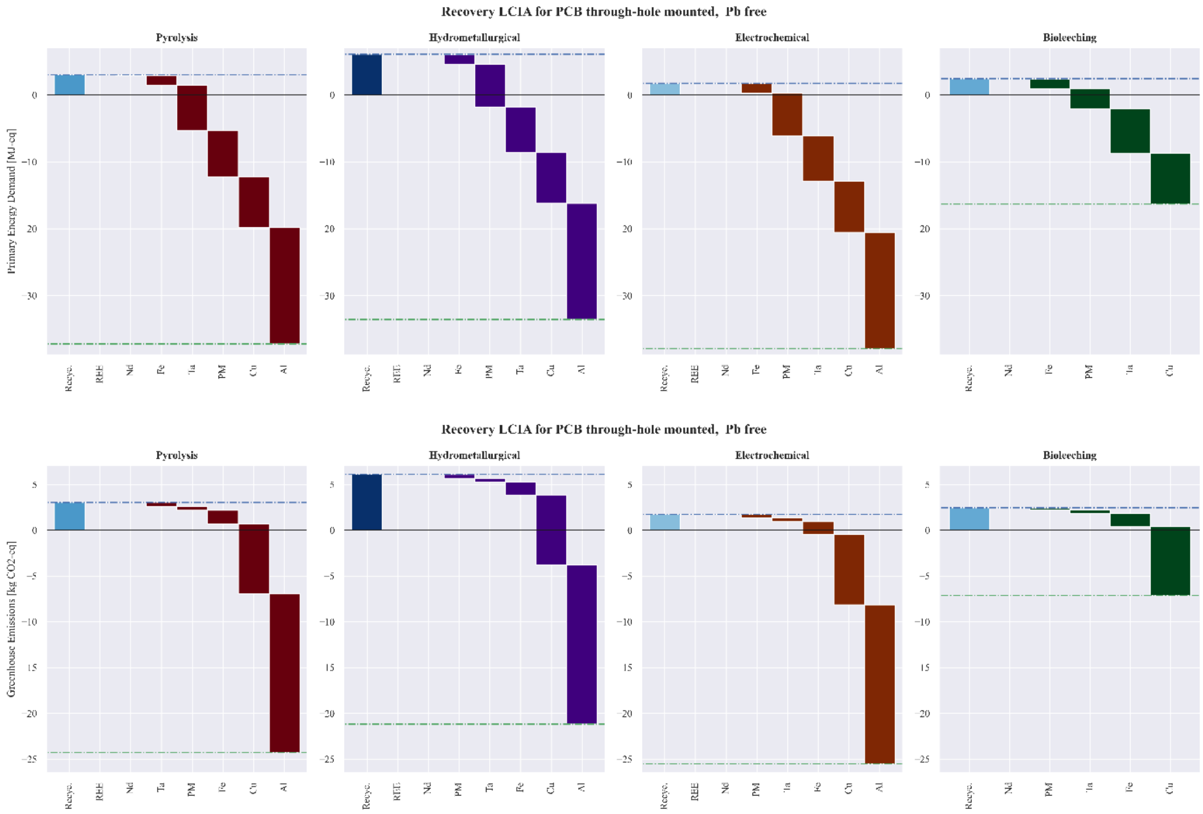


Figure 7-25: LCIA for recovery of a low-grade PCB per kg of recycled module. The top line represents direct impacts of the recycling process. Bottom line represents net impacts after material gains are included.

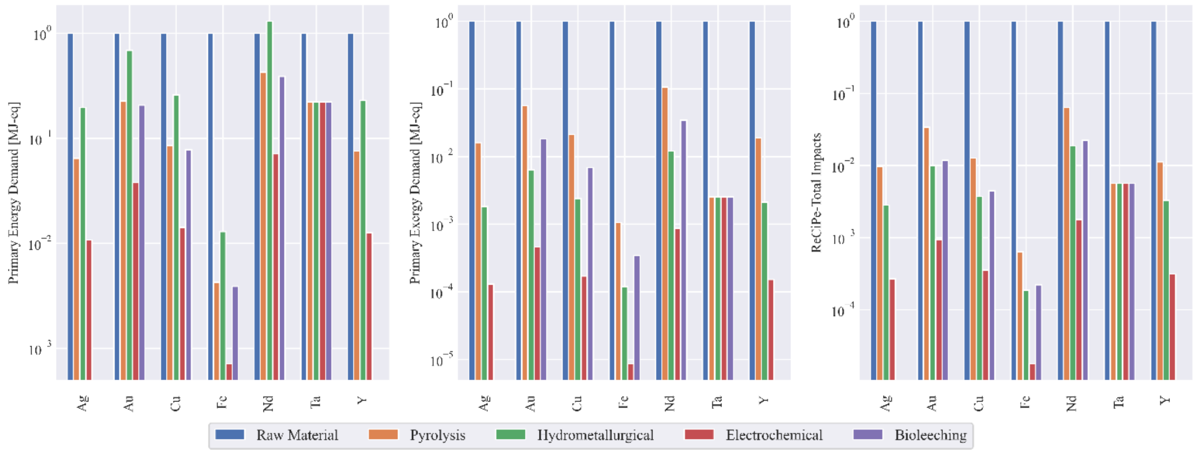


Figure 7-26: Equivalent impacts for production of secondary materials from recycling from a low-grade PCB.

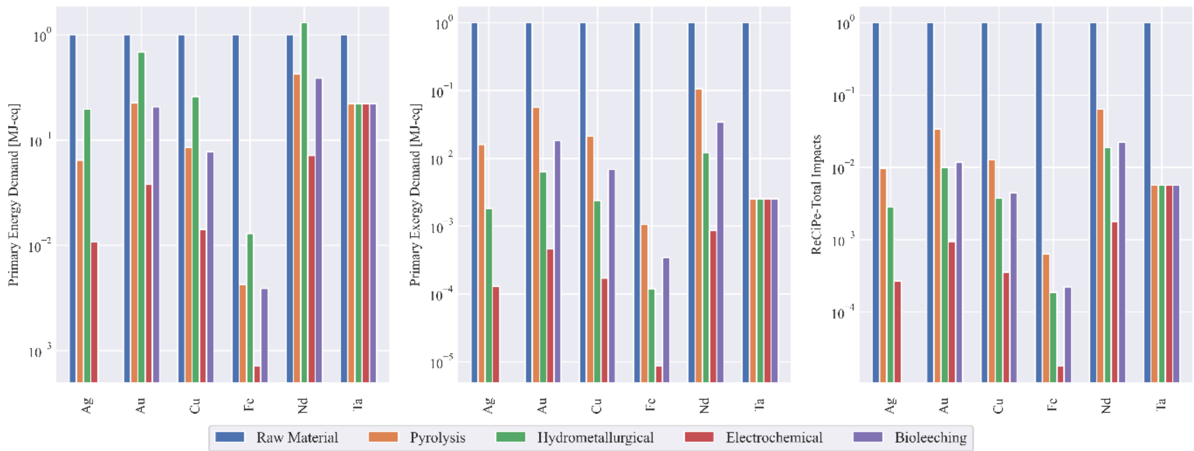


Figure 7-27: Equivalent impacts for production of secondary materials from recycling from a high-grade PCB.

Figure 7-28 presents a comparison between the impacts avoided from recovery for a high-grade PCB and the impacts related to production of all the metals present in the modeled process. This gives an insight into the potential for recovery and of the impact of the different strategies selected. As a sensitivity parameter, the factors of efficiency on pretreatment of **Table 5-1** are included as factors in the material flows before entry to the recycling process. Impacts related to direct energy consumption offer a limited benefit on avoidance of primary energy use (between 5-30%) and on GHG emissions avoidance (3-20%). Higher benefits are seen in the avoidance of exergy consumption (related to material degradation) and on avoidance of depletion of critical materials (related to direct material use). Slight differences are found in material related impacts for the different recycling processes. The key factor here is then the separation process, which has a much higher influence than recycling process in material related impacts. However, when considering energy related impacts (including GHG emissions), pyrometallurgical and electrochemical processes offer clear advantages over hydrometallurgical and bio-leeching processes. Bio-leaching presents the limitation of limited material recovery.

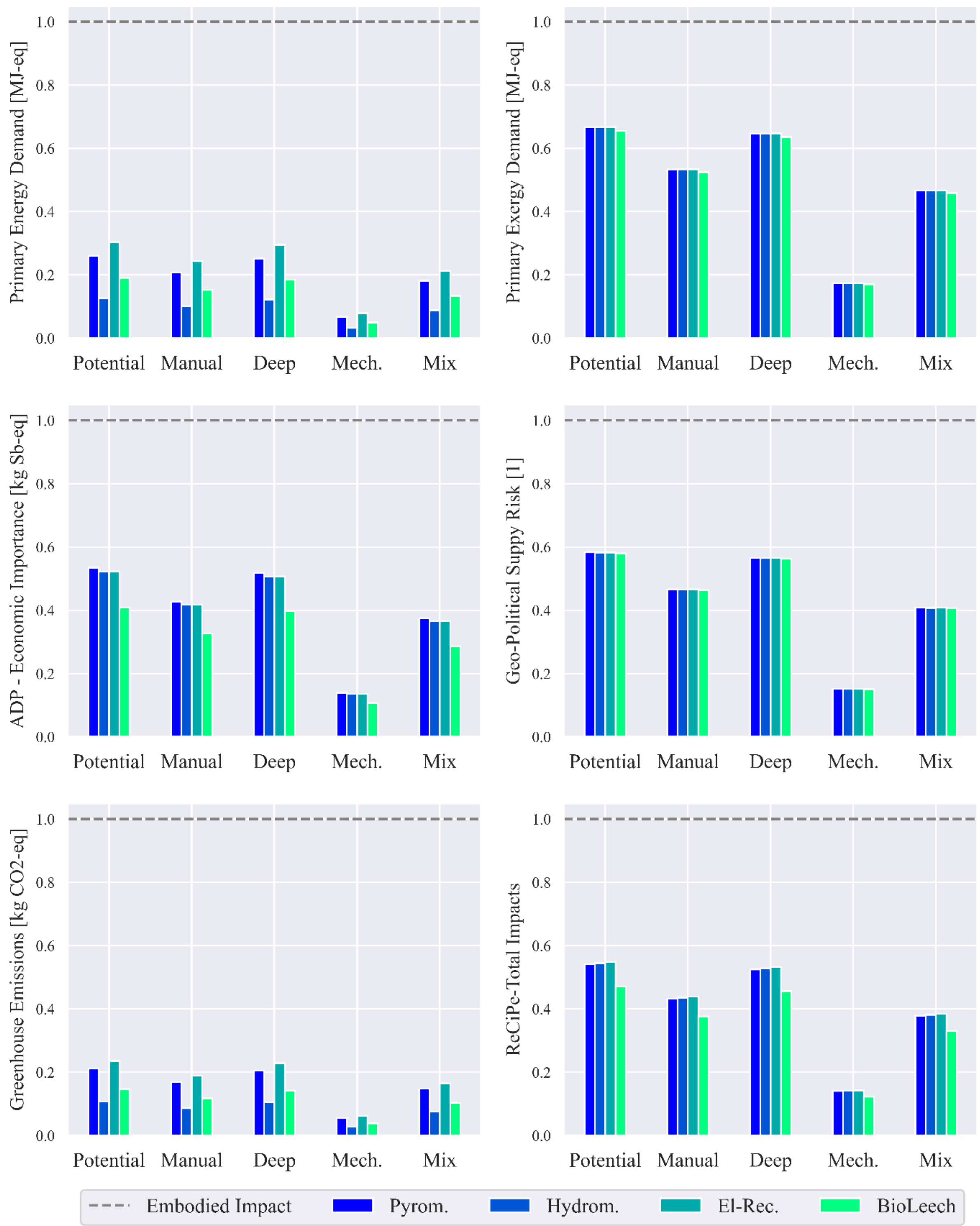


Figure 7-28: Comparison of impacts from different recovery scenarios for a high-grade PCB.

