January 2015

Data Representation Methods For Environmentally Conscious Product Design

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PURDUE UNIVERSITY
GRADUATE SCHOOL
Thesis/Dissertation Acceptance

This is to certify that the thesis/dissertation prepared

By DEVARAJAN RAMANUJAN

Entitled
DATA REPRESENTATION METHODS FOR ENVIRONMENTALLY CONSCIOUS PRODUCT DESIGN

For the degree of Doctor of Philosophy

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Head of the Departmental Graduate Program Date

DATA REPRESENTATION METHODS FOR ENVIRONMENTALLY CONSCIOUS PRODUCT DESIGN

A Dissertation

Submitted to the Faculty

of

Purdue University

by

Devarajan Ramanujan

In Partial Fulfillment of the

Requirements for the Degree

of

Doctor of Philosophy

December 2015

Purdue University

West Lafayette, Indiana

I would like to dedicate this thesis to my grandfather T.E. Alagiasingan. Your teachings will always guide me.

ACKNOWLEDGMENTS

Foremost, I would like to express my gratitude to my advisor Dr. Karthik Ramani for helpful discussions and guidance throughout the duration of this work. I am thankful to have a played a part towards realizing his vision for the future of design.

I would like to thank Dr. Fu Zhao and Dr. John Sutherland for helping shape my thoughts related to environmental sustainability and their helpful suggestions. I would like to thank Dr. Niklas Elmqvist for his guidance and valuable feedback. My sincere thanks to Dr. Dave Anderson and Dr. Shreeram Abyankar for insightful discussions. They exemplify the values an educator seeks to impart in their students. I would also like to thank Dr. Monica Cardella, Dr. Tahira Reid, Dr. Mikko Koho, Dr. Jitesh Panchal, and Dr. Devadatta Kulkarni for their guidance and help.

I would like to acknowledge National Science Foundation for supporting this work through grants CMMI 1100619, CBET 1512217, DGE 1144843, and EEC 0935074. Part of this thesis was done in collaboration with the TCS Cincinnati Innovation Lab.

I would like to thank my parents and my family for their support and encouragement. Paati, Kal, Anu, Rama, and Raji chitti – you are the best. Thanks to all my friends and colleagues in the C Design lab, especially Cecil, Bill, Senthil, Sujin, Sundar, Vinayak, and William. I would also like to thank my roomies, Arun, Vineet, Sriram, and Sidharth for their support. My thanks to Praveen, Arun, Smita, Lalitha and all my friends and well wishers. To us!

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ABSTRACT

Ramanujan, Devarajan. Ph.D., Purdue University, December 2015. Data Representation Methods for Environmentally Conscious Product Design. Major Professor: Karthik Ramani, School of Mechanical Engineering.

The challenge of holistically integrating environmental sustainability considerations with design decision-making requires novel representations for design and sustainability-related data that allow designers to understand correlations among them. Challenges such as (1) lack of suitable data & information models, (2) methods that simultaneously consider environmental sustainability as well as design constraints, and (3) uncertainty models for characterizing subjectivity in environmental sustainability-based decision making, pose serious impediments towards this goal.

A wide body of previous research has focused on developing computational methods for modeling environmental impacts and indicators for products and processes. However, a significant majority of these methods stop short of providing a decision-making framework based on the calculated metrics. Additionally, most of these methods are built from the stand point of an environmental sustainability expert. They stop short of creating data representations that contextualize this information to designers and other stakeholders in product lifecycle management. Such gaps create a significant cognitive barrier which can prevent decision makers from integrating environmental sustainability considerations within product design. Imminent regulations that limit the environmental impact of products and services will compound these knowledge gaps as decision makers will begin utilizing existing tools without a well defined understanding of assessment results. More importantly, only using assessment-focused tools prevents decision makers from developing insights about correlations between environmental impact indicators and design parameters. Without this understanding, designers cannot apply findings from environmental assessment to design

processes. Addressing these gaps necessitates methods for representing environmental sustainability data in a manner that makes it congruent to the design process. To this end, this thesis explores (1) novel data representations, (2) decision-making methods, and (3) exploration-support tools that facilitate integration of design and environmental sustainability-related parameters for eco-conscious product design.

We start our discussion by looking at existing tools and methods for integrating environmental sustainability assessment within product design. Next, we discuss decision-making models for eco-conscious design and methods for evaluating uncertainties in this context. Following this, we make the case for information visualization-based tools for environmentally conscious exploration of design alternatives. A consistent theme within this thesis is translating learnings from research into educational and industrial practice. Realizing a more sustainable world requires training engineers and students in concepts of decision-making for environmental sustainability. Along these lines, we conclude the thesis by discussing a guided discovery-based instruction framework for teaching environmental sustainability in existing undergraduate mechanical engineering curricula.

1. INTRODUCTION

1.1 Motivation

Design engineers can make significant contributions to the sustainability challenge by designing products and processes that satisfy societal needs while minimizing the associated environmental consequences. Decisions made at the initial product design phase determine the environmental and economic impacts of future decisions [1]. Therefore, it is critical that engineers shift their focus from meeting cost and performance requirements to a balance of economic, environmental, and societal considerations. This is essential for environmental sustainability practices to transform from end-of-pipe remediation towards an integral part of design and process planning [2–5]. That said, designing products with the objective of minimizing it's environmental footprint is by no means an easy task. Engineered products interact with the environment through energy and material flows at every stage of the lifecycle; from raw materials extraction and acquisition, manufacturing, transportation and distribution, use and maintenance, reuse and recycle, all the way through to disposal and waste management [6]. Figure 1.1 illustrates material and information flows in a traditional product lifecycle. The presence of forward and backward flows in both material and information increases the complexity in the system. This makes environmentally conscious decision-making a particularly challenging task. This is especially true for decisions taken at the design stage as very little information about downstream stages is available. Additionally, current eco-design methods remain incongruent to the design process [7]. An integrated framework for environmentally-conscious design requires additional methods and tools that can translate environmental sustainability assessment to practical design outcomes.

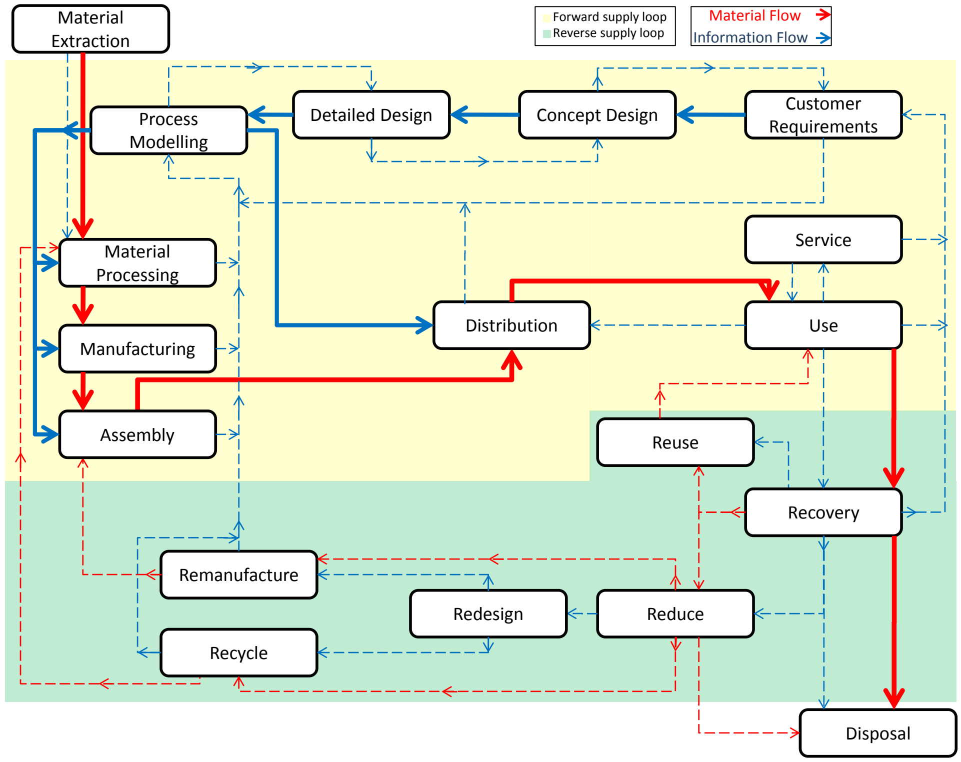

Figure 1.1. Material and information flows in a product's lifecycle [8].

As pointed out by Pugh, the wrong choice of concept in a given design situation can rarely, if ever, be recouped by brilliant detail design [9]. This is also expected to be the case for environmentally-conscious design. Up until now, design methods such as Quality Function Deployment (QFD), functional component analysis, and the Pugh charts have gained prominence in the product design community as a means of developing better products [10]. Unfortunately, decisions based on these tools typically rely on experience, intuition, or at best, a few simplified calculations [11]. As a result, there is a considerable amount of subjectivity introduced into design decisions which makes them being viewed with skepticism. These tools fail when environmental performance is considered as a design factor, since a limited amount of experience and knowledge have been accumulated by the designer. This usually results in designers missing a lifecycle perspective on developed designs [13, 14]. During the past

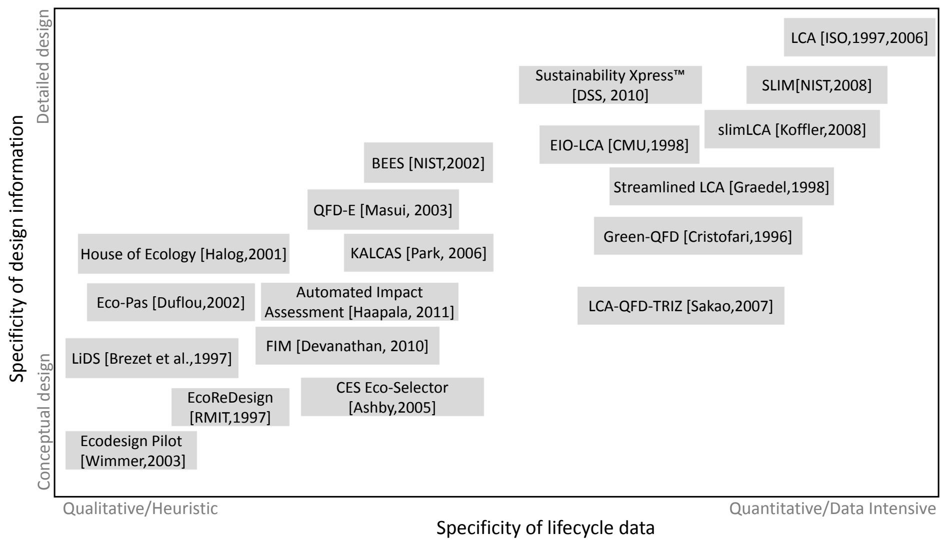

Figure 1.2. Specificity of existing tools for supporting decision making in the context of environmentally sustainable design. The *x-axis* represents the specificity of required lifecycle information for characterizing the environmental performance of the product. The *y-axis* represents the specificity of the design variables characteristic of a particular design stage. This figure is based on a map of existing eco-design tools by Ramani et al. [12]. Please note that the list of eco-design tools is by no means comprehensive.

decade, quite a few eco-design tools have been developed with the aim of remedying the above limitation. Figure 1.2 provides an overview of existing tools for eco-design based on the specificity of lifecycle information required for conducting the environmental assessment and the design stage at which they can be applied. On a coarse scale, these tools can be categorized into various levels based on, (1) the nature of assessment, i.e. qualitative/quantitative, (2) on temporal/spatial scales, and (3) on their integration of environmental, economic and social systems. There are a variety of limitations associated with all the types of existing eco-design tools. Robert et al. [15] suggest that the discontinuity between these various tools has slowed progress towards achieving sustainable development. Moreover, these tools generally take the form of standalone applications, which further limit their use in the design stage of product development. There are some efforts bridging this limitation by integrating various technologies such as, (1) life cycle costing and LCA [16], (2) multi-criteria decision making and LCA [17,18], (3) mathematical decision modeling and constrained optimization approaches [19,20]. However, these methods are limited by the fact that they are usually expert driven, time intensive, and not flexible. Therefore, it is of no surprise that they have achieved limited penetration into design practices within design teaching and the industry [7,21].

Realizing environmental sustainability in a real-world setting requires a shared responsibility towards implementation of product design systems that support collaborative and dynamic knowledge transfer among the involved stakeholders. However, product designers often lack access to reliable data regarding the environmental impacts of products and processes, that are essential for making decisions involving complex trade-offs between competing objectives [22]. Although data gathered for lifecycle impact assessment offers one way to bridge this knowledge gap, problems are often compounded by unfamiliarity with environmental issues among product development personnel. In such a setting, methods and tools which augment the capability of a designer in making the right decisions can prove to be a critical factor for conceiving a sustainable product. This necessitates further research regarding the acquisition, manipulation, representation, and user perception of lifecycle data. Exploration and discovery of lifecycle data offers an untapped potential for product/process innovation as well as resource optimization. This requires simultaneous consideration of environmental as well as business concerns using the concept of multi-criteria decision analysis for selecting relevant design for environment strategies [23].

With the imminent explosion of data through ubiquitous computing and data collection hardware, data intelligence through visualization will become a priority for facilitating eco-conscious decision-making. To meet this need, eco-design tools must shift from being assessment driven towards an enabler for design exploration. This requires novel representations for sustainability-related data that allows results from similar products to be made reusable. These results should be made available to

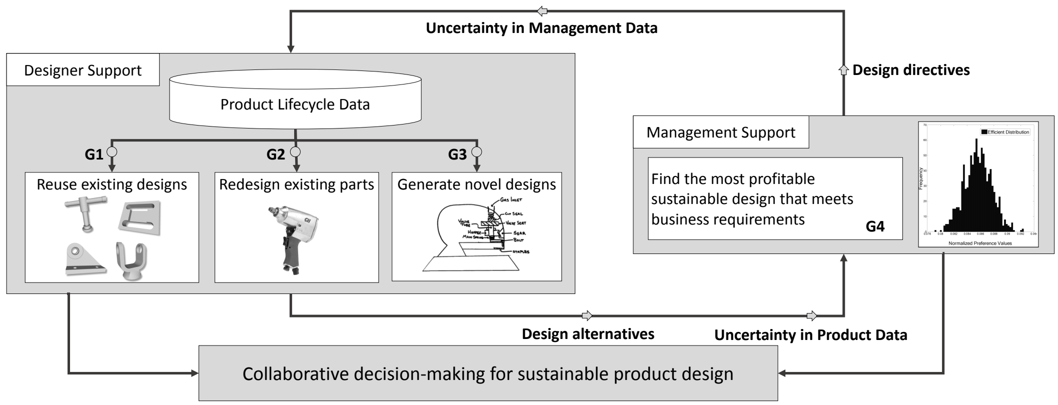

Figure 1.3. The overarching goal of this thesis is to explore representations of product metadata and sustainability related data that can aid design decision-making. This is divided into four goals (G1–G4) that focus on supporting various facets of design decision-making.

designers during critical decision-making stages in conceptual and early embodiment design stages for guiding lifecycle decision-making.

1.2 Research Goals

This thesis discusses methods for representing design metadata and sustainability-related data to aid eco-conscious design decision-making. Figure 1.3 establishes the research goals for this thesis. Our overarching goal is to facilitate eco-conscious product design through integrative decision-making approaches that relate product metadata to environmental sustainability data. For this, we discuss techniques, and create tools for achieving four specific goals:

- *Methods for estimating the environmental impact of parts contained within a design repository (G1):* For this, we discuss the nature of data required for estimating potential indicators of environmental sustainability. Instead of conducting a complete life cycle assessment (LCA), we focus on developing approximate measures which are useful for screening out parts that are significantly impactful. To facilitate exploration of parts within the repository, we quantify part similarity and develop visual representation for these similarity measures and the computed environmental indicator.

- *Methods for assessing the potential for redesign from an environmental sustainability perspective (G2):* For supporting redesign of existing parts, this thesis proposes a method for guiding redesign decisions based on ease of redesign, the business case for redesign as well as potential environmental benefits.

- *Supporting design-decision making with regards to novel product concepts (G3):* For this, we propose a method for representing the environmental of an existing part in terms of its functions. By allocating environmental impact to product functions, the designer can develop a measure of function-impact, useful for guiding the generation of novel embodiments for that product.

- *Balancing business decisions with redesign decisions in the context of eco-design (G4):* To achieve integration of business and sustainability based design decision-making, we propose a decision-making framework that uses results from a life cycle assessment (LCA) along with subjective evaluations by design and management experts. By involving a large majority of the stakeholders in the redesign process, we ensure that the resulting decision has a high likelihood of being successfully implemented.

In all our methods, we explore data representation methods that aid human decision-making in the context of eco-conscious design. The ambiguity and subjectivity involved in design decision-making represents a unique challenge for computation. Also, fully automated decision methods are often too restrictive in a realistic design setting. Although we use computational methods for estimating sustainability indicators, similarity measures, and visualizing the resulting data, they serve to augment and not replace human judgment. Any data representation method needs to account for uncertainty present in the data. Uncertainties in design decision-making arise from ambiguity in product metadata, measurement errors, approximations in lifecycle models, uncertainties in interpreting LCA results, and the subjective nature of the decision-making process. Therefore, a significant portion of this thesis discusses methods for quantifying data uncertainties and techniques for robust decision-making.

1.3 Contributions

In this thesis, we propose:

1. A method for representing uncertainties in environmental impact as well function allocation weights to support conceptual design. Using information gap decision theory, we develop methods for determining the range of uncertainty for which a particular product function has the highest expected utility.

2. A framework for integrating results from life cycle assessment with a multi-criteria decision analysis in order to facilitate rational decision-making with regards to eco-conscious product design. For this, we use a stochastic analytic hierarchy process and quantify the robustness of a redesign decision.

3. An algorithm for estimating cradle-gate environmental indicators based on material, manufacturing, and shape data present in design repositories.

4. An algorithm for estimating part similarity based on material, manufacturing, shape, and function data. By classifying part data using a taxonomy-based description, we facilitate variable levels of data abstraction as well as quantification of pairwise similarities.

5. A visual representation framework that represents computed environmental indicators and product metadata in a manner that aids part retrieval, selection, and design exploration.

6. An information visualization interface that is designed for eco-conscious design exploration of 3D repositories by visualizing similarities in part attributes. A screenshot of this interface is shown in Figure 1.4.

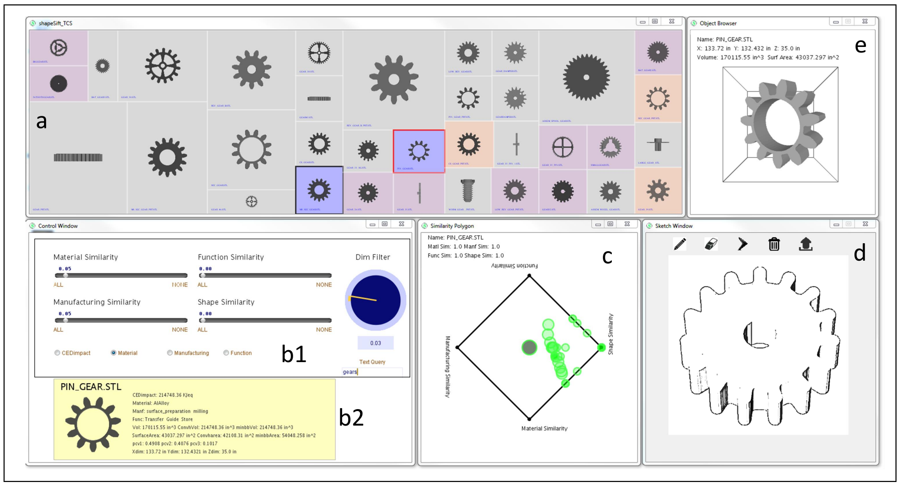

Figure 1.4. A screenshot of the shapeSIFT interface. This interface consists of a squarified layout window that displays the retrieved results (a), a control window with sliders (b1) & labels (b2), a similarity polygon viewer (c), a sketch window (d), and a 3D viewer (e).

7. A guided discovery-based instruction framework for contextualizing sustainability assessment within mechanical engineering curricula. Our approach makes it possible for embedding environmental sustainability-related concepts within traditional engineering courses and facilitates discovery learning among students through iterative design exploration.

We begin this thesis by discussing previous research and state-of-the-art tools for environmentally conscious product design. Chapter 2 introduces the reader to current eco-design tools developed in previous literature and highlights prominent commercially available packages for the same. Chapter 3 extends our understanding of eco-design tools by reviewing background work aimed at providing computational support to the designer in the form of impact estimation methods and decision analysis. Chapters 2 and 3 aim at establishing a foundation in environmentally conscious product design for the reader and expose limitations in current approaches. It is our hope that these chapters will serve to motivate the research that is discussed in the proceeding chapters of this thesis.

2. TOOLS FOR ENVIRONMENTALLY CONSCIOUS PRODUCT DESIGN

The following chapter discusses current eco-design tools by classifying them into three categories: (1) tools based on checklists, (2) tools based on quality function deployment (QFD), and (3) tools based on life cycle assessment (LCA), as suggested in [14]. Following this, we review commercial tools that are aimed at supporting environmental sustainability assessment at the design stage.

2.1 Tools Based on Checklists

Qualitative tools such as checklists are simple, easy-to-use, and therefore are among the tools prevailing in most small and medium size companies [25]. An example checklist for raw material selection provided by the Center for Sustainable Design to electronic manufacturers and suppliers in order to prepare for the European Energy using Products Framework Directive 2005/32/EC is shown in Figure 2.1. A common feature of such tools is the checklist, which is a set of items used for assessing a product from environmental perspective over its entire life cycle. Those items include, for example, "is less energy consumed during the use phase of the product than the existing ones? " or "are less toxic materials used in the product?" [26]. These tools are developed particularly for the early stages of the product development process. Compared with LCA based tools, these tools are much more subjective. The proper use of the tools requires extensive experience and knowledge. Even with that, it remains a challenge when trade-offs exist between different life cycle stages or different environment impacts categories. Moreover, these tools can rarely offer concrete solutions or design strategies.

No	Criteria/attributes	Y	N	N/A	Comments
1	Material Resources: o Weight minimisation o Volume minimisation o Waste generation o Recyclate content o Part reuse				
2	Energy Consumption: o Primary Energy o Electrical Energy o Feedstock o Impact on product use				
3	Water Use: o Process o Cooling				

No	Criteria/attributes	Y	N	N/A	Comments
1	Air Emissions: o Greenhouse gases o Acidifying agents o Volatile organic compounds o Ozone depleting substances o Persistent organic pollutants o Heavy metals o Fine particulate o Suspended particulate matter				
2	Water Emissions: o Heavy metals o Oxygen balance disruptors. o Persistent organic pollutants				

No	Criteria/attributes	Y	N	N/A	Comments
1	Noise Pollution: o Minimise o Legal compliance				
2	Vibration Pollution: o Minimise o Legal compliance				
3	Radiation Pollution: o Avoid o Legal compliance				
4	Electromagnetic Field Pollution: o Minimise				

No	Criteria/attributes	Y	N	N/A	Comments
1	Extraction: o Minimum material waste (RoHS and non-RoHS)				
2	Manufacture: o Minimum machining waste (RoHS and non-RoHS) o Waste from poor quality control (RoHS and non-RoHS)				

No	Criteria/attributes	Y	N	N/A	Comments
1	Reuse: o Material quality suitable for reuse.				
2	Recycling: o Economic for recycling				
3	Material Recovery: o Can be incinerated cleanly				

Figure 2.1. Checklist for raw material selection provided by the Center for Sustainable Design [24] in order to prepare for the European Energy using Products (EuP) Framework Directive 2005/32/EC.

2.2 Tools Based on Quality Function Deployment (QFD)

QFD based tools are typically used to convert customer needs into engineering characteristics while simultaneously improving the quality level of the product. Eco-design tools based on QFD introduce lifecycle environmental impacts of the product into the QFD matrix in the form of customer needs. Examples of QFD based eco-design tools include and are not limited to Quality Function Deployment for the Environment, Green Quality Function Deployment, and House of Ecology [27, 28]. In general, application of these tools starts from collecting both customer needs and environmental needs, and developing correlations between these needs and quality characteristics. A functional analysis is then performed to identify how quality characteristics are correlated with engineering characteristics (including structure or components) and hot spots from both environmental as well as traditional qualities point of views. It can be seen that QFD based tools are significantly different from LCA based tools since the focus here is on the product specification development stage.

One serious drawback of these QFD based tools (similar to traditional QFD) is that the development of correlations between environmental needs and quality and engineering characteristics is totally on designers, and usually the correlations developed are based on knowledge from traditional environmental engineering discipline without the consideration of the entire lifecycle [29].

2.3 Tools Based on Life Cycle Assessment (LCA)

Life cycle assessment (LCA) has emerged as the most objective tool available for evaluating the environmental profile of a product or process [30]. In order to conduct an LCA, detailed product design information is required, which makes it unsuitable for use in early design (when a detailed specification is not available as yet) [31]. This is especially true for novel product designs as information from reference products (previous generation or competitors) is not available. Also, conducting a detailed LCA can be very costly and time consuming. Therefore, only large companies can afford conducting such assessments. There have been some efforts in addressing these issues by developing simplified or streamlined LCA for screening purposes. Even so, these methods tend to ignore environmental impacts from certain life cycle stages, material/energy flows, or impact categories [32, 33]. Recent efforts have been made to implement LCA during the early design phase [34]. Lofthouse [7] describes a web-based framework for eco-design tools, a combination of guidance, education and information, that considers appropriate presentation and easy access. Dewulf et al. [35] present a novel web-based eco-design tool called Eco-PaS. In these methods, uncertainties in early design embodiment (i.e. shape, component interactions, etc.) remain a major obstacle. To what level the fidelity can be maintained remains largely unaddressed. Another serious obstacle associated with applying LCA based tools to early design lies on the fact that inherently LCA is not design-oriented. LCA's are able to associate the environmental cost with regards to a product's structure and bill of materials. This is because the environmental impact of a product is a function

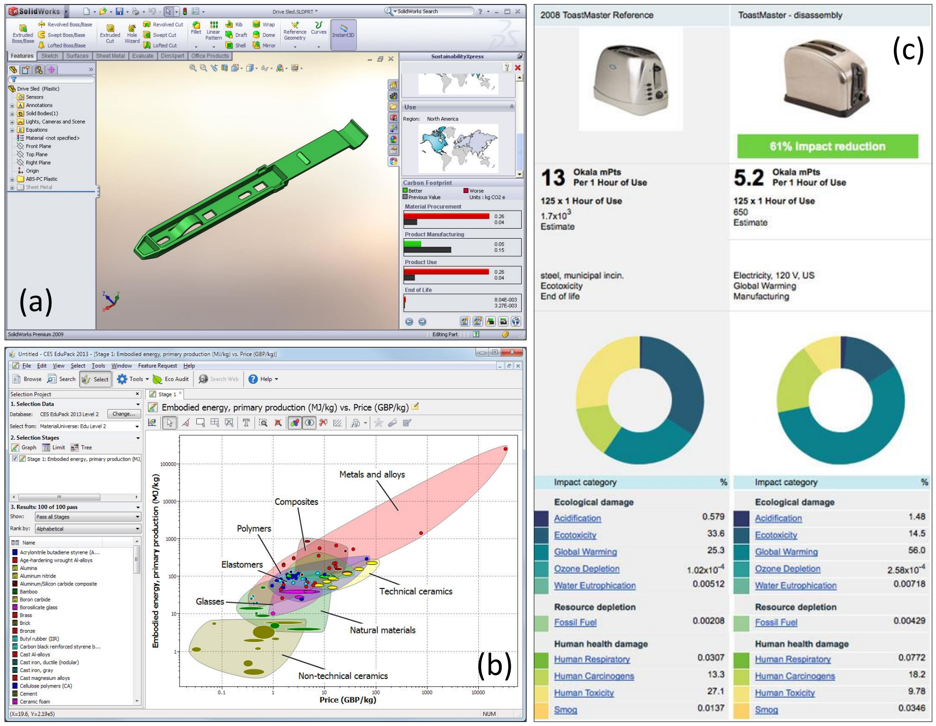

Figure 2.2. A screenshot of commercially available software packages for eco-design. (a) Solidworks Sustainability Xpress™ [36] (b) Granta Design's Eco Audit™ Tool [37] (c) Sustainable Minds® [38].

of a product's embodiment and the processes involved in creating that embodiment. In their current form, LCA's cannot determine the environmental cost of product functions required by a customer or the technologies used to achieve those functions.

2.4 Commercially Available Tools

An area that has a large potential for successfully incorporating environmental sustainability principles into an existing engineering design framework is computer-aided design (CAD) and computer-aided engineering (CAE). Three prominent efforts to embed eco-design within software are SolidWorks Sustainability Xpress™ [36], Granta Design's Eco Audit™ Tool [37], and Sustainable Minds® [38]. Each software, depicted in Figure 2.2, provides designers with distinct advantages. SolidWorks Sustainability Xpress™ estimates environmental impacts associated with the material and manufacturing selections chosen by the user. The software also provides a module that computes the impact associated with transportation based on the geographic location of the manufacturer and the end consumer. This tool is mostly suited for the detailed design stage as complete dimensions, material definitions, and manufacturing details are required to run the simulation. At this level of detail, most design parameters are already fixed. Hence, the tool is mostly useful for benchmarking the impact of the designed product or for guiding minor changes to the design. Exploring alternate design embodiments that can meet the same performance requirements becomes a challenge as a full-scale CAD model for alternatives is necessary. Granta Design's Eco Audit™ Tool leverages Granta's CES Edupack; a material database that has been in development for over fifteen years. It contains detailed datasheets for over three thousand materials. Most materials in this database have estimates for energy consumption (specified in Mega Joules per kilogram of material) and the carbon footprint (kilogram equivalent of CO_2 per kilogram of material) corresponding to material extraction and common manufacturing processes. This tool is mostly relevant for material selection at the design stage and does not offer support in terms of selection of shape, manufacturing processes, or function requirements. Sustainable Minds® provides a refined graphical user interface in which designers can run LCAs and see trade-offs between alternate designs of a product. A step in the right direction, Sustainable Minds® offers the same capabilities as conventional life cycle assessment software such as SimaPro® [39] and GaBi® [40] with more attention towards simplifying user interaction. Apart from the software discussed above, several other commercial CAD and CAE-based tools allow designers to estimate the environmental impacts of their designs at varying levels of fidelity.

2.5 Summary

This chapter has discussed eco-design tools from previous literature as well as commercially available tools. From discussions in this chapter, and as illustrated in Figure 1.2, we can observe that tools developed for early/conceptual design tend to be more subjective due to the lack of detailed product information. At this stage, tools tend to act as guidelines for eliminations significantly impactful options by narrowing the design space. Ideally, such tools should also facilitate or guide designers in exploring the design space of feasible outcomes with the goal of minimizing environmental footprint. Furthermore, a majority of existing tools are aimed at providing an estimation of the environmental impact of the product and offer limited guidance for relating impact to design variables. For this, we have to look at methods that provide computational support at the early design stage with the aim of integrating design and sustainability knowledge. Even these methods are not immune from the fact that, early on in the design stage very little (and often unreliable) information is available about the actual part. Therefore, these methods should use existing and previous design knowledge to extrapolate the environmental impact of a design. In this light, Chapter 3 reviews computational support methods for supporting environmentally conscious product design.

3. COMPUTATIONAL SUPPORT FOR ENVIRONMENTALLY CONSCIOUS PRODUCT DESIGN

Numerous computer-aided methods have been developed with the aim of supporting environmentally conscious product design (ECPD). With regards to ECPD, it is necessary to measure of the environmental impact of a design/part, benchmark the estimated value with other alternatives, and decide on a particular alternative, often while balancing multiple competing objectives. In this light, we discuss previous literature by categorizing them into the following three topics, (1) methods that estimate environmental sustainability indicators for novel designs/parts based on data from existing design/part data, (2) decision analysis methods for interpreting results of life cycle assessments, and (3) representation methods for environmental sustainability data that aid decision-making in design processes.

3.1 Estimating Environmental Sustainability Indicators from Part Data

Previous research for promoting environmentally sustainable design has looked at bridging gaps in lifecycle related information by techniques that leverage implicit knowledge embedded in existing parts. Approaches that are preferred among researchers in this area include, (1) using surrogate measures of environmental impact, (2) developing indices that relate environmental impact to part attributes, and (3) extrapolating impact on the basis similar existing products.

Sousa et al. [41] develop a method for generating approximate life cycle analysis (LCA) metrics through neural networks trained using pre-existing product attributes. On similar lines, a knowledge-based approximate life cycle assessment system (KALCAS) is discussed by Park et al. [42]. KALCAS consists of four modules: (1) a product information module, (2) a product LCA module, (3) a database management system module, and (4) a knowledge-based approximate LCA module. Dewulf et al. [35] discuss Eco-Pas; a methodology that uses *eco-cost estimating relationships* for anticipative weak point analysis of a product's environmental impact. This framework is implemented on web-based application developed using MATLAB® and MS Access®. A design method that correlates estimated life cycle impacts by with product function has been detailed by Devanathan et al. [34]. Herein, the authors develop the *function-impact matrix* that associates impact embodied by a structure to its corresponding function. This allows designers to look at less impactful embodiments for realizing a specific function. Another method for impact estimation based on functional modeling of similar existing products is discussed by Haapala et al. [43]. The advantage offered by this method is that it is automated and therefore scalable to design repositories. Tagged product attributes such as material, manufacturing processes, and mass are used for estimating impact. However, this method does not use information contained in three dimensional part models nor does it allow variable levels of data specification with regards to subjective product attributes such as material or manufacturing processes.

Although the discussed methods develop solutions from a computational perspective, most of them stop short of developing data representations that effectively communicate this data. The process of design inherently deals with decision making that involves people. Therefore, using the right representation for data can significantly alter the quality of the analysis. In this thesis, we posit that integrating meaningful data representation schemes with environmental sustainability assessment can help designers observe covariation among product attributes and enable better decision making for environmentally conscious product design.

