Design Forecasting:
A Method for Performing DFX Analyses in Complex Product Design

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Abstract

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Design Forecasting is modeling methodology for performing DFX analyses such as Life Cycle Assessment and the Modified Westinghouse Method earlier in the design of automobiles and other complex products. Specifically, Design Forecasting uses probabilistic design methods to supplement DFX analyses in a systematic, yet flexible, manner that reduces data collection ambiguity and effort for the design team. In addition, the methodology uses scenario analyses to evaluate potential design decisions or alternatives. Finally, the methodology allows for rigorous review, improvement, and customization of individual, underlying models. In this dissertation, Design Forecasting is developed, illustrated, and validated using two automotive case studies. The first is a material substitution case study used to evaluate Design for Environment metrics for a Ford C-class sedan. The second case study evaluates Design for Assembly metrics for the washer and wiper systems on the same C-class sedan. The research presented in this dissertation is significant because it defines a previously informal or even nonexistent process within design decision-making, and provides a sound framework for future, scholarly research.

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Acknowledgements

"No man is able of himself to do all things." – Homer

Given the opportunity to acknowledge all those who have made this possible, I am overwhelmed. I feel as if an entire chapter would not allow me to devote more than a sentence to every person deserving of my gratitude and acknowledgement. No words can possibly express the appreciation I have for all of the family, friends, colleagues, and mentors who have enriched my life. Faced with this challenge, all I can give is my best. In return, all I ask is… If, in the words of Sam Goldwyn, you can say, "I read part of it all the way through," I ask that this be that part. Thank you, one and all.

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Dedication

To my grandmother and all of the other outstanding individuals who are ABD.

Chapter 1 – Introduction

1.1. Research Summary and Significance

Life cycle modeling is the use of quantitative or qualitative models to evaluate the life cycle performance or cost of a product or system. Typically, life cycle models are used to create inventories of material and energy flows in terms of physical units such as kilograms and joules. Life cycle modeling may also quantify cost, manufacturing or environmental impact, or other consequences resulting from the extraction, production, transformation, consumption, recycling, and disposal of materials and energy within a system. Some examples of life cycle modeling include the use of mass and energy flow models for a product in Life Cycle Assessment (LCA) (SETAC, 1991; ISO, 1997) and the use of production and service models in Life Cycle Costing (Brown & Yanuck, 1985; Fabrycky & Blanchard, 1991). Life cycle models may also be used to support quality and risk analyses such as Failure Modes and Effects Analysis (FMEA) (Ford, 1988; Stamatis, 1995). Life cycle modeling is an important Design for Environment (DFE) tool because it facilitates consideration of impacts to health, natural resources, and the Environment in the design process.

This research began with a question: Why is life cycle modeling not commonly used in the development of complex products such as automobiles? Investigation of this question revealed that despite the potential benefits to design, life cycle models are rarely used early in the design of complex products because: (1) they require considerable information about the system being developed, and (2) *design uncertainty* – uncertainty related to knowledge of a product design's final attributes (e.g., materials, geometries, manufacturing processes) – hinders the application of life cycle models early in design. In response, a systematic life cycle modeling methodology called Life Cycle Modeling for Design (LCMD) was developed.

LCMD:

1. provides systematic techniques for modeling design uncertainty, and
2. reduces the effort required to collect data for models of complex products.

By using LCMD to evaluate material options for an automotive case study, this research demonstrated the value and effectiveness of the methodology during design.

Seeking to extend the value of the methodology, this research found that a more broadly applicable framework based on reducing design uncertainty could offer benefits to product design beyond environmental assessment. To test the applicability of LCMD and the nature of design uncertainty outside of DFE, a Design for Assembly (DFA) case study was developed using the fundamental design uncertainty modeling concepts embodied in LCMD. The final product of this research is a more robust methodology that may be used to perform both quantitative DFE and DFA analyses earlier in complex product design. This methodology, called Design Forecasting, is presented in this dissertation as broadly applicable framework for performing detailed Design for X (DFX) analyses earlier in complex product design.