Figure 7-29 presents a similar evaluation for a complete Server (1U). Here, the lower specific content of precious metals and the higher content of base metals (Fe and Al for housing, Cu for cables) makes the differences between each recycling process less noticeable across all the impacts. However, the potential for avoidance of primary energy and GHG emissions is higher due to the recovery of bulk metals. The limited recovery factors on other metals lower the benefits of recovery for other material related impacts. At a device level, the importance of the pretreatment process is increased, as impacts seem less distinct between different PCB-recovery strategies. This is because bulk materials are sent to the same scrapping process, lowering the influence of the PCB metal recycling process.

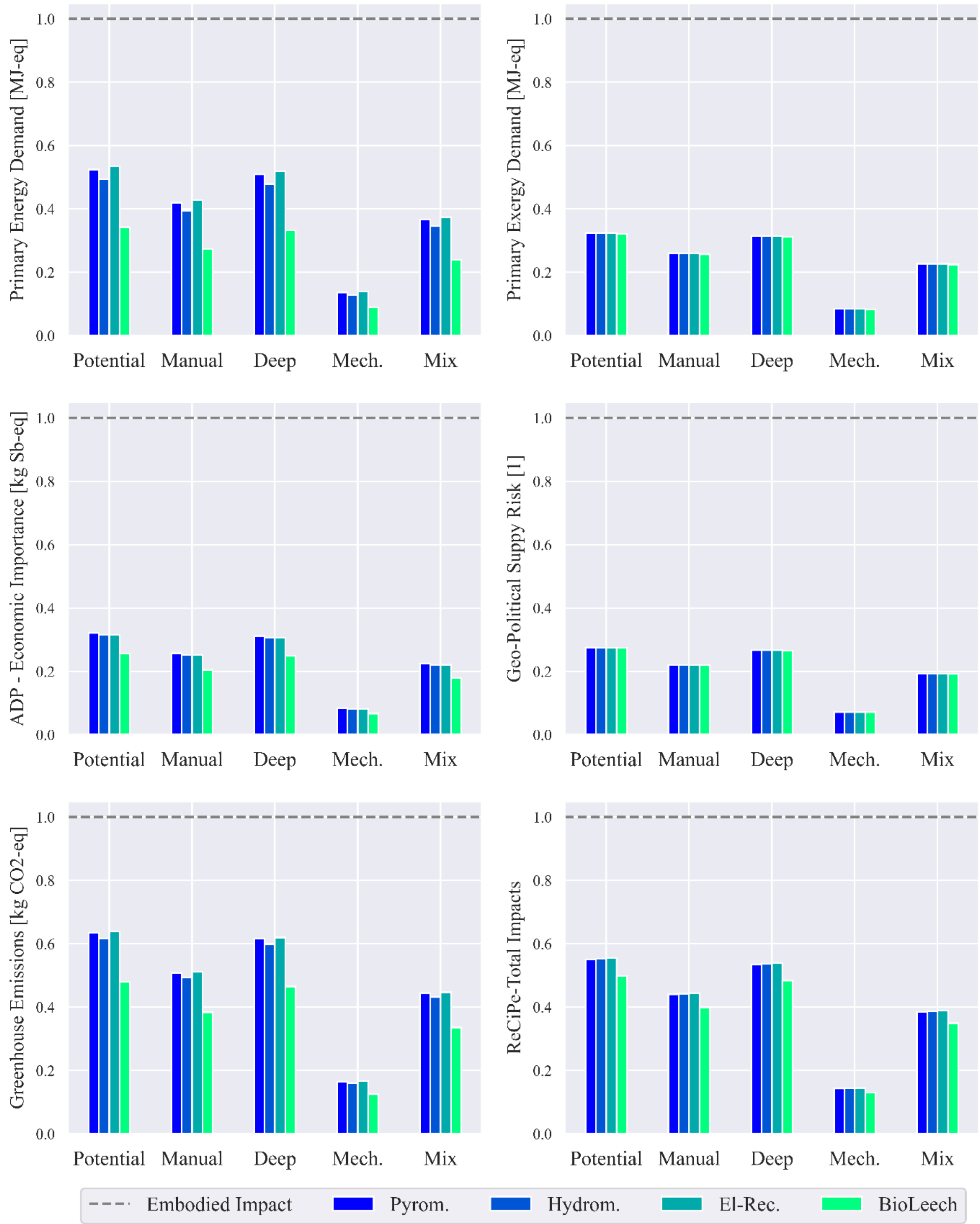


Figure 7-29: Comparison of impacts from different recovery scenarios for a Server -1U.

7.4.1. Material flow analysis for data centers

The results of LCIA can be used to establish material flow analysis (MFA) and obtain visualizations that allow inspecting material flows and indicating where the material hotspots are. **Figure 7-30** shows the material flows for gold considering also the material gathering and the recovery of metals. Since the gold content in a data center is concentrated on the PCB components, recycling of these offers the most recovery potential in the data center for recuperating this metal. For this example, a deep-manual separation process (97% efficiency rate) and a pyrometallurgical recycling process for PCBs is modelled (98% recovery rate) yield the maximal amount of material recycled and inserted back into production. **Figure 7-31** shows a comparison with a mixed separation (70% efficiency) with the same metal recycling process. Differences in non-recovered content come mostly from losses at the separation stage.

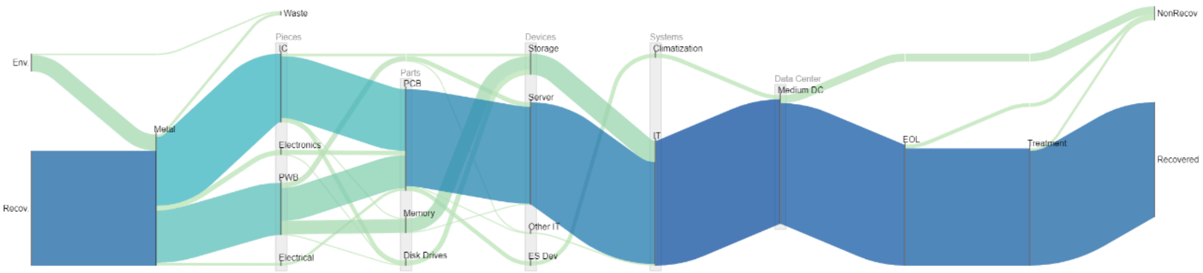


Figure 7-30: MFA for Au with deep manual recovery for a medium DC.

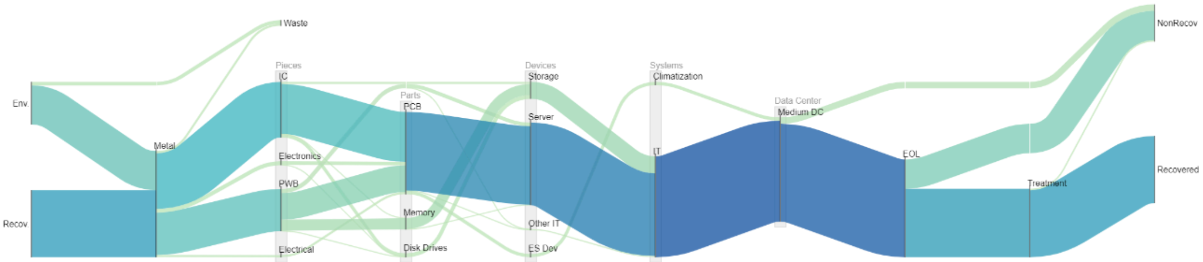


Figure 7-31: MFA for Au with mixed recovery for a medium DC.

Figure 7-32 offers a similar visualization for Cu for a deep-manual PCB pretreatment and pyrometallurgical process. Cu is contained mostly in cables for energy supply and for infrastructure, and thus the separation process for PCBs has reduced influence on the result, since the cables are sent directly as scrap, and the Cu content in PCBs loss during pretreatment has less overall impact.

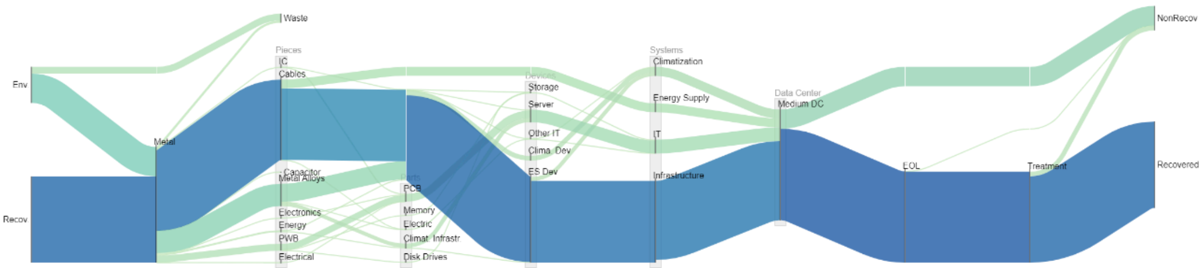


Figure 7-32: MFA for Cu with deep manual recovery for a medium DC.

Figure 7-33 shows that when changing the pretreatment strategy to a mixed method (70% efficiency for PCB) the results do not differ significantly from the previous figure.

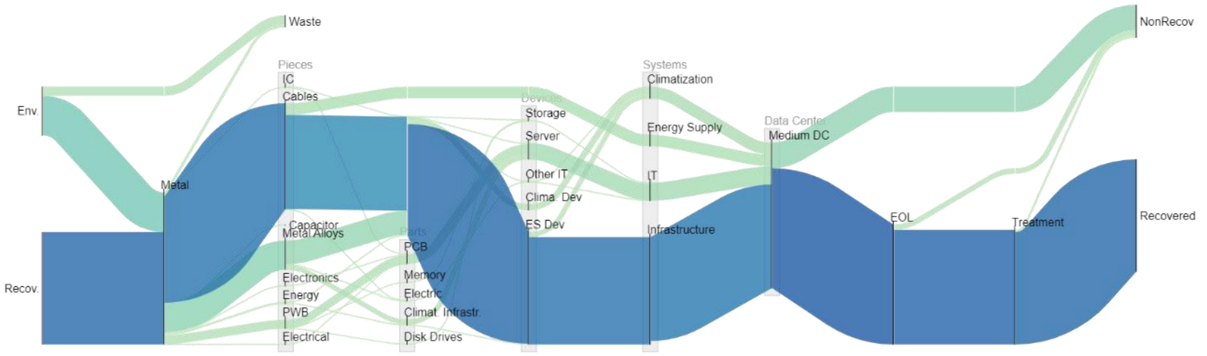


Figure 7-33: MFA for Cu with mixed recovery for a medium DC.