3.2 Decision Frameworks for Interpreting Life Cycle Assessment Results

Most of the applications of decision analysis in conjunction with LCA have been confined to the weighting of inventory data issues [44–49]. Few papers, discuss the integration of LCA and multi-criteria decision analysis (MCDA) either for ranking alternative processes or for prioritizing strategies that enable environmentally conscious product design (ECPD) [18, 50–53]. This is primarily due to the fact that LCA has been developed without an explicit link to a specific decision analysis framework. Weil et al. [54] and Xiong et al. [55] address integrating MCDA within the LCA framework whilst considering uncertainties in the input data for robust selection among given alternatives. However, the focus of these papers is not on facilitating decisions in regards to environmentally sustainable product design. Moreover, the expressed preferences in these methods are implicitly assumed to be deterministic, as scenarios with independent evaluations by a group of experts are not accounted for. Whenever multiple decision makers are involved, additional analyses regarding the combined consistency of the group's evaluations and the relative importance of the each specific judgment is required [56]. Kiker et al. [57] present a review discussing applications of different MCDA methods towards eco-conscious decision-making. Previous research also details methods for addressing uncertainty related to product design [58–60], but issues related to ECPD are not considered. Duncan et al. [61] extensively discuss modeling uncertainties for environmentally benign decision making using the information gap decision theory (IGDT). Uncertainties in life cycle inventory and those that arise in the process of applying IGDT for design decision making are considered.

3.3 Data Representation Methods in Environmental Sustainability

The right representation for data can significantly alter the quality of the resulting analysis. The importance of placing data in the right context and allowing decision makers to make quantitative comparisons among them is emphasized by Tufte in [62]. In this section, we specifically review two distinct methods for contextualizing sustainability related data to involved stakeholders, (1) representation methods that contextualize sustainability data by relating them to traditional design variables in a particular domain, and (2) visual representations for sustainability related data aimed towards insight generation.

3.3.1 Relating Environmental Sustainability Indicators to Design

Measures for environmentally sustainability can be leveraged towards redesign tasks, if they are contextualized to a set of related design variables. Dewulf et al. [63] develop eco-cost estimating relationships (E-CERs) which can be used to relate environmental performance indicators to functional requirements and design parameters. The authors also develop environmental impact growth laws for parameterizing impact with regards to a specified design parameter. Huang et al. [64] develop a life cycle performance index based on function, constraint, and objective analysis for the design. In their paper, they also discuss an example application for designing a support plate for an air conditioner. Guidice et al. [65] develop a framework for material selection that integrates the mechanical and environmental performance of parts. Devanathan et al. [34] develop a method for correlating life cycle analysis results with the function descriptions of a given part. This mapping, allows designers to perceive environmental impact in terms of functions to be met and generate more sustainable embodiments for that function.

3.3.2 Visualizations for Enabling Environmentally Conscious Design

Visualization can act as a powerful enabler of environmental conscious design by its ability to make data transparent. This includes means for, (1) generating awareness about specific data, (e.g. consumption patterns, toxicity levels, etc...) (2) facilitating better decision making by emphasizing trends and correlations for sustainability-related data, and (3) making design exploration more intuitive. Creative real-time visualizations that quantify energy consumption and carbon loads have been used to promote resource conservation [66]. Developing meaningful visualization of sustainability indicators presents a challenge due to its high dimensionality. An interface for visualizing the QUEST environmental sustainability model is presented by Munzner et al. [67]. The authors provide insights into the successes and challenges in designing visualization schemes required for engaging communities in environmental policy making. An additional requirement for a visualization scheme applicable to three dimensional repositories is the ability to query and convey shape information. Pousman et al. [68] discuss integration of sustainability related visualizations for paper printing. The primary goal of their work is to motivate conversations among community members. Providing feedback on individual/group behavior for reducing environmental impact is detailed by Froelich et al. [69]. Reducing the energy consumption and carbon load of data centers is discussed by Marwah et al. [70]. The authors provide cases that use visualizations of sensor data (e.g. temperature, power load) to understand trends and anomalies in daily operation.

3.4 Summary

This chapter has discussed computational support for environmentally conscious product design (ECPD). Among them, a large number of methods leverage design knowledge from similar existing designs for estimating the impact of a new design. Automating this process has meant that it is possible to extend these methods to large-scale design repositories. However, most of these methods stop short of developing representations for this data that are useful for decision-making. In this chapter, we have also seen that visualization offers a strong potential for bridging this decision-gap. Design decision-making can potentially benefit from methods that couple data visualization with design exploration. Another important consideration is the lack of a uncertainty framework for quantifying the subjectivity and inaccuracies in both lifecycle data and decision-making processes. Integrating a robust decision-making framework within eco-design tools and related computational methods is necessary for weighing the risk involved with design decisions for ECPD.

Having provided the reader with an understanding of the types, functionalities, and limitations of the current methods/tools for environmentally conscious product design, we proceed to discuss research contributions in this thesis that can potentially address some of the outlined gaps. The proceeding chapters outline our original research contributions and are organized as follows.

Chapter 4 introduces a a novel method for representing environmental impact data at the early design stage. Our method distributes lifecycle environmental impacts across product functions allowing designers to choose alternate, more benign embodiments. This chapter also discusses an uncertainty quantification framework based on Information Gap Decision Theory (IGDT) for robust selection of redesign alternatives. Having discussed a method for representing environmental impact from the perspective of a designer, we look at method for collaborative decision-making among multiple stakeholders in the product lifecycle management process. Chapter 5 discusses a representation method based on the Analytic Hierarchy Process that allows multiple experts (across domains) to communicate redesign preferences and arrive at a common Design for Environment strategy (DfE) for reducing the lifecycle impact of the product. Our method is capable of quantifying uncertainties arising due to disagreements between stakeholders and measure the sensitivity of decision alternatives. The methods discussed in Chapters 4 and 5 are expert driven and are not readily adaptable towards more natural design paradigms that require dynamic collaboration among designers across domains as well as expertise levels. Chapter 6 aims at extending concepts established in the previous chapters by developing a visualization framework for representing sustainability and product data. Our framework focuses on enabling designers to develop insights regarding relationships between sustainability and product attributes through design exploration. Using a more general representation framework allows experts to interpret data from their individual areas of expertise and collaboratively work towards a more benign design. Finally, Chapter 7 presents a guided discovery-based instruction framework for embedding environmental sustainability principles in mechanical engineering curricula.

4. A FUNCTION BASED FRAMEWORK FOR REPRESENTING ENVIRONMENTAL SUSTAINABILITY IN PRODUCT DESIGN

This chapter discusses the function-impact method (FIM), a method for representing environmental impact data in terms of product functions. The FIM uses information from the function-component matrix to distribute life cycle environmental impacts across product functions. The main goal of the FIM is to identify the importance level of each function and determine the functions which should be re-examined to obtain a better design from an environmental perspective. After introducing the FIM, we discuss a novel method that formalizes uncertainties present in FIM-based redesign decision-making. This is achieved by modeling the uncertainties present in life cycle assessment (LCA) and the uncertainties in function-structure affinities using Information Gap Decision Theory (IGDT). Section 4.1 introduces the function-impact method to the reader and discusses the nature of uncertainties associated with the method. Section 4.2 lays the groundwork for uncertainty quantification based on information gap decision theory (IGDT) and its application to sustainable design. Section 4.3 outlines a novel method for estimating the desirability (or opportuneness) of redesigning a particular product function identified through the FIM. Following this, we develop a framework for robust decision making with regards to this selection. Section 4.4 discusses a case study performed on a pneumatically powered Campbell Hausfeld (C.H.) 1/2 inch impact wrench to demonstrate the proposed frameworks. Section 4.5 discusses results obtained for the case study and Section 4.6 concludes this chapter and discusses future work.

4.1 The Function-Impact Method

The function-impact method [34] is an eco-design methodology that facilitates the use of LCA data to support the integration of sustainability concepts during the early design phase. The core idea behind the FIM is to distribute life cycle environmental impacts across product functions. The main goal of the FIM is to identify the environmental impact of each function with respect to the overall system performance in order to reveal potential areas for redesign. The mathematical representation of environmental impacts attributed to each function is given in Equation (4.1).

$$FI = [\beta_{i,j,n}] = [\{\Sigma_k(M_{i,j,k} + \Sigma_m P_{i,j,k,m}) * \alpha_{k,n}\} + U_{i,j} * \gamma_n] \tag{4.1}$$

Here, $\beta_{i,j,n}$ is environmental impact of category j due to function n for benchmark product i. γ_n is the percentage of function n contributes to the overall functionality (i.e. the use) of the product. For example, if a product included a motor to perform a specific function, the environmental impact associated with powering the motor would carry some percentage γ_n of the total impact during the product's use phase. In general, γ_n allows the designer to trace functions back to a component level from a use phase perspective. $\alpha_{k,n}$ indicates the percentage distribution of each component to a given function during all other significant phases of a product's life cycle. Furthermore, $M_{i,j,k}$ is the environmental impact category j associated with component k due to material, $P_{i,j,k,m}$ is the environmental impact of category j associated with component k due to the m^{th} manufacturing step. $U_{i,j}$ is the environmental impact of category j during the use of the product.

To summarize, in order to use the FIM for product development, an LCA must first be conducted on market leading designs of existing products (e.g., staplers, coffee makers, compressors). The environmental impacts can then be distributed among product functions to establish function-impact correlations, which can be used to support both novel concept generation as well as redesign decisions. A tabular representation of the FIM is shown in Figure 4.1.

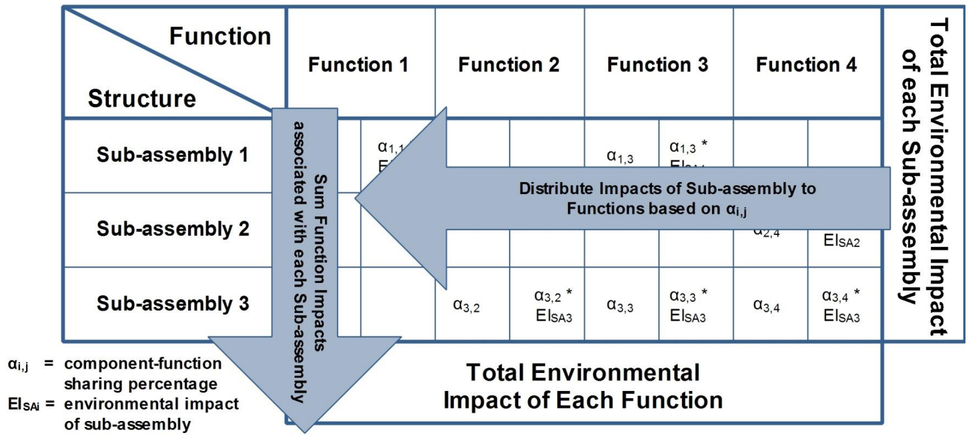

Figure 4.1. Table representing the function-impact method [34]. The columns correspond to functions obtained by function decomposition of the object. The rows represent the related sub-assemblies and structures obtained by disassembly of the object.

In the FIM, the function-structure allocations can carry significant uncertainties due to their subjective nature. Devanathan et al. [34], perform a sensitivity analysis by perturbing the chosen allocations using a uniform distribution by ±10% of their mean value. A Monte Carlo Simulation (MCS) was then performed and the function-impacts were ranked as per their magnitude. A redesign option was chosen if it carried the largest probability of having the highest function-impact rank. The MCS is useful in that it assigns a probabilistic confidence to the chosen redesign decision. However, it is limited by the fact that, (1) an assumption about the probabilistic distribution of the uncertain data has to be made, and (2) it offers no information about the nature of the uncertainties, or the robustness of the chosen decision unless additional information in terms of confidence intervals are specified. To address the limitations outlined above, we develop an uncertainty quantification model based on Information Gap Decision Theory.

4.2 Information Gap Decision Theory

Information Gap Decision Theory (IGDT), developed by Yakov Ben-Haim [71] is an approach suited for making decisions under sparse information. Its core objective is to organize information and the lack of it in terms of families of clusters or nested sets. IGDT has been successfully applied to several interdisciplinary fields including ecological conservation [72], electricity procurement [73], and product redesign [74]. Within this study, the focus is limited to decision-making in early design. Therefore we use an interval bound info-gap model as it has been shown that they are well suited for analysis of design decisions [61]. An interval bound info-gap model is characterized by the following parameters:

- u : The uncertainty variable whose nominal value (ũ) is known
- α : The level of nesting, i.e. the horizon of uncertainty
- r_{cr} : A critical value of performance that must be achieved
- d : A set of design options
- $R(d, u)$: A reward model for the system under consideration
- $\hat{\alpha}(d, r_{cr})$: The info-gap robustness function, which details the largest info-gap uncertainty tolerable to deliver the minimum acceptable performance (r_{cr}) for a specific design option

Then the corresponding info-gap model $U(\alpha, \hat{u})$ is given in Equation (4.2).

$$U(\alpha, \hat{u}) = \{u : |u - \hat{u}| \leq \alpha\};\ \alpha \geq 0 \tag{4.2}$$

In cases where the maximal variation is proportional to the nominal value of the uncertainty variable, the info-gap can be modeled using Equation (4.3).

$$U(\alpha, \hat{u}) = \left\{u : |\frac{u - \hat{u}}{\hat{u}}| \leq \alpha\right\};\ \alpha \geq 0 \tag{4.3}$$

The robustness function in info-gap decision theory is formulated as an optimization problem with the objective of maximizing α whilst satisfying the critical performance constraint, r_{cr}. In cases of larger the better, it can be mathematically represented using Equation (4.4).

$$\hat{\alpha}(d, r_{cr}) = max\{\alpha : (min_{u \in U(\alpha,\hat{u})} R(d,u)) \geq r_{cr}\} \tag{4.4}$$

If smaller performance is better, the robustness function is mathematically defined using Equation (4.5).

$$\hat{\alpha}(d, r_{cr}) = max\{\alpha : (max_{u \in U(\alpha,\hat{u})} R(d,u)) \leq r_{cr}\} \tag{4.5}$$

The design option that yields the greatest magnitude of robustness for a specified critical performance is preferred as per the robust satisficing model. Robust satisficing unlike many other uncertainty models does not yield a design optimized for performance. Instead, a design option is selected based on its likelihood of surviving failure. This analogy is appropriate for situations such as environmental sustainability, as the penalty of failure is very high.

4.3 Proposed Method for Quantifying Uncertainties in FIM using IGDT

4.3.1 Function-Coupling Metric

To establish a measure for function-coupling, the product is represented as a bipartite graph $FS = (F, S, E)$, where $\{F_1, \ldots, F_m\}$ represent product functions and $\{S_1, \ldots, S_n\}$ represent product structures. The bipartite graph can be represented by an adjacency matrix, whose elements establish a correlation between the i^{th} product function and the j^{th} product structure. The matrix can be mathematically represented as shown in Equation (4.6).

$$FS = [c_{i,j}], i = 1, \ldots, m; j = 1, \ldots, n \tag{4.6}$$

Here,

$c_{i,j} = 1$ if $F_i \rightarrow S_j$ ($\exists$ an edge)

$c_{i,j} = 0$ otherwise

To establish function-function correlations, a function adjacency matrix is constructed as given in Equation (4.7). The coupling, or the connectivity, of a particular product function to all other functions is obtained as the row sum of the function adjacency matrix as given by Equation (4.8).

$$FF = FS * FS^T \tag{4.7}$$

$$conn_i = \sum_{\substack{j=1 \\ i \neq j}}^{n} ff_{i,j} \tag{4.8}$$

Here,

FS : function-structure matrix representing the design

FF : function-function adjacency matrix

$conn_i$: The connectivity of the i^{th} product function to all other product functions. It should be noted that the diagonal elements of FF are omitted for the calculation of the connectivity metric because it represents the total number of connections between the i^{th} product function and the j design structures.

4.3.2 Desirability Estimation

The desirability (or opportuneness) of redesigning a particular product function, is determined by Equation (4.9). The measure depends on (1) the normalized magnitude of function-coupling, and (2) the normalized function-impact. Axiomatic design, defines design complexity/information as a logarithmic function of the probability of achieving the specified Functional Requirements (FRs) [75]. Thus, an exponential scale is used in Equation (4.9) to linearize the measure of function-coupling, which in this case is a measure of the complexity within a given design. The desirability measure indicates that a function is preferred for redesign if it has a high function impact and if it is relatively uncoupled. The coupling measure is critical for redesign as it identifies functions that are easier to rework from a modularity perspective [76]. Thus, the best possible case for redesign is when a function is fully uncoupled and has a high value of function impact. To account for the difference in scales between the values of the function-impact and the function-coupling, these values are normalized before calculating the function's redesign desirability measure. Thus, the magnitude of desirability has a theoretical maximum of $1 + k$ and a minimum tending to zero. The scaling factor k in Equation (4.9) is a fraction which signifies the preference one wishes to allocate to function-coupling as compared to function-impact for redesign.

$$D_i = k * \exp^{-conn_i} + FI_i \tag{4.9}$$

Here:

D_i : desirability measure for redesign of the i^{th} product function

k : preference factor that establishes the relative redesign preference between function-coupling and function-impact

$conn_i$: normalized function-coupling measure for the i^{th} product function

FI_i : normalized function-impact of the i^{th} product function

4.3.3 Info-Gap Model for Uncertainties in FIM

The calculation of function-impact is given by Equation (4.10). In this calculation, both environmental impact (I_j) and the function-structure allocation w_{ij} (same as $\alpha_{k,n}$ in the FIM description) are treated as uncertain variables whose nominal values are known. The info-gap models for these variables are given by Equation (4.11) and Equation (4.12), respectively. The info-gap models are such that the maximal variation is proportional to the nominal value of the uncertainty variable.

$$FI_i = \sum_{j=1}^{n} w_{i,j} * I_j \tag{4.10}$$

$$U_I(\alpha_I, \hat{I}) = \left\{ I : |\frac{I - \hat{I}}{\hat{I}}| \leq \alpha_I \right\};\ \alpha_I \geq 0 \tag{4.11}$$

$$U_w(\alpha_w, \hat{w}) = \left\{ w : |\frac{w - \hat{w}}{\hat{w}}| \leq \alpha_w \right\};\ \alpha_w \geq 0 \tag{4.12}$$

The reward or utility function for the present model is represented by the desirability to redesign a function as given in Equation (4.13).

$$R(d, u) = D_i = k * \exp^{-conn_i} + FI_i \tag{4.13}$$

The objective of this formulation is to maximize the robustness function as given by Equation (4.14).

$$\hat{\alpha}(i, d_{cr}) = max\left\{ \alpha : (min_{\substack{I \in U_I(\alpha_I, \hat{I}) \\ w \in U_w(\alpha_w, \hat{w})}} [d_i]) \geq d_{cr} \right\} \tag{4.14}$$

Here:

d_{cr} : the critical or the minimum allowable value of the desirability measure

w_{ij} : function-structure allocation of the i^{th} product function to the j^{th} component

$\hat{w}$: the nominal value of the corresponding function-structure allocation

I_j : environmental impact of the j^{th} component

$\hat{I}$: the nominal value of the corresponding environmental impact

α_I : the horizon of uncertainty for the corresponding environmental impact

α_w : the horizon of uncertainty for the corresponding function-structure allocation

The next section discusses a case study that was conducted to demonstrate the applicability of the proposed methods towards robust decision making in environmentally conscious product design.

STRUCTURE (Subassemblies) / FUNCTION		Transmit Motion		Convert Pressure to		Import Air		House Components		Regulate Output		Prevent Wear		Prevent Slippage		Prevent Leakage		Disengage Motion		Locate Bolt		STRUCTURE IMPACT (Pt)
		Percent	Impact	Percent	Impact		Impact	Percent	Impact	Percent	Impact	Percent	Impact	Percent	Impact	Percent	Impact	Percent	Impact	Percent	Impact	
Housing Assembly	Housing, Back Plate, Paper back, casing crews, gasket, set					0.05	0.264	0.80	4.231					0.05	0.264	0.10	0.529					5.2893
Grip	grip													1.00	0.006							0.0064
Extender Assembly	replacement choke, extension	0.50	0.451																	0.50	0.451	0.9028
Rotor Assembly	rotor, housing, rotor Fins	0.50	0.669	0.50	0.669																	1.3374
Chuck	washer, thin washer, chuck	0.80	0.370															0.20	0.093			0.4630
Valve Assembly	hose connector, valve ball, rod, spring					0.75	0.166									0.25	0.055					0.2218
Regulator Assembly	knob, switch, spring, set screw					0.25	0.057			0.75	0.170											0.2266
Trigger	trigger, washer, spring, cover, screws, trigger rod, rod					0.10	0.003			0.90	0.023											0.0253
Hammer	hammer cage, hammer, dowel pin, gear	0.40	0.480															0.60	0.720			1.2005
Bearing Block	thin bushing plate, thick bushing plate			0.25	0.243							0.75	0.729									0.9725
FUNCTION IMPACT (Pt)		**18.5%**	**1.971**	**8.6%**	**0.912**	**4.6%**	**0.490**	**39.7%**	**4.231**	**1.8%**	**0.193**	**6.9%**	**0.729**	**2.5%**	**0.271**	**5.5%**	**0.584**	**7.6%**	**0.813**	**4.2%**	**0.451**	**10.6457**

Figure 4.2. Tabular representation of the FIM for the pneumatic impact wrench.

	Transmit Motion	Convert Pressure to Torque	Import Air	House Components	Regulate Output Torque	Prevent Wear	Prevent Slippage	Locate Bolt	Prevent Leakage	Disengage Motion	$conn_i$	e^{-conn_i}
Transmit Motion	X	1	0	0	0	0	0	1	0	2	4	0.0183
Convert Pressure to Torque	1	X	0	0	0	1	0	0	0	0	2	0.1353
Import Air	0	0	X	1	2	0	1	0	2	0	6	0.0025
House Components	0	0	1	X	0	0	1	0	1	0	3	0.0498
Regulate Output Torque	0	0	2	0	X	0	0	0	0	0	2	0.1353
Prevent Wear	0	1	0	0	0	X	0	0	0	0	1	0.3679
Prevent Slippage	0	0	1	1	0	0	X	0	1	0	3	0.0498
Locate Bolt	1	0	0	0	0	0	0	X	0	0	1	0.3679
Prevent Leakage	0	0	2	1	0	0	1	0	X	0	4	0.0183
Disengage Motion	2	0	0	0	0	0	0	0	0	X	2	0.1353

Figure 4.3. Matrix representation detailing the function-coupling metric for the pneumatic impact wrench.

4.4 Case Study on a Pneumatic Impact Wrench

The pre-mentioned methodology was applied to a redesign project for a pneumatically powered Campbell Hausfeld (C.H.) $\frac{1}{2}$ *inch* impact wrench. The impact wrench was disassembled and a bill of materials (BOM) was constructed, including each component, its weight, its material, and any processing steps necessary to produce the part. The BOM is essential for conducting a life cycle analysis of the product. The entire list of components in listed in the thesis appendix. For each component, material and manufacturing processes were estimated based on queries within CES Material Selector [77] and availability within SimaPro™ 7.1 [39]. The LCA was conducted via SimaPro™ 7.1 [39] and the Ecoinvent 2.0 database [78]. A full functional analysis was completed to understand the inter-structural component relationships. Extracting design knowledge from the product through disassembly helps construct the function-structure matrix (FSM). After estimating the environmental impact of

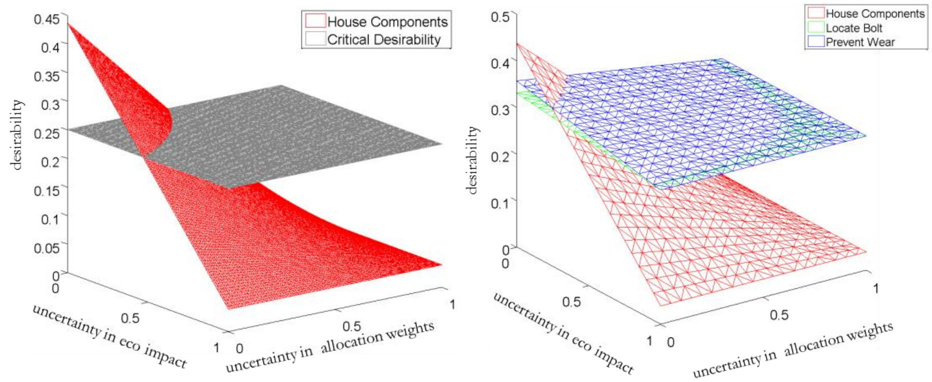

Figure 4.4. Three dimensional uncertainty plot for the desirability values of functions of the pneumatic impact wrench.

each component and the FSM, the FIM was completed by assigning weights based on structure to function. In this case, two design experts independently assigned weights to each function-structure relationship, and then concurred on the final weights. A tabular representation of the FIM is shown in Figure 4.2.

Utilizing Equations (4.6), (4.7), and (4.8) the measure for the connectivity metric ($conn_i$) is derived for each function as shown in Figure 4.3. Simply surveying Figure 4.2, it is evident that the function *House components* carries the heaviest environmental burden, 39.7% of the total environmental impact, which makes it the most suitable candidate for redesign. However, when analyzing the design structure, it becomes clear that the function *House components* is highly coupled with other product functions. Therefore, the redesign of this particular function becomes rather complex. This is an example of a case where the designer has to associate a preference between the environmental impact that can be saved and the ease of the redesign process itself. This preference is captured using the multiplicative factor k in our measure of the desirability for redesign. The desirability measure proposed is an effort to capture this tradeoff, and also estimate the robustness of this decision under uncertainty as discussed in the results section.

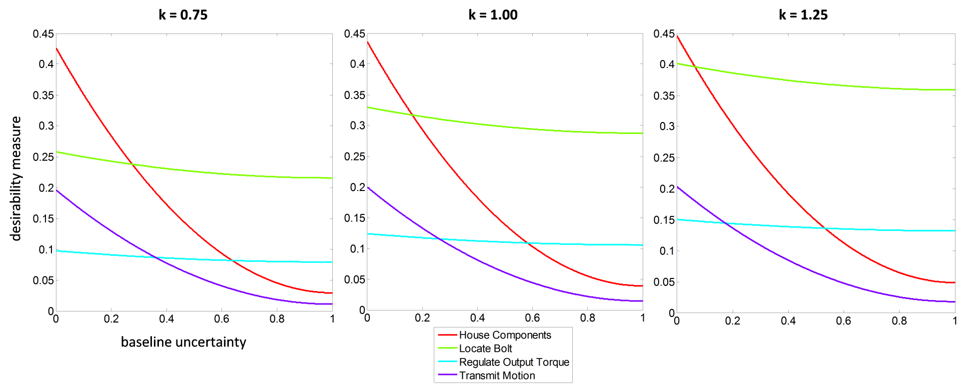

Figure 4.5. Normalized two-dimensional robustness plots with varying values of scaling factor (k) for functions of the impact wrench.

4.5 Results

The data from the FIM along with function-coupling data derived from the FSM were used to construct an IGDT model for the case study. Figure 4.4 shows the plot of uncertainties with respect to the desirability measure of the function *House Components*. It is clear that at certain high values of uncertainty the set critical limit of desirability (0.25) is exceeded. This underscores the importance of assessing the uncertainties present in the FIM. Figure 4.4 shows the robustness plot between a value of desirability and the corresponding uncertainties present. As shown, the functions *Prevent Wear* and *Locate Bolt* do not have a significant drop in the value of desirability with increasing values of uncertainty. Therefore, they are robust selections from a redesign perspective. On the other hand, *House Components* has a higher desirability measure at zero uncertainty, but drops off rather rapidly. The plots in Figure 4.4 are useful in making a particular decision only if the desirability measure of one function dominates the others for all values of critical desirability. However, as shown in the above case there is a switch in dominance depending on the value of critical desirability. In such cases, unless the interval of critical desirability is negligible, there exists a region where an alternative cannot be chosen without providing additional information to the decision maker [74]. This required information provides details of trade-offs between competing uncertainties. Scaling weights specified by Ben-Haim and Laufer [79] is one such way of trading-off uncertainties. The information-gap model considering scaling factors is given by Equation (4.15).

$$U(\alpha, \hat{u}) = \left\{ u : |\frac{u_n - \hat{u_n}}{\hat{u_n}}| \leq s_n \cdot \alpha \right\};\ n = 1, 2, \ldots, N;\ \alpha \geq 0 \tag{4.15}$$

Here, s_n is a unitless scaling factor that modifies the magnitude of α to be of appropriate scale for each uncertain variable u_n. Scaling factors are determined on available prior knowledge of the nature of uncertainties in question. However, in the present case, the designer has access to no such information. Therefore, equal scaling factors are adopted for modeling uncertainties. If the decision maker can obtain reliable information on the nature of these uncertainties in the future, IGDT can be employed with those specific scaling parameters. By the use of scaling parameters, the problem is condensed into trading of robustness between the critical value of desirability and a baseline value of uncertainty, which contains information on both the environmental impact and function-structure uncertainties.

Figure 4.5 displays the robustness factors with equal scaling factors, for three different values of preference factors (k). When it is assumed that there is no uncertainty, the function *House Components* achieves the maximum of desirability of 0.44, and is the obvious candidate for redesign. However, as the baseline uncertainty increases, the alternative to be chosen switches. For example, in the plot with $k = 1$, the functions *House Components* and *Prevent Wear* intersect at the baseline uncertainty value of 0.13 (13% deviation from the nominal). Thus, beyond this value of uncertainty, *Prevent Wear* achieves a higher desirability measure and is to be chosen as the function to be redesigned. This indicates that the function *House Components* is not robust to uncertainty as much as *Prevent Wear*. If a designer is prepared to accept a critical desirability (maximum achievable value of desirability) of 0.34, then *Prevent Wear* should be chosen for redesign due to its robustness to uncertainty. Or else, if the designer is certain that the uncertainty in his calculations lies under 0.13, *House Components*. The other significant feature observed from the above figures is that as the need for product modularity becomes more important during redesign *Prevent Wear* tends to approach the maximum desirability value of *House Components* and beyond k=1.33 emerges as the function which has both the highest value of desirability measure robustness to uncertainty. Thus, it dominates all other functions in entirety and is the logical choice for redesign, without the need for further deliberations from the designer.

4.6 Conclusions and Future Work

This chapter discusses a method for incorporating a formal uncertainty framework within the function impact method (FIM). An Information Gap Decision Theory (IGDT) based model is used to quantify uncertainties in the FIM. The proposed model accounts for uncertainties in environmental impact as well function allocation weights. Using IGDT, it is shown that decisions taken without any regard to uncertainty may lead the designer down the wrong path. The case study conducted in the C.H $\frac{1}{2}$ inch impact wrench highlights the fact that IGDT can determine the range of uncertainty for which a particular product function has the highest expected utility. Our case study uses equal fractional scaling within the IGDT, as there are no existing means of obtaining this data. Future work that can refine our approach include, conducting studies among designers to elicit preference, expanding the desirability measure for functions to incorporate elements such as cost, available manufacturing methods, and an objective methodology to estimate the multiplicative preference factor within sustainability-based design decision-making.

5. ENABLING MULTI-STAKEHOLDER DECISION-MAKING IN ENVIRONMENTALLY CONSCIOUS PRODUCT DESIGN

In this chapter, we present a framework for integrating life cycle assessment/analysis (LCA) with multi-criteria decision analysis (MCDA) to facilitate rational decision-making with regards to aiding environmentally conscious product design (ECPD). In group-based decision analyses, a deterministic preference score may mislead the designer, especially when competing decision criteria (i.e. design for environment (DfE) strategies) have similar scores, as described by Choi et al. [5]. Therefore, we develop a framework for incorporating uncertainty and sensitivity analyses within the decision-making process by means of a Monte Carlo Simulation (MCS). This process allows the decision maker to develop an understanding of the spread/variance of feasible decision criteria. Although different companies have different strategies and criteria, a general framework will allow companies to systematically prioritize DfE strategies, enabling more robust decisions for ECPD. We start this chapter by introducing the reader to the Analytic Hierarchy Process (AHP) and extend this discussion towards a stochastic AHP. Section 3.2 describes the proposed methodology, including an LCA module, a DfE module, and an MCDA module with uncertainty analysis. Section 3.3 describes the process of applying the proposed framework to a real-world case study. This case study involves prioritizing DfE strategies for the redesign of a surface drilling rig within a leading mining equipment manufacturer based in Finland. Section 3.4 summarizes results and discusses statistical methods for ranking decision alternatives analyzed using our proposed framework. Section 3.5 concludes this chapter and outlines future research.

5.1 Introduction to the Analytic Hierarchy Process

The Analytic Hierarchy Process (AHP), developed by Saaty [80], is a flexible MCDA tool for complex problems where both qualitative and quantitative aspects are considered. It helps the analyst organize the critical aspects of a problem into a hierarchical structure. Equations for an AHP are shown below.