This research is significant because it: (1) defines a previously informal or even nonexistent process within design decision-making and (2) provides a sound framework for future, scholarly research. Design Forecasting, based on LCMD, uses probabilistic design methods to supplement DFX analyses in a systematic, yet flexible, manner that allows rigorous review, improvement, and customization of individual, underlying models. The methodologies and case studies presented in this dissertation demonstrate the applicability of design uncertainty to both DFE and DFA and provide a blueprint for the future development of additional design uncertainty models.

1.2. Dissertation Overview

This dissertation presents the previously described research in the following manner:

- *Section 1.3* describes the challenges of using existing life cycle modeling methodologies during complex product design and briefly introduces LCMD as a method that significantly reduces these challenges.
- *Section 1.4* describes how the fundamental design uncertainty concepts embodied in LCMD can be distilled into a more broadly applicable framework for performing detailed DFX analyses earlier in complex product design.
- *Chapter 2* outlines this more robust methodology called Design Forecasting.
- *Chapters 3 and 4* present two automotive case studies used to develop and illustrate LCMD and Design Forecasting.
- Finally, *Chapter 5* provides discussion, future opportunities, and conclusions for this research.

As stated previously, this research began with a question: Why is life cycle modeling not commonly used in the development of complex products such as automobiles? The following section answers that question.

1.3. Life Cycle Modeling and Complex Product Design

During the process of developing a new product, consciously or unconsciously, a number of decisions are made that have environmental ramifications, thus making a company responsible not only for the technical performance but also for the *environmental performance* (e.g., energy consumption, material resource consumption, and chemical emissions) of a product (Mildenberger & Khare, 2000). Numerous other authors, including Graedel & Allenby (1996) and Dieter (2000), also note the importance of decisions made during product design. Unfortunately, the environmental ramifications of product design decisions can be complex and involve tradeoffs between multiple stages of the product's life cycle. For example, using structural foam to strengthen automotive bodies and reduce vehicle mass reduces fuel consumption but also reduces the percentage of vehicle material that may be recycled. Because of these issues, one must consider a product's entire *life cycle* (Otto & Wood, 2001): material extraction and production, component manufacture, product assembly, use, maintenance, and end-of-life.

Despite this need for a holistic perspective, life cycle modeling still finds limited use during the design of complex products such as automobiles. Data collection and modeling complexity are primary reasons for this lack of use in all different types of design: variant design, adaptive design, and original design (Pahl & Beitz, 2001; as defined by Otto & Wood, 2001). One specific reason, related to data collection, stems from the existence of *design uncertainty* – uncertainty related to knowledge of a product design's final attributes (e.g., materials, geometries, manufacturing processes). As shown in Figure 1.1, design uncertainty decreases during product design and is largest for entirely original designs. This research focuses on adaptive and variant design because complex system designs, especially those for automobiles, are most often adaptations or variants of previous designs.