7.5. Uncertainty and data quality

The different models created were established using a mixture of laboratory data, case study inventory data, and use of proxy data from industrial databases. These data sources have distinct characteristics regarding data quality. Therefore, the results produced by the analyses are bound to uncertainties. Results with high uncertainty are not desirable, independent from the application of the LCA model, be it “accounting” (a mere report on impact figures linked to a product system) or, more frequently, decision-support [Ci21]. To provide a basis for comparison of the quality of the results, the improvements in the quality of the results are shown by means of the uncertainty obtained.

Reporting the uncertainty of LCIA results and LCA models as quantitative increases the overall quality and reliability of the study. [Su05] suggested applying the Pedigree matrix approach to literature-based data but to use statistical methods to quantify the uncertainties in industrial inventories. This is the method used in this study, where laboratory data and case study inventory data case assigned a geometric uncertainty of “1” and correspondingly, high markings in the data quality indicators. The resulting value of total uncertainty is calculated using the propagation method and the pedigree matrix uncertainty factors.

Monte Carlo simulations are then executed to evaluate the uncertainty of the results on impact assessments introduced by the statistical variability or temporal, geographical, or technological gaps in the LCI data. The simulation results for selected impact categories are presented as a detailed example of the application of statistical methods at the LCI level. Based on the uncertainty of LCI data expressed as a probability distribution, the Monte Carlo simulations are conducted using the openLCA calculation engine and multithreading, using in total 2500 runs. **Figure 7-34** presents the distribution of impacts calculated for distinct categories for a reference module. **Figure 7-35** presents similarly the results for a reference device. Results present a lognormal distribution, where the geometric standard deviation represents the quality of the result obtained.

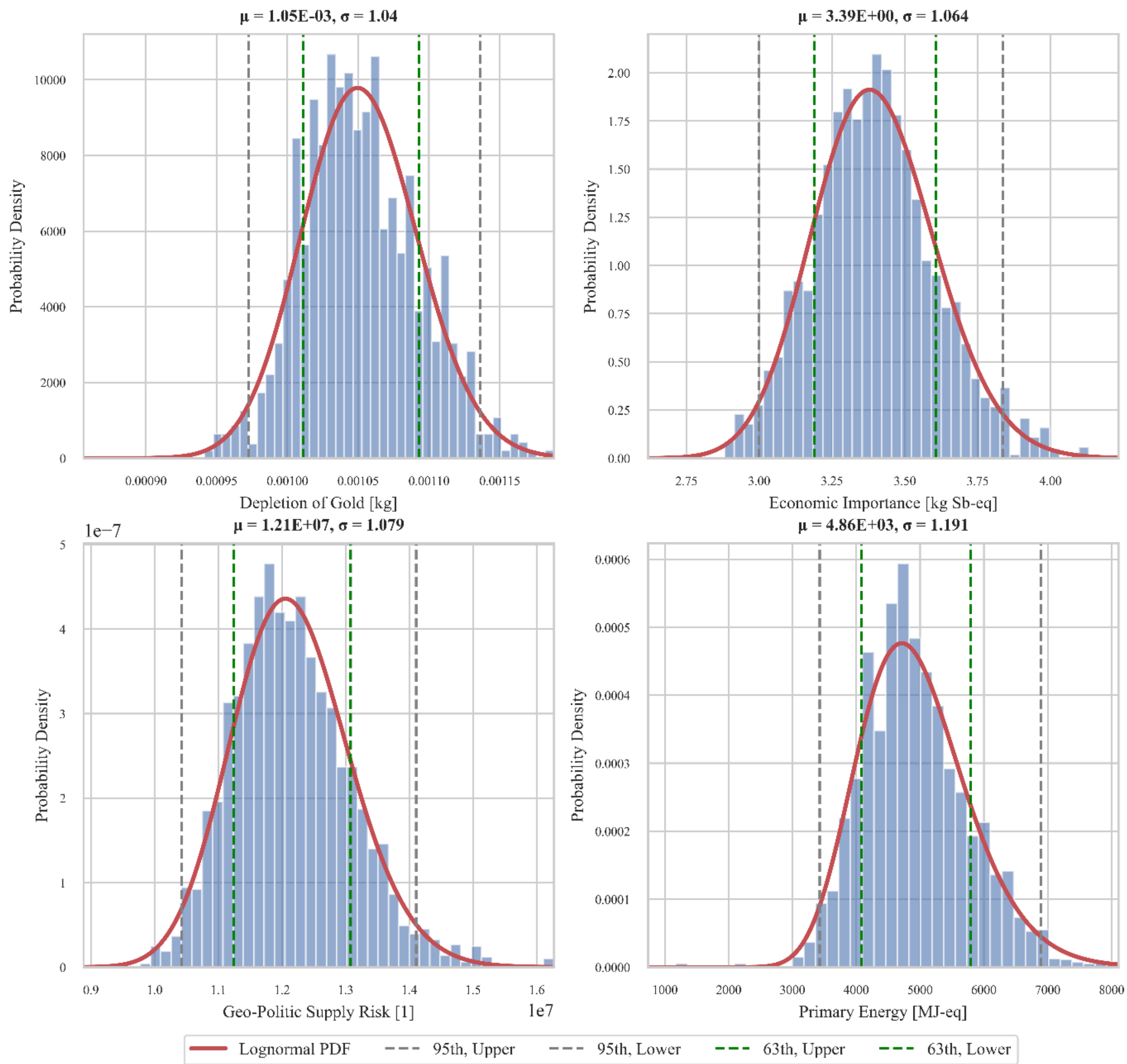


Figure 7-34: Distribution of results of LCIA for a PCB with a mounted CPU.

The nature of these distributions was also analyzed since some distributions did not fit entirely in the lognormal probability density function. **Table 7-2** shows the corresponding P-Value calculated for the statistical test under the assumption of a lognormal distribution for different products analyzed. Values above 0.01 are considered to indicate no evidence to reject the null hypothesis, and thus a lognormal distribution is considered as appropriate to represent the data. Indicators such as ADP do not fit this distribution and other distributions (such as Weibull-Exponential) fit the obtained results better. Further analysis is excluded.

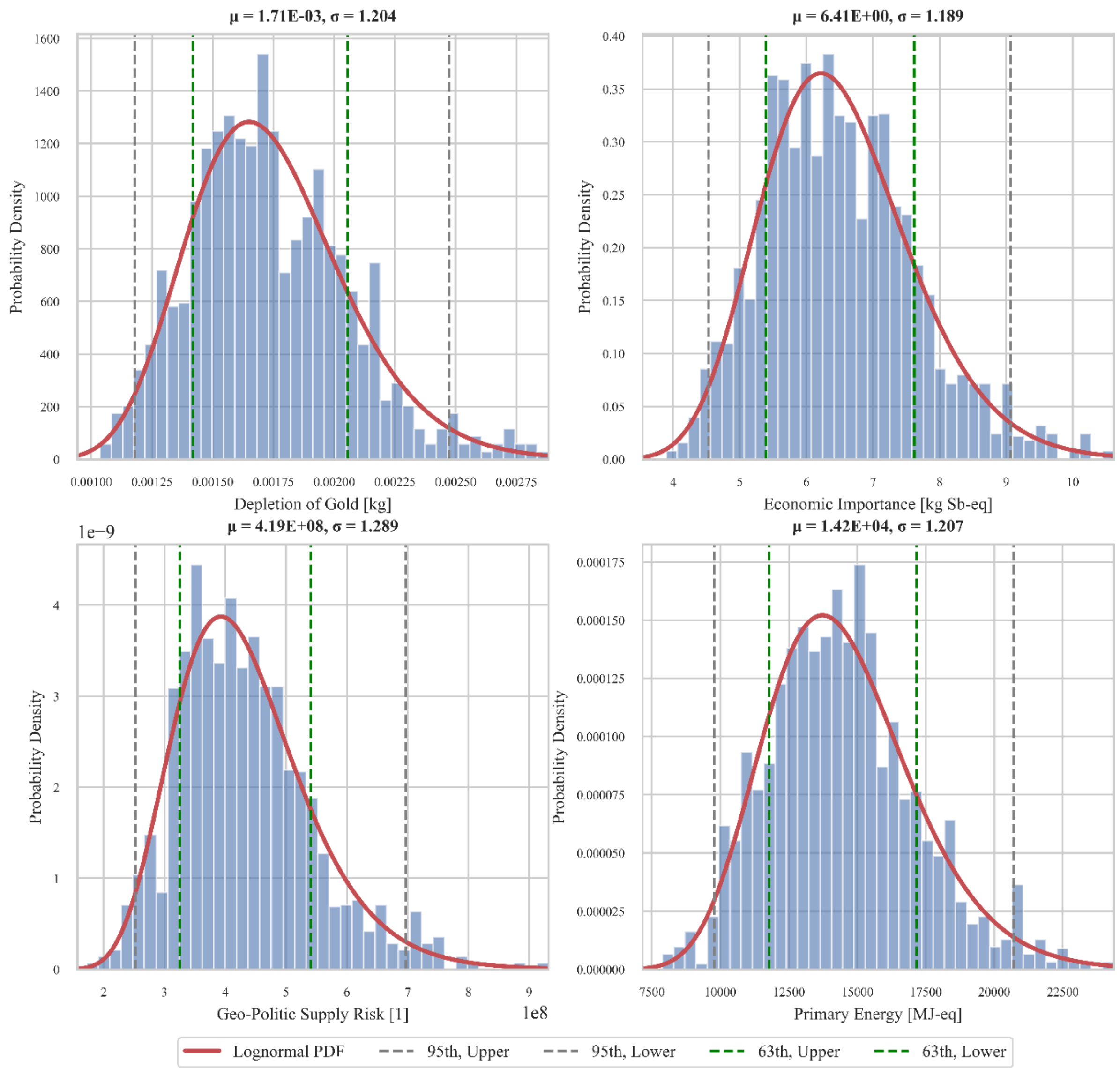


Figure 7-35: Distribution of results of LCIA for a Blade Server.

Table 7-2: Results of the evaluation of the P-Value for the statistical test of the lognormal distribution. Green values show a rejection of the null hypothesis under the threshold implemented.