Equation (5.1) calculates the consistency index (C.I) between decision criteria and provides a confidence level of the decisions provided by the subjective experts and Equation (5.2) calculates its consistency ratio (C.R). Equation (5.3) calculates the global weight of each sub-criteria and Equation (5.4) captures the global priority score which provides a deterministic, single value of the relative importance of each decision criterion analyzed using the AHP.

$$C.I = (\Psi_{max} - N)/(N - 1) \tag{5.1}$$

$$C.R = C.I/R.I_N \tag{5.2}$$

$$GW_j = LW_i \times LW_j \tag{5.3}$$

$$GPS_k = \sum (GW_j \times RS_{j,k}) \tag{5.4}$$

Here,

N: number of activities/size of the pair-wise comparison matrix

$C.I$: Saaty's consistency index

$C.R$: consistency ratio of the pair-wise comparison matrix

$R.I_N$: random consistency index for the pair-wise comparison matrix of size N

Ψ_{max}: max. Eigenvalue of the pair-wise comparison matrix of size N

GW_j: global weight of j^{th} criteria

LW_i: local weight of i^{th} criteria

LW_j: local weight of j^{th} criteria

GPS_k: global priority score of k^{th} DfE strategy

$RS_{j,k}$: rating of k^{th} DfE strategy w.r.t. j^{th} sub-criteria

People lacking experience in the fundamentals of AHP might encounter difficulties when directly inputting ambiguous judgments into the preference matrix. Questionnaires provide a more systematic approach for constructing the AHP matrix. Structuring a questionnaire includes defining the main elements of the hierarchy at each level and eliciting their importance through specific questions. It is important to avoid possible misunderstandings with the respondent, as the phrasing of the questions and recording of the answers could influence the final result. The perceived direction of the objectives (i.e. positive or negative) plays an important role within the design of the questionnaire. All the objectives on a common level should share a common perceived direction. For example, objectives such as *improved use of recycled material* for the raw material criteria and *enhanced supplier relationship* need to have a positive direction with respect to the external driver.

Although a traditional AHP can be a useful tool, it requires decision makers (DMs) to translate ambiguous judgments into a deterministic preference value for estimating pair-wise comparisons of objectives and decision alternatives. The accuracy of the comparisons of all pairs of criteria and the resulting decision alternatives may be significantly influenced by the information available to the DMs, their understanding of the problem under consideration, as well as their previous perceptions [81]. These issues are of special concern when dealing with a complex global issue such as design for environment (DfE). Misconceptions based on media outlets and specific design experiences can greatly affect decisions within sustainable product development [82].

Moreover, design decisions within an organization are taken by a group of DMs. It is reasonable to assume that each DM in a group has a different value scheme that may significantly deviate from the value scheme held by another DM in the group. This assumption is especially true when considering decision groups for DfE which are usually formed from people belonging to diverse work groups (i.e. product designers, financial managers, environmental engineers, suppliers etc...). By adopting a deterministic weighting scheme in the AHP, any resulting uncertainties or valuable information about individual preferences of the team cannot be analyzed. Therefore, for robust decision-making, the AHP should incorporate means for statistical testing or significance comparison among alternatives. The priority ranking of alternatives resulting from the AHP should also be analyzed for variation with respect to uncertainties in the input data itself.

Constructing a closed-form analytic model in the AHP (to represent output uncertainties as an explicit function of input uncertainties) entails significant complexities. Previous research has approached this problem by incorporating methods such as probabilistic judgments, interval analysis, and fuzzy theory within the AHP. The methods described above aid DMs in reaching a statistically significant conclusion regarding their decisions. However, these methods are limited by the fact that they need a large sample size of decision weights and consequently DMs. An additional problem when dealing with purely probabilistic judgments is the fact that the small sample size of input data prevents accurate parameterization of this data by a statistical distribution [83]. The Modified Analytic Hierarchy Process (MAHP) developed by Banuelas et al. [84] tries to address the above issues and also considers management related factors in decision-making. The MAHP makes use of a Monte Carlo simulation (MCS) through random sampling of an estimated statistical distribution of input preferences. Uncertainties associated with the model are propagated through the decision-making framework. It should be noted that an MCS based approach can be considered the most effective quantification method for uncertainties and variability among the tools available for environmental system analysis [85]. However, the MAHP is limited by the fact that it forces the DMs to parametrize decision weights using a triangular distribution. Although the assumption of a triangular distribution for decision weights works well when they converge to a unique modal value, this assumption may not be valid in cases where they are uniformly distributed across a range or multi-modal. Also, the process of surveying a small sample of DMs can be considered as polling a subset of expert DMs from the available population. Using a triangular parametrization prevents DMs from making inferences about the population as a whole.

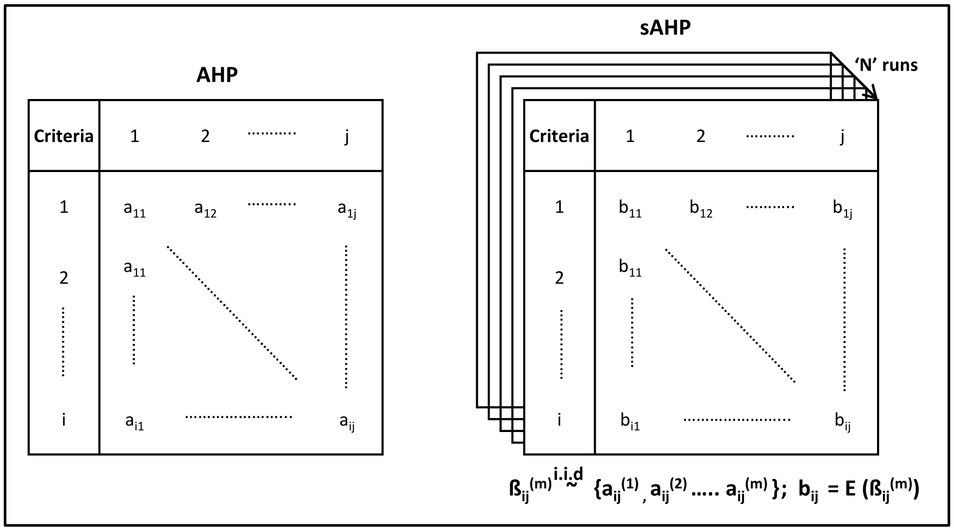

Figure 5.1. Figure illustrating the structure of the pairwise comparison matrix of the deterministic and the stochastic AHP.

To overcome the above limitations, we propose an MCDA framework that incorporates a stochastic Analytic Hierarchy Process (sAHP) using Bootstrap resampled decision weights. Bootstrap resampling is applied in this case as it, (1) is non-parametric in nature (i.e it does not assume that the data is representative of a specific statistical distribution), and (2) allows for measuring the variability of input data by independent and identically distributed (i.i.d) sampling. Also, the resulting bootstrap distribution is centered on the expected value of the true distribution and thus the performed sAHP analysis will be centered on an AHP analysis conducted by averaging individual preferences. In an sAHP, instead of deterministic preference values of a traditional AHP, an (i.i.d) sample (β_{ij}(m)) is drawn from a set of preference values. The expected value of these preference values (b_{ij}) from all the parameters are plugged into a pair-wise comparison matrix, producing a possible prioritization of the alternatives under consideration. Repeated calculations ('N' times) produce a distribution of the predicted output values reflecting combined parameter uncertainties. Thus, this process is akin to performing a Monte Carlo Simulation (MCS) with bootstrap resampling. It should be noted that uncertainties in the reference data (i.e. LCA results) can influence the results of the sAHP. Even though our proposed framework does not explicitly model uncertainties in reference data, a highly uncertain reference data will cause a large variance in priority weights, which will in turn, result in overlapping decision alternatives. Figure 5.1 illustrates the difference between the deterministic and the stochastic AHP. In a traditional AHP, the pairwise comparison matrix contains deterministic values that indicate how much more important the i^{th} criteria is than the j^{th} criteria. On the other hand the pairwise matrix of a sAHP contains one of the many possible expected values of that criteria weight. The sAHP leads to the construction of a set of priority vectors corresponding to each possible evaluation of importance criteria. Consequently the sAHP generates a statistical distribution of prioritized alternatives and their consistency ratios (C.R).

5.2 Proposed Multi-Criteria Decision Analysis Framework

The proposed methodology for incorporating multi-criteria decision making within environmentally conscious product redesign is detailed in Figure 5.2. Our framework consists of four distinct modules: (1) a life cycle assessment (LCA) module, (2) a design for environment (DfE) module, (3) a multi-criteria decision analysis (MCDA) module, and (4) an uncertainty module.

5.2.1 Life Cycle Assessment Module

The LCA module identifies the environmental impact of the specified product system. There are various types of LCA: traditional SETAC LCA or a process based LCA [86], economic I/O (input/output) based LCA [87, 88], and a hybrid LCA [89]. Each LCA has a scope that defines the system boundaries. SETAC LCA provides the most accurate result in the finest level within limited system boundaries while an economic I/O based LCA provides the most comprehensive result on an aggregated economic sector level perspective. A hybrid LCA combines these two types to mitigate the weaknesses of each methodology. Since the proposed framework is intended

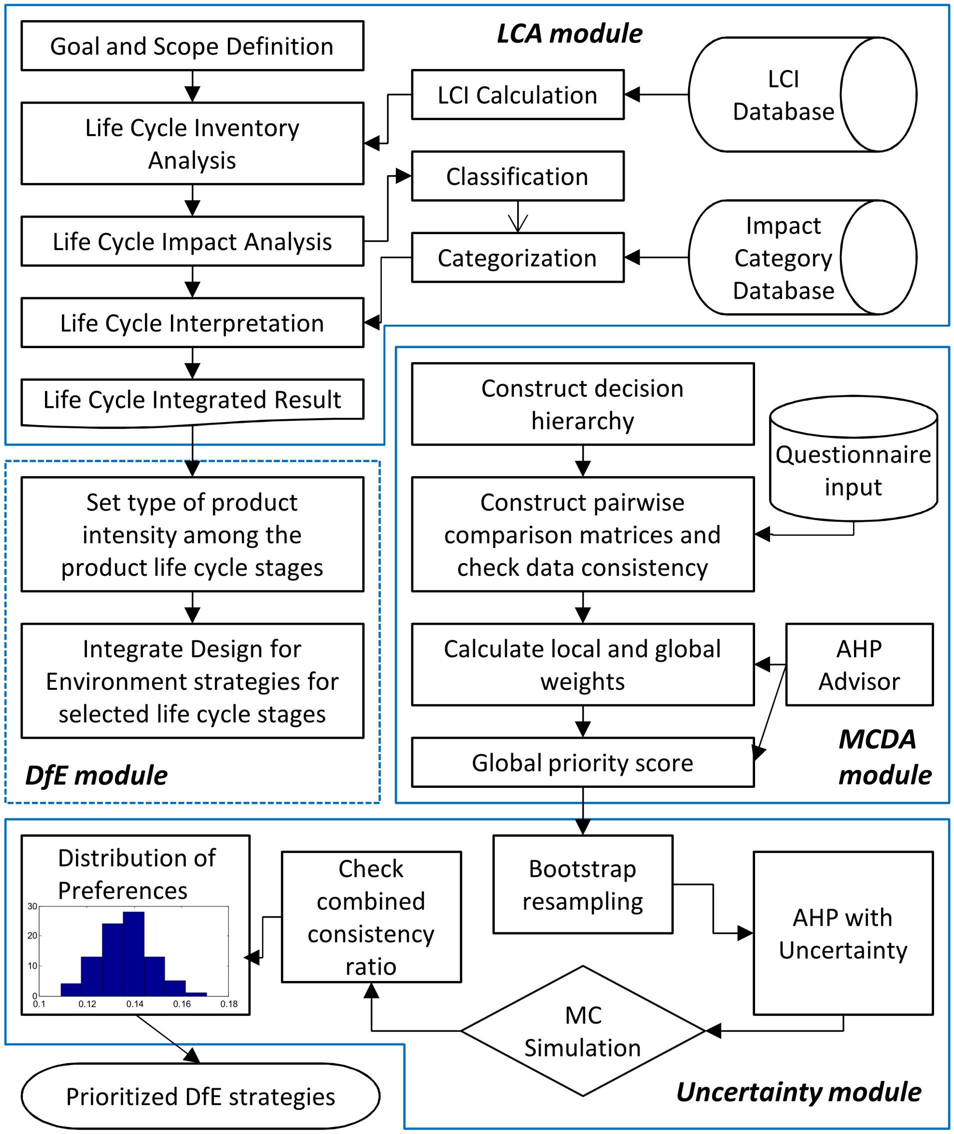

Figure 5.2. Proposed pipeline for incorporating multi-criteria decision making within environmentally conscious product redesign.

for application in a business setting, there are severe constraints on available resources and time which require the set system boundaries to be relatively fine. Therefore, a SETAC LCA is preferred. Also, the use of existing life cycle inventory databases greatly simplifies the life cycle inventory analysis. Although lifecycle inventory analysis provides insight regarding the environmental hotspots of the product system, it cannot be applied directly to judge the environmental performance of a product system due to the lack of specific judgment criteria. Therefore, life cycle impact assessment is conducted to convert the inventory results to normalized environmental impact results. Once the inventory parameters are classified into impact categories, the relative contribution of each inventory parameter to a given impact category is quantified using a characterization factor [90]. The next step in this module is life cycle interpretation where key issues such as the activities, processes, materials, components, and life cycle stages are identified [91].

5.2.2 Design for Environment Module

Each life cycle stage has a set of associated DfE strategies each contain various sub-criteria for improving the environmental aspect of a product system. In our framework, we adopt the list of DfE strategies developed by Brezet et al. [92]. Within a DfE module, the DMs analyze the LCA results to determine how the corresponding sub-criteria should be prioritized. The selected set of DfE strategies will be evaluated for feasibility of implementation using the MCDA module.

5.2.3 Multi-Criteria Decision Analysis Module

In this module, an AHP hierarchy is constructed such that the prioritization of a particular DfE strategy from the pre-mentioned DfE list is placed on the first level of the hierarchy. The second level of this hierarchy provides the local weights of environmental and business-related criteria. Each criterion consists of sub-criteria which represent the desired improvement options and thus provide local weights for sub-criteria. The lowest level of the hierarchy consists of the alternatives, namely the different Designs for Environmental (DfE) strategies. To elicit the importance of the involved alternatives, we construct a survey that evaluates pair-wise weights relevant to the AHP hierarchy. This survey is distributed to a group of expert DMs that have sufficient knowledge of the lifecycle of the product as well as an understanding of its environmental impacts. It is recommended that individuals are drawn from different organizational divisions (such as design, management, maintenance etc...). Following this, we setup the sAHP process such that each pair-wise weight is an i.i.d sample drawn from the set of all such pair-wise weights obtained from the survey. Next, priority vectors and principal Eigenvalues are evaluated for screening out runs which do not meet the desired consistency ratio. The, we generate a set of global priority scores obtained from multiple runs of the above. Finally, we generate a ranking scheme for the DfE strategies using confidence bounds of the normalized preference for that particular design for environment strategy.

5.2.4 Uncertainty Module

While conducting an MCDA involving independent assessments by a group of DMs, it is also essential to identify the decision variables that can significantly affect the final outcome. In the present study, this is achieved by performing a sensitivity analysis on the model. A sensitivity analysis reduces the evaluation space and thus the amount of time necessary to refine evaluations. In the context of this study, the term sensitivity can be defined as the degree of correlation between the renormalized DfE preference values and the input criterion of the sAHP. A detailed explanation of the above in addition to the method for performing sensitivity analysis is explained in the context of the case study in the next section.

5.3 Case Study

The proposed methodology was applied within a leading manufacturer of mining equipment (henceforth titled *Company A*) based in Finland. *Company A* manufactures a wide variety of drilling rigs among which a hydraulic, surface drilling rig (henceforth titled *Product 1* for confidentiality). *Product 1* was earmarked for environmental assessment based on the principles of Life Cycle Assessment. It should be understood that *Product 1* is an assembly of over 5000 individual parts and con-

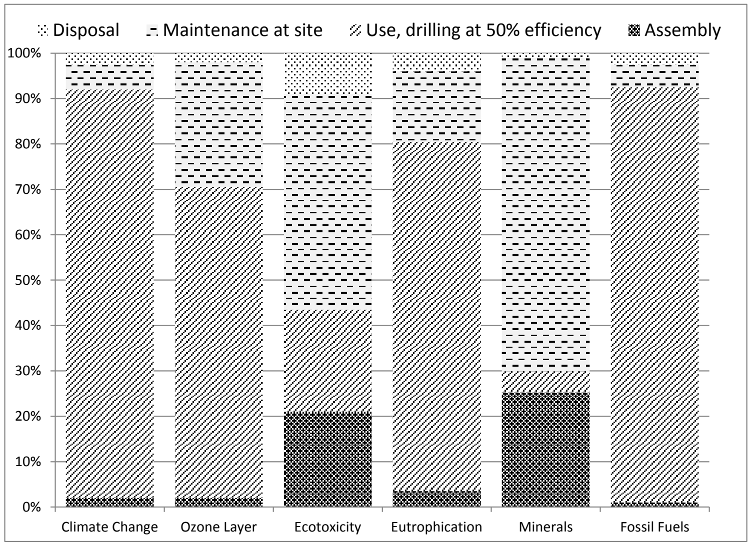

Figure 5.3. Stacked bar chart outlining the significance of use and maintenance phase in the LCA of *Product 1*.

ducting an extensive LCA requires accessing material and design specifications from highly confidential inventory data. Therefore, the present study is based on a prior LCA conducted internally by the company on *Product 1*. We were directly involved in interpreting the results of the conducted LCA and designing the DfE and the MCDA module as per *Company A's* requirements.

5.3.1 LCA Procedure for Product 1

The LCA on *Product 1* was conducted according to the ISO14040 and 14044 standards on environmental management. The LCA includes the following stages of the lifecycle, (1) raw material acquisition, (2) part manufacturing and assembly, (3) transportation, (4) use phase, (5) maintenance, and (6) product's end-of-life. The end-of-life phase examines scenarios of remanufacturing, reuse, disassembly, recycling, and disposal. It should be noted that the review of post-use phase is largely based on qualitative inputs due to non-availability of real world data. Listed below are the definitions of the conducted LCA.

1. **Goal and Scope:** The LCA in the present case is an exploratory study of the life cycle resource consumptions and emissions of *Product 1*. The primary goal of the LCA is to develop and implement practical guidelines that minimize impacts resulting from the production processes as well as the product itself. The intention is to use this method to identify business-related risks and strategies from an environmental point-of-view to aid future purchasing decisions and incorporate recommended design changes or improvements. The short term goal is to improve the lifecycle resource efficiency of *Product 1* and to implement cleaner, less expensive, and smarter solutions in the business process. This involves discovering factors of environmental impact which are not only the most significant but exhibit economically feasible redesign opportunities. The long term goal is to gain useful information for future product planning to make all products more eco-friendly. A special point of interest within the LCA is evaluating the feasibility of a selective take-back program and a systematic disassembly scheme.

2. **Functional unit:** The functional unit is defined as the production, use, and disposal of one drill rig which fulfills the functional requirements set to its life time service and which is constructed with inputs (material and energy) of as low environmental impact as possible. Expected service life is taken into account. The product's lifetime under normal conditions of utilization and maintenance is expected to be 25 years.

3. **Reference Flow:** The reference flow of this LCA study is the manufacture of one *Product 1* drill rig containing mainly steel and hydraulic parts.

4. **Impact categories selected and LCIA methodology**: The used impact categories are climate change, acidification, eutrophication, toxic effects on humans and ecosystems, ozone formation, depletion of fossil fuels and minerals. The used LCA methodology is comprehensive and follows standards of Life Cy-

cle Assessment using the EcoInvent database for inventory analysis [78] and the EI99 scheme provided by SimaPro™ [39].

5. **Allocation procedures/boundaries in relation to other life cycles:** Allocation is avoided by splitting the process in specific separate processes. The manufacturing process does not include any clear co-processes or co-products.

6. **Intended audiences:** The LCA of *Product 1* is to be used for internal purposes in *Company A*.

7. **Report Generation**: The report of the LCA follows the requirements of ISO 14048 LCA data documentation format. The documented report contains LCA data, tables, and figures.

5.3.2 Results of the LCA of Product 1

The results of the conducted Life Cycle Assessment revealed the following significant details.

1. The most significant lifecycle phase from an environmental perspective is maintenance and use. Close to 95% of the lifecycle impact of *Product 1* is due to high diesel fuel consumption and resulting emissions. Figure 5.3 outlines the normalized LCA result outlining the impact contribution of this stage.

2. Oil consumption along with maintenance of change rods and crowns also contribute towards significant use phase impacts.

3. There is a strong potential for reducing end-of-life environmental impacts by pursuing strategies related to substitution with recyclable materials and elimination of toxic materials.

4. Planning for disassembly is a key criterion for enabling better management of the end of life of *Product 1*. This process should be coupled with consumer awareness programs.

5. Design for durability can greatly aid in reducing use phase impact by reducing the frequency of oil and part changes.

6. Reducing material flow and waste at the assembly plant could lead to significant savings in environmental impact.

Based on the results of the Life Cycle Assessment, the following specific recommendations were made in order to reduce the lifecycle impact of *Product 1*.

1. Reduce use phase oil consumption.

2. Reduce percentage of Nickel and Chromium in the steel mixture of *Product 1*.

3. Increase part reliability to minimize the number of part replacements over the lifetime of the product.

4. Incorporate a recycling program for minimizing the end-of-life environmental impact associated with *Product 1*.

5. Reduce consumption of drilling consumables.

6. Reduce part count of *Product 1* through design for manufacturing strategies.

7. Reduce assembly phase consumables, including electricity and water usage.

8. Reduce use phase noise pollution.

Although the above recommendations would greatly help in reducing the lifecycle impact of *Product 1*, the feasibility of implementing these strategies or their effect on the business performance of the company were not analyzed within the LCA.

5.3.3 DfE and MCDA Module

Figure 5.4 illustrates the overall hierarchical structure of the MCDA conducted within *Company A*. In this case, the AHP hierarchy is constructed as per the procedure detailed in the methodology section. For this case study, the list of DfE

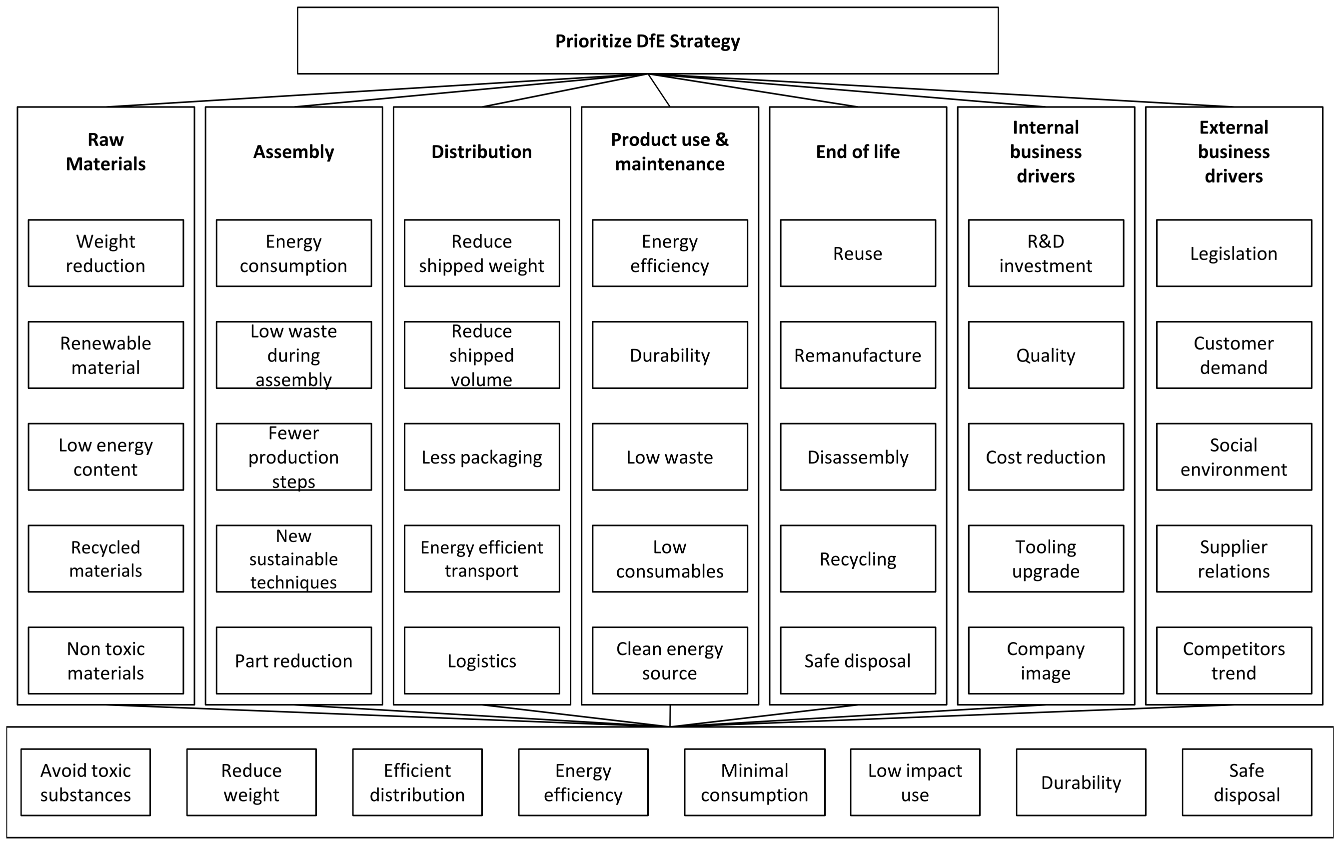

Figure 5.4. Structure of the overall AHP network used for prioritization of DfE strategies for *Product 1*.

strategies are chosen from an exhaustive list compiled by Brezet et al. [92]. However, conducting an AHP based on the entire set of strategies is time and resource intensive (n DfE strategies with m assessment criteria will require $\frac{n^2m}{2}$ evaluations). Thus a pre-assessment of DfE strategies is performed for narrowing the selection before incorporating them within the AHP hierarchy. Within this case study, product managers from *Company A* ranked the criteria as per their relevance to the project and its applicability. Two product managers of *Product 1* independently ranked the DfE criterion on a Likert scale ranging from very important (9), to least important (1). The top eight DfE criteria were chosen for detailed analysis based on the sAHP. It should be noted that the number of DfE strategies selected for final evaluation is a function of available project resources (time, applicability of the DfE strategies in the context of the product, relevance of DfE strategies to company goals, etc..) and the outcome of the rankings. Although the pre-assessment of DfE strategies reduces the scope of the final evaluation, strategies that are of most interest to the company with regards to feasibility of implementation pass through the pre-assessment stage. If these strategies do not correspond to specific recommendations made after the LCA, the company can choose to re-evaluate their selection methodology at the pre-assessment stage and re-select better candidate strategies.

After performing the DfE pre-assessment module, a pair-wise comparison survey was sent to fifteen personnel involved in lifecycle planning and environmental assessment for *Product 1*. Of these, ten complete responses were returned. Each survey was accompanied with supporting documents as detailed in the methodology section. The survey template was designed on Microsoft Excel® for ease of distribution and data extraction. The respondents were required to allocate pair-wise weights within the survey based on the LCA results and their inherent knowledge about the feasibility of the design process. Detailed information regarding the survey questionnaire can be found in the thesis appendix (see Figure B.1). These sets of ten unique pair-wise weights for a specific comparison factor were used for data resampling through the

Table 5.1. Comparison of the normalized preference values of the sAHP with the deterministic AHP.

DfE strategy	**sAHP mean**	**AHP**
Avoid toxics	0.13638	0.13533
Weight reduction	0.10370	0.10601
Efficient distribution	0.08593	0.08630
Energy efficiency	0.13470	0.13625
Minimize consumption	0.17283	0.17230
Low impact operation	0.13668	0.13590
Durability	0.12528	0.12345
Safe disposal	0.10450	0.10446

sAHP. For conducting the sAHP, a custom simulation tool was created using Visual Basic for Applications (VBA) in Microsoft Excel®.

5.4 Results

Figure 5.5 illustrates an example of the results of the simulation (n=1500) run of the sAHP. A frequency distribution of the normalized preference of the DfE strategy *Ensure efficient distribution* is plotted on the left and the overall consistency ratio of the sAHP is plotted on the right. Each bar on the plot of the overall consistency ratio is analogous to the likelihood of having a given consistency ratio. The spread of the Overall C.R's is between 0.035 and 0.07, which is well below the acceptable score of 0.1 as defined by Saaty. The variance of the normalized preference values represents the variability in the input preference weights combined with the errors resulting from bootstrap re-sampling. Similar results can also be obtained for all the other DfE strategies. Figure 5.5 also visualizes all the DfE strategies plotted on the same scale by smoothing the histograms using a normal kernel density estimate.

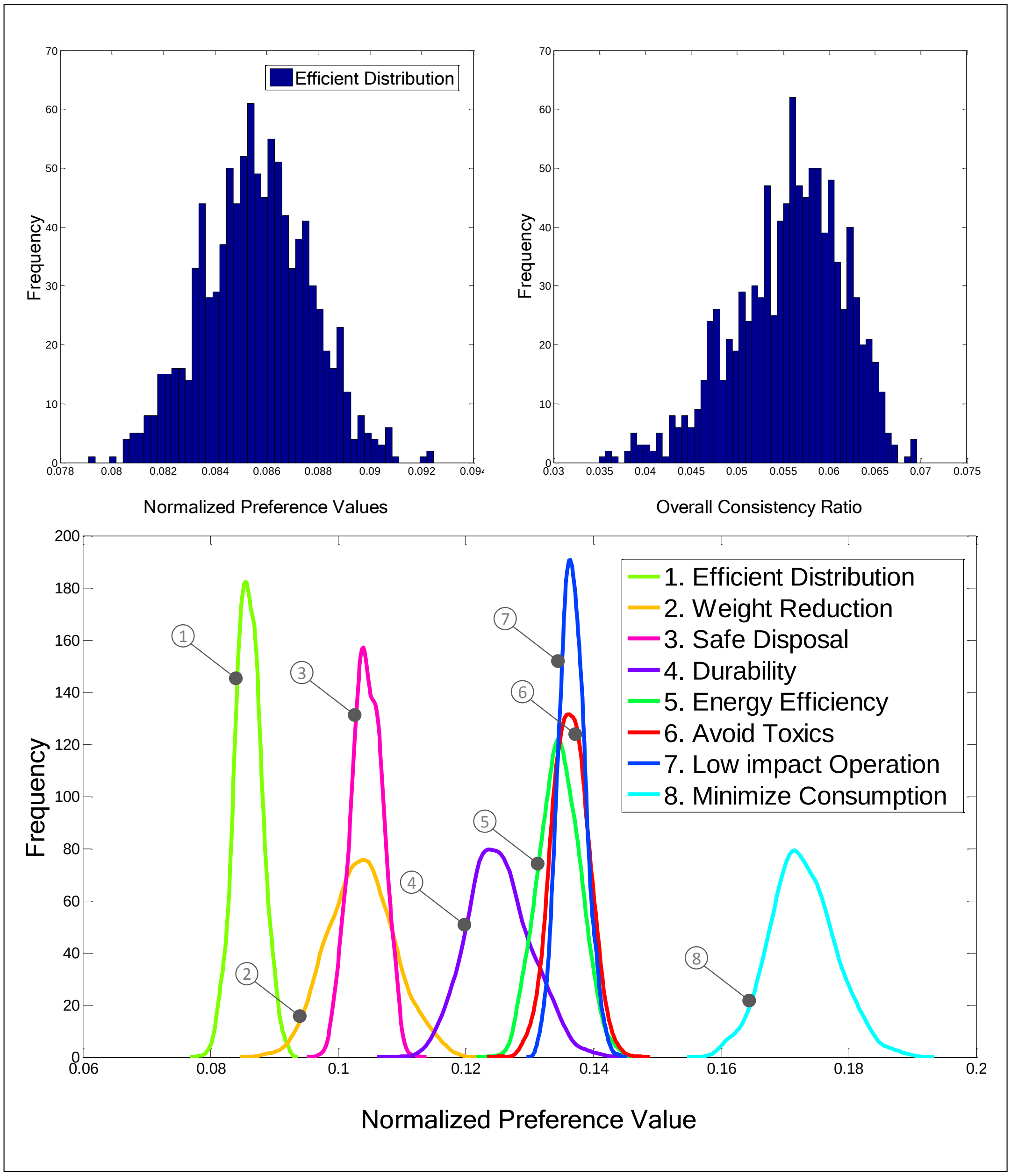

Figure 5.5. A snapshot of example results from the sAHP framework.

The kernel density estimate is a probability density estimate of the sample, based on a normal kernel function evaluated at 100 equally spaced points that cover the range of the data. As all the DfE preferences are plotted on a normalized scale, the magnitude of the expected value of each DfE distribution gives a measure of its overall preference. For example, from Figure 5.5 it is evident that *Minimize Consumption* and *Efficient Distribution* are the most and least preferred DfE strategies respectively.

Table 5.1 compares the results of the sAHP with the preference values obtained by conducting a deterministic AHP by averaging the pairwise comparisons provided by the ten DMs. As seen, the mean value of normalized preferences in the sAHP is approximately equal to the former, the difference resulting from errors in the process of bootstrap re-sampling. The sAHP framework allows for estimating the variability in the resulting preference values due to differences in pairwise comparisons by multiple DMs. On the other hand, this information is lost while averaging the weights a priori for the sake of conducting a deterministic AHP.