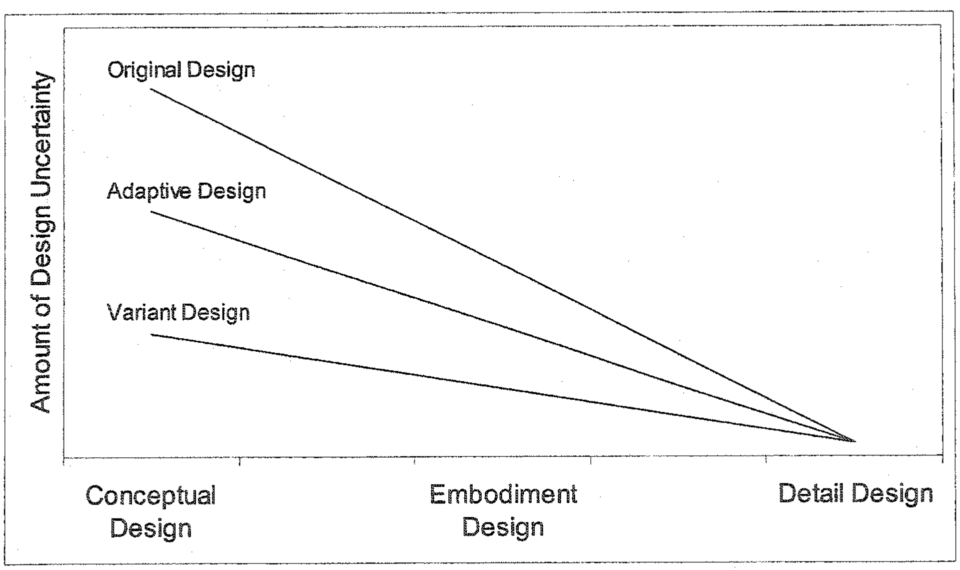

Figure 1.1. Decreasing Design Uncertainty through Product Design

1.3.1. Existing Methods

Numerous authors have proposed methodologies for incorporating life cycle modeling into product design. Table 1.1 compares eleven existing methods identified in engineering and scientific literature. The methods differ in the motivation for modeling, the scope of the life cycle analyzed, the type of models used, the phase(s) of design they support, and the treatment of uncertainty. Specifically, environmental assessment is the primary impetus for many of the design methodologies in Table 1.1, while analysis of production efficiency and cost, and concurrent design motivate others. When environmental assessment is the motivation for modeling, one or more of five levels of appraisal are included:

1. creating an *inventory* of material and energy use and waste,
2. *classifying* material and energy use and waste in relation to the damage or costs they might cause,
3. *characterization* of the amount of damage or costs,
4. *normalization* or comparing the amount of damage or cost to that at the corporate, regional, national, or global levels, and
5. *weighting* or rating of the importance of the potential damage or costs.

When concurrent design is the motivation for life cycle modeling, the results can be used at the same time for environmental, economic, and other assessments (Kalyan-Seshu et al., 1998; Borg et al., 2000).

In addition to different motivations, the methodologies presented in Table 1.1 vary in recommended and applied scope. Most may be applied to the entire life cycle of a product. However, the scope of the methodology presented by Barton & Love (2000) is limited to production and distribution activities, from gate to gate. Also, although the majority of methodologies may be used for cradle-to-grave analyses, some of the examples used to demonstrate these methodologies in their respective papers are limited to simpler, cradle-to-gate analyses.

Table 1.1. Life Cycle Modeling in Product Design

Authors	Title	Goal	Treatment of Uncertainty	LC Scope LC Example	Modeling Techniques	Simulated LC Flows	Environmental Impact Quantification	Appropriate Stage(s) of Design
Azapagic & Clift (1999)	Life Cycle Assessment and Multiobjective Optimisation	Process Parameter Optimization	N/A	Cradle to Grave Cradle to Gate	Analytic Modeling	Economic, Energy, Material	Characterization	Detail Design
Barton & Love (2000)	Design Decision Chains as a Basis for Design Analysis	Whole Business Simulation	N/A	Gate to Gate Gate to Gate	Analytic Modeling	Economic	N/A	Embodiment Design, Detail Design
Borg et al. (2000)	Exploring Decisions' Influence on Life-Cycle Performance to Aid "Design for Multi-X"	Consequence Identification for Design Decisions	N/A	Cradle to Grave No Example	Knowledge-Based Modeling	N/A	N/A	Embodiment Design, Detail Design
Borland et al. (1998)	Integrating Environmental Impact Assessment into Product Design	Quantitative Environmental Assessment	Data Uncertainty & Variability	Cradle to Grave Cradle to Gate	Analytic Modeling with Monte Carlo Simulation	Energy, Material	Characterization	Embodiment Design, Detail Design
Eisenhard et al. (2000)	Approximate Life-Cycle Assessment in Conceptual Product Design	Approximate, Quantitative Environmental Assessment	N/A	Cradle to Grave Cradle to Grave	Automated Neural Networks	N/A	Characterization	Conceptual Design
Graedel & Allenby (1996)	Design for Environment: Section 9.2 – Efficient Assessment Tools	"Semi-qualitative" Environmental Assessment	N/A	Cradle to Grave No Example	N/A	N/A	Weighting	Conceptual Design
Jackson & Wallace (1997)	A Modular Method for Representing Product Life-Cycles	Time-Dependent, Quantitative Environmental Assessment	N/A	Cradle to Grave Cradle to Grave	Analytic & Parametric Modeling	Energy, Material	Characterization	Detail Design
Kalyan-Seshu et al. (1998)	Integrating DFX Tools with Computer-Aided Design Systems	Integration of DFX and CAD	Unspecific Recognition of Uncertainty	Cradle to Grave Cradle to Grave	Unclear	N/A	Weighting	Detail Design
Nielsen & Wenzel (2002)	Integration of Environmental Aspects in Product Development: A Stepwise Procedure Based on Quantitative Life Cycle Assessment	Quantitative Environmental Assessment	Design Uncertainty	Cradle to Grave Cradle to Grave	Analytic Modeling	Energy, Material	Normalization	Embodiment Design, Detail Design
Regnier & Hoffman (1998)	Uncertainty Model for Product Environmental Performance Scoring	Probabilistic, Quantitative Environmental Assessment	Data Uncertainty & Variability, Model Uncertainty	Cradle to Grave Cradle to Grave	Monte Carlo Simulation	N/A	Weighting	Embodiment Design
Umeda et al. (2000)	Study on Life-Cycle Design for the Post Mass Production Paradigm	Optimal Life Cycle Selection	Unspecific Recognition of Uncertainty	Cradle to Grave Cradle to Grave	Analytic Modeling	Economic, Energy, Material	Inventory	Detail Design