Indicator	Mainboard	PCB with CPU	Low-grade PCB for UPS	Server, 1U, no storage	Blade Server
Au	1.58E-01	1.11E-02	5.20E-02	9.42E-02	1.07E-01
Cu	1.44E-01	3.27E-02	3.46E-03	1.07E-01	2.39E-02
CExD	3.28E-01	4.19E-02	3.07E-02	4.86E-02	2.10E-01
CED	4.86E-13	2.65E-01	4.12E-13	2.08E-18	1.93E-01
ADP	7.80E-16	1.41E-03	1.49E-10	2.79E-22	1.16E-01
ADP-Mins	2.17E-02	3.82E-03	1.24E-01	5.58E-01	7.56E-02
ADP-EI	4.27E-03	5.69E-03	1.70E-01	2.83E-01	1.92E-01
ADP-EI-PM	1.89E-01	3.78E-02	4.92E-02	2.10E-01	5.22E-02
ADP-SR	5.52E-05	9.63E-04	1.60E-01	2.21E-01	6.60E-02
GPSR	9.54E-04	1.01E-02	3.61E-02	1.64E-01	1.35E-01
GWP	5.07E-16	2.03E-01	4.23E-12	1.34E-24	3.45E-02

The inclusion of different parameters with uncertainty values allows also studying the dependencies that different impact indicators have between each other. **Figure 7-36** shows visualization of these indicators. Selected indicators for a reference device (Server 2U with) are compared to each other and their correlations are analyzed. The resulting Pearson-correlation coefficient allows evaluating the dependencies between indicators of different areas, such as material depletion or energy depletion. For the plotted example of a server, the content of Au has a direct incidence on indicators such as CED. Indicators such as depletion of supply risk materials have low correlation on the value of primary energy depletion.

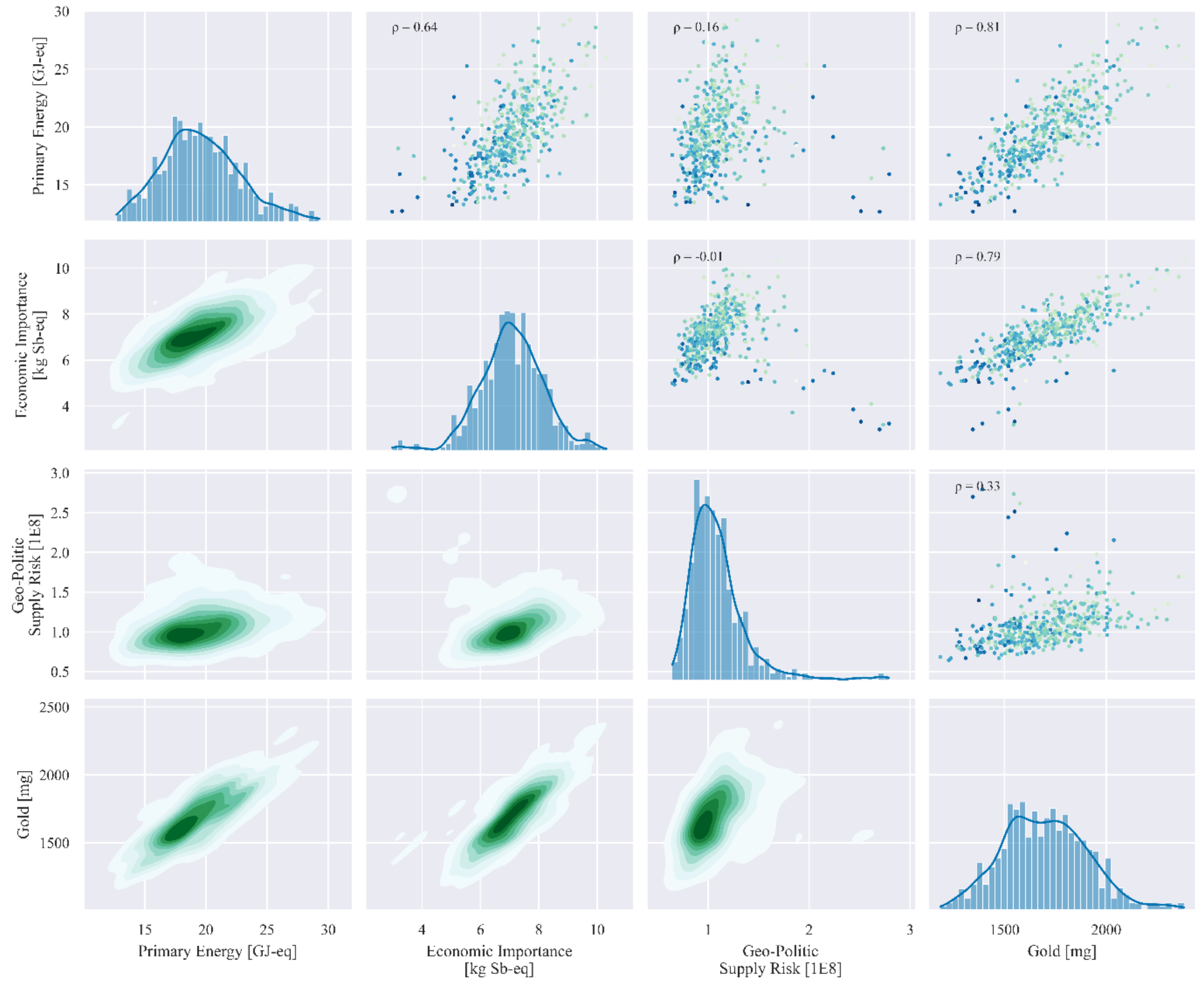


Figure 7-36: Correlations between the different indicators of material and energy depletion. Darker points indicate lower total aggregated impacts (ReCiPe method).

Figure 7-37 presents a summary of the correlations between different indicators for a product system modelling a Server of 1U without storage unit. The developed indicators of Supply Risk (SR) and Economic Importance (EI) show a high value of correlation, but they are nondependent of other material depletion indicators such as Metal Depletion Potential (MDP). Geo-Political Supply Risk (GPSR) presents a good correlation with Exergy consumption (CExD), this is due to their focus on mineral quality and on normalization by quantity. Cumulated Energy Demand (CED) and Abiotic Depletion Potential (ADP) also present good correlations due to the impact of fossil fuels in these categories. Gold depletion is highly correlated to Economic Importance, due to the high characterization factors they present for this indicator. Copper depletion has a strong influence on MDP. It is of notice that the “Total“ aggregated impacts (ReCiPe) hold a low correlation with the rest of the studied indicators across the board. This can be explained when considering that this “Total“ indicator is an aggregation of the different impacts across various categories, and all domain dependencies are lost when evaluating a single indicator representing the totality of impacts over different areas of protection.

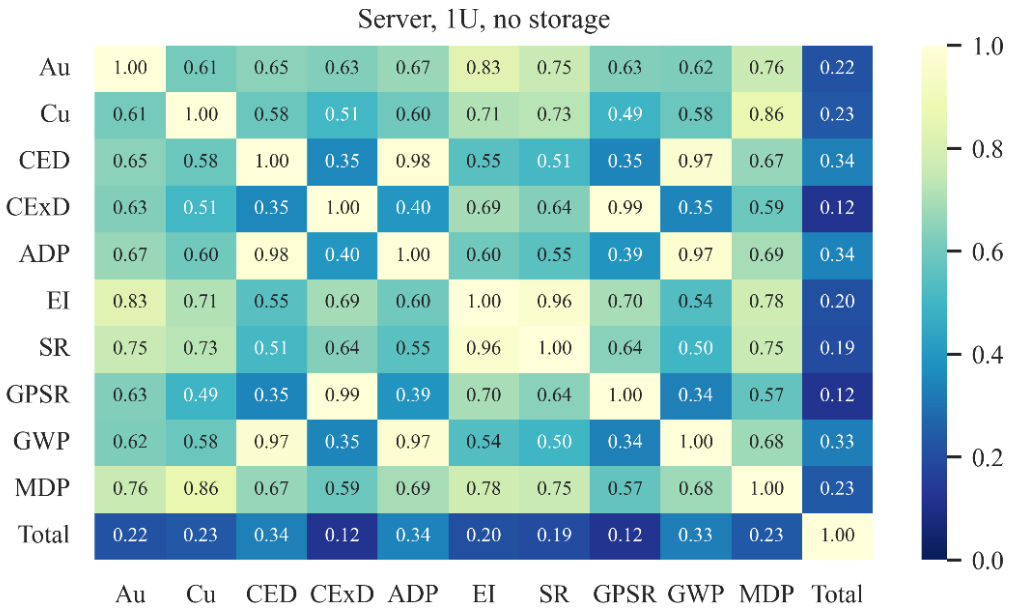


Figure 7-37: Pearson coefficient for covariance of lognormal distributions of studied indicators for a Server.

To study if any improvement on data quality has been achieved by this work, two different sets of models were created. The first one is based purely on the ecoinvent database and on inventory data. The second set of models includes the results of laboratory analysis on material content as presented in **Figure 4-4** and in **Figure 4-5**. The goal is to evaluate what are the changes on the different impacts obtained by including this data on the models, and to evaluate the improvements on results data quality obtained.

Figure 7-38 compares the product system created with only ecoinvent data and with the input of laboratory data on material content. The differences can be observed in the results on mean and standard deviation. First, the mean is increased, meaning that a higher result on depletion of materials is expected, this being a reflection on the higher quantities of valuable minerals found in the laboratory analysis. Second, due to the improved data quality at the input, the geometric uncertainty is reduced, producing better data quality. **Figure 7-39** repeats this comparison for energy depletion. For this indicator, no substantial change in the results can be inferred, although the data quality of the resulting indicator has slightly improved.

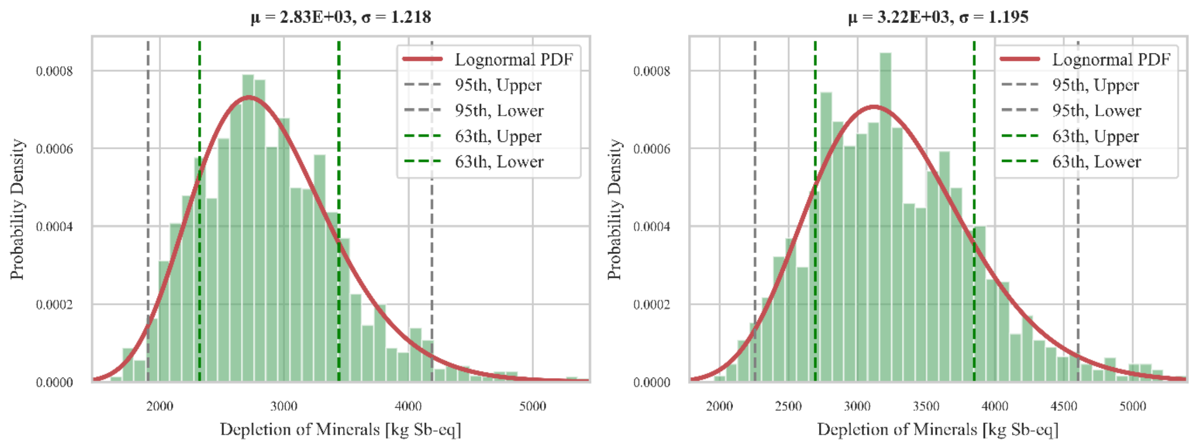


Figure 7-38: Comparison of results for a Blade Server between models created using the ecoinvent data (left) and the laboratory data (right) for Depletion of Minerals.