To ensure that the decisions made based on the results of the sAHP are statistically valid we compute, (1) a measure of confidence bounds for characterizing the error due to bootstrap re-sampling, and (2) the difference in the normalized preference values of the DfE alternatives to test statistical significance ($p = 0.05$). For characterizing the error in bootstrap re-sampling, a 95% bootstrap percentile confidence interval (i.e the interval between the 2.5% and 97.5% percentiles) of the statistic is generally used. However, when the resulting bootstrap distribution has a small bias and approximates a Gaussian distribution, the confidence interval can be approximated by Equation (5.5) [93] as shown below.

$$[BCI_h, BCI_l] = \mu \pm t^* S \tag{5.5}$$

In the given case, a Lilliefors test is performed to confirm the normality of the resulting bootstrap data. The Lilliefors test is a two sided goodness of fit test that tests the hypothesis that the sample data comes from a distribution in the Gaussian family against the possibility that the sample data does not come from a Gaussian

	AT	WR	ED	EE	MC	LIC	DY	SD
AT	0	1	1	0	0	0	0	1
WR	0	0	1	0	0	0	0	0
ED	0	0	0	0	0	0	0	0
EE	0	1	1	0	0	0	0	1
MC	1	1	1	1	0	1	1	1
LIC	0	1	1	0	0	0	1	1
DY	0	1	1	0	0	0	0	1
SD	0	0	1	0	0	0	0	0

DfE Strategy	Rank
Minimize Consumption	1
Low Impact Operation	2
Durability	3
Avoid Toxics	3
Energy Efficiency	3
Weight Reduction	4
Safe Disposal	4
Efficient Distribution	5

Figure 5.6. Results of the statistical hypothesis testing.

distribution [94]. To compute whether the means of the preference values are statistically different, the differences in the means of DfE alternatives are computed as shown in Equation (5.6) (i.e. inspecting whether this difference is greater than the maximum value of bootstrap standard error).

$$\mu_1 - \mu_2 > t^*(S_1 + S_2) \tag{5.6}$$

This analysis is performed for each of the DfE alternatives with respect to all the other seven DfE alternatives. The results of this analysis are displayed in matrix form within Figure 5.6 where a '1' indicates that the null hypothesis, $\mu_1 \leq \mu_2$ can be rejected at a significance level of 5%. Figure 5.6 also shows that the DfE principle of *Minimizing Consumption* has the highest mean, and thus is the most preferred alternative. *Efficient Distribution* is the least preferred alternative.

Although, the above analysis is sufficient for ranking the alternatives in the sAHP, it is important to characterize the sensitivity between the various alternatives with respect to the input data in the sAHP model. More specifically, the Spearman's rank correlation coefficient, a non-parametric measure of the statistical dependence, is used. The null hypothesis is that the rank of the normalized preference value of the DfE alternative does not co-vary with the rank of the values of a particular sAHP

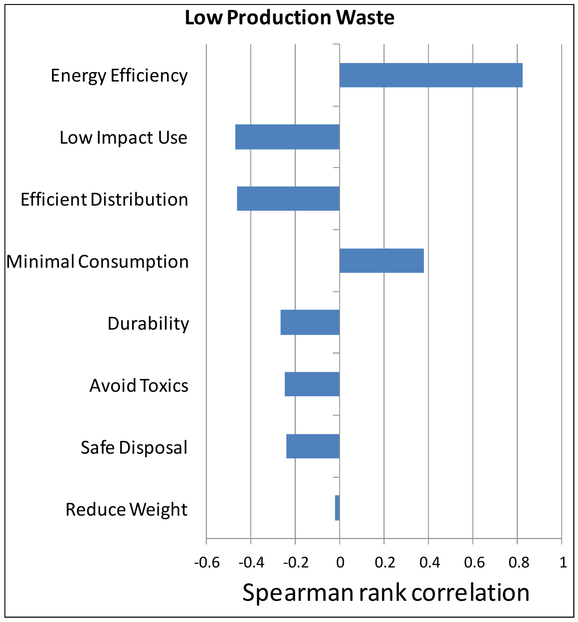

Figure 5.7. Sensitivity of alternatives for an example sAHP input.

input. A highvalue of the Spearman coefficient along with a p-value of less than 0.05 rejects the null hypothesis.

The DfE alternatives in the present case study are the most sensitive to the input weight of *Low Production Waste*. Figure 5.7, visualizes the sensitivity plot. Therefore, the DM team may wish to investigate this criterion further in the hopes of reducing its uncertainty involved in constructing a pair-wise comparison matrix. A similar analysis can be performed for all the factors present in the sAHP.

The final recommendations made to *Company A* based on the results of the LCA with MCDA pipeline proposed in this study are shown in Figure 5.2. The feasibility of adopting a particular recommendation made using the results of the Life Cycle Assessment are rated according to the rankings of the corresponding Design for Environment strategies as per the sAHP. The results show that *Minimizing consumption* of assembly phase consumables and *Reducing use phase oil/noise consumption* are the most feasible recommendations. However, they account for a minor fraction of

Table 5.2. Recommendations for adopting LCA strategies based on DfE rankings.

Recommendation based on LCA	**DfE strategy with rank**
Reduce use phase oil consumption	Low impact operation (2)
Reduce percentage of Nickel and Chromium in Steel mixture	Avoid toxics (3)
Increase part reliability to minimize replacements	Durability (3)
Incorporate recycling program for Product 1	Safe disposal (4)
Reduce consumption of drilling consumables	Energy efficiency (3), Low impact operation (2)
Reduce part count of Product 1	Weight reduction (4), Efficient distribution (5)
Reduce assembly phase consumables (i.e. electricity, water, etc...)	Minimize consumption (1)
Reduce use phase noise pollution	Low impact operation (2)

the overall lifecycle impact for *Product 1*. Conversely, use phase impacts (including operation and maintenance) amount to nearly ninety five percent of the total impact.

The corresponding DfE strategies i.e. *Designing for energy efficiency* and *Low impact operation* are viewed by *Company A* as mid-level feasible. Therefore it was suggested that *Company A* immediately address the issue of reducing assembly phase impacts and develop a long term strategy to redesign *Product 1* for lower operation phase impacts. Upcoming European Union energy regulations such as the Energy using Products (EuP) further strengthen the cause for such a long term goal. Reflecting on the least favored strategies namely ensure efficient distribution and safe disposal, it can be hypothesized that *Company A* has little or no control over the sustainability practices of its suppliers and end users. Since drilling rigs operate in remote areas, product recovery is a formidable task.

Furthermore, these two stages do not significantly contribute to the overall lifecycle impact of *Product 1*. The primary motivation for pursuing one of these strategies would be to comply with possible regulations in the domain. The above discussion makes a case for adoption of the presented decision framework within the industry to abate environmental impact of their products in cognizance of the company's goals, business needs and constraints.

5.5 Nomenclature

i: Type of criteria i$\in 1, 2...I$

j: Type of sub-criteria j$\in 1, 2...J$

k: Type of DfE strategy k$\in 1, 2...K$

N: Number of activities/Size of the pair-wise comparison matrix

$C.I$: Saaty's consistency index

$C.R$: Consistency ratio of the pair-wise comparison matrix

$R.I_N$: Random consistency index for the pair-wise comparison matrix of size N

Ψ_{max}: Max. Eigenvalue of the pair-wise comparison matrix of size N

GW_j: Global weight of j^{th} criteria

LW_i: Local weight of i^{th} criteria

LW_j: Local weight of j^{th} criteria

GPS_k: Global priority score of k^{th} DfE strategy

$RS_{j,k}$: Rating of k^{th} DfE strategy w.r.t. j^{th} sub-criteria

BCI_h: Upper bound of the Bootstrap confidence interval

BCI_l: Lower bound of the Bootstrap confidence interval

μ: Expected value of the Bootstrap distribution

t^*: Critical value of the t(n-1) distribution at a p value of 0.05

S: Bootstrap standard error

5.6 Conclusions and Future Work

An MCDA based tool that allows designers to balance business decisions, process feasibility, and environmental considerations is likely to enhance the willingness of decision makers to pursue environmentally conscious product design (ECPD). Although there are numerous business vendors within design and engineering solutions/services that package individual modules such as LCA, AHP, and Monte Carlo Simulation, the real challenge is to develop an easy-to-use, holistic platform which integrates all these modules in order to facilitate systematic decision-making for ECPD. This chapter details a framework for addressing the above, with the primary goal of improving the environmental aspect of the product through DfE whilst integrating business and feasibility parameters. The proposed framework integrates the qualitative and quantitative aspects of decision-making by correlating LCA with an AHP-based stochastic analysis. It is a qualitative method in the sense that it utilizes subjective data collected from experts through a developed questionnaire. At the same time, it is a quantitative method since it calculates the global priority scores (GPS) and estimates the Eigenvalue/Eigenvectors for each decision criteria based on a LCA results and redesign feasibility. Furthermore, the process for solving Eigenvalues and Eigenvectors of each pair-wise comparison matrix evaluates that the data provided by the design team is logically consistent, facilitating a rational decision-making process. One of the major contributions of our framework is the integration of an uncertainty analysis module within this integrated framework through the use of a stochastic AHP with bootstrap re-sampling. Additionally, statistical significance testing and a sensitivity analysis enable decision makers in taking robust decisions as well as refining the accuracy of the analysis. Methods for designing the questionnaire, constructing the pairwise comparison matrix, and calculating GPS are illustrated in order to understand the proposed methodology. Finally, the implementation of the methodology within *Company A* verifies its ease of applicability in a real-world industry setting.

Although an integrated framework that incorporates environmental and business considerations was presented, it should be understood that the method only identifies management level strategies to support ECPD. Decisions that support ECPD activities need to consider product information from both a company level as well as the product component level perspective. Future research should focus on extending this framework so as to translate the presented DfE strategies to the product component level with the goal of generating specific redesign instructions.

6. VISUALIZATION FRAMEWORKS FOR SUPPORTING ENVIRONMENTALLY CONSCIOUS DESIGN EXPLORATION

Reducing the environmental impacts of products and services has become an important focus for industries [95]. Among the various opportunities available for reducing the environmental footprint of a product, usually the design stage offers the most potential [12]. Integrating environmental aspects of a product with its design creates the need for searching environmental information, performing environmental assessments, and outlining a suitable strategy [92]. This chaper is focused on the *search* part of this process and looks at computer supported methods and tools for exploration. Since we specifically look at design exploration activities in the context of eco-design, we refer this process as *eco-conscious design exploration* (ECDE). We define ECDE as, designer-driven exploration of previous designs to support eco-design. The goals of this process can be to, (1) compare environmental impacts of previous designs, (2) generate an understanding of correlations between design attributes & environmental impact, and (3) discover more benign alternatives for a design.

6.1 Challenges in Supporting ECDE

Consideration of environmental sustainability adds parameters and constraints to the design process which increases design complexity [82]. Cognitive load resulting from complex inter-relationships between design parameters can hinder insight generation. Studies conducted by Mathias [96] reveal that presenting design parameters in a structured manner can help the designer to succeed. This structuring is particularly important in the case of novice designers, who tend to overlook the complex dynamic relationships between design parameters. In the case of eco-conscious design exploration (ECDE), the issue of having to deal with multiple inter-related parameters is compounded by the fact that methods and computer support tools for eco-design are disconnected from those focused on design exploration. One primary reason for this *disconnect* is the mismatch in data representations used in these two contexts [97]. To illustrate, conducting a Life Cycle Assessment for a part does not require knowledge about its function, or shape. However, these attributes are considered to be vital towards assessing design intent and similarities during design exploration. Reducing such gaps is essential for easing the barrier to ECDE.

6.2 Motivation for Applying InfoVis to ECDE

Information visualization (InfoVis) is defined as the use of computer-supported, interactive, visual representations of abstract data to amplify cognition [98]. An important aspect of InfoVis and Visual Analytics – automated analysis techniques with interactive visualizations for decision-making [99], is keeping the human-in-the-loop. This forms a strong basis for applying InfoVis to tasks in ECDE as it often requires reasoning through heterogeneous, complex, and often incomplete data. Although automated approaches such as machine learning and expert systems are beneficial for eco-design, their application to ECDE is limited due to the fact that such approaches are directed towards close-ended tasks within focused scenarios. In contrast, ECDE involves tasks wherein, although the end goal is known, designer's rarely know how the best approach the problem, what questions to ask, and which among them are the right questions to consider. Such exploratory tasks are often best served by creating InfoVis tools that combine the powerful pattern detection properties of the human visual system with the large-data processing and manipulation capabilities of a computer system [100]. Another advantage of using InfoVis tools in ECDE, is the ability to create a common representation between domains (in our case environmental assessment and design exploration) by transforming data into graphical primitives [101]. This allows InfoVis-based tools to support designers' insight generation processes and leverage their expertise and experiences in subjective decision-making which is necessary for most tasks in ECDE.

6.3 Addressing Challenges in ECDE through InfoVis

A first step for applying InfoVis techniques in ECDE is identifying existing challenges in ECDE, and identify ones that can be addressed using InfoVis-based methods or tools. To this end, we compile a list of challenges in ECDE that are (1) relevant to, and (2) can be addressed by applying established techniques and methods in InfoVis. Our goal for compiling this list is not towards creating an encyclopedic collection of challenges in ECDE. Instead our focus is on enumerating only those challenges that we think *make sense* when applying InfoVis to ECDE. As an example, product lifecycle databases usually contain missing or incomplete lifecycle information due to non-standardization, errors, and complexities in current measurement and archiving practices. Although this is an important challenge which needs to be overcome for ECDE, it cannot be solved by directly applying InfoVis techniques in ECDE. However, InfoVis techniques can be useful for aiding designers in decision-making under missing or uncertain information. This distinction forms a central part of our rationale in compiling such a list. We categorize this list based on (1) the role of the user in ECDE, (2) nature of tasks in ECDE, (3) limitations in environmental assessment, and (4) challenges in design exploration. Each challenge in our list is drawn from our review of relevant literature in ECDE and sustainable design.

6.3.1 Role of the User in ECDE:

By definition, ECDE is a designer-driven process. Therefore, challenges in design exploration such as (1) designer's limited expertise, (2) facilitating collaboration among a diverse team of stakeholders, (3) human subjectivity in characterizing and resolving conflicting objectives, extend to ECDE. In the context of creating InfoVis-based tools for ECDE, relevant challenges include,

- *Most designer's are non-experts in environmental assessment:* Environmental assessment for products can involve a variety of techniques such as checklists, DfE guidelines, and life cycle assessment (LCA). Although designer's may be familiar with a subset of them, in most cases designer's are not trained in performing quantitative estimations of environmental indicators [102].

- *ECDE is a multi-stakeholder process involving experts across several domains:* At the very least, ECDE requires an active dialog between the product designer and the environmental engineer. Usually, multiple domain experts will collaborate and contribute to this process. In these settings, it is challenging to facilitate collaborative exploration as data representations and lifecycle metrics are dependent on a designer's expertise level and expertise type.

6.3.2 Nature of Tasks in ECDE:

Tasks in ECDE include (1) comparing similar parts in the context of eco-design , (2) exploring correlations between design and sustainability-related data, and (3) discovering more benign design alternatives. In such tasks, designers face challenges arising from a mismatch in representations between design and sustainability-related data. This is further complicated by the open-ended nature of these tasks and the fact that designer's rarely know the best approach towards solving these tasks.

- *Exploring alternatives across system boundaries and life cycle stages:* Often, designers' tasks span system boundaries. For example, a designer might be interested in exploring alternatives at a part, module, sub-assembly, or assembly level. Similarly, a supply chain exploration problem might require decisions at multiple supplier tiers. Therefore, an ideal ECDE-support tool should allow designers to traverse such hierarchies across a collection of designs/architectures. Design decisions have an effect on all downstream processes. Therefore ECDE-support tools should allow designers' to consider implications across affected product lifecycle stages.

- *ECDE processes contain and require subjective assessment of alternatives:* ECDE often required designers to work with heterogeneous, uncertain, and qualitative data. This forces them to make assumptions for streamlining ECDE processes. Limitations in data quality, time, and resources also means qualitative assessment methods such as checklists, QFD-based tools, and LIDS wheel find widespread use in sustainable design [12]. Subjectivities in environmental assessment are often compounded by designers' biases [82] Thus apart from facilitating design exploration, ECDE-support tools should also contain affordances for bringing about conceptual changes, and maintaining them.

- *Most methods for ECDE are not scalable to a large collection of alternatives:* Environmental assessment of multiple alternatives, requires methods for automating computation of environmental indicators from standardized representations of data, and a means to meaningfully display results. A major challenge is the ability to visualize results of "what if?" questions in ECDE and present results in an easy-to-understand manner [67].

6.3.3 Limitations in Environmental Assessment

Conducting a quantitative life cycle analysis for comparing designs is a time and resource intensive process. Simplifying the analysis through streamlined quantitative assessments, or through semi-quantitative/qualitative tools, introduces significant uncertainties in the resulting environmental indicators. Another important barrier is that most methods environmental assessment are difficult to integrate with design processes. This is because of a relative lack of methods for translating results from such assessments to actionable design instructions.

- *Environmental indicators for ECDE are not contextualized to the design process:* The outcome of ECDE processes are either selection, or redesign of previous existing designs. Presenting results from environmental assessment in the context of design parameters is vital for designers to easily interpret the data, and make it actionable towards design practice [82].

- *The relationship between design parameters and corresponding environmental indicators is complex, making it difficult to form explicit correlations between the two:* The environmental indicator is a function of a multiple attributes such as material, manufacturing processes, part geometry, geographic location of suppliers, and end-of-life mode. Formulating parametric relationships that capture variation in the indicator as a function of an attribute is complex, time intensive and more often than not impossible to do [103].

- *Quantitative environmental assessments contain significant uncertainties:* Often, designers' have very little knowledge about the nature of uncertainties in environmental assessments. Even so, they are required to take decisions based on partially missing, and uncertain data. Choosing from multiple available formalisms for such data [104], and its presentation are significant challenges for supporting ECDE.

6.3.4 Challenges in Design Exploration

The large number of relevant sustainability and design-related variables in ECDE result in a high dimensionality of the exploration space. Furthermore, representing such data using analytical expressions is rarely possible, making it challenging characterize these explorations spaces. Another significant challenge is the non-standardization of representations for design and sustainability-related data in the context of ECDE.

- *Design metadata contains variable levels of abstractions:* Availability of accurate information, and varying levels levels of specificity design metadata, presents a challenge in conducting and presenting results of environmental assessment [43]. Such variations results in environmental assessments with variable levels of fidelity. The same is true for ECDE, wherein the designer has to compare designs with varying specificities in both design-related and sustainability-related parameters [103].

- *ECDE adds to the dimensionality of the exploration space, thereby increasing the complexity of the process:* ECDE requires designers' to explore and make decisions in multi-dimensional spaces containing difficult to interpret LCA and LCIA-related parameters. This requires use of dimensionality reduction techniques such as multi-dimensional scaling [67], weighting schemes [105], or aggregating dimensions (i.e. checklists, LIDS wheel). A consequence of such methods is a reduction in transparency of the environmental assessment process to designers involved in the decision-making process.

6.4 InfoVis-Based ECDE for 3D Part Repositories

In the proceeding sections, we present the design and evaluation of an InfoVis-based framework for selection of similar previous designs in a part repository that is guided by environmental sustainability principles. This example, is presented as a case study that demonstrates the usefulness of applying InfoVis principles to ECDE in order to overcome the chaallenges that we have listed above. In this context, our hypothesis is that integrating meaningful visualization schemes with sustainability assessment can help designers observe covariation among product attributes and enable better decision-making in the context of product reuse.

The proposed framework allows automated computation and visualization of, (1) similarities in part attributes, and (2) corresponding environmental indicators. We integrate representations for sustainability indicators and part attributes based on the insight that environmental impact is an inherent part attribute that can be derived from other part attributes such as geometry, material, and manufacturing. The complex nature of the relationship between environmental impact and other part attributes is difficult to explicitly quantify. However, allowing the designer to develop

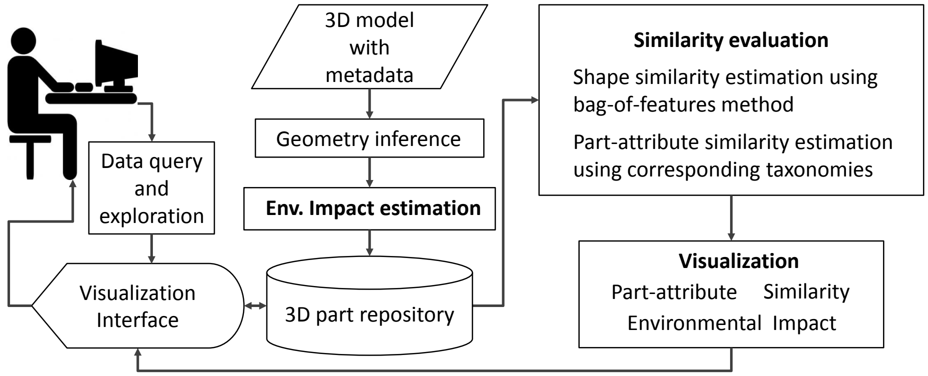

Figure 6.1. Overview of the proposed framework for supporting sustainability based decision-making in part repositories with material, manufacturing and function data. Core components of the pipeline are highlighted in bold.

an intuition about *impact-attribute* relationships can significantly aid the sustainable design process. We address this challenge by encoding these relationships as *visual variables*. We envisage our method to enable designers to hypothesize and evaluate their mental models pertaining to *impact-attribute* relationships and lead to better insights regarding the factors correlating environmental sustainability and design decisions. Additionally, we quantify similarities on multiple product dimensions such as shape, function, material, and manufacturing. By allowing the designer to explore existing part data through multiple lenses, our framework provides a richer context in the design exploration process. We also present a prototype interface that is designed for eco-conscious design exploration of part repositories by visualizing similarities in part attributes. This prototype interface uses sketch-based querying for enhancing the intuitiveness of the interaction. Figure 6.1 gives high level overview of our framework. The primary interaction mode for users of our framework is query-based exploration of part similarities. A range of visualizations can be designed to guide these processes. An interface with one such visualization scheme is discussed in this chapter. We also discuss interaction modes that are currently implemented in our prototype interface. We start this discussion by detailing the methodology behind the three core modules in our framework, namely the (1) environmental impact assessment module, (2) similarity evaluation module, and the (3) visualization module and prototype interface.

Applying our framework requires access to 3D part data with metadata regarding material, process planning, and functionality. Feature level information is often absent in existing repositories. Therefore, we work with 3D part repositories that do not contain a direct mapping of manufacturing processes to specific part features. For example, if the process plan has two material removal operations such as milling and turning, we cannot estimate how much material was removed by milling as compared to turning in order to produce the final shape. In order to make our framework relatively independent of the representation of data present in a part repository (i.e. file formats and granularity), we use low level representations that can be derived from common high level representations of design data. This approach allows users to adapt the developed framework towards their preferred data schemes. Figure 6.2 illustrates the data model for a part class contained in our framework. The primary inputs to our framework are, (1) a 3D model of the part, represented as a mesh, (2) a material definition, (3) an ordered list of manufacturing processes, (4) a function description of the part, and (5) part identifiers for indexing and retrieval. All other part metadata, such as the environmental indicator, shape descriptors, and metadata similarities, are derived from these inputs.

6.5 Environmental Impact Assessment

In this work, we focus on developing an automated indicator for approximating cradle-to-gate impact for mechanical parts. Consequently, our framework is applicable towards parts whose lifecycle impacts are dominated by resource extraction and manufacturing processes. Although this reduction in scope results in higher uncertainties in environmental impact assessment, it is necessary, since information regarding downstream lifecycle stages (i.e. use phase and end-of-life) is rarely available at the

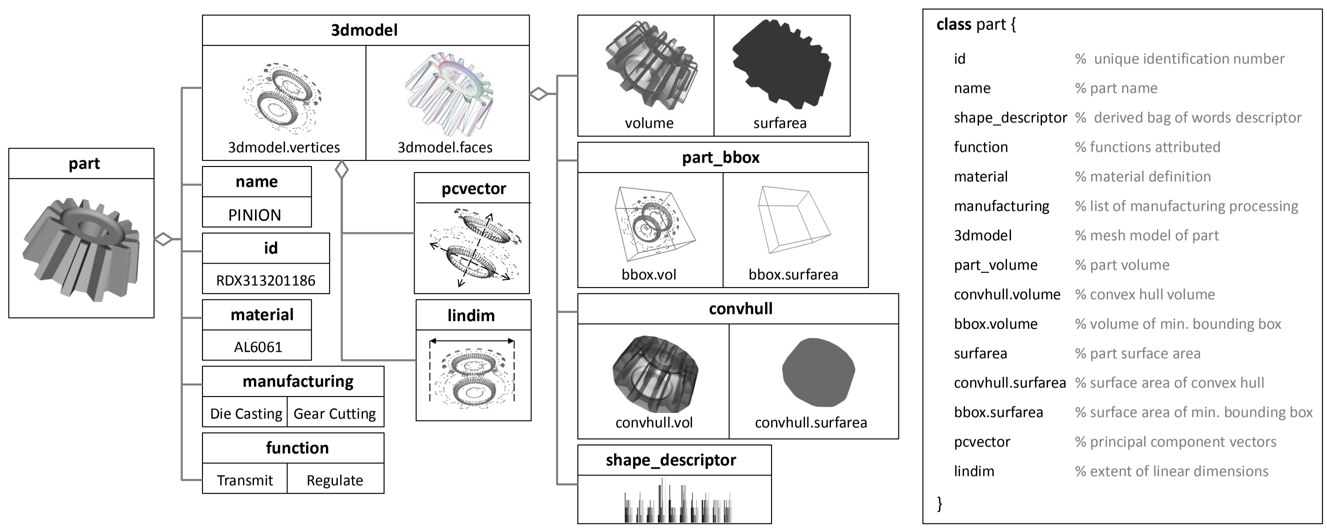

Figure 6.2. Data representation model for defining a “part class” in our framework. Here, the arrows represent an aggregation relationship. Metadata contained in the class are either specified as input data during instantiation or subsequently derived from input data. Minimum input data that needs to be specified include (1) the part geometry in the form of a 3D model, (2) the part material, (3) an ordered list of manufacturing processes, (4) part functions, and (5) identifiers for indexing and query.

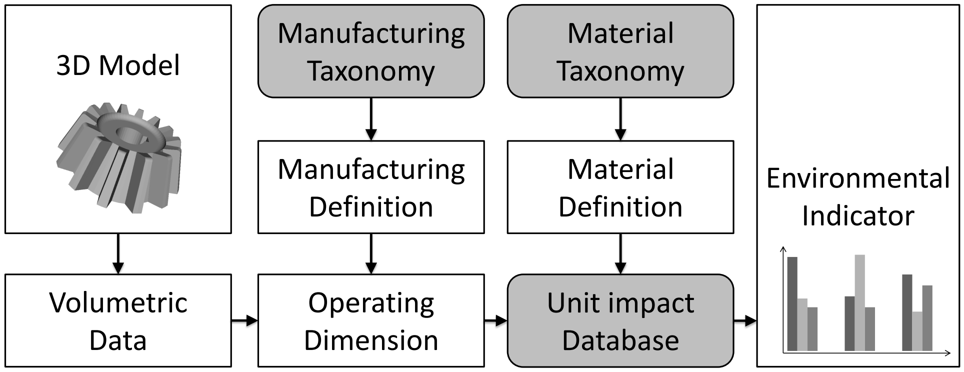

Figure 6.3. Pipeline for estimating environmental impact indicator from input data. Gray squares represent reference taxonomies and databases used for standardizing data description.

design phase. Moreover, our framework is aimed at design-phase exploration with the goal of screening out designs with significant environmental impact.

Given a 3D model of a mechanical part with corresponding metadata, we start by extracting volumetric as well as shape-related data as shown in Figure 6.2. This information along with process data is used for estimating the approximate environmental impact of the product. Since a mesh-based representation of the solid model is used, feature level information is unavailable for estimating the cradle-to-gate indicator.

6.5.1 Taxonomy-Based Representation of Lifecycle Data

Manufacturing processes are specified in our framework as per the Allen and Todd taxonomy [106]. This taxonomy categorizes processes into 14 major families. This classification taxonomy takes into account workpiece geometry, resulting tolerances, workable materials, and cost. This taxonomy was preferred as the classifications described correspond closely with volumetric information of parts. One of the reasons for incorporating a taxonomy-based specification for manufacturing is the flexibility that it allows in the level of specificity of a process. For example, a repository might contain a part that is described as being *cast* without further information on the exact nature of the casting process (e.g. die casting, investment casting, and sand casting). However, estimating environmental impact data requires a more specific unit process. In such cases, an approximate measure for environmental impact can be established by averaging the unit impacts of the set of manufacturing process in the induced sub-tree. Similarly, it is possible that unit process information regarding a specific process is unavailable in the used LCI database. Here, we can approximate the resulting impact by substituting it for the most similar manufacturing process that has data available in the LCI. For this, we develop a similarity measure among manufacturing processes based on the structure of the taxonomy.

A corresponding taxonomy for material specification described by Ashby [107] is also incorporated in our framework. Within this scheme, materials are grouped into five classes: ceramics and glasses, fibers and particulates, hybrids, metals and alloys, as well as polymers. Each material class is further classified into multiple material groups. A complete classification scheme is available within the CES Edupack software [108]. In addition to material and manufacturing taxonomies, we implement a function taxonomy adapted from the categorization of functions by Hirtz et al. [109]. Here, the authors develop a reconciled functional basis, where functions are grouped into 8 primary classes. They are further divided into multiple sub-classes. The authors also provide a list of correspondences that allow users to correlate their functional basis with related efforts. By implementing this function taxonomy, we allow designers to compare and filter parts based on similarities in part function.

6.5.2 Estimating the Cradle-to-Gate Indicator

The pipeline for estimating the environmental indicator is described in Figure 6.3. First, we extract volumetric properties from a 3D model of the mechanical part stored in the database. Properties, such as volume, surface area, convex hull volume, and minimum bounding-box volume, are calculated from the Stereolithography (.STL) file and indexed. Next, we estimate the operating dimension (O^{dim}) for each manufacturing process associated with the part. O^{dim} is defined as the physical variable pertaining to part geometry (i.e. volume and surface area) that is processed by a manufacturing operation. Table 6.1 illustrates the definition of O^{dim} for different kinds of manufacturing processes as per the Allen and Todd taxonomy. Thus, the O^{dim} for a manufacturing process can be used as a scaling factor on its corresponding unit process. Scaling the impact of a unit process by O^{dim} results in the net impact of that unit process on the part geometry. In an ideal setting, the operating dimension for each process is specified as input data or encoded as shape changes of the three dimensional model of the part.

Although a well-defined product lifecycle management (PLM) system might also archive such data, most repositories today do not provide any means for obtaining this information. Therefore, we estimate the O^{dim} for a specific manufacturing process based on the following approximations.

- If the volume of the starting stock/blank is not specified, it is taken to be equal to the smaller value of (1) the convex hull volume of 3D part, and (2) the volume of the minimum bounding box of the 3D part.
- If there is more than one material removal operation in the list of manufacturing processes, the total removed volume is divided equally among these processes.
- The Allen and Todd taxonomy is used to categorize manufacturing processes into one of the following four types:

  → Mass conserving volumetric (e.g. forging, annealing)

  → Mass reducing volumetric (e.g. turning, drilling)

  → Surficial (e.g. anodizing, electrocoating, dust coating)

  → Joining (e.g. welding, adhesive bonding)

Thus, any process that appears before the first *mass reducing* process always operates on the convex hull volume or surface area. Similarly, any process that

Table 6.1. Definition of $O^{\,dim}$ based on the manufacturing process.

Type of Manufacturing Process	**Operating Dimension** ($O^{\,dim}$)
Mass conserving volumetric	Volume of the part before/after the manufacturing process
Mass reducing volumetric	Volume of the material removed in the manufacturing process
Surficial	Surface area that is coated/transformed by the manufacturing process
Joining	Functional dimension (volume, surface area, length, etc..) depending on to the type of joining process

occurs after a *mass reducing* process operates on the reduced volume. Although units such as volume and surface area are easily computable from a 3D model, extracting feature level information for calculating the operating dimension for *joining* processes present significant challenges. Therefore, information about the operating dimension (i.e. length of weld, surface area of bonded surfaces) is required to be specified by the user as input to the framework. Once the $O^{\,dim}$ for each manufacturing process is estimated, the cradle-to-gate environmental indicator is computed as a linear sum of the impact of material extraction and manufacturing processes (see Equation (6.1)).

$$EI = e * b_v + \sum_{i=1}^{n} p_i * (O_{dim})_i \qquad (6.1)$$

Here,

EI = Net environmental impact

e = Environmental impact associated with the unit process for material extraction

b_v = Blank/Initial volume of material used for manufacturing the part

p_i = Environmental impact associated with the i^{th} unit manufacturing process. Note that this quantity is also dependent on the type of material that is manufactured.
O_{dim} = Operating dimension of the i^{th} manufacturing processes
n = Total number of unit manufacturing processes associated with the part

Approximating the O^{dim} introduces additional uncertainties in estimating the cradle-to-gate environmental impact computed using Equation (6.1). These uncertainties result from a lack of detailed information pertaining to the material extraction and manufacturing stages. As discussed, the availability of detailed lifecycle data in design repositories obviates the need for this approximation. However, we present and discuss uncertainties for a scenario in which feature information (that maps manufacturing process data to part geometry) is absent from the design repository. Apart from inherent uncertainties in the life cycle assessment process, additional approximation errors resulting from our method can be formalized as follows.