In addition to scope, it is important to consider the types of models and results proposed for each methodology. Most of the life cycle modeling methodologies presented in Table

1.1 use analytic modeling to simulate material, energy, and economic flows throughout a system's life cycle. Some, however, use parametric and knowledge-based modeling to produce results without simulating flows.

In addition, most of the methodologies in Table 1.1 do not allow for easy assessment of numerous design scenarios. Within this context, a *design scenario* represents the outcome of a series of design decisions. For example, during conceptual design, product developers must evaluate and select from numerous design concepts such as steel vs. aluminum vehicle frames and gasoline vs. electric powertrains. Each legitimate concept, or combination of concepts, is a potential design scenario.

When multiple design scenarios are not assessed, the use of life cycle modeling in conceptual design may not only be difficult but also inappropriate. In fact, only the methodologies presented by Eisenhard et al. (2000) and Graedel & Allenby (1996) are expressly targeted for use in conceptual design. Specifically, the limited number of design variables used by Eisenhard et al.'s automated neural network model allows for quick evaluation of numerous, divergent concepts. However, as concepts converge during design, the effectiveness of the methodology decreases because the model is unable to reliably differentiate between design alternatives. Thus, the methodology presented by Eisenhard et al. is not appropriate for use during embodiment and detail design. Also, the matrix method presented by Graedel & Allenby is not detailed enough to reliably differentiate between similar design alternatives (e.g., among metals or among thermoplastics) and is not appropriate for use during embodiment and detail design.

Of the articles presented in Table 1.1, only five cite the need to accommodate uncertainty in life cycle modeling. Most generally, Umeda et al. (2000) and Kalyan-Seshu et al. (1998) state that there is a need to handle uncertainty and to understand its effects. Others provide more particular instruction related to data uncertainty (related to the true values of input data), data variability (related to the heterogeneity of data values over time, space, or different members of a population), model uncertainty (related to how well a model represents the true nature of a system), and design uncertainty (related to knowledge about the final product design such as what materials will be used).

Specifically, Borland et al. (1998) allows the use of both discrete and continuous input variables to accommodate both data uncertainty and variability. Regnier & Hoffman (1998) progress one step further by also incorporating model uncertainty. Finally, among the methodologies characterized in Table 1.1, only Nielsen & Wenzel (2002) addresses the issue of design uncertainty. The authors propose an iterative series of analyses that become increasingly focused and detailed as information becomes available. This allows assessments to be performed throughout the product design process. However, Nielsen & Wenzel provide no specific methods for estimating missing design information or for capturing design uncertainty; making assessment during conceptual design difficult.