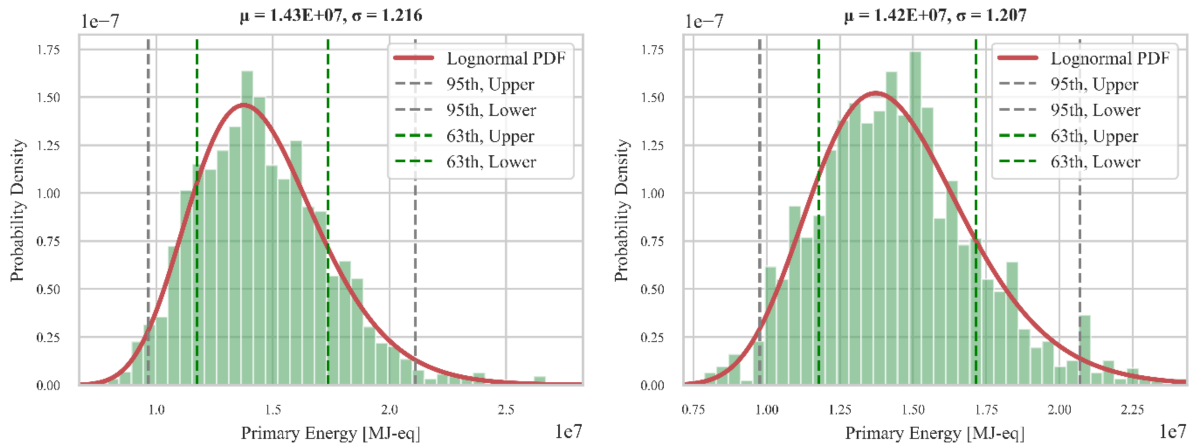


Figure 7-39: Comparison of results for a Blade Server between models created using the ecoinvent data (left) and the laboratory data (right) for Depletion of Energy.

To summarize these results, **Figure 7-40** presents a comparison between the results obtained for data quality and the related geometric uncertainty for selected indicators. There is an increase in the calculated amounts of raw material consumed, and a visible increment on the resulting impacts related to material depletion, including economic importance and supply risk indicators. There is however no notorious change in indicators related to energy demand or GWP. Since the Total (ReCiPe) indicator aggregates other indicators based on areas of protection including material depletion, these values are also increased, with the most relative increments found at the module level (such as Mainboard).

A better visualization of the improvement of result quality is obtained comparing normalized values obtained from the two datasets (**Figure 7-41**). The sharper shapes of the updated values show a higher concentration around the (normalized) mean and thus a lower uncertainty, demonstrating improvements in the results quality. These effects are mostly seen in material-related impacts. There is however a reduction in the quality of energy related categories. This can be explained due to the increased amount of materials present, which despite having higher data quality, contribute to the increment on primary energy demand and on the number of flows which increases the uncertainty of the results due to the propagation of uncertainty.

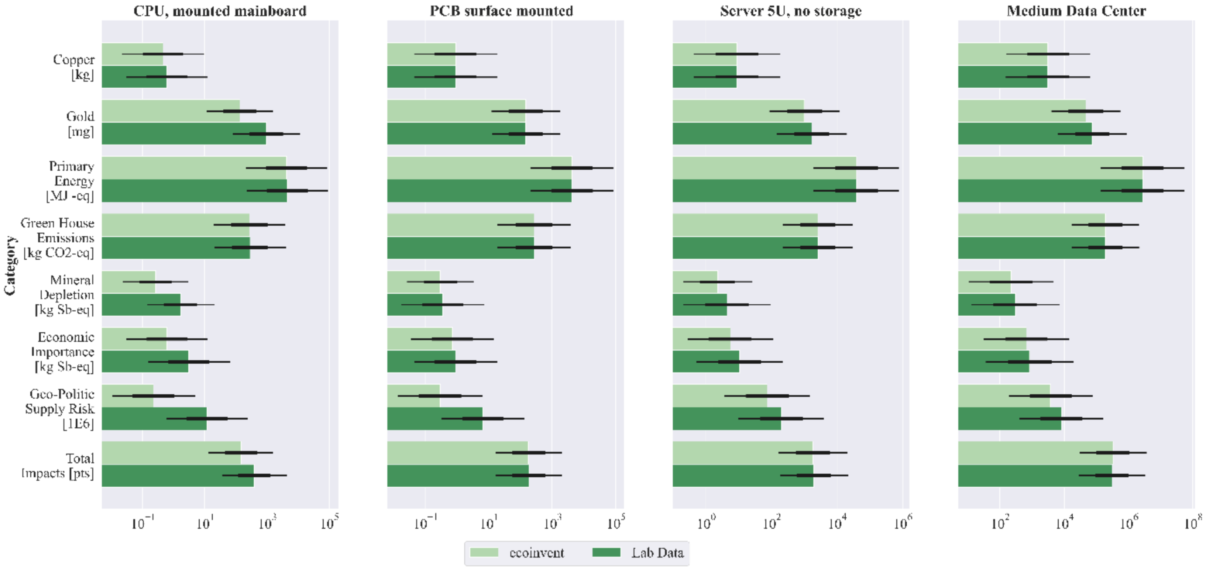


Figure 7-40: Comparison between results data quality for different product systems

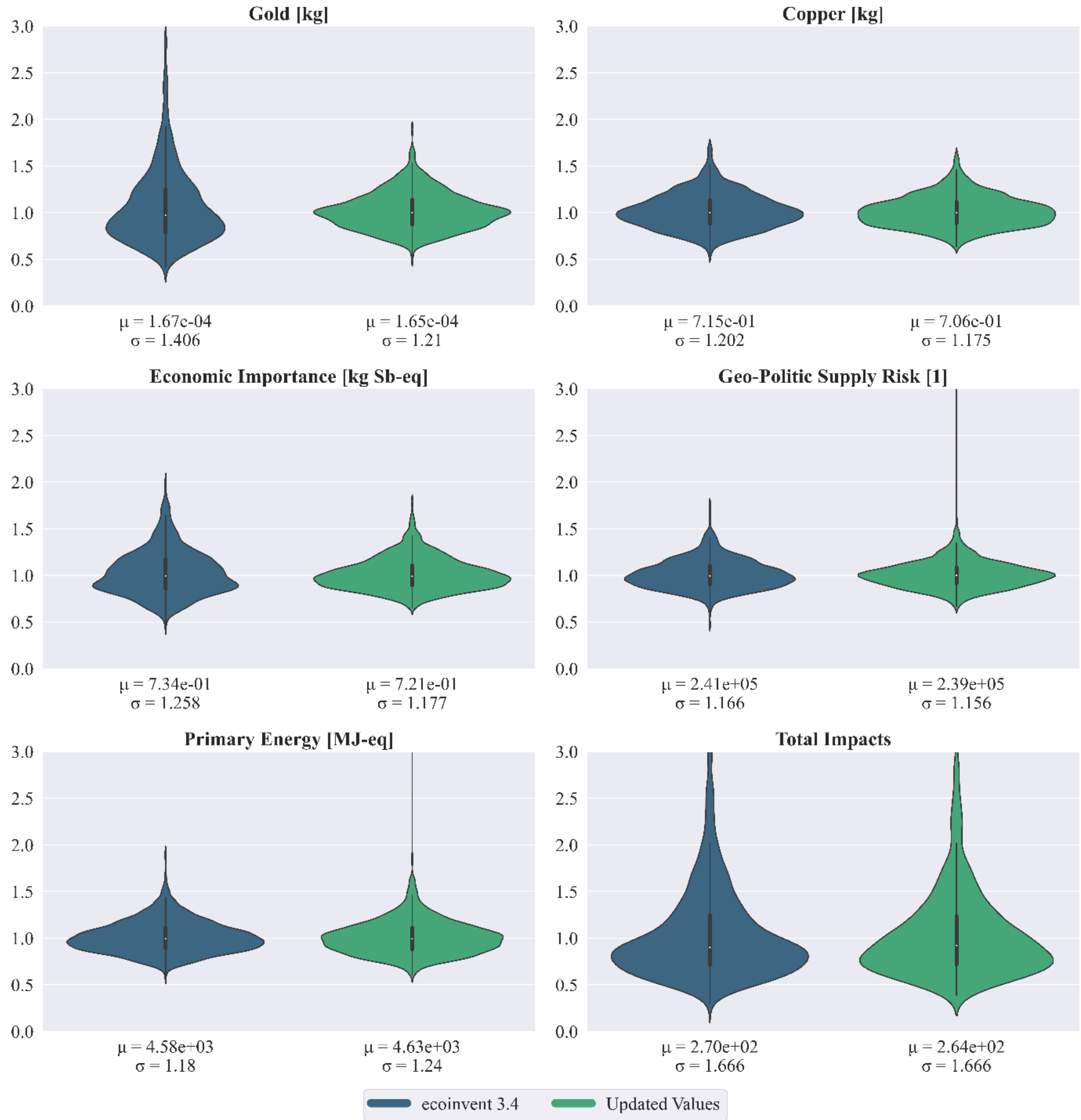


Figure 7-41: Violin charts representing the improvements on data quality for a Mainboard with mounted CPU.

7.6. Conclusions

In this section, the different results obtained from Life Cycle Impact Assessment calculations were analyzed, with a focus on answering the research questions established in Section 1.

Based on the results obtained, an overview of the interactions between the results of raw material and primary energy consumption can be assessed. The methodology here used applies indicators developed to assess critical material use and is built upon evaluation of the impacts of raw material gathering. These methods allow to evaluate separately the depletion of critical materials, based on economic importance and supply risk, and to evaluate energy depletion, by means of primary energy or primary energy quality (exergy). Links between the results obtained for these indicators are then studied.

Different reference components, devices, and case studies of inventoried data centers are used as research objects for the application of these indicators, which aligns with the goals of this work. The dependencies between material and energy indicators are stronger at the lower disaggregation levels at the electronics components cluster. This is due to the higher material concentration and the wide variety of materials present, including critical materials.

Studying correlation between indicators allows assessing quantitatively how these interactions between indicators are. Commonly used methods (such as global warming potential, abiotic material depletion, cumulated energy demand) have strong correlations amongst them due to the heavy influence of fossil fuels consumption in the calculation of these indicators. It was then of advantage to develop and to use criticality-based indicators to highlight the importance of material consumption for these specific products. The endpoint indicators (such as ReCiPe v1.13-Total) lose correlation since they aggregate various aspects of environmental affectation in only one indicator linearly constructed. These endpoint indicators, however easier for communication, omit information relevant for the evaluation of material and energy resource use.