- $\triangle V$: The error resulting from approximating the initial blank volume b_v by the convex hull/minimum bounding box volume.
- $\triangle w_i$: Error in removed volume fraction for i^{th} material removal operation. This results from our approximation that the total removed volume is divided equally among all material removal processes.

$$\triangle EI^{ext} = \triangle V * e \tag{6.2}$$

$$\triangle EI_i^{rem} = p_i * \left\{ \frac{\triangle V}{n} + \triangle w_i * (b_v - V_{mesh} + \triangle V) \right\} \tag{6.3}$$

$$\triangle EI_i^{con} = p_i * \left\{ \frac{\triangle V\,(n-1)}{n} - (b_v - V_{mesh} + \triangle V) \sum_{j=1}^{i-1} \triangle w_j \right\} \tag{6.4}$$

By putting Equations 6.2, 6.3, and 6.4 this together we have a closed form solution for the errors in the environmental indicator shown below.

$$\triangle EI = \triangle EI^{ext} + \sum_{i=1}^{n} \left\{ H(\Phi_i) * \triangle EI_i^{rem} + H(-\Phi_i) * \triangle EI_i^{con} \right\} \tag{6.5}$$

Here,

$H\,(\Phi)$ is the Heaviside step function

$\Phi_i = 1$ if the i^{th} process is volumetric & mass removing

$\Phi_i = -1$ if the i^{th} process is volumetric & mass conserving

Equations (6.2), (6.3), (6.4), and (6.5) represent a closed form solution for the cumulative error in estimating EI due to approximations in estimating $O^{\,dim}$. These equations are derived by substituting the error terms in Equation (6.1). Please note that uncertainties with respect to surficial and joining processes are not considered in these equations due to the dependencies of these errors on the shape of a specific part. Here, we use Equation (6.1) to compute a cradle-to-gate indicator for the purpose of demonstrating our visualization pipeline. For this, the Cumulative Energy Demand (CED) is used as an indicator of environmental impact. Cumulative Energy Demand for a product is defined as the total quantity of primary energy needed to produce, use, transport, and dispose of that particular product. Previous literature has outlined the usefulness of CED to serve as a screening indicator for environmental performance [110]. A lookup table is hard-coded into our system that contains CED values of unit processes for material extraction as well as a given material-manufacturing process combination. The data for these entries have been referenced from the methods library available through SimaPro 7.1 [111]. Our current setup is also capable of estimating cradle-to-gate impacts based on the Eco-Indicator 99 method referenced in SimaPro 7.1. Developing a more holistic indicator is possible if data concerning the transportation, use-phase and end-of-life is made available within the repository. An additional point of concern while estimating environmental indicators is the change in variables related to process planning. Methodologies such as environmentally conscious process planning (ECPP) have the potential to optimize *process selection and control* with respect to sustainability. In order to account for these changes, our framework is designed to link to efforts such as the unit process life cycle inventory (UPLCI) database [112]. By adopting the same manufacturing taxonomy as per the UPLCI database, any changes made in the impact estimation for unit manufacturing processes can be readily updated within our framework. Future efforts in this direction will look at achieving a greater level of interoperability between the systems.

6.6 Similarity Estimation

A natural way of quantifying similarity between elements of a set is by establishing a measure of similarity/distance between them. The similarity between two objects is a function of the commonality and the differences they share [113]. We capture these properties using a distance function $d : \varepsilon \times \varepsilon \rightarrow \Re$ that operates on elements of a taxonomy ε and returns a real valued ($\in \Re$) distance measure. Although we do not strictly enforce the distance function d to meet the required conditions to be defined as a metric, we develop a function that possesses the following properties:

1. Non negativity : $d(e_1, e_2) \geq 0; \{e_1, e_2\} \in \varepsilon$
2. Symmetry : $d(e_1, e_2) = d(e_2, e_1)$
3. Identity : $d(e_1, e_2) = 0 \Leftrightarrow e_1 = e_2$

We begin the discussion on similarity computation by defining the involved terms. All mechanical parts are considered to be elements of a set ρ, with associated materials $m \in M$, manufacturing processes $r \in R$, functions $f \in F$, and a specific shape s. Here, M, F, and R are the respective taxonomies adopted to represent these attributes. A manufacturing process $r \in R$ is treated as an operator $r : \rho \times \rho \rightarrow P$ such that it operates on a certain part and returns another part with either same or different material and shape properties. Thus, the entire sequence of manufacturing processing can be viewed as a composition of operators that transform an initial blank $P_0\{m_0, s_0, f_0\}$ to the final part $P_n\{m_n, s_n, f_n\}$. The material, manufacturing, function, and shape definition represent significant decisions towards framing design intent. Therefore, we interpret the similarity among parts as a composition of similarities in these four attributes. For this, we define a set of distance functions $\{d_m$, d_f, d_r, and $d_s\}$ associated with these attributes respectively. Since material, manufacturing and function definitions are represented using corresponding taxonomies, we develop a generalized similarity measure that can be adapted to taxonomies. The distance function for shape is defined using similarities in *shape features* outlined by Squire et al. [114].

6.6.1 Material, Manufacturing, and Function Similarities

Classification trees and taxonomies increase in specificity as we proceed lower down the hierarchy. Therefore, a pair of siblings at a lower level are more similar than siblings higher than them. For example, in a manufacturing taxonomy, any two types of milling processes are more similar to each other than any two mass reducing processes. Exploiting this property for similarity computation requires making use of the hierarchal nature of the taxonomy. The distance measure discussed here builds on concepts described in Ganesan et al. [115] and applies them towards the used material, manufacturing, and function taxonomies. Given any two elements in a taxonomy, we calculate a distance measure as follows.

- *Tree Depth Equalization:* When computing the similarity between any two elements of the same tree, only elements at the same depth from the root are evaluated. This normalization step accounts for the variation in levels of input specificity. For example, as shown in Figure 6.4, the difference between the two manufacturing processes *casting* (not very specific) versus *drop forging* (more specific) is essentially the difference between *casting* and *forging* (on a similar level of specificity as casting). Thus, the depth equalization step normalizes the specificity of the items being compared.

if $depth(a_1) > depth(a_2)$
then $a_1^* = ancestor(a_1)$ at $depth(a_2)$ && $a_2^* = a_2$
else if $depth(a_2) > depth(a_1)$
then $a_2^* = ancestor(a_2)$ at $depth(a_1)$ && $a_1^* = a_1$
else $a_1^* = a_1$ && $a_2^* = a_2$

- *Distance Estimation:* The next step is to calculate the numerical value of similarity between the entities substituted in the first step. Our distance function is based on the generalized vector-space model discussed in Ganesan et al. [115, p. 71]. We focus on illustrating the applicability of this distance function to material, manufacturing, and function taxonomies by demonstrating its hierarchy preserving behavior on the Allen and Todd taxonomy [106]. The corresponding distance function is defined in Equation (6.6).

$$D(a_1, a_2) = \frac{d_{pl}\left(a_1^*, a_2^*\right)}{d_{pl}(a_1^*, a_2^*) \, + \, d_{lca}\left(a_1^*, a_2^*\right)} \tag{6.6}$$

As both d_{pl} and d_{lca} lie in the interval $[0, \infty)$, the distance measure D is confined to the interval $[0, 1]$. However, when $d_{pl} = d_{lca} = 0$, the similarity measure is indefinite. These cases occur only when comparisons are made among elements of taxonomy and its root. As these comparisons do not hold any meaning, we exclude them from the set of allowable comparisons. It can be easily verified that this distance function satisfies the non-negativity, symmetry, and identity conditions mentioned earlier. The distance between two elements in a taxonomy $D(a_1, a_2)$ is equal to 1 only if $d_{lca} = 0$. In other words, two elements in the taxonomy are considered to be entirely dissimilar if their lowest common ancestor is the root node of the taxonomy.

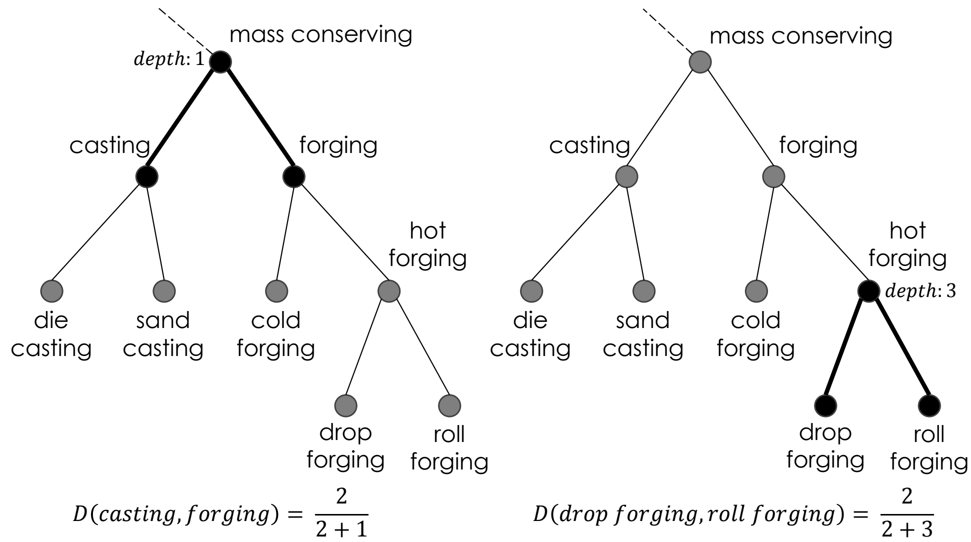

Figure 6.4. An example subtree from the Allen and Todd taxonomy [106] for manufacturing processes. This figure illustrates computation of pair-wise dissimilarities among manufacturing processes using Equation (6.6). We can see that this distance measure accounts for hierarchies as it allocates a decreasing value of dissimilarity to a pair of siblings lower down the taxonomy tree. Here, we illustrate that D(drop forging, roll forging) $<$ D(casting,forging) because the former pair of siblings are at a lower depth.

Figure 6.4 illustrates the application of the distance measure to an example subtree. Here, the distance between *casting* and *forging* is 2/3 which is greater than 2/5; the distance between *drop forging* and *roll forging*. This shows that the distance function accounts for the hierarchical structure of the taxonomy while calculating pair-wise similarities.

Figure 6.5 shows the result of applying our distance measure to the Allen and Todd taxonomy [106] with $\lambda = 1$. The hierarchical structure of the taxonomy is preserved by the distance function. This is seen in the box-within-a box structure of the similarity plot. The clear distinction between the largest two boxes represent the split in the taxonomy for *shaping* and *non-shaping* processes.

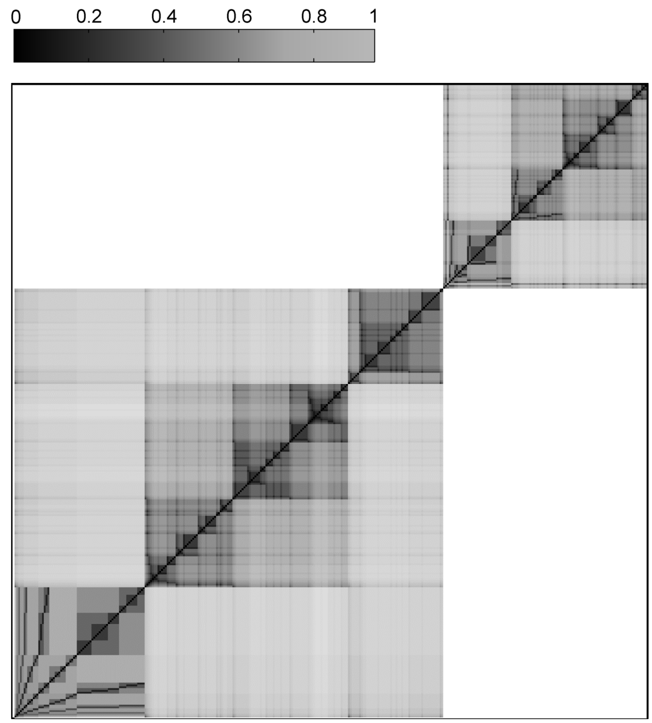

Figure 6.5. Distance-plot matrix for the Allen and Todd taxonomy [106] generated using distance function D in Equation (6.6). Here, each pixel represents a pairwise distance measure calculated between two manufacturing processes in the taxonomy. As shown in the colorbar, lighter values represent a larger value of the distance measure. For computing pairwise distance, the value of the scaling constant λ was set to 1.

Given that we have established a method to compute pair-wise similarities between any two nodes in a taxonomy, we proceed to define our method for composing a scalar distance measure for the specified material, manufacturing, and function definitions. The definition of a part attribute can consist of a single element or, in other cases, a set of elements from the taxonomy. Additionally, the ordering of the associated elements may hold significance in cases such as the definition of a manufacturing process plan. Hence, we develop a measure of each of the attributes that encodes dissimilarity as the maximum deviation of one set of attributes from the other.

In our repository, each part is associated with a single material type. Therefore, for any two materials $m_1, m_2 \in M$, the distance function, d_m, is directly given by the function operating on the material taxonomy as shown in Equation (6.7). A manufacturing description $r = \langle e_{r1}, e_{r2}..., e_{rn} \rangle$, $r \in R$ is considered as an ordered n-tuple of manufacturing processes. Given two manufacturing descriptions, r_1 and r_2, we define a set $r_1 \circ r_2$ whose elements are 2-tuples formed by the element-wise product of r_1 and r_2. The reason behind performing an element-wise operation is that, given two manufacturing descriptions it only makes sense to compare primary production processes with other primary processes, secondary processes with other secondary processes and so on. For example, consider two parts with the following process plans: $\{casting, annealing\}$ and $\{forging, nitriding\}$. Comparing a primary process of one part ($casting$) with a surface treatment process of another ($nitriding$) will wrongly indicate that the process plans for the two parts are highly dissimilar. Instead, comparing primary processes separate from secondary processes provides a more meaningful measure. In cases where the cardinalities of r_1 and r_2 are different, we restrict the similarity computation to the first n elements, where n is the lower of the two cardinalities. The distance function d_r is defined as the maximum possible value of dissimilarity among the sets of descriptions as given in Equation (6.8). A function description $f = \{e_{f1}, e_{f2}...e_{fn}\}$ is considered as a set of functions wherein the ordering of the elements are immaterial. Like d_m, the dissimilarity between two sets of function descriptions is governed by the maximum possible value of dissimilarity among the descriptions. Given two sets of function descriptions, f_1 and f_2, the distance function d_f is detailed in Equation (6.9). Here, $f_1 \times f_2$ represents the Cartesian product of the sets f_1 andf_2. Unlike the manufacturing description, we choose to compare all possible function pairs because there is no concept of *function ordering* in our definition scheme.

$$d_m(m_1, m_2) = D(m_1, m_2) \tag{6.7}$$

$$d_r(r_1, r_2) = max(D(r_1 \circ r_2)) \tag{6.8}$$

$$d_f(f_1, f_2) = max(D(f_1 \times f_2)) \tag{6.9}$$

6.6.2 Estimation of Shape Similarity

For estimating shape similarity, we convert 3D models into 2D projections of sketch-like renderings using *suggestive contours* [116]. This allows comparing user sketches and images to 3D models in the repository. Here, we use the bag-of-features method (BoF) [114] to develop a metric for shape similarity due to its robustness to noise introduced by affine deformations. Previous literature [117, 118] has shown that the BoF method has commendable performance with regards to 2D shape classification and retrieval. The core idea of the BoF method is to represent images as a histogram of occurrences of *visual words*. The procedure for computing shape similarity is described below.

- *Feature Detection:* In this step, we compute locations of interesting features given by computing the *feature points* on the image using the Harris Detector [119]. Finding such discriminative locations helps in identifying differences between shapes.

- *Feature Description:* In this step, we compute patch descriptors for each detected feature using the Scale Invariant Feature Transform (SIFT) [120]. SIFT embeds these features in a high dimensional space by assigning a 128 dimensional descriptor to the features.

- *Quantizing Features using Visual Vocabulary:* The feature descriptors computed using SIFT have high dimensionality and the complexity of computation increases with the number of features that are detected. To reduce some of the involved complexity, we compute a *visual vocabulary* by clustering features in the image database.

- *Image Descriptor Generation:* In this step, we transform the image data into a histogram representing a count of occurrences of cluster center matches. Given any two histograms x and y that represent two images S_x and S_y respectively, a p-norm distance can be computed by Equation (6.10).

  $$d_s(x, y) = \left(\sum_{i=1}^{n} |x_i - y_i|^p \right)^{1/p} \tag{6.10}$$

  In this implementation we use a simple L^1 norm by setting $p = 1$. Additionally, in the interest of supporting fast retrieval, we use the fast approximate nearest neighbor method [121] to index queries.

Thus, the overall distance between two parts is given by $\{d_m, d_r, d_f, d_s\}$ which is a set comprising of pairwise distances among corresponding part attributes. Although it is possible to compose a scalar pair-wise distance measure from this set, there is a possibility that reducing the dimensionality of the data might result in excessive loss of similarity information. Interpreting whether two parts are more similar due to similarities in material, function, or any such attribute is largely decided by the context of the application and therefore by the user. Hence, we focus on creating meaningful multi-dimensional information visualization schemes that aid users in exploring the part repository. The main idea of our visualization scheme involves overlaying computed environmental indicators on similarity information of part attributes for enabling sustainability-aware design exploration of part repositories.

6.7 Visualization and Prototype Interface

Although there are numerous schemes for visualizing sustainability related data, a handful of them try to merge these visualizations with the design process. For creating a seamless interface between the two, we develop a list of the following design goals that are sensitive to needs of the designer.

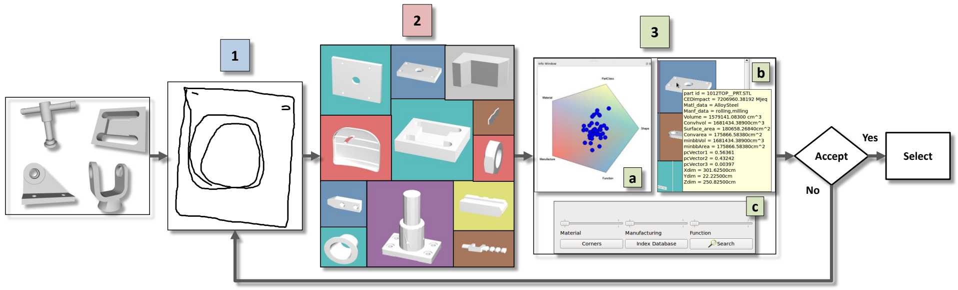

Figure 6.6. Visualization pipeline for exploring 3D repositories. Users begin by sketch based querying as shown in (1). Our system organizes search results using a squarified layout (2) that is constructed using Brul's squarified treemap algorithm [122]. Here, each color corresponds to a particular material class. The area of a cell is scaled in negative proportion to the calculated environmental impact indicator. Parts are ordered by shape similarity relative to the query. Users can explore these results. Further using a similarity polygon (3a), sliders that set values for distance threshold (3b) and interactive tooltips (3c). The combination of these steps forms a unit iteration that can be repeated as desired by the user.

6.7.1 Design Goals

- *Ability to explore product repositories from a design similarity and sustainability perspective.* The process of exploration should allow the user to build engineering intuitions of the relationship between shape, material/manufacturing data, and environmental sustainability.

- *Intuitive Interaction.* One of our goals is to simplify the design exploration process by providing an intuitive means for navigating and searching for alternate design solutions from a given part database.

- *Exploration Support for Design Process.* We posit that human spatial and visual reasoning skills can be leveraged for effective exploration in the design process. An important element within developing intuitive exploration schemes is the use of cognitively prominent visual variables such as variations in shape, size,

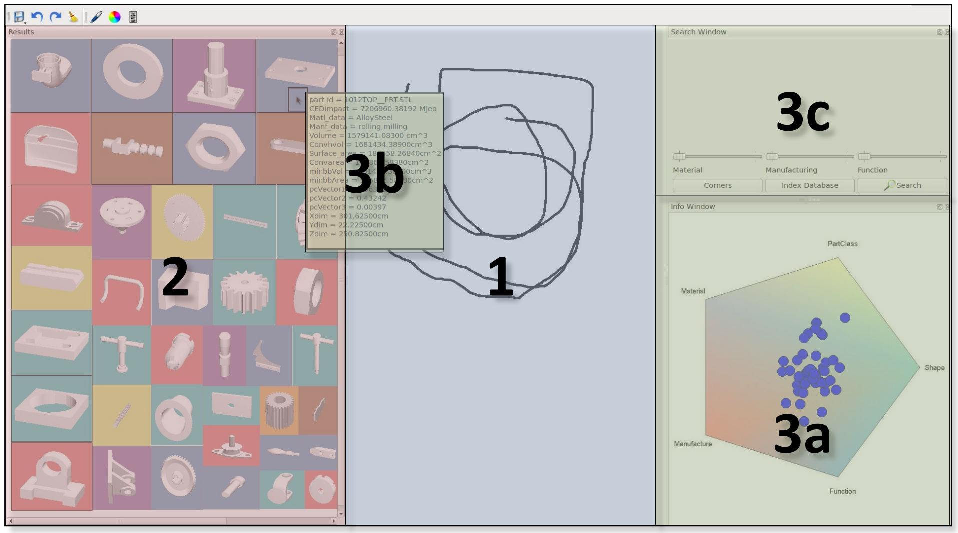

Figure 6.7. Screenshot of the prototype interface that integrates elements discussed in the visualization pipeline. The numbers on the interface represent implementations of corresponding elements discussed in Figure 6.6.

and color. This allows pre-attentive processing of decision variables, allowing designers to easily narrow down their focus.

6.7.2 Interface Elements

Based on these design goals, we implemented a visual interface titled shapeSIFT, that supports eco-conscious design exploration. In this section, we list the interface elements implemented in the interface.

6.7.2.1 Sketch-Based Input:

Adopting sketching as the primary method for query within our framework gives us the advantage of utilizing one of the dominant modes of artifact creation among designers. Sketching is shown to provide a visible graphic memory that facilitates creativity by providing an easily accessible repository of generated ideas and by stimulating building on earlier ideas [123]. Using sketch-based input gives users the ability to modify their input with relative ease.

6.7.2.2 Squarified Layout Visualization:

Squarified layouts are useful for visually providing a summary of the search results. They can also provide visual cues that allow users to aggregate and discriminate search results. Figure 6.7-2, shows an example result that is automatically generated from a sketch-based retrieval process. In this visualization, environmental impact calculated through Equation (6.1) is divided by part volume to develop an indicator for representing the sustainability of a unit shape. Squares larger in area contain parts with a lower value of the environmental indicator. By representing the indicator using a prominent visual variable, we hope to nudge designers away from selecting unsustainable options. The color of each cell corresponds to the taxonomic class that the part's material belongs to. For example, in the current visualization a red background indicates that the part material is a kind of *Alloy Steel*. A legend of colors is available to the user, and we ensure that we always maintain color continuity for the same material class in the visualization. The coloring information can be changed to represent classification along other attributes such as manufacturing or function class. Users can also filter results either by setting individual or multiple thresholds for the set of computed similarities $\{d_m, d_r, d_f\}$. Parts that are dissimilar to a query part in terms of these attributes are represented with a grayed out background as seen in the top right corner of Figure 6.7-2. The current visualization is organized according to the shape similarity (d_s) relative to the best sketch query. Similarity decreases as we move from top-left to bottom-right in a horizontal raster. More specific information about part attributes such as volume, surface area, material are displayed using interactive elements such as tooltips.

6.7.2.3 Similarity Polygon

The similarity polygon visually represents a barycentric embedding of similarity metadata along chosen attribute dimensions. Each plotted point corresponds to a specific search result in the squarified layout. Figure 6.7-3a shows an example similarity polygon that allows quantitative comparison of similarities. Using the similarity polygon, designers can assess the presence of a dominant similarity metric.

6.7.2.4 Sliders and Tooltips:

Users can also filter results using sliders (see Figure 6.7-3c) either by setting individual or multiple thresholds for the set of computed similarities $\{d_m, d_r, d_f, d_s\}$. Parts that are dissimilar to the query part in terms of these attributes are grayed out in the squarified layout. Metadata information pertaining to a part is viewable using tooltips illustrated in Figure 6.7-3b.

6.7.3 Prototype Interface:

A screen capture of the prototype interface for shapeSIFT is shown in Figure 6.7. This prototype implements interface elements discussed in the previous section. We conducted a pilot study involving two domain experts, for analyzing the usefulness and the interface design for shapeSIFT. The first domain expert had extensive development and research experience in the field of information visualization. The second expert had research and industry experience in product design and design for sustainability. A general demonstration of the functionality and interface controls was provided to the experts following which they were allowed to explore and ask questions about the interface. A talk-aloud protocol was followed, during which experts were asked to vocalize their actions. The experts, were free to ask questions regarding the interface and the underlying data at any point during the study. Results from the pilot study indicated that the experts found shapeSIFT useful in the context of design exploration within repositories. However, a list of concerns were pointed out that limited the utility of the shapeSIFT interface.

- The experts felt that the squarified layout was a useful visualization scheme. However, the ordering of results from top left to bottom right resulted in some confusion about the shape similarities.
- The visualization expert pointed out that it was difficult for users to associate a color to a particular taxonomic class without prior training or extensive use of the interface. Therefore, the expert was concerned with the use of a particular color code for a material/manufacturing class.
- We noticed that the tooltips brought up on the squarified layout impeded experts while they were using shapeSIFT.
- We also noticed that the lack of a 3D view for a retrieved result presented difficulties in comprehending the part.
- A significant point brought up by the experts was the lack of a means to filter out results that significantly differed in dimensions. For example, querying for a gear shaped object might return a small plastic gear used in a toy as well as a significantly larger gear in an automotive gear train. Not filtering out such disparate results in terms of part dimensions can impede the user from reaching potential alternatives.
- Finally, both the experts felt that the inclusion of a text-based search to query and highlight items would greatly increase the utility of the shapeSIFT interface.

6.7.4 Modified Interface

Based on the feedback provided during the expert evaluation of the prototype application, a new version of shapeSIFT was constructed from the ground up. One

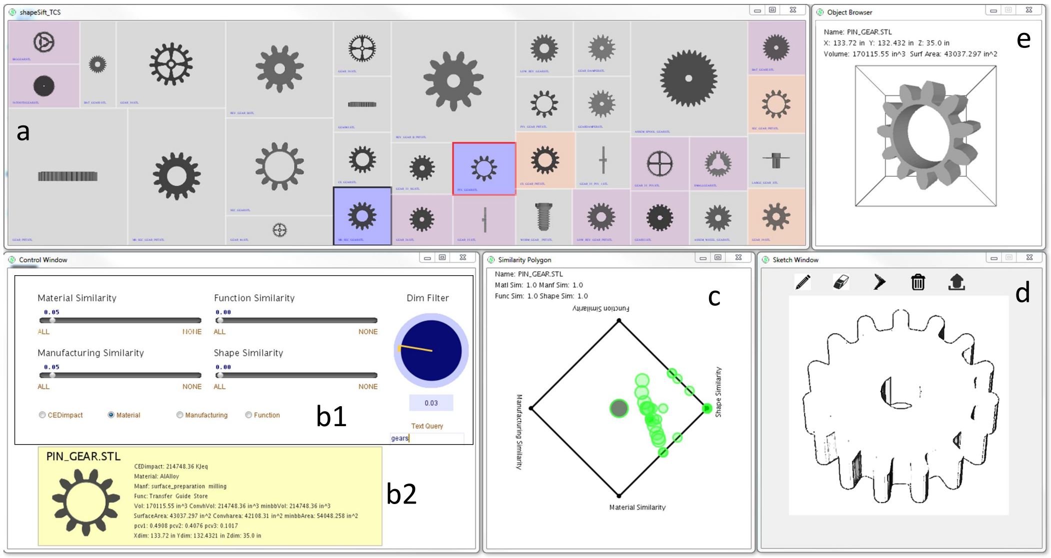

Figure 6.8. A screen capture of the modified shapeSIFT interface. It consists of a squarified layout window that displays query results (6.8-a). A control panel (6.8-b1) is used for setting similarity thresholds for material, manufacturing, function, and shape similarities. A dimension filter knob that allows for screening out parts that are significantly larger or smaller than the reference part. A text query box is also provided for users to query part metadata. Corresponding matches are automatically highlighted in the squarified layout. A label (6.8-b2) is used to display metadata information and a picture of a particular part that is selected from the squarified layout. As shown in (6.8-c), the similarity polygon allows the user to obtain an understanding of the four similarity attributes. The sketch window (6.8-d) contains a canvas and related controls for creating/modifying the sketch, uploading an image, and querying the repository. The object viewer window (6.8-e) displays a 3D model of a selected part.

of the goals of the the new implementation was the ability to make it cross platform and potentially develop it into a web-based tool. For this, we reimplemented the interface on JAVA using Processing®, an open source programming language that is geared towards visual design. The new interface uses a mutually coordinated, multi-window framework that allows users to customize the size and position of the windows. This feature allows users to seamlessly move their focus to different parts of the tool without having to allocate valuable screen space to features that are not required at that particular time. We have implemented a server-client framework for loading and querying the repository through sketch input. This allows the possibility for implementing a collaborative framework between multiple instances of shapeSIFT. A screenshot of this modified shapeSIFT interface is shown in Figure 6.8. Our modified implementation retains functionalities of the prototype implementation while improving the usability and the scalability of shapeSIFT. The implementation and the improvements made in the modified shapeSIFT interface are detailed below,

- *Squarified Layout Window:* Similar to the prototype implementation, this window (Figure 6.8-a) shows the retrieved results in a layout in which each cell is scaled inversely to the computed environmental indicator. If a particular part does not lie within the threshold set using the control panel, the corresponding cell background is grayed out. Building on the expert feedback, we removed the shape similarity based ordering of the results. We also changed the coloring scheme from representing a particular metadata class towards a representation of similarities between metadata. Thus, parts with similar metadata are shown using similar colors. Clicking a cell selects the part and displays it on the label, 3D object viewer, and highlights it on the similarity polygon. An additional feature available to the user is changing the reference part from the set of retrieved results by right clicking a cell from this layout.

- *Control Window:* The control window implements the control panel (Figure 6.8-b1) and the dynamic label (Figure 6.8-b2). The control panel contains: (1) sliders for setting the similarity thresholds for material, manufacturing, function, and shape similarity, (2) radio buttons that can be used to set the coloring scheme on the squarified layout based on the environmental indicator, material, manufacturing or function metadata, (3) a dimension filter that screen out parts that are larger or smaller than the reference part in terms of its maximum dimensions, and (4) a text query box that can be used for querying part metadata.

- *Similarity Polygon Window:* This window (Figure 6.8-c) visualizes the similarity polygon for the set of retrieved results. Since the similarity polygon uses a barycentric embedding of similarity values for plotting, data points with the same relative weights (i.e [1,1,1,1] and [0.5,0.5,0.5,0.5]) are plotted at the same coordinate. This makes it difficult for the user to judge the overall magnitude of the similarity values of a part with respect to the reference part. Therefore, we have implemented a visualization scheme that scales the radius of the circle with the total measure of similarity with respect to the reference part. We have also removed the similarity dimension based on *part class* present in the prototype in favor of a text query box in the control window. Selecting a part from the squarified layout, highlights the corresponding part on the similarity polygon. Conversely, selecting one/multiple parts from the similarity polygon highlights the corresponding cells on the squarified layout using a red border.

- *Sketch Window:* The sketch window (Figure 6.8-d) implements a canvas and controls for creating a two-dimensional sketch query. We have also provided means for users to upload an image onto the sketch canvas. The uploaded image is converted into a sketch-like representation using a high-pass filter that performs edge detection. On submitting a query, the squarified layout and other windows are automatically updated to reflect the retrieved results.

- *Object Viewer Window:* This window (Figure 6.8-e) displays a 3D model of the .STL file associated with the selected part. Users can rotate the displayed model and view the geometric parameters of the selected model on a text label located on the top left of that window.

6.8 User Study

To verify the validity of the modified shapeSIFT interface and its underlying framework, we conducted an expert evaluation of the tool within an industry setting. For generating input data as specified by our framework, we programmatically generated a design repository consisting of engineering parts. 3D parts used for constructing the pilot database were obtained from the Engineering Shape Benchmark (ESB) [124]. The ESB contains a total of 479 models in Stereolithography (.STL) file format that are classified into 45 shape classes. Synthetic data regarding material, manufacturing, and functionality was added to the part data. We tried to ensure that the selected parts have a reasonable degree of variability in their shape, material, and manufacturing definitions. Data from the repository is pre-processed and converted into an XML file which is read into shapeSIFT. The sections below details the setup and results of the conducted user study.

6.8.1 Procedure for Expert Review of the ShapeSIFT Interface

To verify the applicability of our visualization framework in the context of design exploration, we conducted a user evaluation of the modified shapeSIFT interface. The focus of our study was to understand the applicability and utility of our framework and the shapeSIFT interface among design engineers in a real-world setting. We were interested in eliciting useful comments, guidelines, and issues from the participants rather than measuring efficacy or performance criteria. Therefore, we decided on adopting an expert review based assessment [125] for our study. Expert reviews are known to be useful in scenarios where the system to be evaluated requires specific knowledge or skills [125]. Usually, expert reviews are conducted among a smaller pool of participants without an aim of strictly evaluating performance measures [126]. The following sections discuss our setup, procedure, and results from our study.

6.8.1.1 Setup and Participants

We conducted the expert evaluations on a Lenovo T530 laptop PC connected to a 20 inch external display. We encouraged participants to vocalize their thoughts and actions while performing each task. They were also asked to comment on the utility and the ease of use of the system after each task. To analyze this data, we voice recorded participants throughout the duration of the tasks. A total of 5 domain experts (3 male, 2 female) were recruited to validate applicability our framework and the usability of the shapeSIFT interface. The experts in this study were employees with a leading provider of engineering consulting services and had prior experience in product and process design. We recruited a diverse pool of experts between 21-55 years of age with 1-15 years of industry experience. To prevent bias with evaluation, we followed accepted practices such as voluntary consent, control, user confidentiality, and participant blinding.

6.8.1.2 Tasks

A total of 3 tasks were required to be completed by the experts in order to evaluate various elements present in the modified shapeSIFT interface. The tasks were designed to validate shape-based querying, metadata-based visualization, and the exploration framework implemented in shapeSIFT. Each participant was monitored by a proctor with experience in the use of the shapeSIFT interface. When required, the proctor assisted participants in using the different elements of the interface. We ensured that the proctor refrained from providing any form of conceptual or design-related suggestions. Participants were initially trained in shapeSIFT through a 15 minute familiarization session before conducting the tasks. This session consisted of a 10 minute guided demonstration of the framework and the functionality of various interface elements present in shapeSIFT, followed by 5 minutes of *free play*. We logged the experts activities using event triggers that recorded interactions with interface elements in shapeSIFT. Our intent was to analyze these event logs for patterns in behavior defined by switching visualizations, selection, filtering, and querying. After each task, participants were required to respond to a task load index survey and discuss open-ended questions asked by the proctor. A questionnaire for assessing the usability of the interface was also handed out at the end of the study. Please see the thesis appendix for a copy of the documents distributed in this user study.