Difficulty in capturing design uncertainty is one reason detailed life cycle models are rarely used in the design of complex systems such as automobiles. Under design uncertainty, the exact materials, geometries, and other features of the product are unknown. As a result, the exact material flows and life cycle processes to be analyzed are also unknown. Without a systematic method for modeling design uncertainty, the life cycle modeler has two choices:

1. wait until the new design is nearly complete, thus significantly reducing the usefulness of the modeling results; or
2. make numerous assumptions about the final product design, thereby disguising the amount of influence design decisions may have on the final cost and performance of the system.

Both options are reasonable, but being able to perform analyses throughout product design with a minimal number of hidden assumptions is preferable for effective decision-making.

This research has sought to develop a systematic life cycle modeling methodology that may be used effectively within the basic framework presented by Nielsen & Wenzel (2002). For effective use during conceptual design, life cycle modeling must allow for easy assessment of numerous design scenarios (e.g., scenarios such as steel vs. aluminum vehicle frames and gasoline vs. electric powertrains). Following conceptual design, evaluation of multiple design scenarios is still necessary during embodiment design; however, the scenarios under consideration are typically less numerous and varied (e.g., extruded vs. cold-rolled reinforcing beams and steel vs. aluminum oil pans). As a result, design uncertainty is smaller and higher accuracy is required for modeling results. Finally, during detail design, design uncertainty is minimal and modeling accuracy is of greatest importance.

1.3.2. Life Cycle Modeling for Design

Life Cycle Modeling for Design (LCMD; Figure 1.2) is a systematic life cycle modeling methodology that may be used effectively within the basic framework presented by Nielsen & Wenzel (2002). It was developed to forecast the potential life cycle environmental impact of an adaptive or variant design for complex products during conceptual, embodiment, and detailed design. The methodology combines probabilistic design methods (Haugen, 1980; Shigley & Meschke, 2001) with LCA, and incorporates the four phases recommended by LCA guidelines (ISO, 1997; Curran, 1996; Klöpffer & Hutzinger, 1997): (1) goal and scope definition, (2) inventory analysis, (3) impact assessment, and (4) interpretation.

In the first phase of LCMD, the goal and scope of the life cycle model are defined. This includes selecting a baseline design and a variety of alternative design scenarios (i.e., concepts) for the product of interest. The purpose of Phase 1 is to generate an array of baseline and alternative design scenarios that: (1) communicate the range of designs being considered by the design team and (2) provide modeling input data for later analyses.