The analysis of inventories at different granularity levels allows material flow analysis to be conducted for the stages of the lifecycle, including recycling and recovery of metals. The different recovery strategies are evaluated by means of parametrization of collection rates, pretreatment efficiencies, and metal recovery fractions from recycling processes. While the modelling focus is on recycling technology, the selection of a proper pretreatment route presents more relevance to the whole End-of-Life chain. Of the recycling technologies evaluated, pyrometallurgical, being the most mature, offers clear advantages in terms of avoided primary energy use and avoided greenhouse gas emissions. Experimental technologies, such as electrochemical recovery, can potentially offer higher advantages in terms of avoidance of impacts, while presenting similar recovery rates. This is due to the reduced specific energy consumption for material recovery. An economical assessment of these routes would also be required in a prospective study to analyze the benefits of experimental technologies, such as bioleaching, at an industrial scale. As the evaluation did not consider cost aspects, no information on the economic advantages of the different recycling routes was obtained.

The use of Monte Carlo analysis paired with data quality and inventory uncertainty evaluation allows evaluating the quality of the results, and to evaluate the improvements on said quality obtained through this work. A complete separate database with products built only based on reference ecological databases was constructed to quantify the improvements achieved through the incorporation of data from laboratory analysis. While a clear improvement can be observed in the material-related indicators at the resource accounting and midpoint level, the quality of energy and emission related results at the midpoint level did not show substantial improvement. This reflects the methodologies for construction of such indicators and shows the effects of incorporating more material flows and higher quantities of material use for manufacturing of electronic components. Reporting of the uncertainty increases in general the quality of any LCA study, with a full quantitative uncertainty assessment giving high transparency on the quality of the results provided.

By using a variety of indicators for evaluation, this work presents novel insights on material depletion and on energy use for various products, whose high specific critical material content make them of relevance for urban mining and for securing secondary material sources. Additionally, the use of Monte Carlo simulations paired with data quality to evaluate the results is a procedure not commonly observed within LCA studies, mostly due to time and to computer resource constraints. This last evaluation provided an insight on methodologies for evaluation of results quality and on the improvement of said quality, while also providing a basis for studying interdependences of indicators. However, limitations on the methodology are reflected when evaluating the distribution of the results. For example, it was assumed that all flows are lognormally distributed. The effects of these assumptions and the use of other PDFs can be implemented in future studies.

When compared to similar studies, advances in results quality here presented reflect the benefits of using state-of-the art data and existing data centers as sources of information for building case studies for evaluation. This is a challenging task in the data center sector, as much of the information on inventory and architecture of data centers remains unavailable. Additionally, the implementation of an information and calculation system to build models and calculate results allowed obtaining and processing considerable amounts of data for evaluation in this chapter. Further analysis may include updated inventories, bigger data centers, refinement of the service unit, and a techno-economical evaluation of recycling strategies of data center components.

8. Conclusions

In the context of the present work, a software architecture for building Life Cycle Assessment models of different data centers under study and their components was developed. The LCA models were built based on updated information on material composition of printed circuit boards, bill-of-materials obtained from disassembly of servers and IT devices, and on inventories of existing data centers. The goal was to establish a basis for the evaluation of embodied energy and material consumption for data centers, and to evaluate strategies for end-of-life for their components. Seven specific objectives were defined arising from three secondary research questions regarding the appropriateness of indicators for evaluation, potential environmental benefits of recycling, and on the data quality of the results. The specific goals were developed in accordance with a complete LCA study to answer the research objectives. The developed software was constructed to satisfy the requirements of this study.

The defined objectives were used firstly to evaluate the existing indicators for evaluation of data center resource consumption outside of the operation phase. After an evaluation of the literature on data centers and the indicators used for the evaluation of their environmental impacts, it was concluded that several indicators needed to be created to better assess aspects such as economic importance or supply risk of material consumption for the manufacturing of data center components. After literature research on information on data for building LCA models for data center components, most of the available information was found to be of low quality due to the use of loosely technologically related process and outdated information for creation of models of components. Additionally, when considering recycling, few information was available on inventories of recycling processes and on specific advantages of recycling. This justified the need for creation of new indicators for assessment of depletion of critical raw materials, improving information on data center components for LCA modelling, and on modelling of different recycling processes for EoL scenarios.

As tools for resource depletion evaluation, different environmental impact assessment methods were analyzed. Based on the requirements of the research, criticality of materials was incorporated in new indicators built for evaluation of impacts of data center components. These indicators are formulated based upon existing methodologies and on criticality of materials as per the definition of the European Union.

The data available for LCA modelling of datacenter components existing in environmental databases and on published literature presented low quality to fit the purposes of this research, as the existing information did not fit the purpose and data quality goals. Improvements to this data needed to be made. After first assessments, it resulted that most of the improvements need to be done on the information for manufacturing and on the information on material composition of printed circuit boards, their individual electronic components, and on the inventories of IT devices such as servers and storage units. The updating of this information was done via laboratory tests for the analysis of material content, and on updated BoM for specific devices. To couple this information, case studies were made on data centers operating in northern Germany, whose inventories were gathered to establish models that can allow evaluation of their embodied resource consumption.

Once updated information on material content was gathered, EoL models were built to consider different scenarios for recovery of materials. The various stages of EoL were studied and the technologies for preprocessing and for metal recycling were analyzed. Inventories for models of industrial and experimental metal recycling technologies were built. The goal was to establish different routes for recycling and to analyze which EoL steps have the most influence on the mitigation of environmental impacts through recycling.

As a tool for model building, for data and results saving, and for evaluation and analysis of results of the impact assessment, an information system linking databases, model creation and calculation applications, and results evaluation scripts was built. This allows linking the information on BoM and on manufacturing on components, creating LCA process models based on this information, and performing calculation for the evaluation of different impacts. Results saved on databases can then be evaluated via scripting. The construction of this system was made using a traditional software development methodology, where requirements were gathered from the research objectives, an architecture was build based on performance and usability, and opensource software and packages were use across the development for implementation. The evaluation of the software is done via the assessment of the fulfillment of the requirements previously established.

Results evaluation was done by use of the previously mentioned information system, and with the goal of answering the research questions first established. Impact assessment indicators were selected first for evaluation. These indicators were used to evaluate environmental impacts of data centers, devices, modules, and components, including evaluation specific raw material gathering impacts and evaluation of the potential benefits of recycling and recovery of materials. An analysis of correlations between the resulting indicators allowed to evaluate the appropriateness and representativeness of said indicators to answer the research questions. Evaluation of resulting data quality and Monte Carlo simulation results allowed to investigate the improvements on data quality obtained.

8.1. Results and scientific contributions

The results obtained via the developed application were evaluated according to the research objectives in Chapter 7. Results regarding indicator evaluation highlighted the importance of considerations of criticality during assessment of resource depletion, and on the limitations of existing indicators that either omit these factors or completely overlook certain critical materials. The indicators developed are suited not only for the case of data centers, but also to evaluate any technology where the use of materials comes into question. A further example of the application of these concepts in the domain of environmental sustainability of electromobility has already been published by the author [Pe22].

Results regarding specific impacts for raw material gathering were first required as basis for evaluation of the impacts of manufacturing and later recovery of different components. For this, much of the information on raw material processes on the existing environmental databases had to be updated or new processes entirely created for specific materials initially absent from the databases. This resulted in an updated database for raw material gathering and production, which includes updated information on process impact allocation based on economic factors. This assessment of the impacts of critical materials goes in hand with the current requirements of the EU framework for Critical Raw Materials [EC23a].

The evaluation of results on the models for data centers, devices, modules, and components gave an overview of the linkage between different indicators. The relevance of components such as Integrated Circuits and RAMs is first recognized, which can reach orders of magnitude higher specific impacts than other components. This translates to a higher specific importance of electronic parts such as PCBs and memory units. Most of the material depletion impacts come from the use of precious metals, platinum group metals, and metals such as tantalum and neodymium. Whereas a link can be identified between different indicators commonly reported, such as greenhouse gas emissions and abiotic depletion potential, some impacts such as supply risk are often decoupled of energy related impacts such as primary energy use. This, to a lesser extent, can be seen for Economic Importance related impacts. This decoupling highlights the importance of presenting separate indicators to remark these two aspects of resource depletion. The methodology applied allowed to evaluate data centers at different granularity levels, so that key contributors to impacts under various categories can be identified, as exemplified in the Sankey diagrams for impacts contributions. The resulting Life Cycle Inventories are then created and can be further used to evaluate environmental impacts of other data centers. Testing with mock-up configurations verified the viability of the application of the inventories here developed, and later use in case studies showed their use for resource impact assessment of existing facilities.

Using recovery and process efficiency factors for various stages of EoL, different scenarios were created to evaluate the benefits of recycling. For this, it was first necessary to develop recycling inventories for modules, devices, and data centers, which consider how much recyclable components are contained, and which recovery processes are connected to each component recycling flow. This required first a compilation and inventorization of recycling processes, which serves for evaluation of recovery potential of any electronic component. Different models and scenarios were combined to evaluate recycling strategies. As a result, most of the potential benefits of EoL management recovery can be lost in improper preprocessing, where most of the material can be lost. Recycling shows limited benefits on avoidance of primary energy consumption and greenhouse gas emissions due to use of secondary mineral sources instead of primary ores but is clearly advantageous when considering savings on avoidance of depletion of critical minerals. This analysis is of use when evaluating the advantages of different recycling strategies and serves to stress the importance of recycling methods under development. Additionally, the benefits of a correct pretreatment process are here highlighted and can serve as basis for policy development on EoL management.

The value of the contributions presented here is reflected in the data quality of the results, which reflects the improvements of the results obtained through this work. The inclusion of the analysis of data quality is an aspect commonly omitted in LCA studies, mostly due to time constraints and to the complexity of the execution of this analysis. The inclusion of an analysis of inventory and results data quality in general improves any LCA study. The use of the methodology presented here is advantageous to the improvement of the quality of this work.

An important contribution comes with the developed tools created and adapted for model building and calculation. A key advantage is the use of open-source LCA software, which allowed the creation of applications for model building and for calculation of environmental impacts. This accelerated the development of this study. The use of further open-source tools for data and results saving, and for results postprocessing and visualization was a key component of this dissertation, since the amount of gathered and generated data demanded the use of automation for calculations and results analysis. The creation of these tools followed the software development process, whose implementation allowed the obtainment of the stablished research goals.