- *Retrieving similar parts via querying (T1):* In this task, participants were required to select parts similar to a reference part provided to them by the proctor. For this task, we generated two reference parts with data related to its material, manufacturing, function, dimensions, and shape (shown as a picture). In order to encourage exploration of the design space, we ensured that the reference part did not have an exact match in the provided repository. Thus, participants were required to assess similarities based on multiple part attributes and actively make trade-offs among them. We allowed participants to select one, multiple, or no parts based on their assessment of similarity to the two reference parts. Upon selection of a similar part, users were asked to estimate the environmental indicator for the reference part based on the values for the selected part and suggest if it was a more benign alternative. A total of 10 minutes was allocated towards completion of this task.

- *Exploring a set of functionally similar part concepts (T2):* This task was designed to focus on the metadata exploration framework facilitated by the squarified visualization and the various similarity filters in the control window. In this task, users were provided with an example design concept for a gear (without shape or function information) with high level data related to its material and manufacturing processes. Using this design as a reference part, users explored a set of existing gears from the ESB repository in order to estimate the possible environmental impact of the design. As this task focuses on metadata exploration, we restricted the use of sketch/image-based querying and pre-loaded results through textual querying of parts tagged as gears from the ESB repository. Similar to T1, the answers for this task were open-ended. A total of 10 minutes was allocated for T2.

- *Macro-level estimation of specific metadata (T3):* The goal of this task was to assess the utility of the shapeSIFT framework in answering specific macro-level questions (i.e. "how many gears in the result set are made of Aluminum

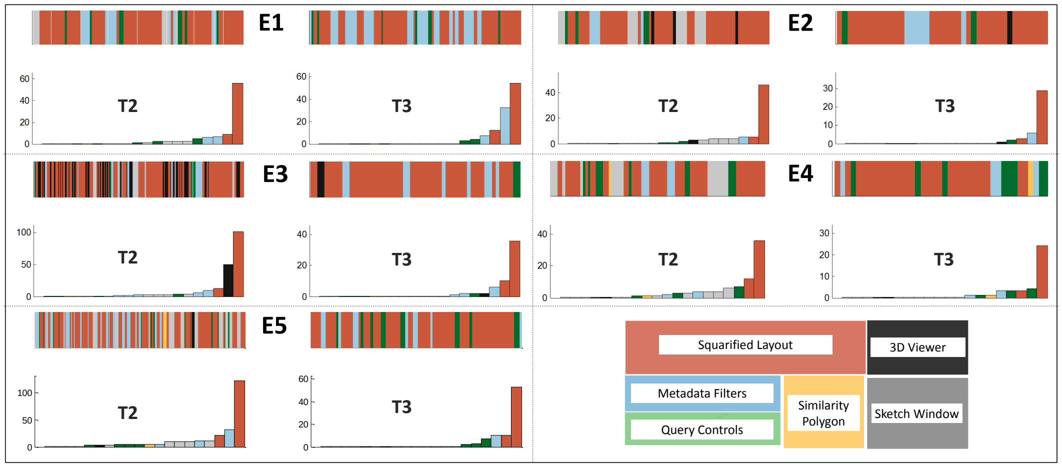

Figure 6.9. Visualization of user interactions events with the shapeSIFT interface. A total of 20 different event types were recorded and categorized into 6 classes based on the interface elements in shapeSIFT. Each class is represented by a particular color type as indicated in the schematic legend (bottom right). For each expert (E1–E5), a sequential plot of interaction events and a corresponding histogram of event count is shown. Please note that event data from the log file is separated by task (T2, T3) to observe similarities/differences between tasks for a particular expert. Interactions for Task 1 (T1) are not shown as they relate to unstructured activities for familiarizing users with shapeSIFT.

alloys?"). Participants were allowed to use all the interface elements present in the control window to answer such questions. Through this, we hoped to judge the utility of visualizing results for such questions in the shapeSIFT squarified viewer. A total of 5 minutes was allocated for T3. Results from the conducted tasks and the questionnaires are detailed in the section below.

6.8.2 Results

Expert feedback regarding shapeSIFT was captured using four different methods: (1) the NASA Task Load Index (TLX)[1] survey, (2) the System Usability Scale (SUS)[2] survey, (3) audio recorded comments provided during the study session, and (4) a system generated log file of interaction events. Results from the TLX survey show that a majority of the participants (4 out of 5) felt that they were successfully able to perform all tasks. From the audio transcripts and the survey, we also observed that participants were able to perform tasks without excessive frustration, (max. TLX rating 40/100) physical demand, (max. TLX rating 15/100) or temporal demand (max. TLX rating 25/100). However, all experts felt that the tasks required appreciable mental demand and effort to complete. This result was expected as all participants commented that they were not used to visual analytics-based interfaces in the context of design exploration, selection, or reuse. Results from the participant comments suggest that the effort required reduced considerably with task progression.

Quoting an expert from the study, *"I feel that participants need some initial experience with shapeSIFT as there are multiple windows, each having several variables. But, I feel that it is a very useful tool once you get used to it."* Another expert said *"I had to pick up a lot of things initially but I think I got the hang of it pretty quick."*

Figure 6.10 illustrates the results from the SUS given to participants at the end of the user study. Overall, experts felt that the shapeSIFT interface was useful in a practical setting and that it was easy to learn and use. One expert pointed out that *"A lot of current systems go by part number which are ad-hoc and confusing. In a big company doing lots of different things, shapeSIFT can help find parts which are already there instead of redesigning from scratch. It will reduce the effort in the design process."* Participants also reported that the system was well integrated and that they would feel confident using the system on a frequent basis. Among the five experts, we observed that one of the experts (E1) had difficulties in using the

[1] http://humansystems.arc.nasa.gov/groups/tlx

[2] http://www.usability.gov

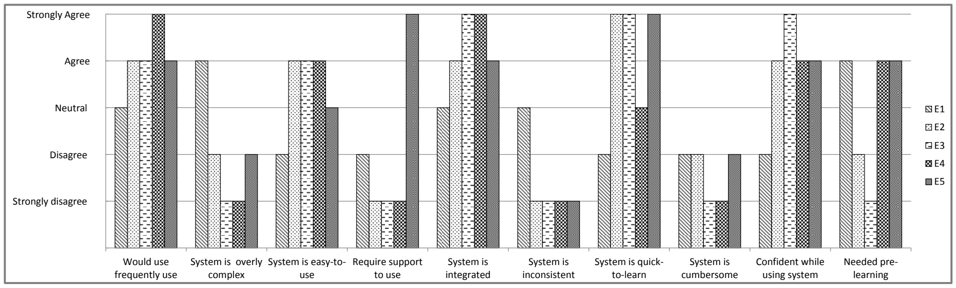

Figure 6.10. Bar chart detailing the results for the system usability scale (SUS) survey[2] handed out to each expert (E1–E5) at the end of the study. As seen, a majority of experts agreed that shapeSIFT was well integrated, easy-to-use and more importantly easy-to-learn. They also felt that some amount of pre-learning was required to be able to use the system but would be able to handle it without the need for technical support. Among all five experts, we observed that E1 was critical of the usability of shapeSIFT and felt that it required more functionality in order to be useful in an industry setting.

system and did not achieve the same fluency as other experts in using the system. E1 reported that shapeSIFT needed more functionality such as automated seed points for starting the exploration and a partial textual query for becoming more practical.

All experts agreed that the shapeSIFT framework and interface aid the process of eco-conscious design exploration. We observed that by visualizing environmental indicators and corresponding metadata, users were able to actively engage in exploration pathways focused on trading materials, manufacturing processes, and part functions. Inspite of shapeSIFT only providing a cradle-to-gate indicator, we observed that experts were actively considering concepts such as total lifecycle impact, use phase energy consumption, recyclability of materials, and waste recovery. This suggests that future work should be directed towards estimating total lifecycle impact of parts archived in design repositories.

The similarity-based assessment framework allowed users to look at alternate components with comparable and lower environmental impact and discuss the relationship between a particular part attribute and its environmental indicator. We believe that allowing users to observe such dependencies can significantly aid the sustainable design process and motivate them to use more accurate impact assessment methodologies to further refine their analyses.

To understand the differences in the behaviors of experts while using shapeSIFT, we analyzed the automated log file generated by shapeSIFT in conjunction with the audio recordings. Figure 6.9 visualizes this data for each expert corresponding to a particular task. On comparing interaction events between experts, we noticed the usage of specific interface elements strongly depended on the experts' view of important dimensions while assessing similarity in the multi-dimensional data. For example, E3 felt that the most critical dimension for assessing part similarity in T2 is the overall shape of the object, while E5 was more interested in the overall dimensions of the part. This behavior is visible in the histogram count which shows high instances of object viewer usage for E2 and high usage of the dimension filter for E5. This aspect of the shapeSIFT interface lends itself for training novice users and observing their exploration patterns and assessment of critical similarity dimensions in multi-dimensional design datasets.

Two kinds of exploration modes were observable based on event data and analyses of the audio recordings. One set of experts focused on narrowing down the multi-dimensional design space to a small set (usually 4-5) of feasible alternatives. This was done by heavily relying on the querying and filtering features present in the shapeSIFT interface. This set of experts proceeded towards selecting the most appropriate part from the filtered set. The second set of experts devoted more focus towards interpreting the various facets of the multi-dimensional design space by switching between multiple data views and changing the reference point in the exploration process. This trend is observable by an increased use of the squarified map, and querying elements in the interface. Self-reported results from the TLX survey show that experts using the latter exploration method ($\mu_1 = 33.75, \sigma_1 = 11.8$) felt that they performed significantly better than the former group ($\mu_2 = 50, \sigma_2 = 12.6$). An independent sample T-test assuming unequal variances shows the presence of a significant difference ($T(11.66) = 2.8889$, one-tailed p-value= .0063). Furthermore, the mental demand associated with using the interface dropped for experts in the latter set whereas it increased (or remained the same) for experts in the former set. These results seem to indicate that certain exploration strategies and similarity assessment methods, can be more beneficial for users while exploring multi-dimensional data in design databases. We hope to explore such aspects using controlled testing with a larger pool of participants in the future. Another important observation from the event data, is that there was little interaction with the similarity polygon based representation for similarity metrics. Analysis of the audio recordings revealed that most experts felt that the similarity polygon was a useful visualization technique before starting with tasks T2 and T3. However, we found that the experts faced difficulties in translating results from this visualization into actionable items. This indicates that the design of this interface element needs to be rethought so as to allow easier interpretation of the data. Analyzing the event data across the two tasks for all experts, we clearly see that the number of jumps/transitions between interface elements is reduced in T3. This behavior seems to indicate that the users were more focused and comfortable with the tool in T3. Audio transcripts also confirmed the fact that experts were significantly more comfortable with the shapeSIFT interface allowing them to focus on the exploration steps needed to complete T3.

6.9 Conclusions and Future Work

This chapter has discussed the motivation and potential benefit offered by InfoVis-based tools and methods for supporting eco-conscious design exploration. Along these lines,we presented shapeSIFT, a novel framework for visualization-driven, eco-conscious exploration of part repositories. Part similarities are quantified on multiple dimensions such as material, manufacturing and function-based on the structure of their corresponding taxonomies. The framework describes methods for automating the computation of environmental impact indicators and similarities in part attributes. This data is visualized using a squarified layout which provides an overview of similar parts and their attributes. Finally, this chapter discusses a prototype interface that integrates the visualization with sketch-based querying for supporting intuitive exploration of 3D part repositories. Future work will be focused on extending the capabilities of the current interface by developing alternate visualization and interaction schemes. We plan on conducting full fledged user studies to evaluate our interface from a human computer interaction perspective. An important direction for future work is allowing users the additional flexibility of assessing the environmental impact of novel design concepts. Supporting environmental and similarity assessment for novel 3D parts, requires estimation of their geometric properties. Recently developed natural user interfaces for rapid virtual prototyping such as [127, 128] are particularly applicable in the this context. These interfaces allow designers to iterate over several designs and can be possibly used to guide sustainability-based decision-making. Another important consideration that we wish to address is more accurate estimation of sustainability indicators. We will research methods for quantifying and visually representing uncertainties present in sustainability assessment.

7. A GUIDED DISCOVERY-BASED LEARNING APPROACH FOR CONTEXTUALIZING SUSTAINABLE DESIGN IN MECHANICAL ENGINEERING CURRICULA

The previous chapters have looked at methods, and computer-supported tools for promoting eco-conscious design from the perspective of designers, and product managers. These works show that creating environmentally efficient products and services requires rethinking current design processes. Disseminating such methods requires changes in both, (1) industry-based processes, and (2) engineering curricula. This chapter focuses on developing methods for incorporating environmental sustainability concepts in engineering design curricula

Preparing engineering students with sustainability-related design skills would help them to meet the growing demands for such designers in the industry. To illustrate, a survey by American Society of Mechanical Engineering (ASME) and Autodesk research has shown that approximately 60% of the 4000 respondents from engineering organizations expected an increase in their organizations' involvement in sustainable design the following year [129]. However, recent studies have reported that engineering students have significant knowledge gaps in understanding and applying sustainability concepts in design tasks [130]. Thus, engineering educators need to explicitly teach students on applying sustainability knowledge in engineering design. et, most current engineering programs are in lack of sustainability-related instruction models, or are limited to introducing sustainability concepts as systemic problems (e.g. spill cleanup [131], water conservation [132], and energy management [133]). Although such approaches teach concepts of systems modeling and life-cycle thinking, they are not suited for promoting a deep understanding of the relationships between domain specific design variables and environmental performance. For this, it is crucial to situate sustainability learning within fundamental engineering contexts. To this end, we present an instructional model for sustainability that embeds it in existing engineering design classes. Our goal is to address mechanical engineering students' knowledge gaps in environmental sustainability (ES) and enable students to, (1) identify the relations between design variables and environmental performance, and (2) apply ES principles in design settings. We developed our instructional model based on the hypothesis that students can better understand and apply ES principles through guided discovery activities that help bridge relations between design variables and ES.

7.1 Related Research

We begin this chapter by discussing previous work on sustainability learning in engineering curricula. Following this, we review learning approaches for guided discovery applicable to engineering education. Finally, to provide context for the user study conducted to validate the proposed instruction framework, we introduce shape synthesis and discuss its relevance to applying guided discovery in mechanical design.

7.1.1 Sustainability Learning in Engineering Curricula

Pioneering efforts in sustainability learning focused on developing holistic approaches to increase awareness of interdependencies at the system level. Tilbury [134] states that environmental education for sustainability should focus on developing closer links between environmental quality, ecology, socio-economics, and the underlying political threads. Reorienting education for promoting sustainable development is discussed by Fien et al. [135]. Their primary focus is the development of an educational system for learning the knowledge, skills, perspectives, and values, that motivate people to lead sustainable livelihoods. Similarly, Ashford [136] argues that sustainability learning should be interdisciplinary in nature to broaden the *design space* for engineers. In spite of such efforts, surveys [129, 130] have shown significant knowledge gaps among engineering students and their inability to apply ES-related concepts into practice.

To address such gaps, a large portion of recent efforts have focused on developing courses, workshops, games, and practical experiences, promoting active learning of ES concepts. For example, Brundiers et al. [137] investigated the role of experiential learning in the *acquisition of key competencies* in sustainability. The effects of experiential learning games for teaching ES is explored in Dielman & Huisingh [138]. The authors group games based on the type of knowledge and the phases in learning cycles. This classification forms the basis for three types of games, (1) self-analysis games, (2) system games, and (3) communication & collaboration games. Similarly, other researchers [139, 140] have looked at simulation games and the gamification of real-world tasks to promote awareness of ES and conservation-related concepts. In these studies, the goal is to provide ES-related feedback to users to positively influence their behavior. Although such efforts are vital for promoting and maintaining peoples' (including students') interest in ES, a handful of these efforts have focused on contextualizing this learning towards engineering practice.

Approaches that use project-based learning (PBL) has also been previously investigated by researchers. Stienemann [132] discusses the challenges and success in designing PBL to promote hands-on experiences of ES learning. Ameta et al. [141] develops a collective learning approach to teaching ES in a systems design course. These studies underscore the need to consider the feasibility of implementing ES learning activities and use approaches that can maintain student engagement. However, a majority of project-based courses that teach ES, focus on system-level problems such as water purication and urban infrastructure planning. A notable exception is a PBL approach for teaching Design for Environment (DfE) strategies discussed in Bernstein et al. [142]. The authors develop a critique-based module that motivates students to include ES considerations into their designs. Results showed the critique-based module is an effective method for teaching sustainable product design. Despite its important role in sustainable design learning, PBL-based approaches have significant limitations. For instance, the high level of complexity entailed in such projects restricts their applicability to graduate-level classes. Furthermore, such projects are often open ended and involve complex interactions between multiple domains and systems. Thus, it is challenging for students to explicitly define and understand relationships between design variables and environmental impact. To bridge this gap, researchers have argued for integrating ES learning in regular engineering classes.

Peet et al. [143] argue that students find it difficult to integrate sustainable development into engineering practice unless learning activities are incorporated in regular coursework. Approaches for integrating ES concepts in mechanical engineering are reviewed by Kumar et al. [144]. The authors conclude that, (1) sustainability education should be integrated in design & manufacturing courses, and (2) infusing ES into engineering curricula is essential for equipping students with the tools for achieving a sustainable future. An important aspect in ES-related education is assessing the involved learning processes. Warburton [145] makes a case for the importance of deep learning in environmental education. The author argues that the multidisciplinary and interconnected nature of environmental education necessitates deep learning. Shephard [146] discusses educational theories for ES learning. The author reports that most teaching methods in higher education focus on the cogitative skills of knowledge rather than the affective outcomes. Potential changes identified include, (1) changing measures for learning outcomes, (2) rethinking guidelines for course evaluation, and (3) designing realistic learning outcomes in the affective domain.

In summary, achieving a synergistic integration of ES in design engineering curricula requires embedding *sustainability assessment* in existing *engineering courses*. For this, it is vital to develop approaches that achieve this integration whilst students are learning fundamental concepts of engineering design.

7.1.2 Guided Discovery-Based Approaches for Learning

Building on constructivism theories, guided discovery advocates that instruction should guide students to identify theories and principles through hands-on tasks and solving real-world authentic problems, rather than directly provide target information [147]. A meta-analysis review of existing discovery learning literature in science, math, and computer science is presented by Alfieri et al. [148]. Previous research has found that the scientific discovery learning process has greater resemblance to real world knowledge acquisition, where students go through planning, executing, and evaluating stages [149]. Thus, discovery learning can help engineering students develop intuitions for a given domain to solve novel problems. Although some have argued that discovery learning without guidance is not necessarily better than direct instruction [150], guided discovery has distinct advantages, such as providing direct feedback, working through examples, scaffolding student learning and eliciting explanations. More importantly, researchers have suggested that guided discovery has greater ecological value than expository type of learning [151].

Despite its benefits, guided discovery has been rarely used to teach ES concepts in engineering. Therefore, we developing a guided discovery-based instruction framework that to support students' learning processes.

7.1.3 Structural Shape Synthesis

Structural synthesis represents a challenging design problem as it can include a wide range of subjective as well as quantifiable goals [152]. From a geometric standpoint, it requires the selection of a suitably sized member with an appropriate topology. Additional constraints, such as weight, stress & strain limits, allowable materials, and manufacturing processes, add complexity to this problem by limiting the design space. Rules of thumb and guidelines for synthesizing machine parts are well established in engineering literature [153] and are a part of existing undergraduate curricula [154]. Conventionally, the goals for synthesis involve, (1) inducing a uniform load distribution over as much of the body as possible, and (2) minimizing the weight or volume of the material as consistent with cost and manufacturing processes. Based on the specified loading criterion, students learn generic principles and optimal seed shapes for synthesizing structural members. Designers in the industry often use such principles to guide the synthesis process. Analysis tools such as finite element methods (FEA), are used as a means for validating and/or refining synthesized designs.

Papalambros [155] looked at the processes used by students for synthesizing the shape of a structural member. In this study, student teams were required to design a bracket to transmit a specified force. Constraints for the design problem include, ease of manufacture, ability to carry the load without failure, and weight reduction. The author observed that students mostly used intuition, some amounts of low fidelity prototyping, and FEA for designing the bracket. Thus, structural synthesis presents itself as a suitably complex exploration framework for enabling discovery learning. Embedding ES concepts in the *synthesis problem* can potentially allow students to explore relationships between environmental impact and domain specific design variables. It is our hope that this exploration process will allow students to develop deeper insights regarding ES. Such learning can be valuable for transitioning sustainability from an afterthought to an integral part of the design process.

7.2 Research Motivation

The motivation for our work is based on a pilot survey was conducted by Bernstein et al. [142] within a graduate-level product design course to assess general awareness of issues related to sustainability. To better understand awareness of sustainability related concepts, the authors compiled a list of topics based on the survey conducted by Azapagic et al. [130] and asked students to rate their self-perceived knowledge in these topics. For this, an online survey was distributed to students before they began developing ideas for their course projects. After the respondents completed their semester long project, another survey was conducted to determine what sort of sustainable and eco-design principles were used within their course projects. Students were asked to submit a detailed report on the life-cycle stages and processes in their design that would significantly contribute to the environmental footprint of their product concept and suggest design changes to mitigate it. Although the prod-

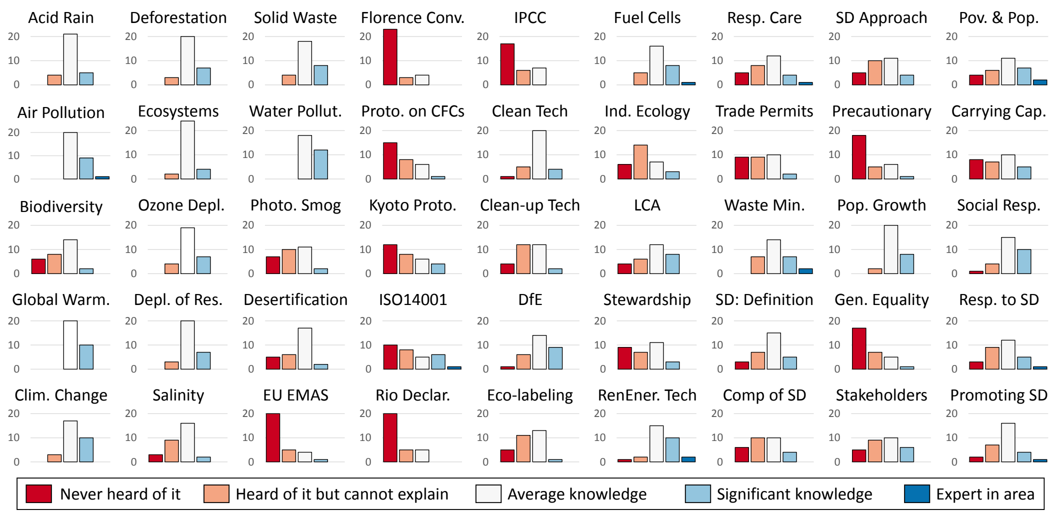

Figure 7.1. Summary of results from the preliminary user survey adapted from Berntein et al. [142] (total of 28 respondents). Each barchart shows responses for self-perceived awareness in that particular topic. Topics chosen for this survey are based on a previous survey conducted by Azapagic et al. [130]. In general, participants had a low level of understanding related to eco-design and sustainability principles. Also, concepts that are popularized by media (climate change, global warming, corporate social responsibility) or have a direct bearing on engineering design (waste minimization, renewable energy) outperformed other categories.

uct/service ideas generated by the student groups are quite diverse, all of them have aspects that could be designed around the principles that were outlined in the first survey. Significant observations are detailed below.

- Participants had a low level of understanding related to eco-design and ES principles. The analysis of participant responses of self-perceived proficiency (based on a 5 point scale) showed that students perceived themselves as having significantly lower than average levels of knowledge in ES-related concepts ($t(27)=-4.09$, $p < .001$). Specifically, students confirmed they have *less than average knowledge* in 22/45 sustainability-related concepts and *less than signif-*

icant knowledge in all other tested concepts. A visual summary of the results obtained from this survey can be seen in Figure 7.1

- Analyzing self-perceived awareness of ES concepts from the survey with the project reports yielded no significant correlations. Further examination of the reports confirmed that a greater self-perceived knowledge of ES concepts did not translate into a more comprehensive consideration for sustainable design principles in the student's project.

Based on these findings, we can conclude that apart from lacking awareness in ES concepts, students also have knowledge gaps in applying known principles of ES and eco-design to design practice. The process of acquiring expertise in applying ES-related principles to specific cases in design can be viewed as resolving disagreements between a specific problem's constraints and the generality of the applied heuristic. In order to build expertise in such contexts, non-experts must overcome potential shortcomings, including, (1) a lack of structured/functional knowledge, (2) an inability to integrate generalizable knowledge into existing knowledge structures, and (3) an inability to determine if a solution makes sense [156]. To mitigate such gaps, we developed an instruction framework for teaching ES within existing classes.

7.3 Guided Discovery Learning in Design Contexts

In traditional engineering curricula, students are often given simplified design problems with specific objectives. For example, machine design often deals with factors, e.g. material selection and shape synthesis, to design structural members that can withstand specified loading conditions. Engineering domains such as heat transfer and fluid mechanics also deal with similar problems. Although these design problems simplify complicated real-world problems, they teach students about related physical principles and interdependencies among design variables. We posit that framing *sustainability-related concepts* by using *domain dependent design variables* will allow better integration and application of the concepts. Furthermore, we believe that using a design exploration-based context for achieving this integration promotes a deeper understanding of these concepts. Thus, we propose an instruction framework based on guided discovery that correlates dependencies of environmental impact and design performance on a set of design variables. Our guided discovery instruction procedures are designed to align with the primary propositions of constructivism [157]. We present the procedural steps of our framework below and relate them to constructivism principles below.

1. **Identify design variables:** Within an engineering domain, identify design variables that are commonly used for problem based learning. Among them, identify the relation between these variables to environmental performance.

   • *Related Principles in constructivism:* Anchor the learning activity to a larger task or problem.

   • *Explanation of the relationship:* Students should have a clear understanding of the purpose of the learning activity and how it relates to the domain context. It is important to align student expectations with the learning objectives. In our case, the design variables have a quantifiable relationship to environmental impact. Developing a direct correspondence between design variables and ES allows students to better understand the purpose of the learning activity and relate to the larger context.

2. **Setup design space exploration:** Construct a problem that requires the selection/tuning of variables to meet domain dependent design requirements. The problem should require insights about relationships of the design variables to reach an optimal solution through conflicting objectives and/or violations against rules of thumb.

   • *Related Principles in constructivism:* Design an authentic task. The problem should reflect complexities of real world tasks to prepare students.

   • *Explanation of the relationship:* Learning activities should reflect the level of cognitive demand required by the activities which we expect students to master at the end of learning. In our study, we setup a scenario involving complex trade-offs between multiple design variables. This helps us create cognitive conflicts for students by presenting scenarios that involve multiple conflicting objectives which are characteristic of real-world design problems.

3. **Anchor the solution:** Provide students access to domain experts and technical resources related to ES and impact assessment. This will allow reflection on wrongly formed insights and developing a better understanding of relationships between ES performance and the involved design variables.

   • *Related Principles in constructivism:* Offer learner the ownership of the process. Support and challenge the learner's thinking.

   • *Explanation of the relationship:* We discouraged students from following a set of predefined solutions or thinking strategies. Students were to anchor their solutions independently by adjusting design parameters and observing the resulting changes in environmental impact. Here, students developed solutions that met constraints and accounted for practical concerns, e.g. weight minimization. These strategies align with guided discovery learning, where students had ownership of the design.

4. **Motivate the exploration process:** Motivate students so that they can create non-conventional solutions by providing grade incentives. We can also provide intrinsic motivation by gamifying learning tasks.

   • *Related Principles in constructivism:* Encourage testing ideas against alternative perspectives.

   • *Explanation of the relationship:* It was critical that students did not stop after reaching a feasible solution. We motivated the students to search for viable alternatives and better performing solutions. This process encouraged students to construct new knowledge and help them bridge unfamiliar contexts.

5. **Observe user behavior:** Explicitly record mistakes as well as new insights gained by the students. When viable, store parameters for every unit iteration in

the exploration process. Understanding decision rationale is critical for breaking existing student mindsets and motivating the case for ES-centered design.

• *Related Principles in constructivism:* Provide means for and support reflection on the content learned & the learning process.

• *Explanation of the relationship:* Demonstrating methods for reflection (on the content learned & the learning processes) can help students self-regulate their learning in discovery learning contexts. We explicitly recorded mistakes as well as new insights proposed by the students. Here, we tried to model reflection strategies that experts use to monitor problem solving processes in their field.

7.4 Application to a Shape Synthesis Task

We discuss applying our framework to a shape synthesis task. The design exploration problem formulated below, is used to validate our instruction framework in an in-class study involving 71 undergraduate students. The shape synthesis task requires students to create a suitably sized part (with appropriate topology) that is capable of carrying a specified load without failure. The goal is to simultaneously minimize the weight and the net environmental indicator (EI) of the designed part. We setup design constraints to introduce complexity (and realism) in the task.

- Students must choose from a specified list of materials adding complexity by making material selection an integral part of the task.

- If no starting shape is specified, the design should lie within a specified bounding box that restricts its maximum size.

- Once the starting shape is fixed, all subsequent modeling operations should remove material. This allows us to estimate the environmental impact of each removal operations.

Table 7.1. Single scores for process specific unit impacts calculated using the Ecoinvent 99(I) method on SimaPro®.

	k1 (Pt/lb)	k2 (Pt/lb)	k3 (Pt/lb)
Cast Iron (GGL-NiCuCr)	1.4043	0.15836	1.4043
Aluminum (Al 2036)	1.9238	1.6108	1.9238
Carbon Steel (35S20)	0.04997	1.21009	0.04997

- The allowable equivalent Von Mises stress, used as the failure criterion for the design task, is less than half the value of *maximum stress* specified for each of the three materials.

A computer-aided design (CAD) software (such as PTC Creo or SolidWorks) is used for shape modeling. A finite-element package (such as ANSYS or IDEAS) is used to analyze resulting stresses. Most CAD software have environments that integrate 3D modeling and FEA. This greatly reduces the effort and the time required for performing a design-analysis iteration. In our setup, we provide an an automated calculator written in Microsoft Excel® VBA to simplify the estimation of cradle-to-gate indicator for approximating environmental impact. Allowing students to perform a detailed life cycle assessment for estimating environmental impact was not practical due to the amount of time required to train students. Furthermore, the goal of our instruction framework is not to teach methods for ES assessment. As this simplification introduces uncertainties, students were provided with a percentage estimate of the uncertainties in this calculator. The process for estimation the cradle-to-gate indicator for approximating environmental impact is discussed below. Equation (7.1) provides a mathematical representation of the cradle-gate environmental indicator of the structural member.

$$EI = k_1 * W_b + k_2 * \sum_{i=0}^{n} MRW_i - k_3 * \sum_{i=0}^{n} MRW_i \tag{7.1}$$

Here,

→ W_b: weight of the starting blank

→ MRW_i: weight of material removed in the i^{th} manf. step

→ n: total number of manufacturing steps

→ k_1, k_2, k_3: Material/manufacturing process specific unit impacts calculated using the Ecoinvent 99(I) method on SimaPro®

– *Material extraction*: The environmental impact associated with this life-cycle stage is given by the product of the weight of the initial blank and the impact associated with producing a blank of that material per unit weight.
– *Manufacturing*: The design task only allows operations that remove material from the blank. Thus, any removal operation was treated as a machining operation and its impact was calculated by multiplying the weight of material removed with the impact of the unit process associated with machining that material.
– *Material recovery from manufacturing*: In addition to the impact associated with manufacturing, it was assumed that 100% of the machined volume was recycled. An "environmental credit" equal to the weight of the machined volume multiplied with the impact of producing a blank of that material per unit weight was provided.

Table 7.1 shows the values for k1, k2, & k3 depending on the selected material. These values are calculated assuming that all material removal processes are machining and applying a 100% recycling credit. To calculate the EI for a given design, students enter the current volume of the design in the Microsoft Excel® calculator. At each step MRW_i is calculated by multiplying the volume difference from the previous design with the density of the chosen material. Thus, the EI cumulatively accounts for impacts resulting from material extraction, and all material removal operations. The units for EI are expressed in Pts where 1 Pt represents one thousandth of the yearly environmental load of an average European inhabitant.

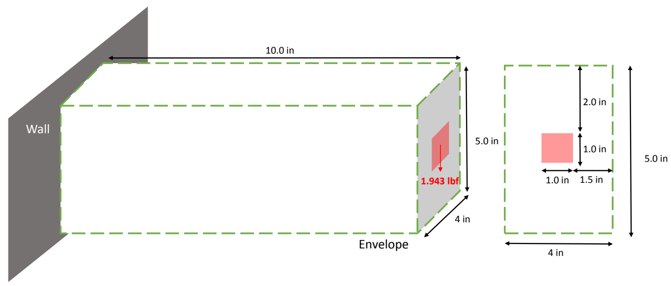

Figure 7.2. Loading condition for both the design tasks in the user study. The box shown in dashed green represents the bounding envelope (10in×5in×4in) for the design. The square filled in red represents the area of application of the total load of 1.943 lbf.

7.5 Pilot User Study

User studies were conducted to test the validity of our instruction framework. To understand the needs, constraints, and potential limitations imposed by our methods, a pilot study consisting of a small user group was initially conducted to make detailed observations (on a casewise basis) of user behavior. Insights generated from the pilot study were used in a follow-up user study conducted in a senior elective class on computer-aided design (CAD) and prototyping. To avoid scope creep, our studies were specifically focused towards integrating ES concepts within shape synthesis for machine design. This allowed us to obtain a deeper understanding of the learning effects in our framework.

Before conducting an in-class study for validating our framework, we ran a pilot study with 12 paid participants (10 male, 2 female), aged between 18 and 30 years. The goal was to validate our setup and tasks in a more controlled environment before scaling it up a larger sample.