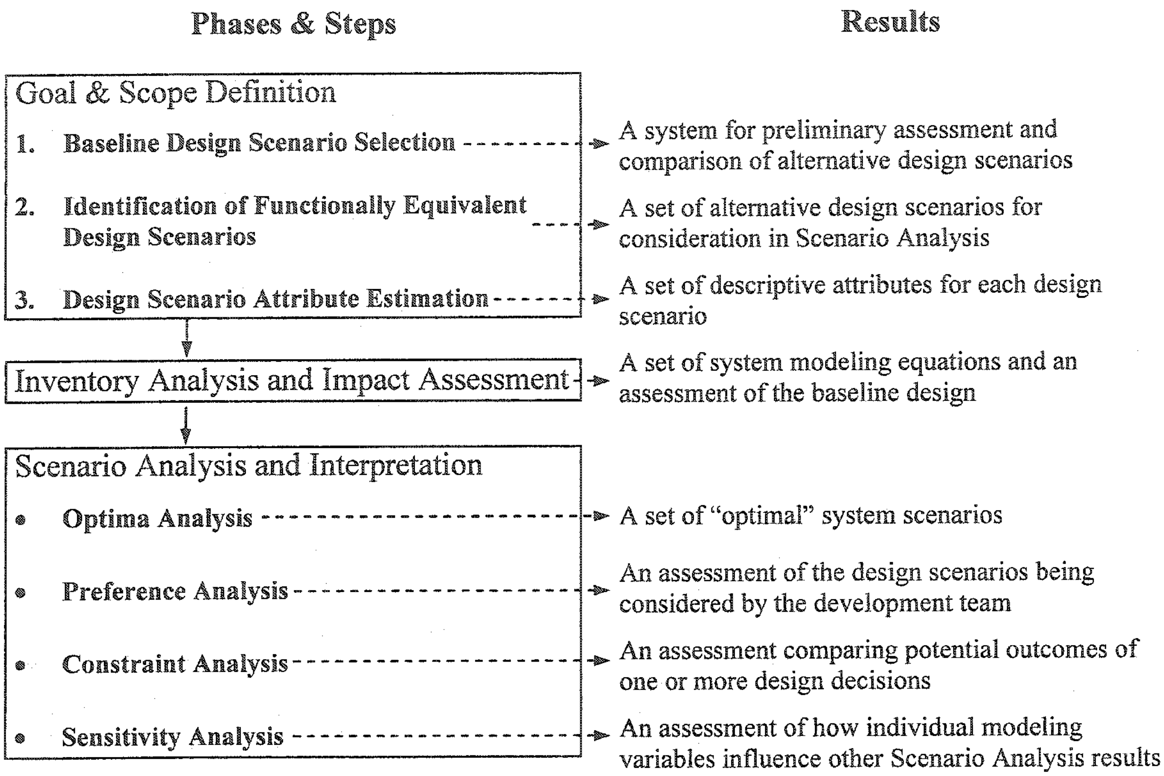

Figure 1.2. Life Cycle Modeling for Design Methodology

The purpose of Phase 2 of LCMD, which corresponds to Phases 2 and 3 of LCA, is to: (1) develop a set of life cycle modeling equations for evaluating competing design scenarios and (2) evaluate the baseline product design as a benchmark for further development. Using this set of modeling equations, material and energy use, recovery, and waste for the baseline product and the processes of the life cycle are estimated. In addition, the contribution of material and energy use, recovery, and waste to select impacts to the environment, economy, or society may be analyzed.

The third phase of LCMD involves four analyses: Optima Analysis, Preference Analysis, Constraint Analysis, and Sensitivity Analysis. These analyses evaluate optimal system scenarios, likely system characteristics, and the sensitivity of system characteristics to individual design decisions. In this phase of LCMD, alternative, product design scenarios are evaluated relative to material and energy use, recovery, and waste metrics.

LCMD is a systematic design methodology that: (1) provides systematic techniques for modeling design uncertainty and (2) reduces the effort required to collect data for models of complex products. Though LCMD is not thoroughly developed here, it represents the core of this research. Its phases and steps provided the foundation for Chapter 2, and the case study presented in Chapter 3 directly illustrates the application of the LCMD methodology (thoroughly presented in Appendix A).

1.4. Beyond Life Cycle Modeling

After developing LCMD, the opportunity to apply design uncertainty modeling to design concerns beyond environmental performance was identified. The goal of this additional research was to develop a more broadly applicable framework for considering design uncertainty in Design for X (DFX) (Bralla, 1996) domains in addition to Design for Environment. The remainder of this chapter provides a detailed presentation of DFX and a brief description of how LCMD was adapted into the more general Design Forecasting methodology presented in Chapter 2.

1.4.1. Design for X

According to Layendecker & Kim (1993), DFX is the process where the full life cycle needs of a product are addressed during the product's design, and the goal of DFX is greater customer satisfaction through improved quality and reduced life cycle costs. Dieter (2000) identifies several DFX subcategories, Design for: Assembly (Boothroyd & Dewhurst, 1987), Environment (Graedel & Allenby, 1996), Manufacturability (Bralla, 1986), Quality (Bralla, 1996), Reliability (Rao, 1992), Safety (Hunter, 1992), and Serviceability (Moss, 1985). Numerous other DFX terms also exist, for example, Design for: Castings (Dieter, 2000), Cost (Merino & Merino, 1994), Disassembly (Dewhurst, 1993), Forgings (Dieter, 2000), Machining (Dieter, 2000), Powder Metallurgy (Dieter, 2000), Producibility (Boothroyd, 1982), Recycling (Henstock, 1988), Sheet-Metal Forming (Dieter, 2000), Time-to-Market (Bralla, 1996), Variety (Martin & Ishii, 2002), and Welding (Dieter, 2000). However, this latter set of terms typically refer to subcategories of those listed by Dieter and will not be explicitly discussed here.