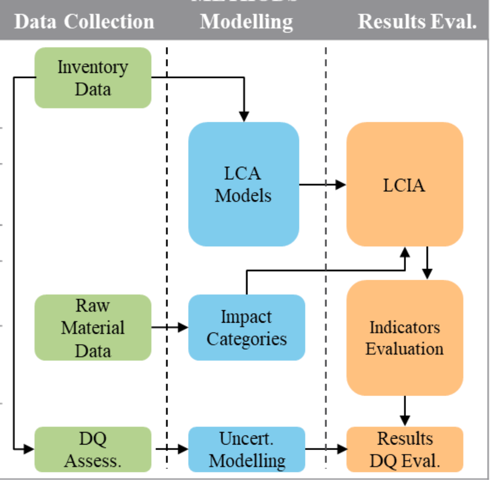
8.2. Gap closing and research questions

Key aspect to the evaluation of the achievements of this work is on the gap closing. First presented in **Table 1-1**, the various aspects regarding attempted gap closing were formulated, and gaps were identified based on existing literature reviews and on current methodologies. Regarding the gap closing, different methods were applied to close these gaps in the context of a Life Cycle Assessment study (Table 8-1). The updated inventoried data consists of material data, bills-of-materials, and data center inventories, which are used to build LCA process chains for modelling. The raw material data is an update on the existing environmental databases which includes production of metals previously absent from the database. The data quality assessment is a semi-quantitative valuation following the pedigree matrix methodology. The LCA models were created for different granularity levels of data centers and their components. Impact categories include traditional methods and newly created methods that focus on critical material resource depletion. Uncertainty modelling is based on the propagation of uncertainty methods and on transformation of qualitative to quantitative assessment. Life Cycle Impact Assessment on the developed models was conducted using the mentioned categories to obtain results to evaluate material and energy resource depletion of product systems. The evaluation of these results allows studying the interdependencies of these indicators via a study of correlations of results. Finally, the quality of these results was evaluated by means of the data quality assessment and by using Monte Carlo simulations. The applied methodology was used to answer the secondary research questions on indicators selection, benefits of EoL strategies, and on data quality. This allowed to evaluate the material and energy demands of existing data centers and to provide a baseline for future evaluation of urban mining potential from these sources.

Table 8-1: Attempted gap closing and methods applied.

	Concept	Thesis Objectives
Data Sources/ Inventories	Parts/Devices Composition Data	Update from Lab Analysis Disassembly Data Data Center Inventory Data
	Embodied Energy	LCA modelling
	Raw Material Consumption	LCA modelling, updated material data
	Material Recovery	LCA modelling for material recovery
Indicators	Indicators for Energy Consumption	Cumulated Energy/Exergy Demand GHG Emissions, …
	Indicators for Material Consumption	Depletion Potential Critical Material Consumption Indicators
Data Qual	DQ Assessment	DQ Assessment Uncertainty modelling

METHODS



8.3. Limitations of this work

The models created and the software built were developed based on the obtainment of the research objectives derived from the research questions. The models built follow the framework established at the beginning of this work, where the focus was on evaluation of material and energy demands for a specific application in the IT sector. The indicators constructed were designed independent of the application constructed, but this has been formulated using concepts of criticality built for the European Union [EC20b]. Thus, their understanding must be achieved within this framework. Expansion to other regions is possible but has not been formulated and would require reassessment of criticality in other contexts and on the adjustment of the resulting factors.

The models developed refer to data centers, subsystems, devices, modules, and components. Further devices were not considered, and thus not present in the resulting LCI databases. The models built correspond to decommissioned devices, and the quality of data for their representativeness was assigned accordingly to indicate a phasing on temporal correlation. The models of devices and modules, which were then considered as “reference” may not be representative for future technological developments. Moreover, for other process flows (such as manufacturing energy or other resource demands) proxy data from the environmental databases were used. Though these data can be improved by obtaining first-hand manufacturing data, this aspect was out of the scope of the research and remains a point which has improvement potential. Although this point may not present a strong influence on the results regarding material demand, the prevalence of fossil fuels in the energy mixes can suggest a strong influence on the results for impact indicators for primary energy demand and on greenhouse emissions. This is reflected in the quality of the results for these energy-related indicators, where limited improvements in data quality were obtained.

Furthermore, the recycling models were developed using literature data obtained from publications which assessed one or more existing facilities. Other processes were done by using escalated experimental data on technologies under development. These models, while providing a solid basis for comparison and scenario evaluation, need to be refined if the processes are scaled to industrial and mature levels. The positive results found for experimental technologies may be used to justify further development of these and to include them in EoL strategies.

Finally, while the evaluation of the software developed showed that the implemented solution works for the achievement of the research objectives, the potential application to other case studies remains limited due to the structure of the databases, which was built to reflect the architecture of a data center and its subsystems. However, the same principles for building said solutions may apply to another domain, and similar solutions can thus be developed for sectors such as construction or manufacturing. A limit on the capacities of this work was also found while performing calculations, as time and computational resources limitations made it feasible to perform Monte Carlo analysis for a limited number of product systems, which were selected on basis of representativeness and material concentration.

8.4. Reflection on the methodology

Life Cycle Assessment as a scientific methodology provides several advantages, including the required transparency of the data collected, the possibilities to evaluate impacts on different areas of protection, and the quantitative nature of the results. This makes it suitable to evaluate issues regarding primary energy and material demands, since the inclusion of raw material gathering in the product manufacturing process chains, and the possibility of including avoided raw material production in the EoL models, make it possible to evaluate aspects concerning energy savings and material efficiency coming from recycling strategies. Its iterative nature makes it suitable to be continuously improved until reaching the desired results quality.

Challenges were recognized first regarding quality of data sources. The modelling process and results evaluations is in general a very data-intensive and time-consuming process, and more challenging when the available environmental databases have processes that are outdated and representing completely different technologies. Very few information regarding data center inventories and material content of their components is available. The methods for assessing this issue, namely laboratory analysis on material content, disassembly, and inventorization of operating data centers, were executed in cooperation with partnering research institutes and companies, and thus of high value to the obtainment of research goals. This provided a unique case where the data obtained is of the highest quality.

Methodologies for evaluation of data quality are based on qualitative valuation methods, since for many of the process flows evaluated no information on uncertainty factors was available. Thus, the evaluation of results quality is dependent on the methodology for data quality assessment selected and on the process background information. However, an improvement in the data sources is translated into an improvement in the results quality, as observed on the evaluated uncertainty for product systems, especially for the material-related impacts.

LCA as a method also requires an interdisciplinary approach, since knowledge on the system under study is also required, and additional input from different areas was needed to formulate models through the different stages of the lifecycle of the products under study. Information from various disciplines, such as IT devices and components manufacturing, data center architecture, and recycling technologies suitable for waste electrical and electronic equipment, had to be harmonized. Moreover, the data-intensive nature of this study constituted the main reason for the development of an information system as presented in Chapter 6, which was developed using principles of software development, which was evaluated upon the fulfillment of requirements derived from this thesis objectives.

In the context of this work, the results obtained of demand of material and energy resources for data center present a first basis for the evaluation of the material needs for the further development of data center sector, which is under continuous growth. The high quality of the results on material consumption means that the methodology can be applied to assess present and future demands, and strategies for mitigation of scarcity of critical materials.

8.5. Future work

Future development of the topics presented in this study arise from limitations found and from the methodology used. First, the evolving nature of the global supply and demand of materials and of material uses in different areas means that the criticality indicators are constantly evolving, as already observed in previous criticality reports presented by the European Union [EC17, EC20]. This means that a constant update of the criticality values is expected, and thus a periodic update of the developed methods is periodically required.

As previously mentioned, the constructed indicators were already used to evaluate sustainability of material use of other technologies. Further work can include use of these impact assessment methods to keep evaluating critical material depletion of other technological sectors known for the high content of critical materials, such as the energy sector. This can, for example, provide interesting insights into the amounts of emissions saved and relate them to the depletion of critical minerals consumed for manufacturing of energy technologies.

The IT hardware manufacturing sector is one of fast paced development and technological improvement. This means that temporal correlations with process models chains degrade quicker, and the resulting models here constructed may be obsolete in future applications. Thus, a continuous update of the material content information and of the manufacturing process databases is required to keep the relevance of this study. Similarly, the growing trend to build bigger datacenters with ever-growing computing capacities means a continuous grow on products such as servers and storage devices, which translates to higher material demand. Hence, incorporating this kind of study to provide a holistic sustainability evaluation of this sector is of growing interest at a regional level.

Models for recycling and recovery were done within the scope of recycling of high-grade WEEE coming from EoL devices from data centers. The inventories and models were built based on process information for recovery of these type of devices. However, the methodologies here used can be replicated to evaluate recycling of other types of WEEE, where more information on material content and on existing industrial process exists. This can use a similar framework as the one here presented and can be expanded to include more areas of WEEE and expand the analysis of urban mining potential.

While the information system was developed and tested locally, the implementation of this as a tool for evaluation of data centers was proposed by the author in [Pe21]. The developed architecture was built using a layered architecture, and expansion to present a user interface is feasible. This can allow it to be deployed as a tool for quick assessments that provides initial information on material content and recycling potential, but further concerns on data privacy and data security need to be considered.

The evaluation of results is limited to the devices and to the data centers under study, and extrapolations were excluded since these were out of scope. The use of the methodologies developed in this work, combined with statistical evaluations on existing data centers, on their infrastructure, and on current trends on the data center sector, can allow to obtain regional results on material end energy demands for manufacturing on data center components, evaluate potentials of urban mining, and on recovery and recycling strategies to assess and improve the sustainability of raw material consumption within the European Union, aligned with current proposed frameworks for the Union [EC22, EC23a, EC20a].

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Annex 1

Lists of symbols and abbreviations

Table A1-1: List of abbreviations

Symbol	Meaning
AADP	Anthropogenic Stock Extended Abiotic Depletion Potential
ADP	Abiotic Depletion Potential
ADP-M	Abiotic Depletion Potential of Minerals
API	Application Programming Interface
BIM	Building Information Modeling
BoM	Bill-Of-Materials
CED	Cumulated Energy Demand
CED	Cumulated Energy Demand
CEENE	Cumulative Exergy Extraction from The Natural Environment
CExD	Cumulated Exergy Demand
CExD	Cumulative Exergy Demand
CMD	Cumulated Material Demand
CPUs	Central Processing Unit
CRM	Critical Raw Materials
CWADP	Criticality Weighted Abiotic Depletion Potential
DAO	Data Access Objects
EDIP	Environmental Development of Industrial Products
EEE	Electrical and Electronic Equipment
EI	Economic Importance
EoL	End-Of -Life
FDP	Fossil Fuel Depletion Potential
GPSR	Geo-Political Supply Risk
GS	Global Supply
GSD	Geometric Standard Deviation
GUI	Graphical User Interface
GWP	Global Warming Potential
HDD,	Hard Disk Drive
HHI	Herfindahl-Hirschman Index
HREE	Heavy Rare Earth Elements
HVAC	Heat, Ventilation, And Air Conditioning
ICP-OES	Inductively Coupled Plasma - Optical Emission Spectrometry
IR	Import Reliance
IT	Information Technology
JDE	Java Development Environment
KDE	Kernel Density Estimate
LCA	Life Cycle Assessments
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
LREE	Light Rare Earth Elements
MDP	Metal Depletion Potential
MFA	Material Flow Analysis
MRD	Mineral Resource Depletion
MRE	Material Reuse Effectiveness
MRQ	Main Research Question
MRR	Material Reclamation Ratio
PCB	Printed Circuit Boards
PDU	Power Distribution Units
PGM	Platinum Group Metals
RAM	Random-Access Memory
REACH	Registration, Evaluation, Authorization, And Restriction of Chemicals
RoHS	Restriction of Hazardous Substances in Electrical and Electronic Equipment