7.5.1 Apparatus and Software

We conducted our study on a Desktop PC with dual display screens. Participants used PTC Creo Paramteric 2.0 for constructing computer-aided-design (CAD) models of their design. For conducting finite element analysis (FEA) on the designs, the prescribed loads and constraints were applied using PTC Creo Simulate 2.0. The same software was also used for generating a tetrahedral parabolic mesh of the designs. ANSYS 14.0 was used for solving the loading condition as well as visualizing equivalent Von Mises stress. To simplify the calculation process of cradle-gate impact (computed using Equation (7.1)) an automatic calculator written in Microsoft Excel® VBA was provided to users. Users were also allowed to use a notebook for sketching out design and performing hand calculations. For this study, we did not permit users to look up relevant information from online or textual sources. However, each subject was closely monitored by a proctor with extensive experience in sustainable design and use of the involved software. When required, the proctor assisted subjects in using the involved software. We ensured that the proctor refrained from providing any form of conceptual or design related suggestions to users.

7.5.2 Participants

We recruited 12 paid participants (10 male, 2 female), aged between 18 and 30 years. Among them, 5 participants were in the graduate program and the rest (6 seniors, 1 junior) were in the undergraduate program within the School of Mechanical Engineering. Since our design tasks made use of specific engineering software (PTC Creo 2.0 and ANSYS), we ensured that participants were proficient in using them. All users were given a fixed remuneration for their participation in the design task. A list detailing the final weight and the single score of the top three performers was prominently displayed in the study area so that users could gauge their current level of performance. These measures allowed us to make the design tasks more competitive.

7.5.3 Tasks

For analyzing the effects of introducing sustainability-related learning in the context of shape synthesis, users were required to complete two separate design tasks. In both tasks, the primary objective was to design a cantilever to be used in an automobile for a specified loading condition. The loading condition (common to both tasks) is shown in Figure 7.2. There was no set number of design iterations. However, a total of 20 minutes was alloted for each design task. The differences between the two tasks stemmed from the design parameters that were required to be optimized.

- **Design Task (DT1) -** Design task 1 was set up to familiarize users with the exploration framework and use of involved software. In DT1, users were required to minimize the total weight (and thus the volume) of the cantilever member such that it satisfied the specified set of constraints specified in section 7.4. The primary design constraint involving maximum allowable stress is purely a function of material geometry which means that a weight optimal solution will require a geometry that has a uniform distribution of stress close to the upper limit. Thus, DT1 enables users to iteratively explore several designs and understand the implicit relationships between shape, stress and weight.
- **Design Task 2 (DT2) -** This task was setup to present a conflicting case between weight minimization (similar to DT1) and cradle-gate environmental impact of the designed member. In DT2, users were asked to select from three material alternatives: Cast Iron (GGL-NiCuCr), Aluminum (Al 2036) and Medium Carbon Steel (35S20). Each material had different values for the involved physical variables i.e. density, Young's modulus, maximum stress, and environmental impact. Performing a complete life-cycle assessment (LCA) was outside the scope of this study. Therefore, a streamlined assessment was performed using Equation (7.1).

To measure the outcomes of the user study, a *think-aloud* protocol was used wherein participants were asked to vocalize their thoughts, observations and their

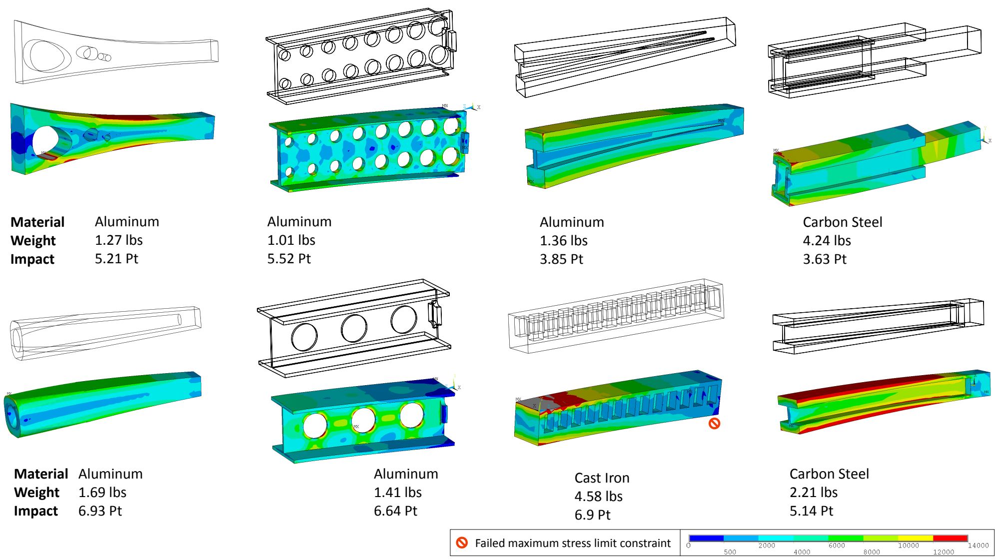

Figure 7.3. Example results from design task 2. The contour plot below each design shows the equivalent Von Mises stress (SEQV) calculated using FEA. The magnitude of SEQV is represented in *psi* and corresponding gradations are detailed in the color-scale located bottom right. As seen, designs based on Aluminum tend to be lighter, but environmental impact reduction is easier in Carbon Steel designs. A majority of users chose Aluminum blanks but only one of them was able to reduce the impact below 4 Pt (Ecopoints).

approach for generating a solution. We also probed participants with questions relating to any significant observations that we made during the user study. An audio recorder was setup to capture this data and we also made extensive observation notes for every session. Our intent was to conduct a post-hoc analysis for understanding heuristics used to generate solutions, user conception of sustainability related topics and the effects of integrating sustainability based variables in a shape synthesis setting. An online survey related to possible learning outcomes, comments regarding the study, and the task-load was administered at the end of DT2. Please see the appendix in this thesis for the list of questions asked in the survey. Observations made from the audio recordings and notes were cross-checked with user comments from the survey to confirm our hypotheses.

7.5.4 Results

The main goal of DT1 was to familiarize users with the workflow and have them draw insights on the implicit relationships between shape synthesis and induced stress. All 12 users had previously taken a course that taught design principles for static loading. Among them, 9 users had taken a computer-aided-design course that also dealt with finite element analysis. Given the background of the participants, it is surprising to note that only half of them had been exposed to a design problem similar to DT1. We observed that DT1 enabled such users to develop a richer understanding of the involved concepts. One participant reported that *"It was good to visualize the effect of variation in dimensions on the stress. The visualization of stress on the designed part helped on further refinement of the design by eliminating the low stress materials."*. Other users, who had previous exposure to similar problems reported that this task helped validate design insights that they had developed from previous mechanics courses. For example, one participant said *"The task confirmed my insight the material should be located as far away from the neutral axis to reduce the amount of material required. The system can be reduced to a shear force at the attachment points and a bending moment on the beam."* Feedback from the online survey also indicate that tasks similar to DT1 offer new insights that students miss within traditional mechanical engineering courses. Users commented that,

- *"It was interesting to use finite element analysis (FEA) for a real problem as being able to see where maximum stress occurs is very helpful in learning where to take out more material from"*

- *"The selection of base shape material is important to enhance the chance of shape change in the design process. For example if I select circle, one way I can imagine to change the material shape is changing radius. However, the I-shape could provide more possibilities in the change of shapes (changing each dimension of sides)"*

Material	Blank C.S	Weight (lbs)	Single Score (Pt)	Blank Volume (in^3)	Final Volume (in^3)	Weight (lbs)	Single Score (Pt)
Aluminum	I-shape	2.08	4.49	24.00	20.92		
		1.01	5.52	32.50	10.18		
		1.42	6.65	38.75	14.25		
	Rect.	1.36	3.85	21.40	13.71		
		1.21	5.18	30.00	12.16		
		1.27	5.20	30.00	12.78		
		1.69	6.93	40.00	17.00		
		2.15	**7.08**	**40.00**	**21.62**		
Carbon Steel	I-shape	4.24	3.63	25.00	14.99		
	Rect.	3.05	3.31	20.00	10.78		
		2.21	5.14	22.50	7.82		
Cast Iron	Rect.	**4.59**	**6.90**	**30.00**	**18.34**		

Figure 7.4. Results from all the twelve user studies. In this figure *material* and *blank cross-section* are attributes defined for the user chosen blank within DT2. *Weight* and *Single Score* (cradle-gate as per Equation (7.1)) are calculated with respect to the final design in DT2. *Blank volume* and *Final volume* are also calculated based on user responses within DT2. The last two columns of the table provide a visual overview of the numerical values of *Weight* and *Single Score*. Values highlighted in red represent designs that failed the maximum allowable stress constraint.

From the think-aloud data we observed that in several cases, the design task helped disprove false intuitions and mental models formed by student engineers. The exploratory nature of the task allowed students to critically examine previously learnt concepts and forced them to make sense of unexpected results. As one participant said; *"Sometimes intuition and experience is not enough to know exactly where high stress will occur with complex geometry and FEA is a useful tool in those cases."*

For DT2, users were asked to build on insights from DT1 and simultaneously consider the effects of the cradle-gate impact of their designs. A snapshot of selected user solutions for DT2 is illustrated in Figure 7.3. From a total of twelve designs, two of them failed to meet the criterion for limiting the maximum value of equivalent Von

Mises Stress. Analysis of data from the study shows that users primarily relied on past experience for initially selecting a material type. For example, a majority of users (7 of 12) preferred Aluminum over Cast Iron and Medium Carbon Steel because of their intuition that they could make the design very light as well as use lesser material in the process. Although this intuition worked for a few designs, students immediately realized that this selection significantly constrained the design space. A rectangular shaped blank was preferred in DT2 as most users (7 of 12) felt that it offered more flexibility in terms of material removal operations. The I-shaped blank was chosen by three users who reasoned that the shape offers much more stiffness in bending when compared to the other shapes. All 12 results for DT2 are detailed in Figure 7.4.

Similar to the results from the preliminary user survey, the online survey shows that the entire user group felt that learning concepts about sustainable design was important for design engineering. However, only 2 participants had previous training in concepts related sustainability and 1 participant (with no previous training) was considering taking related coursework. Previous surveys we have conducted have also shown similar results supporting the hypothesis that current engineering curriculum does not motivate students to enroll in a separate course devoted to sustainability. This issue is compounded by the fact that most sustainability courses that teach life-cycle and systems engineering related concepts fail to link them to common design practice. Our analysis of the think-aloud data shows that inclusion of exploratory design tasks that contextualize sustainability within existing curriculum can overcome these shortcomings. User feedback on DT2 strongly supports this view as all 12 users felt that the design task was within the context of current engineering mechanics curricula. The think-aloud data shows several instances where users formed new insights relating sustainability and shape synthesis. User comments on DT2 support this observation. They pointed out,

- *"It was interesting to see how certain materials are better for certain types of problems; Aluminum is expensive to cast but relatively cheap to machine down after the casting has been done"*

- *"I tend to forget that the scrap material can be recycled. When I approach design I try to minimize the amount of scrap"*

- *"This task also caused one to balance carrying the load along with not wasting material, which really changes the thought process for designing"*

- *"Normally, we tend to only focus on minimizing volume when considering sustainable design. Rarely do we think about how much energy is required to minimize that volume. We come up with fancy and intricate designs to reduce volume, but neglect the manuf. effects associated with this process. In most undergrad courses, this is not even mentioned as an important factor"*

Furthermore, results from the online survey show that 11 users out of the 12 agreed that DT2 could be easily integrated into existing mechanics courses that they had previously taken. Additionally, a total of 7 users reported that this exercise convinced them to take a deeper look into sustainable design concepts. Results also show that the average likelihood for participants to use sustainability as one of the guiding principles in future designs was equal to 4.08 (on a linear 1-5 scale).

7.5.5 Discussion on Pilot Study Results

Results from the pilot user study underscored the importance of contextualizing sustainability teaching to specific engineering domains. Furthermore, results showed that 11 of the 12 users agreed that this task could be easily integrated into mechanics courses that they had previously taken. However, our observations and participant feedback highlighted important limitations in our pilot study.

- Participant feedback indicated the design constraints such as the initial shape of the blank and time for completion prevented some students from generating a more optimal solution.

- We observed that providing a variety in initial blank sizes tended to complicate the question. Students would focus a lot more on starting off with an optimal *sized* and *shape* blank rather than iterating over subsequent features. Also, the selection of the initial blank had a significant effect on impact, sometimes more than subsequent shaping operations.

- The Excel spreadsheet provided to the students allowed calculation of impact one material at a time. Most participants expressed the need for simultaneous calculations for all three material types.

- Participants would often ask for how much better is a small change in impact vs savings in weight. Since there was no actual measure of uncertainties in impact, small incremental savings in impact really made no sense.

Based on our insights and user feedback from the pilot study, we developed a design problem that was suitable for an in-class study.

7.6 In-Class Follow Up Study

The follow-up study was conducted within ME444, a CAD and prototyping class in the School of Mechanical Engineering at Purdue University. This undergraduate course covers concepts in solid modeling as well as FEA and includes laboratory sessions that require students to use PTC Creo 2.0 and ANSYS. Students are required to design and build a fully functional toy as a course project, exposing them to product design and rapid prototyping. To obtain a significant number of results for our study, we decided to distribute it as a graded class assignment. However, the web-based surveys distributed with this study was optional and did not account for class grade.

7.6.1 Setup & Participants

The study was conducted in a class consisting of 71 students (60 male, 11 female), aged between 18 and 25 years. The user study consisted of a pre-assessment survey, a 10 day take home design assignment (see Figure 7.5), and a post-assessment survey.

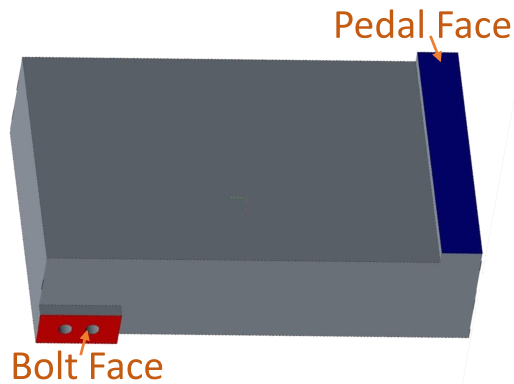

Figure 7.5. Loading condition for the study. A brake pedal is attached to a frame using two bolts with a 5 psi load uniformly distributed on the pedal face. Contacts are assumed frictionless.

The pre-assessment survey was used to understand the existing level of knowledge related to sustainable design among the participants. Please see the appendix in this thesis for the list of questions asked in both the surveys. At this point, students were unaware of the design task. Along with ES-related questions, we also asked students about other factors such as cost and aesthetics. This helped in shaping the survey as an assessment of overall design practice as opposed to directly focusing on eliciting ES-related knowledge. Thus, we expected student answers to reflect design decisions that they would have made without any additional exposure to an ES module. This survey was also used to understand demographics of the user population in terms of current standing and completed courses. Before handing out the assignment, we conducted a 30 minute demonstration of a similar task and went over important considerations for design and ES evaluation. Students were free to raise questions or concerns during the study. We provided guidance for the assignment, using a a combination of instruction documents and expert-support. We distributed, (1) a step-by-step instruction document detailing the software usage, (2) a reference manual that explained the methodology behind ES assessment, and (3) an Excel calculator for environmental indicator along with the assignment. Students were also given access to experts in CAD, FEA, and sustainability assessment during the period of the assignment via email. They could also personally consult with the experts during to 1.5 hour lab sessions. The experts were instructed not to provide any direct design guidance. The helped students overcome problems with the software, understanding of concepts, and guided students' exploration processes. Students were free to discuss and compare their results for weight and environmental performance, but were not allowed to share details about their actual designs. We also motivated students by including a mastery-oriented learning objectives. While ninety percent of the grade was based on correctly setting up loading and displacement constraints and the mesh for FEA, ten percent of the assignment grade was based on relative performance of the student with regards to final environmental impact and weight. We also asked student to submit documentation on design iterations. Students were free to discuss and compare their results for weight and environmental performance, but were not allowed to share details about their actual designs. We also motivated students by providing a grade incentive based on relative performance of environmental impact and weight minimization.

The goal of the design problem was to simultaneously optimize a brake pedal for final weight and environmental impact. The limiting constraint on the design was the value of critical Von Mises stress, which could not exceed the maximum allowable stress (50% of material yield stress). An initial blank (Figure 7.5) along with the following loading conditions was provided.

1. A load of 5 psi is uniformly distributed on the pedal face.

2. Friction between all surfaces can be neglected.

3. The pedal is attached to a frame (not shown) using two bolts which holds the bolt face against that frame.

Students were allowed to iteratively refine their designs using material removal operations. They could choose from one of 3 materials: Cast Iron (GGL-NiCuCr), Aluminum (Al 2036), or Carbon Steel (35S20). The method for calculating the cradle-to-gate indicator is similar to the procedure described in the methods section (see

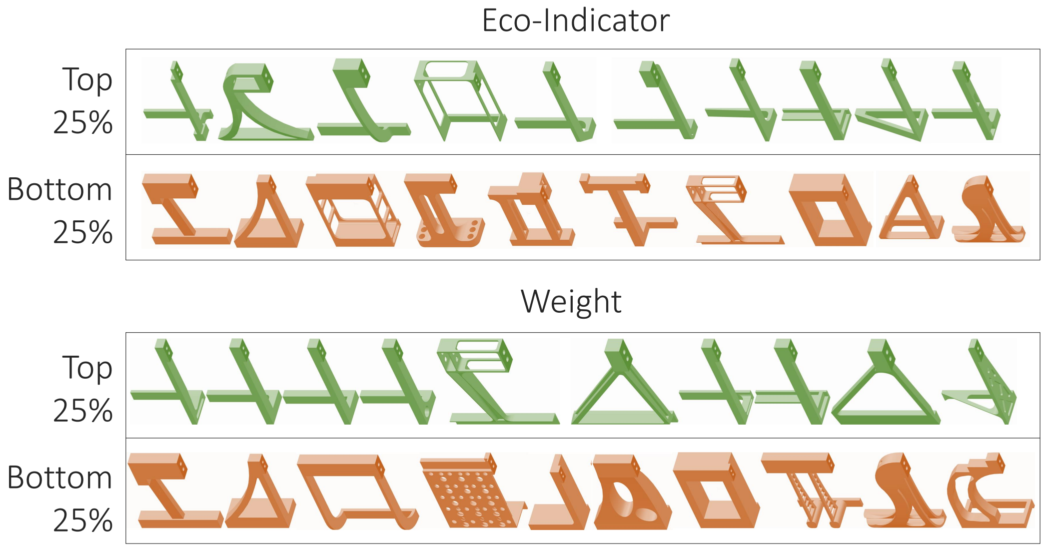

Figure 7.6. Results illustrating the top and the bottom 25% of results sorted by the environmental indicator as well as the weight.

Equation (7.1)). The Excel® calculator was modified to allow users to simultaneously view the weight and the environmental indicator (EI) for all 3 material options. Although we imposed a minimum of 3 design iterations to meet grading requirements, students were free to iterate as many times as they liked. At the end of each iteration, students were required to provide details on the selected material, weight, EI, and assess whether their design met the constraints. A CAD model of the part along with applied loads was required to be submitted for the final iteration. After students submitted their final designs, we provided a link to a voluntary post-assessment survey. In this survey, we asked students whether they found the assignment engaging and if introducing similar modules in other undergraduate courses would help them better understand ES. Results from this survey and the design task are discussed below.

7.6.2 In-Class Study Results

For the pre-assessment survey, we received 59 responses. Out of these respondents, 48 students were pursuing a mechanical engineering degree. and the rest were from the Aeronautical, Biomedical, Computer Graphics, and Multi-Disciplinary engineering programs. All students, expect one 1^{st} year student, were in the 3^{rd} or 4^{th} year of their program.

Given the context of this study, we wanted to understand students' background knowledge. All students reported that they had previously taken a course in either statics, mechanics of materials, or strength of materials. Furthermore, a majority of them (50/59) had previously worked on design projects. Thus, we expected most of them to have developed basic knowledge about design, shape synthesis, and stress analysis. Just as we have previously observed in student teams, most students had little idea on how to reduce the environmental impact of their designs. Worryingly, students did not focus on design variables such as material choice, build layout, or shape changes. Instead, students suggested, *"purchasing a majority of the parts"*, *"adding solar panels instead of batteries"*, & *"changing the power source of the 3D printer to a greener source"*. When asked about the importance of reducing the environmental impact of their designs, only 4 students reported that it was an important consideration and 1 student reported that it was of critical consideration. Results from the pre-assessment survey confirmed our results from the preliminary survey. Both studies emphasize the need for integrating ES considerations in regular mechanical engineering coursework.

For the design task, although students were only required to perform 3 iterations, most students performed additional iterations (*mean=5.6, median=4, variance= 8.76*). Results highlighting the top and bottom 25% designs are shown in Figure 7.6. Here, the results are classified both by the environmental indicator and the weight. We observed that while only 1/10 top 25% designs where common to both the categories, 4/10 designs where common in the bottom 25%. This suggests

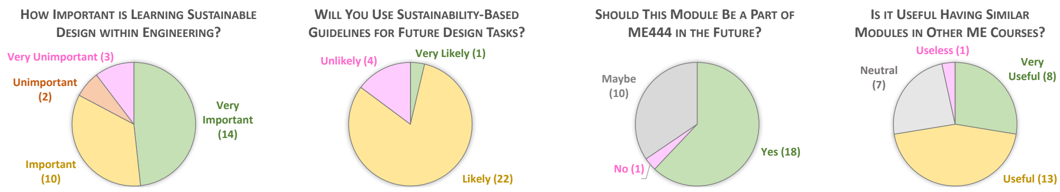

Figure 7.7. Responses to questions related to the future use of this module within ME444 and other ME courses.

a potential knowledge gap in students with bottom performing designs that pervades across environmental assessment and weight reduction. We observed that top designs (in both categories) often leveraged conventional heuristics, such as I-beam type cross-sections, triangular-profiles and filleting corners. In contrast, the bottom designs mainly focused on manipulating shapes. This disparity between top and bottom performing students suggests the need to identify,

1. Students' perceptions of guided discovery, especially if students developed conflicting views about the learning activities.

2. Characteristics of top and bottom performing students. We intend to compare the choices made during design iterations for the top and bottom quartiles. Similar comparison-based approaches have been used in previous studies to understand how students construct new knowledge and to inform educators about methods to bridge performance gaps [158]. In our case, we are interested in formulating guidelines for improving our framework so that it is effective for a wider range of students.

Students' perception of the guided discovery approach: We administered a post-assessment survey after students completed the assignment. This survey was completely voluntary and did not amount to any class credit. From the 71 students in class, we received 29 responses. Among them, only 16 students reported that they were satisfied with their final submission. More than half (17) of the students also reported that they stopped the assignment due to lack of time. One student mentioned that *"assignment 4 so far is the hardest assignment ever assigned. However, the freedom of design allows students to explore their creativity to its max which is very good."* Additionally, a majority of students (21/29) reported that given time they would be able to improve their solution. We received positive feedback for the mastery-based incentive set for the assignment. One student remarked, *"I really liked the 10% of the grade that was based on how the class performed. It gave me more motivation to do well on the assignment."* When asked if this assignment helped them learn new insights or relationships, students commented:

- *"I was able to come up with a very light design using materials that would have low environmental impact. However, it would have been very difficult to manufacture. There are always going to be tradeoffs."*

- *"Different materials have different eco-scores. I didn't realize that acquiring different materials can have drastically different effects on the environment."*

- *"The Von Mises stress plot helped me realize that where there is no stress, there is no need for material. Adding rounds also helps to minimize stress concentrations in the part..."*

Such comments highlight the ability of our guided discovery approach to help students identify the relations between design variables and ES outcomes. On categorizing all 19 comments for the same question, we found 13 positive comments with 1 discussing relationships between ES and manufacturability, 3 highlighting the effect of part volume on ES, and 9 spoke about the effect of material type on ES. Additionally, 3 students commented that they did not develop any new insights as they were unclear on how EI was calculated, and 3 comments were negative without citing any reason. Figure 7.7 summarizes students' perception of the assignment. We noticed an increase in the percentage of students reporting that learning sustainable design is important for engineering design. However, the results are not significant to be considered as an indicator for change in student perception. More importantly, only 4 students indicated that this assignment failed in convincing them to

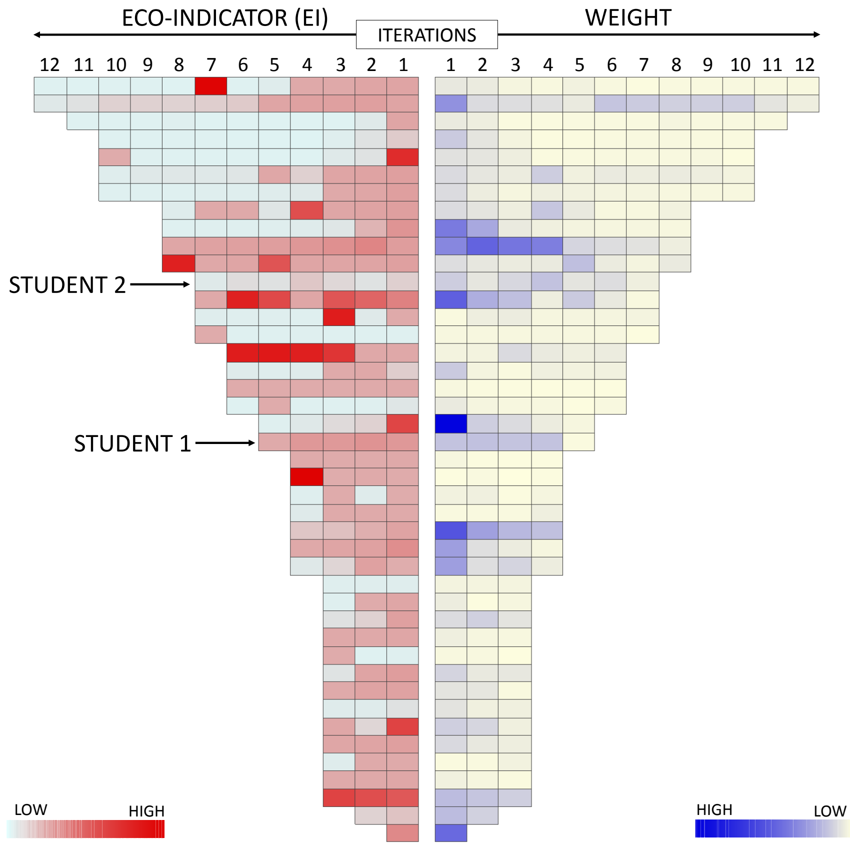

Figure 7.8. Results from all student responses without assignment errors (such as mesh quality, wrong loading conditions). Here, each row represents a student response and each column represents a design iteration. The color for *EI* as well as *weight* are normalized against the best design in class. For *weight* as well as *EI*, a lower value (as shown in the colorbar) indicates a better design. Comparing Students 1 & 2, we can see that Student 2 started out with a good material and shape combination allowing him/her to reach a low value of both *EI* and *weight*.

do additional reading on ES. We also found a significant positive correlation between students wanting to increase their knowledge on ES with the likelihood of applying ES-related principles in future design tasks (*Pearson* $r(38) = 0.42$, $p = .02$). Additionally, students reported that this module should become an integral part of ME444.

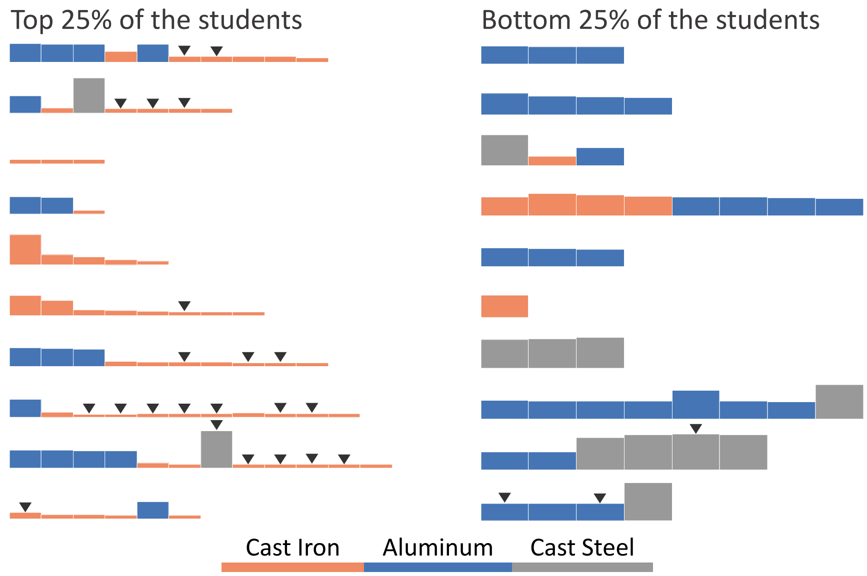

Figure 7.9. Material selection per design iterations for the top and bottom 25% performers. The height of the bar is scaled to the value of the eco-indicator (EI). Iterations that failed to meet the stress constraint have a "▼" marked above them.

Bridging the performance gap: We analyzed students' performance gaps to identify ways to cater to a wider group of students. Specifically, we are interested in identifying the characteristics of the problem solving approaches adopted by the top and less advanced performers. We first validated the set of correct student responses (*n=43*) per design iteration. This validation step was necessary as our goal was to identify valid and successful problem solving solutions. As shown in Figure 7.8, students were more at ease in reducing part weight than changing the EI. Data analysis demonstrated a significantly negative correlation ($Pearson\ r(38) = -0.34$, $p = .031$) between the total number of iterations and final weight. This was expected, as engineering students are more familiar with correlations between weight, shape, and resulting stress when compared to the relationships governing the EI. Interestingly, although there was no significant difference (among students grouped by material choice) in the total number of iterations or final weights, we observed a significant difference ($F(2, 37) = 148.05$, $p < .0001$) in the EI categorized by material type (M_{CI} = 7.71, M_{AL} = 22.32, M_{CS} = 44.80). This result suggests that student performance on ES is largely dependent on the chosen material type. Moreover, the difference in material strength, compensated for the difference in physical density, allowing students to reach similar values of weight. From their exploration patterns, we observed that students who reached this insight opted for the material with the least environmental impact per unit weight and consequently performed better.

To understand whether top performing students (with regards to the EI) explored material choices differently than bottom performers, we analyzed material selections during students' design iterations (see Figure 7.9). We observed that, (1) most (60%) students started with Aluminum, possibly due to intuitions that lighter materials lead to better environmental indicators (EI), (2) a majority (70%) of the bottom performers did not explore cast iron-based designs, and (3) the top performing students were more exhaustive in exploration and flexible in making changes, with a considerably larger number of failed iterations compared to bottom performers ($t(18)$=2.46, p=.012). We also observed that top students utilized heuristics such as I-beam type cross-sections, triangular-profiles and filleting corners while removing material. For bottom performers, there was a greater variety in shape. Furthermore, 4/10 students were common to the set of bottom performers categorized by both EI and weight. This indicates that identifying the relations between weight or EI and part shape or material is challenging for certain students. Based on these observations, we list guidelines for future shape synthesis-based exploration tasks related to teaching environmentally sustainable product design.

1. *Increase the minimum number of iterations:* This is one way to nudge students towards a more detailed exploration process. Our results show that most students significantly change the exploration variables only after 5 iterations. More iterations also lead to a higher probability that students will validate a larger number of internalized heuristics.

2. *Set a significant variable or outcome:* In guided-exploration tasks, it helps to have a *significant variable* without the possibility of easily reaching a dominant solution. In our case, we observed that students who did not select cast iron were often lost and could not elicit meaningful correlations.

3. *Increase scaffolding through interventions:* Results suggest that more instructor intervention in guided-exploration tasks improves baseline class performance. Planned interventions in which instructors help students rethink their exploration strategies alleviate some problems due to time constraints.

4. *Support learning through alternate sources:* Access to alternate educational material such as software packages, and or excerpts from texts is critical for students to make informed choices in exploration variables. For the shape synthesis task, access to material selection software (such as CES EduPack [108]) can help improve student understanding.

5. *Promote friendly competition:* Students reported that they enjoyed mastery-based incentives for the in-class assignment. Students also liked the idea of discussing exploration strategies (without revealing specific results) with peers. Moving forward, we believe that it would help to include a prominent *social element* by sharing hints and certain choices made by top performers in the form of a leaderboard.

7.7 Takeaways

Engineering students have significant knowledge gaps in ES-related learning: Results from our knowledge surveys show that two kinds of gaps exist, (1) a lack of awareness of ES-related concepts, and (2) an inability to apply these concepts in design practice. These findings align with those from previous studies, where students were reported to have difficulties in understanding and applying ES concepts in design tasks [129, 130]. However, such gaps are not explicitly addressed in current engineering curriculum as, (1) most students have no access to classes devoted to sustainable design, and (2) ES-related instruction in engineering usually lacks context to an application domain [144]. We also observed that many students failed to use prior knowledge from related domains (e.g. mechanics, vehicle design, and material science) to guide their designs. This is consistent with previous research where students found it challenging to apply acquired engineering principles in practice [143]. A potential explanation is that the students were not exposed to multi-domain design problems until much later (junior or senior years) in existing curricula. Providing a real-world design context for traditional mechanical engineering courses could help address such issue and connect the isolated silos of knowledge [159].

Another concern is the lack of effective design exploration tools to support ES learning. In many cases, students are forced to either explore solutions by hand or spend a significant time learning design and analysis software before they can ask *what if* questions. In our study, we created an exploration workflow by using commonly available design and analysis software in academia and industry. However, student feedback shows that a lack of a streamlined workflow for design exploration prevented them from realizing better designs. In the post-assessment survey, 5/29 students reported that the solid modeling and stress analysis software used for the assignment significantly impeded their exploration process. Additionally, 11/29 students reported that they stopped the exploration process because it became too tedious. These findings motivate researching exploration-focused tools in early design that concurrently allow ES and engineering assessment.