SCP	Sustainable Consumption and Production
SDG	Sustainable Development Goals
SQL	Structured Query Language
SR	Supply Risk
SRQ	Secondary Research Questions
SSD	Solid State Drive
TEMPRO	Total Energy Management for Professional Data Centers
UPS	Uninterruptible Power Supply
WEEE	Waste Electrical and Electronic Equipment
WGI	Worldwide Governance Indicator

Table A1-2: Symbol of chemical elements

Symbol	Name	Symbol	Name	Symbol	Name
Ag	Silver	**Hf**	Hafnium	**Re**	Rhenium
Al	Aluminium	**Hg**	Mercury	**Rh**	Rhodium
Au	Gold	**Ho**	Holmium	**S**	Sulphur
B	Boron	**In**	Indium	**Sb**	Antimony
Ba	Barium	**Ir**	Iridium	**Sc**	Scandium
Be	Beryllium	**K**	Potassium	**Se**	Selenium
Bi	Bismuth	**La**	Lanthanum	**Si**	Silicon
Br	Bromine	**Li**	Lithium	**Sm**	Samarium
Ca	Calcium	**Lu**	Lutetium	**Sn**	Tin
Cd	Cadmium	**Mg**	Magnesium	**Ta**	Tantalum
Ce	Cerium	**Mn**	Manganese	**Tb**	Terbium
Co	Cobalt	**Mo**	Molybdenum	**Te**	Tellurium
Cr	Chromium	**Na**	Sodium	**Ti**	Titanium
Cu	Copper	**Nb**	Niobium	**Tl**	Thallium
Dy	Dysprosium	**Nd**	Neodymium	**Tm**	Thulium
Er	Erbium	**Ni**	Nickel	**V**	Vanadium
Eu	Europium	**Os**	Osmium	**W**	Tungsten
Fe	Iron	**Pb**	Lead	**Y**	Yttrium
Ga	Gallium	**Pd**	Palladium	**Yb**	Ytterbium
Gd	Gadolinium	**Pr**	Praseodymium	**Zn**	Zinc
Ge	Germanium	**Pt**	Platinum	**Zr**	Zirconium

Table A1-3: Data Center KPIs.

Symbol	Name	Unit	Area
APC	Adaptability Power Curve	Ratio	Facility
CADE	Corporate Average Data Center Efficiency	Percentage	Facility
CPE	Compute Power Efficiency	Percentage	Facility
DCA	DC Adaptability	Ratio	Facility
DCcE	Data Center Compute Efficiency	Percentage	Server
DCeP	Data Center Energy Productivity	UW/kWh	Facility
DCiE	Data Center Infrastructure Efficiency	Percentage	Facility
DCLD	Data Center Lighting Density	kW/ft2	Facility
DCPD	Data Center Power Density	kW/Rack	Rack
DCPE	Data Center Performance Efficiency	UW/Power	Facility
DC-FVER	Data Center Fixed to Variable Energy Ratio Deployed	Ratio	Facility
DH-UE	Hardware Utilization Efficiency	Percentage	Server
DH-UR	Deployed Hardware Utilization Ratio	Percentage	Server
DPPE	Data Center Performance Per Energy	Ratio	Facility
DWPE	Data Center Workload Power Efficiency	Perf/Watt	Server
EES	Energy Expenses	Ratio	Facility
EWR	Energy Wasted Ratio	Ratio	Facility
H-POM	IT Hardware Power Overhead Multiplier	Ratio	IT
ITEE	IT Equipment Energy	Cap/kW	IT
ITEU	IT Equipment Utilization	Percentage	IT
OSWE	Operating System Workload Efficiency	OS/kW	Facility
PDE	Power Density Efficiency	Percentage	Rack
PEsavings	Primary Energy Savings	Ratio	Facility
PUE1-4	Power Usage Effectiveness Level 1-4	Ratio	Facility
PUEscalability	Power Usage Effectiveness Scalability	Percentage	Facility
pPUE	Partial Power Usage Effectiveness	Ratio	Facility
PpW	Performance per Watt	Perf/Watt	Server
ScE	Server Compute Efficiency	Percentage	Server
SI-POM	Site Infrastructure Power Overhead Multiplier	Ratio	Facility
SPUE	Server Power Usage Efficiency	Ratio	Facility
SWaPe	Space, Watts and Performance	Ratio	Rack
TUE	Total-Power Usage Effectiveness	Ratio	Facility
AEUF	Air Economizer Utilization Factor	Percentage	HVAC
CoP	Coefficient of Performance Ensemble	Ratio	Facility
DCCSE	Data Center Cooling System Efficiency	kW/ton	HVAC
DCSSF	Data Center Cooling System Sizing Factor	Ratio	HVAC
EER	Energy Efficiency Ratio	Ratio	Facility
HSE	HVAC System Effectiveness	Ratio	HVAC
RI	Recirculation Index	Ratio	HVAC
WEUF	Water Economizer Utilization Factor	Percentage	HVAC
CO2-R	CO2 Savings	Ratio	Facility
CUE	Carbon Usage Effectiveness	KgCO2/kWh	Facility
EDE	Electronics Disposal Efficiency	Percentage	Facility
ERE	Energy Reuse Effectiveness	Percentage	Facility
ERF	Energy Reuse Factor	Percentage	Facility
GEC	Green Energy Coefficient	Percentage	Facility
GUF	Grid Utilization Factor	Percentage	Facility
MRR	Material Recycling Ratio	Percentage	Facility
Omega	Water Usage Energy / v	Ratio	Facility
TCE	Technology Carbon Efficiency	CO2/kWh	Facility
TGI	The Green Index	Ratio	Facility
WUE	Water Usage Effectiveness	Liters/kWh	Facility
ACE	Availability, Capacity, and Efficiency Performance Score	Ratio	HVAC
CPU	Central Processing Unit Usage	Percentage	Server
DCP	Data Center Productivity	Useful work/Watt	Facility
DEEPI	Data Center Energy Efficiency and Productivity Index	Prod./Watt	Facility
DR	Dynamic Range	Ratio	Server
EP	Energy Proportionality	Ratio	Server

FpW	Flops per Watt	Float. ops/Joule	Server
IPR	Idle-to-peak Power Ratio	Ratio	Server
LD	Linear Deviation	Ratio	Server
LDR	Linear Deviation Ratio	Ratio	Server
PG	Proportionality Gap	Ratio	Server
SWaP	Space, Watts and Performance	Ratio	Facility
UDC	Data Center Utilization	Percentage	Facility
Userver	Server Utilization	Percentage	Server
UCF	Uninterruptible Power Supply Crest Factor	Ratio	UPS
UPEE	Uninterruptible Power Supply Energy Efficiency	Percentage	UPS
UPF	Uninterruptible Power Supply Power Factor	Ratio	UPS
UPFC	Uninterruptible Power Supply Power Factor Corrected	Ratio	UPS
USF	Uninterruptible Power Supply Surge Factor	Ratio	UPS
AirEff	Airflow Efficiency	W/cfm	Facility
BPR	Bypass Ratio	Ratio	Facility
BR	Balance Ratio	Ratio	Facility
CI	Capture Index	Percentage	HVAC
DC_T	Data Center Temperature	C or F	Facility
DP	Dew Point	C or F	Facility
HF	Heat Flux	W/m2	Facility
IoT	Imbalance of Temperature	Percentage	Server
D2	Mahalanobis Generalized Distance (D2)	Unit	Facility
M	Mass Flow Mc, Mn, Mbp, Mr, Ms	cfm	Facility
RCI	Rack Cooling Index	Percentage	Rack
RH	Relative Humidity	Percentage	Facility
RHI	Return Heat Index	Ratio	Facility
RR	Recirculation Ratio	Ratio	Facility
RTI	Return Temperature Index	Percentage	Rack
SHI	Supply Heat Index	Ratio	Facility
bindex	b-index	Ratio	Rack
BJC	Bits per Joule Capacity	bits/joule	IT
CNEE	Communication Network Energy Efficiency	Joule/bit	IT
DS	Diameter Stretch	Ratio	IT
ECR-VL	Energy Consumption Rating Variable Load	Watts/Gbps	IT
NPUE	Network Power Usage Effectiveness	Ratio	IT
NPkW	Network Traffic per Kilowatt-Hour	Bits/kWh	Facility
PS	Path Stretch	Ratio	IT
RSmax	Maximum Relative Size	Ratio	IT
TEER	Telecommunications Energy Efficiency Ratio	Ratio	IT
Unetwork	Network Utilization	Percentage	IT
Sto	Capacity	GB/Watt	Storage
LSP	Low-cost Storage Percentage	Percentage	Storage
MemU	Memory Usage	Ratio	Storage
OSE	Overall Storage Efficiency	Ratio	Storage
RT	Response Time	Milliseconds	Storage
SU	Slot Utilization	Percentage	Storage
B/s	Throughput	Bytes/second	Storage
Ustorage	Storage Usage	Percentage	Storage
ACPR	Average Comparisons Per Rule	Count	IT
AS	Accessibility Surface	Count	IT
ATR	Application Transaction Rate	Bits/sec	IT
CC	Concurrent Connections	Count	IT
CER	Connection Establishment Rate	Connections/sec	IT
CTR	Connection Tear down Rate	Connections/sec	IT
DeD	Defense Depth	Count	Facility
DeP	Detection Performance	-	IT
DTE	Data Transmission Exposure	Count	IT
FC	Firewall Complexity	Ratio	IT
HTTPR	HTTP Transfer Rate	Bits/sec	IT
IAS	Interface Accessibility Surface	Count	IT
IPFH	IP Fragmentation Handling	-	IT

b/s	IP throughput	Bits/sec	IT
ITH	Illegal Traffic Handling	Percentage	IT
LAT	Latency	Milli-seconds	IT
RA	Rule Area	Count	IT
RC	Reachability Count	Count	Facility
RCD	Rogue Change Days	Days	IT
T	Vulnerability Exposure	days	IT
BVCI	Business Value of Converged Infrastructure	Dollars	Facility
CapEx	Capital Expenditure	Dollars	Facility
CCr	Carbon Credit	Tons of Carbon	Facility
MTBF	Mean Time Between Failures	Hours	Facility
MTTF	Mean Time to Failure	Hours	Facility
MTTR	Mean Time to Repair	Hours	Facility
OpEx	Operational Expenditure	Dollars	Facility
ROI	Return On Investment	Ratio	Facility
TCO	Total Cost of Ownership	Dollars	Facility
R	Reliability	Faults/Hour	Facility

Annex 2

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