Guided discovery benefits sustainability learning in design exploration contexts: Our results suggest that using a guided discovery approach in design exploration benefits students' ES learning. Similar benefits of guided discovery learning have also been identified in other disciplines [148]. Our study demonstrates that guided discovery learning allows engineering students to develop insights about implicit relationships between design parameters and ES outcomes, as well as increases the likelihood of applying ES concepts in future design projects. A potential explanation for these benefits is that an exploration process provides students with hands-on experience in manipulating design variables and observing corresponding changes in ES indicators. Furthermore, we guided the discovery learning process by offering immediate feedback to students' designs and made expert consultation available throughout the design process. As previous research has indicated, obtaining experiential insights through hands-on experiences and having access to expert consultation during design can promote learning [137, 143].

Additionally, we show that during guided discovery, top performing students extensively explored design variables in order to enhance ES outcomes. In contrast, bottom students fixated on a limited range of design variables and were disinclined to investigate more promising alternatives. This contrast between top and bottom performing students in guided discovery learning coincides with previous findings [150]. Students are not necessarily able to identify key relations among variables without appropriate guidance. Thus, our study identified a potentially effective model as demonstrated by the top performing students, and suggested the need to provide guidance during discovery learning to help students incorporate such effective models. Despite the promise of using guided discovery in exploration design contexts, most existing engineering classes do not integrate such approaches. As previous work has suggested, only a handful of classes have tried to integrate ES into design [144].

In summary, we propose that in order to promote ES learning, engineering curricula should, (1) embed learning modules within traditional courses and contextualize ES concepts within engineering domains, (2) adopt a design exploration based learning framework, such as guided discovery learning to allow students to identify and apply ES principles, and (3) continue developing courses devoted to teaching a lifecycle and systems level perspective on these concepts.

Finally, it is important to introduce ES modules at an early stage, to allow ample time for students to develop insights on fundamental engineering principles throughout their training in various engineering domains.

7.8 Limitations

Our user population was limited to only junior and senior level students who have a significant knowledge of engineering fundamentals. Our results show that a guided discovery-based approach is valuable for such student groups. However, we cannot generalize the results to less advanced student groups. We could not follow up to examine if students actually applied ES principles in consequent design projects. We are planning on conducting longitudinal studies to test the long-term influence of our instruction approach. The particular setup and the software that we used for the task could have introduced biases that may have altered students' performance and understanding of the ES module. This study is also limited by the domain we selected (shape synthesis). We have not explored the effects of our instruction approach for engineering domains such as heat transfer or fluid mechanics. Although we plan to incorporate our instruction approach in such classes, results from our current study may not be generalizable for these domains. In order to quantify the effectiveness of out instruction approach, a comparative study that benchmarks our approach with existing instruction methods is required.

7.9 Conclusions and Future Work

This chapter has presented mechanical engineering students' knowledge gaps in sustainability concepts. Based on our preliminary surveys of student engineers, we developed a guided discovery-based instruction framework for incorporating ES in engineering classes. To validate our framework, we conduct in-class user study focused on a shape synthesis task. We show that our instruction framework can be integrated in an existing engineering course. Results from knowledge surveys show that students were able to explore relationships between design variables and environmental sustainability and the instruction approach relevant and useful . Although we conducted our study in a CAD class, the developed instructional model can be potentially useful for other engineering domains. In our future work, we intend to examine the applicability of our guided discovery-based instruction approach in other engineering classes, e.g. heat transfer and fluid mechanics. One of our future goals is to embed such guided discovery modules in introductory level engineering classes at the freshman, and sophomore level. We have compiled a table in the appendix (see Table D.1) that presents examples of guided exploration tasks suited for common classes in mechanical engineering curriculum. We hope these illustrative examples are useful for educators interested in adopting a guided discovery-based instruction framework for integrating ES learning objectives in their classes. Holistic integration of ES within design also requires future work on instructional models that facilitate conceptual change, while guarding against misconceptions developed in these processes [160].

8. CLOSURE

8.1 Summary

Maintaining sustainable development is one of the key challenges facing humanity in this century. Among the three pillars of sustainable development, environmental sustainability in itself, is a challenging goal. As designers and engineers, we can make significant contributions towards this challenge by developing new products and processes (and improving existing ones) that satisfy societal needs while minimizing the associated environmental consequences. There has been remarkable progress in the industry, and by academia towards this goal in the last few years. The evidence for this lies in the increasing number of research funds, projects, and publications as well as corporate sustainability efforts in the last decade. While these efforts are commendable, this thesis has tried to explore the next steps for eco-conscious design: *'holistic integration of eco-conscious design practices with traditional design'*. Our hope is that by considering environmental sustainability as an implicit parameter in all design processes, it can achieve as similar footing in design as more traditional parameters (such as cost, time, failure stress, etc...). This thesis has shown that considerable research on multiple fronts in design is required to achieve this integration. An important consideration that is often overlooked is the fact that integrating eco-conscious design practices with traditional design is a two-way street. While it is important to change existing design practices with regards to constraints in eco-conscious design, it is also vital that we consider how we can adapt existing practices in eco-conscious design with regards to the changing nature of design. With the imminent arrival of data-driven design through ubiquitous computing and data collection hardware, practices such as data mining, visual analytics, and crowd-powered tools will become a priority for facilitating eco-conscious decision-making. To meet this change, we believe that environmental sustainability-related tools must shift from being purely assessment driven towards enablers for data-driven design exploration.

In light of such challenges, this thesis has tried to provide potential solutions in the form of new, (1) representations of design and sustainability-related data, (2) methods, tools, and interfaces for eco-conscious design, (3) holistic decision-making strategies that consider all stakeholders, and uncertainties in the product's lifecycle, and (4) instruction frameworks that integrate sustainability-learning within engineering curricula. When considered together, our hope is that these works enhance the ability of engineers and designers to inculcate eco-conscious design as an integral part of their design processes.

While this thesis has remained focus on approaches for eco-conscious design, it is worth mentioning that inculcating an eco-conscious mindset across the lifecycle requires a broader systems-level approach in which life cycle stages such as design, manufacturing, global supply chain, use, and end-of-life are all linked. This integrative outlook on the interdependencies of these networked systems is currently outside the scope of existing engineering design and practice. Understanding and controlling multi-scale, complex, and coupled systems is essential for sustainable development.

8.2 Future Work

The long term goal of this thesis is to facilitate integration of eco-conscious design practices with traditional design by exploring, (1) data-driven representations for product lifecycle data, (2) decision-making methods that integrate design considerations with environmental sustainability constraints, and (3) tools and interfaces for visualization-driven eco-conscious design exploration. To this end, future work will look into the following aspects.

- Exploring function-based representations for sustainability data that incorporate a product's performance constraints as well as related constraints imposed in product embodiment (manufacturing processes, supply chain constraints etc...). An important focus in this work will be to develop a systems-based approach that can be adapted towards complex product systems.

- Conduct user studies with designers with the goal of developing an objective method for estimating uncertainty scaling weights in redesign decision-making. We would like to understand how designers express preferences when trading-off redesign complexity and environmental impact in the proposed IGDT-based model for modeling uncertainties in the function-impact method. We also plan on conducting similar studies in group settings to understand preferences among design teams that are working towards eco-conscious redesign of product systems. These studies will help us develop designer-driven decision-making models for eco-conscious design that consider uncertainties in product lifecycle data.

- Our future work will explore alternate visualization schemes and interaction modalities for eco-conscious design exploration (ECDE). This thesis has presented a framework for integrating information visualization in the context of ECDE and presented an interface for exploring 3D part repositories. We will work on incorporating alternate visualization methods in the same context, as well as expand our framework towards other contexts in design exploration such as manufacturing process selection. We also plan on developing approaches that further reduce the disconnect in design and sustainability parameters by using scientific visualization-based approaches for overlaying the two.

- With regards to the proposed instruction framework, we intend to examine the applicability of the guided discovery-based instruction approach in other classes in mechanical engineering curriculum such as heat transfer and fluid mechanics. We hope to embed such guided discovery modules in introductory level engineering classes in the future in order to understand its ecological validity.

- An important focus in our future work will be to understand crowd-related preferences for shaping designers' interpretation of eco-conscious design. We believe that this work is necessary for bridging the gap between *designer-generated features that reduce environmental footprint* and *customer-perceived features that reduce environmental footprint*. The rise of web-enabled technologies for communication with customers such as crowd marketplaces, survey forums, and web-apps can help designers better understand these gaps and eventually design eco-conscious products that align with customer expectations.

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APPENDICES

A. SUPPLEMENTARY INFORMATION ON THE C.H. $\frac{1}{2}$ *INCH* PNEUMATIC IMPACT WRENCH

Table A.1. : Bill of materials, for the Campbell Hausfeld $\frac{1}{2}$ *inch* impact wrench.

Name	**Matl.**	**Wt. (gram)**	**Area (cm sq.)**	**Manf. process**
Air Hose Connector	X12Cr13(416)I	58		(a) Cold impact extrusion, (b) Milling
Air Regulator Knob	C55I	34		(a) Cold impact extrusion, (b) Milling
Air Spring	55Si7I	0.8		(a) Wire drawing
Anvil	50CrV4I	167		(a) Hot impact extrusion, (b) Turning, conventional
Anvil Actuator	Al, cast alloy	0.9		
Back Plate	X6CrNi18(304)I	74		(a) Hot impact extrusion, (b) Milling
Ball	X12Cr13(416)I	3.5		(a) Cold impact extrusion
Big Set Screw	C55I	1.7		(a) Turning, CNC
Big Spring	55Si7I	1		(a) Wire drawing
Big Washer	50CrV4I	15		
Chuck Gear	25CrMo4I	57		(a) Cold impact extrusion, (b) Milling
Chuck Washer	50CrV4I	4		
Dowel Pin	42CrMo4I	20		(a) Hot impact extrusion, (b) Turning, CNC
End Cover (fat)	G-AlSi8Cu3(380)I	69		(a) Hot impact extrusion, (b) Milling
End Cover (thin)	G-AlSi8Cu3(380)I	52		(a) Hot impact extrusion, (b) Milling
Hammer	25CrMo4I	70		(a) Hot impact extrusion, (b) Milling

Continued on next page

Table A.1 Continued

Name	**Matl.**	**Wt. (gram)**	**Area (cm sq.)**	**Manf. process**
Hammer Cage	GGG40I	338		(a) Hot impact extrusion, (b) Milling
Handle/Arm	Steel, unalloyed	74.75		(a) Hot impact extrusion, (b) Hot rolling
Hollow Rod	X12Cr13(416)I	1.2		
Housing	X6CrNi18(304)I	693		(a) Hot impact extrusion, (b) Milling
Male-female Extension	50CrV4I	140	43.2	(a) Cold impact extrusion, (b) Milling, (c) Powder coating
Paper Gasket	Paper	2		(a) Cutting
Plastic Trigger	PPGF30I	5		(a) Injection moulding
Plate Screws	50CrV4I	0.5	0.2513	(a) Turning, CNC, (b) Zinc coating
Replacement choke	50CrV4I	151	72.57	(a) Cold impact extrusion, (b) Milling, (c) Powder coating
Reversing Switch	25CrMo4I	40		(a) Cold impact extrusion, (b) Turning, CNC
Rotor	25CrMo4I	255		(a) Cold impact extrusion, (b) Milling
Rotor Housing	25CrMo4I	144		(a) Cold impact extrusion (b) Milling
Rotor Vanes	Tetrafluoroethylene	8		(a) Injection moulding
Rubber Gasket	Synthetic rubber	0.7		(a) Injection moulding
Rubber Handle	Synthetic rubber	22		(a) Injection moulding
Screw Trigger Washer	50CrV4I	1.1		
Screws (case)	C55I	16.3		(a) Turning, CNC
Slotted Rod	X12Cr13(416)I	0.4		(a) Sheet rolling
Small Set Screw	C55I	0.5		(a) Turning, CNC
Trigger Cover	X12Cr13(416)I	5		

Continued on next page

Table A.1 Continued

Name	**Matl.**	**Wt. (gram)**	**Area (cm sq.)**	**Manf. process**
Trigger Rod	25CrMo4I	6		(a) Cold impact extrusion, (b) Turning, CNC
Trigger Spring (small)	55Si7I	0.2		(a) Wire drawing

B. SURVEY QUESTIONNAIRE FOR ELICITING IMPORTANCE WEIGHTS FOR PRODUCT 1.

A screenshot of the Microsoft Excel® survey is shown in Figure B.1 Interested readers can download this survey from the C Design Lab's downloads page:
`https://engineering.purdue.edu/cdesign/wp/downloads/`.

The zipped archive file in this page contains,

1. Instruction document provided to survey respondents in a file titled
   `ahpQuestionnaire_Readme.docx`.
2. Microsoft Excel® survey for eliciting importance weights in a file titled
   `ahpQuestionnaire.xslm`
3. The importance weights obtained from the 10 decision makers that responded to this survey in a file titled
   `sAHP_DM_dataset.csv`

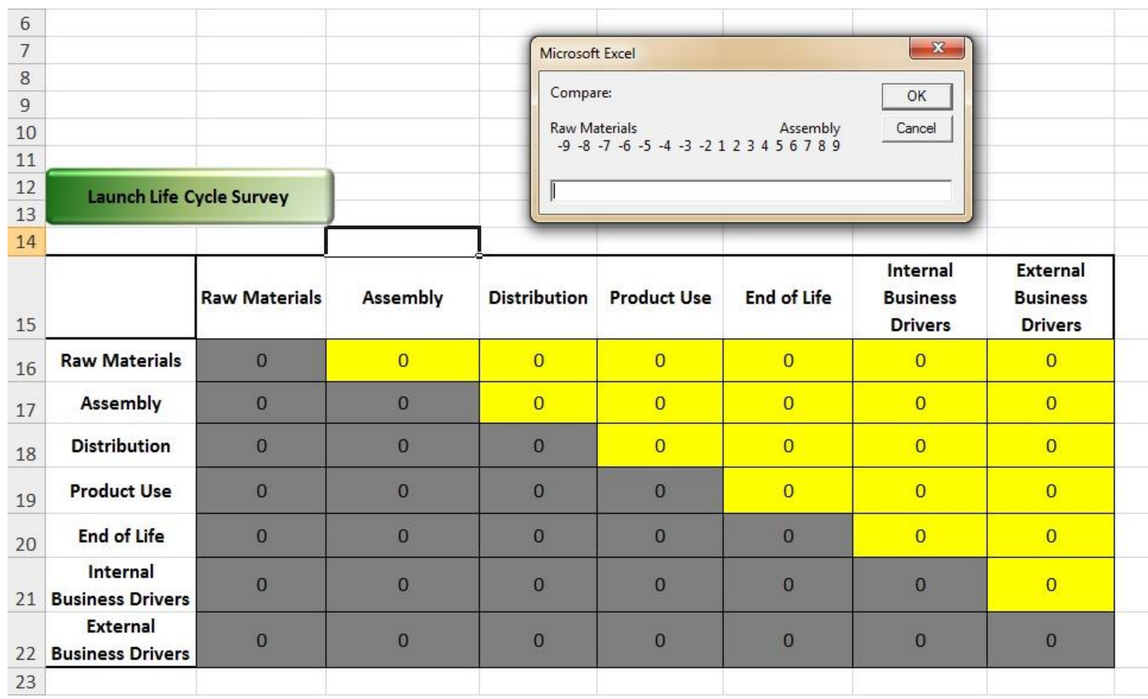


Figure B.1. A screenshot of the Excel-based survey for obtaining importance weights.

C. SHAPESIFT USER STUDY TASK DESCRIPTION AND QUESTIONS

C.1 Preliminaries

Thank you for participating in the shapeSIFT user study!

- Please carefully read the consent form and sign the form before we proceed.
- This user study session is audio recorded so that we can do a post-hoc examination of the sessions.
- We will also use a log file of interactions generated by shapeSIFT for our post-hoc research study.
- We will maintain strict confidentiality regarding your identity and will not publish any identifiable information from this study. Alternatively, if you are OK with associating yourself with the study, we will gladly include your name in the acknowledgments section of any resulting publication.
- Lastly, you are free to terminate or continue the study at a later time if you feel the need to do so.

C.2 Setup

- Before we begin, please adjust the screen to a comfortable orientation. You can also resize/reposition the different windows present in shapeSIFT.
- The proctor will provide you with a brief demonstration outlining the aim of the user study, visualization framework and the features implemented in shapeSIFT.
- If you have any questions/comments at any stage, please talk to the proctor.
- While performing the tasks, we encourage you to proactively convey things you liked, changes that you feel are required and any learning experiences to the study proctor.

- Please note that the repository used for this study has been synthetically generated with random metadata. Some of the material/manufacturing/function metadata might not match real-world data.

C.3 Task 1: Interface Familiarization

The main goal of this task is to familiarize yourself with the visualization and interaction frameworks implemented in shapeSIFT. You are free to try out the different elements present in the interface. A total of 5 minutes is allotted for this task. In case you have any questions/comments please refer them to the proctor. If required, the proctor will guide you through the interaction process and provide suggestions on how to use various functionalities of the tool. At the end of the allotted time, if you are still uncomfortable with the interface, please inform the proctor so that he can allocate extra time towards this task. Before we proceed to Task 2, the proctor will ask for your observations and comments related to this task.

C.4 Task 2: Retrieving Similar Parts

In this task, you are required to estimate the environmental impact of the parts given below by exploring the ESB and finding similar part . We encourage you to identify a set of parts that you think are similar to the given part that would have a comparable environmental impact when compared to the reference part. You are free to use the sketch query module as well as all other interaction modes of shapeSIFT for navigation the repository of parts. Please note that there is no one right answer for this task. The selection(s) of similar parts entirely depends on your judgment. At any point in this study if you think you have any observations/comments please direct them towards the proctor immediately. A total of 10 minutes is allocated towards completion of this task. Before we proceed to Task 3, the proctor will ask for your observations and comments related to this task.

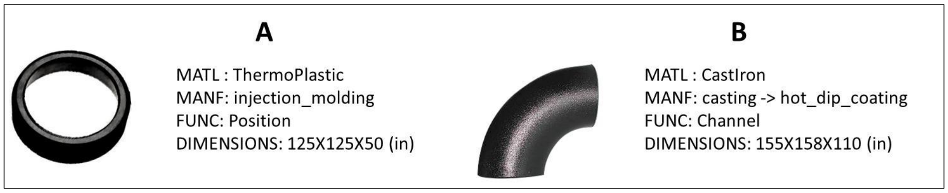


Figure C.1. Example parts and metadata provided for Task 2.

C.5 Task 3: Estimating Environmental Impact

In this task, you are provided with two novel hypothetical design for a gear part. You are tasked with exploring a set of existing gears from the ESB repository in order to estimate the possible environmental impact of the new design.

1. Material: `ThermoPlastic`; Manufacturing: `injection_molding`; Dimensions: `1in X 1in X 0.1in`
2. Material: `AlAlloy`; Manufacturing: `casting, milling`; Dimensions: `150in X 150in X 140in`

For this task, the proctor will pre-load a result set that contains gears present in the ESB. Please refrain from using the sketch window to perform any additional queries. You task is to use the metadata exploration functionality provided by shapeSIFT to reach an approximate answer. At any point in this study if you think you have any observations/comments please direct them towards the proctor immediately. A total of 10 minutes is allocated towards completion of this task. Before we proceed, the proctor will ask for your observations and comments related to this task.

C.6 Task 4: Macro-Level Observations

Please use the similarity and textual query present in the control window to answer the following questions.

1. How many gear shaped parts are made of AlAlloy?

2. How many gear shaped parts are milled?

For this task, the proctor will pre-load a result set that contains gears present in the ESB. Please refrain from using the sketch window to perform any additional queries. You task is to use the metadata exploration functionality provided by shape-SIFT to reach an approximate answer. At any point in this study if you think you have any observations/comments please direct them towards the proctor immediately. A total of 10 minutes is allocated towards completion of this task. Before we proceed, the proctor will ask for your observations and comments related to this task.

C.7 Task 5: NASA Task Load Index (TLX) Questionnaire

Please fill out the return the NASA TLX[1] questionnaire handed out by the proctor. You are free to clarify any information present in the questionnaire.

Hart and Stavelands NASA Task Load Index (TLX) method assesses work load on five 7-point scales. Increments of high, medium and low estimates for each point result in 21 gradations on the scales.

1. Mental Demand: How mentally demanding was the task?
   Please rate on 21 point scale of (0: Very Low – 21 Very High)

2. Physical Demand: How physically demanding was the task?
   Please rate on a 21 point scale of (0: Very Low – 21 Very High)

3. Temporal Demand: How hurried or rushed was the pace of the task?
   Please rate on a 21 point scale of (0: Very Low – 21 Very High)

4. Performance: How successful were you in accomplishing what you did?
   Please rate on a 21 point scale of (0: Perfect – 21 Failure)

5. Effort: How hard did you have to work to accomplish your level of performance?
   Please rate on a 21 point scale of (0: Very Low – 21 Very High)

[1]http://humansystems.arc.nasa.gov/groups/tlx

6. Frustration: How insecure, discouraged, irritated, stressed, or annoyed were you?

   Please rate on a 21 point scale of (0: Very Low – 21 Very High)

C.8 Task 5: System Usability Scale (SUS) Questionnaire

Please fill out the return the SUS [2] questionnaire handed out by the proctor. You are free to clarify any information present in these questionnaires with the proctor.

1. I think that I would like to use this system frequently

   Please rate on a scale of (1: Strongly disagree – 5: Strongly agree)

2. I found the system unnecessarily complex.

   Please rate on a scale of (1: Strongly disagree – 5: Strongly agree)

3. I thought the system was easy to use.

   Please rate on a scale of (1: Strongly disagree – 5: Strongly agree)

4. I found the various functions in this system were well integrated.

   Please rate on a scale of (1: Strongly disagree – 5: Strongly agree)

5. I thought there was too much inconsistency in this system.

   Please rate on a scale of (1: Strongly disagree – 5: Strongly agree)

6. I would imagine that most people would learn to use this system very quickly.

   Please rate on a scale of (1: Strongly disagree – 5: Strongly agree)

7. I found the system very cumbersome to use.

   Please rate on a scale of (1: Strongly disagree – 5: Strongly agree)

8. I felt very confident using the system.

   Please rate on a scale of (1: Strongly disagree – 5: Strongly agree)

9. I needed to learn a lot of things before I could get going with this system.

   Please rate on a scale of (1: Strongly disagree – 5: Strongly agree)

[2] http://www.usability.gov

D. SUPPLEMENTARY INFORMATION FOR THE GUIDED DISCOVERY-BASED SHAPE SYNTHESIS STUDY IN ME444

D.1 Pilot User Study Questionnaire

1. Please enter your participant ID.
2. Please indicate your degree discipline.
   (1) Mechanical Engineering, (2) Other
3. Please indicate your current standing.
   (1) Freshman, (2) Sophomore, (3) Junior, (4) Senior, (5) Graduate
4. Please check the specific courses (or equivalent) that you have completed from the list below.
   (1) Modern Physics PHYS172, (2) Statics ME 270, (3) Dynamics ME274, (4) Mechanics of Materials ME323, (5) Structures and Properties of Materials ME 230, (6) Machine Design 1 ME352, (7) Computer Aided Design and Prototyping ME444, (8) Machine Design 2 ME452, (9) Engineering Design ME463, (10) Other mechanical design courses (Please list out)
5. Do you have any formal training in environmental sustainability (courses, projects, work experience)?
   (1) Yes (Please describe), (2) No
6. Are you planning on taking courses in the future that relate to environmental impact assessment/ sustainability?
   (1) Yes, (2) Maybe, (3) No
7. Design Task 1: What aspects of machine design/mechanics did this task test? What concepts did you learn better?
   (Please describe)

8. Design Task 1: Did you develop any specific insights related to machine design/mechanics in Task 1? If so, what?
   (Please describe)

9. Design Task 1: Have you solved similar problems in any of your courses?
   (1) Yes (Please describe), (2) Maybe, (3) No

10. Design Task 1: Do you think that tasks similar to this help you better understand machine design/mechanics concepts? If so, please explain.
    (Please describe)

11. In your opinion how important is it to learn sustainable design in engineering?
    (Rate on a scale of 1 :not important - 5: very important)

12. Design Task 2: Did you develop any specific insights related to environmental impact assessment/ sustainable design in Task 2? If so, what?
    (Please describe)

13. Design Task 2: Did this task convince you to look into sustainable design further?
    (1) Yes, (2) Maybe, (3) No

14. Design Task 2: Do you think this task was within the general context of engineering mechanics?
    (1) Yes, (2) Maybe, (3) No

15. Design Task 2: Do you feel this task can be a part of existing machine design/mechanics curricula?
    (1) Yes, (2) Maybe, (3) No

16. What is the likelihood that you will use sustainability based design to guide future design tasks?
    (Rate on a scale of 1: not likely - 5: very likely)

17. What is your opinion on having similar modules in other ME courses (Heat Transfer, Fluid Mechanics) ?
    (Rate on a scale of 1:not useful - 5:very useful)

18. If you have any specific concerns/suggestions related to either of the design tasks (Task 1 and Task 2) please elaborate them here.
(Please describe)

D.2 In-Class User Study Pre-Questionnaire

1. Please indicate your degree discipline.
   (1) Mechanical Engineering (2) Other
2. Please indicate your current standing.
   (1) Freshman, (2) Sophomore, (3) Junior, (4) Senior, (5) Graduate
3. Please check the specific courses (or equivalent) that you have completed from the list below.
   (1) Modern Physics PHYS172, (2) Statics ME 270, (3) Dynamics ME274, (4) Mechanics of Materials ME323, (5) Structures and Properties of Materials ME 230, (6) Machine Design 1 ME352, (7) Computer Aided Design and Prototyping ME444, (8) Machine Design 2 ME452, (9) Engineering Design ME463, (10) Other mechanical design courses (Please list out)
4. In your opinion, which of these factors are important considerations for your toy design project?
   (1) Lightweigting, (2) Cost, (3) Environmental footprint, (4) Functionality, (5) Aesthetic appeal
5. In your opinion, which of these factors are critical for being successful in your toy design project?
   (1) Lightweigting, (2) Cost, (3) Environmental footprint, (4) Functionality, (5) Aesthetic appeal
6. In your opinion, are any of the above factors correlated? If so, can you identify any correlations? Please explain.
   (Please describe)
7. Have you previously worked on design projects within Purdue or outside that involved any of the above factors?
   (Please describe)
8. List ideas by which you think the total weight of your design can be reduced.
   (Please describe)

9. List ideas by which you think the total cost of your design can be reduced.
   (Please describe)
10. List ideas by which you think the total environmental footprint of your design can be reduced.
    (Please describe)
11. List ideas by which you think the desired functionality can be achieved.
    (Please describe)
12. List ideas by which you think the aesthetic appeal of your design can be increased.
    (Please describe)

D.3 In-Class User Study Post-Questionnaire

1. Please indicate your degree discipline.

   (1) Mechanical Engineering (2) Other

2. Please indicate your current standing.

   (1) Freshman, (2) Sophomore, (3) Junior, (4) Senior, (5) Graduate

3. Please check the specific courses (or equivalent) that you have completed from the list below.

   (1) Modern Physics PHYS172, (2) Statics ME 270, (3) Dynamics ME274, (4) Mechanics of Materials ME323, (5) Structures and Properties of Materials ME 230, (6) Machine Design 1 ME352, (7) Computer Aided Design and Prototyping ME444, (8) Machine Design 2 ME452, (9) Engineering Design ME463, (10) Other mechanical design courses (Please list out)

4. Do you have any formal training in environmental sustainability (courses, projects, work experience)?

   (1) Yes (Please describe), (2) No

5. Are you planning on taking courses in the future that relate to environmental impact assessment/ sustainability?

   (1) Yes, (2) Maybe, (3) No

6. How many design iterations did you perform for Assignment 4?

   (Indicate on slider: 0-15 iterations)

7. What were the major factors that made you decide to stop the assignment?

   (1) Lack of time, (2) You felt you reached an optimal answer, (3) The task became tedious, (4) You did not know how to better the existing design, (5) Creo and Ansys posed too much of a barrier for me to continue

8. Are you satisfied with your submission?

   (1) Yes, (2) Maybe, (3) No

9. Given more time, do you think you can arrive at a better solution ?
   (1) Yes, (2) Maybe, (3) No
10. Did you develop any specific insights related to environmental impact assessment/sustainable design in Assignment 4? If so, what?
    (Please describe)
11. Did you develop any specific insights related to mechanics/ FEA/ machine design in Assignment 4? If so, what?
    (Please describe)
12. In your opinion how important is it to learn sustainable design in engineering?
    (1) Not at all important, (2) Very unimportant, (3) Somewhat Unimportant, (4) Neither Important nor Unimportant, (5) Somewhat Important, (6) Very Important, (7) Extremely Important
13. Did Assignment 4 convince you to look into sustainable design further?
    (1) Yes, (2) Maybe, (3) No
14. Do you feel this assignment should be a part of the regular ME444 course in the future?
    (1) Yes, (2) Maybe, (3) No
15. What is the likelihood that you will use sustainability based design to guide future design tasks?
    (1) Very Unlikely, (2) Unlikely, (3) Somewhat Unlikely, (4) Undecided, (5) Somewhat Likely, (6) Likely, (7) Very Likely
16. What is your opinion on having similar modules in other ME courses (Heat Transfer, Fluid Mechanics)?
    (1) Very Useless, (2) Useless, (3) Somewhat Useless, (4) Neutral, (5) Somewhat Useful, (6) Useful, (7) Very Useful
17. If you have any specific concerns/suggestions related to Assignment 4 please elaborate them here.
    (Please describe)

Table D.1. : Examples for applying guided discovery-based assessment modules in core engineering classes.

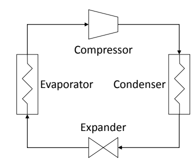
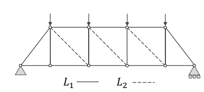
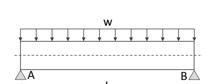
M.E. Subject	**Design Variables**	**Lifecycle Phase(s)**	**Example Problem**
Thermodynamics	mass flow rate, temperature, pressure, power	use phase, end-of-life	Compare the performance of (CO_2, $R32$, $R410A$) as refrigerants in a commercial refrigeration unit. The goal is to maximize the coefficient of performance of the system, while minimizing the total global warming potential due to electricity consumption during use and eventual refrigerant disposal [161]. 
Statics, Dynamics	force, moment, inertia, momentum	material extraction, material processing	Explore truss design configurations under load constraints at a support. Given two link types (L1 & L2) minimize the total weight and cradle-gate environmental impact while meeting loading constraints. 
Mechanics	material selection, stress, strain, geometry	material extraction, material processing, end-of-life	Design a prismatic simply supported beam under uniformly distributed load so that the maximum deflection is below a critical threshold. Explore different grades of structural steel to minimize embodied impacts related to primary material production. 

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Table D.1 Continued

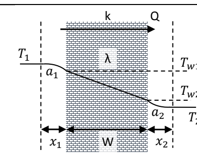
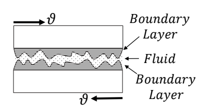
M.E. Subject	**Design Variables**	**Lifecycle Phase(s)**	**Example Problem**
Heat Transfer	length, temp., thermal conductivity, heat flux	material extraction, use phase	Cost, eco-impact and performance tradeoffs exist for different insulation materials for use in buildings. Explore *kg eq.* CO_2, cost and thermal conductivity of materials and develop a weighted score to justify the best option [162]. 
Fluid Dynamics	power, geometry, velocity, drag coeff.	material processing, use phase	Energy is required to move objects through fluids, like air around a car. Trade-off geometric complexity of shape w.r.t the drag coefficient, fuel economy, and estimated impacts of manufacture [163]. 
Machine Design	friction, viscosity, transmission efficiency	material extraction, use phase	Lubrication is vital for efficient machines. However certain types pose environmental concerns. Explore the relationships between kinematic viscosity, cost, & environmental burden for different oil and water-based lubricants. 

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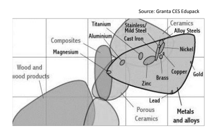
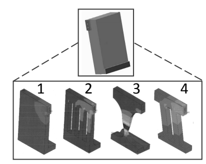
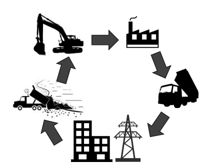
Table D.1 Continued

M.E. Subject	**Design Variables**	**Lifecycle Phase(s)**	**Example Problem**	
Manuf. Processes	material, tolerance, power	material extraction, material processing	Different materials have different manufacturing capabilities. Given a load bearing part (e.g. I-beam), explore the best combination of material and process in terms of cost, eco-impact and strength using a database.	
CAD, CAE	material, stress, weight	material extraction, material processing, end-of-life	Optimize a break pedal for final weight and eco-impact with a Von Mises stress threshold. Offer various material options for selection and provide calculator taking in account end-of-life. See Chapter 7 for details.	
Engg, Design	project dependent	complete lifecycle	Every decision through a products lifecycle has a tangible effect on its ecological footprint. After initial design, provide expert-based critique and describe specific redesign opportunities [142].	

VITA

VITA

Devarajan Ramanujan was born in Bombay, Maharashtra, India on November 20, 1986. He received a Bachelors degree in mechanical engineering with specialization in production technologies from Osmania University, Hyderabad, India in September 2008. During his stay in the School of Mechanical Engineering at Purdue University, he has received the American Society of Mechanical Engineering Design for Manufacturing and the Lifecycle Scholar Development Award in 2014, and the Estus H. and Vashti L. Magoon Award for Teaching Excellence in 2015.

He has co-authored publications in the Journal of Mechanical Design, Journal of Computing and Information Science, Computer-Aided Design, and the Association for Computing Machinery Conference on Human Factors in Computing Systems. His research interests are in data representation and visualization models within product design for supporting environmentally conscious design.