Design for Environment

As used in LCMD and according to Bralla (1996), the objective of DFE is to minimize the adverse environmental effects from the manufacture, use, and disposal of the product. Bralla also states:

> "If a company is to pursue an environmentally friendly approach with its products, there must be some policy statement to this effect. Management must establish the relative importance of DFE as a design objective for the product or products undergoing development and design. This may be easier at the present time than in the past since consumers have become environmentally aware. Environmentally friendly products have appeal in the market."

Bralla's statement about management establishing the relative importance of DFE as a design objective is especially important for ensuring the consideration of environment in product design. In addition to Bralla, Ashley (1993), Fiksel (1996), Graedel & Allenby (1996), and Otto & Wood (2001) all provide detailed discussions related to environment and design. In addition, SETAC (1991), Graedel et al. (1995), and Ishii & Lee (1996) provide examples of specific Design for Environment methodologies.

Design for Assembly

The objective of Design for Assembly (DFA) is ultimately related to cost, which involves deciding on the most appropriate assembly process and then designing the product to accommodate the strengths and weaknesses of the process (adapted from Redford & Chal, 1994). In other words, a product's overall assembly is analyzed in an effort to eliminate and combine components, and then individual components are analyzed to further reduce assembly time, defects, and, ultimately, cost. Andreasen et al. (1983), Boothroyd & Dewhurst (1987), Redford & Chal (1994), and Otto & Wood (2001) provide detailed discussions related to assembly and design. In addition, Miyakawa & Ohashi (1986) and Sturges & Kilani (1992) provide examples of specific DFA methodologies. Within this dissertation, Section 4.2.1 provides a detailed comparison of six, quantitative DFA methodologies.

Design for Manufacture

The objective of Design for Manufacture is the integration of product design and process planning into one common activity (Redford & Chal, 1994) to lead to reduced manufacturing cost and improved product quality. Most broadly defined, Design for Manufacture is synonymous with concurrent engineering and DFX. However, some authors use a narrower definition of Design for Manufacture that is limited to optimized component design for specific manufacturing processes. Regardless, Bralla (1986), Anderson (1990), Corbett et al. (1991), and Boothroyd et al. (2002) all provide detailed discussions related to manufacturability and design. In addition, design guidelines such as provided by Parmer & Laney (1993), Singh (1996), and Fagade & Kazmer (1998) are examples of specific Design for Manufacture methodologies.

Design for Quality

One possible objective of Design for Quality is to design a product that meets customer requirements consistently. Taguchi (1986), Ross (1995), Bralla (1996), and Yang & El-Haik (2003) provide detailed discussions related to quality and design. In addition, Foxx (1990) and Vorba & Oberlender (1991) provide examples of specific Design for Quality methodologies.

Design for Reliability

The objective of Design for Reliability is to ensure a product performs its intended functions for the planned life of the product. McLinn (1988) defines reliability as quality in the time dimension. Therefore, Design for Reliability can be viewed as Design for Lifetime Quality. Smith (1976), Rao (1992), Bralla (1996), Dieter (2000), and Crowe &

Feinberg (2001) all provide detailed discussions related to reliability and design. In addition, Degen (1995) and Booker (2001) provide examples of specific Design for Reliability methodologies.

Design for Safety

The objective of Design for Safety is to ensure a product is safe to manufacture, use, and dispose of after use. According to Dieter (2000), a safe product is one that does not cause injury or property loss. Dieter also states that safety is normally taken for granted, but liability suits, replaced product, and a tarnished reputation can make the recall of an unsafe product very costly. Hunter (1992), Covan (1995), Bralla (1996), Smith (1997), and Dieter (2000) all provide detailed discussions related to safety and design. In addition, Van Beurden & Amkreutz (2002) and Wang (1998) provide examples of specific Design for Safety methodologies.

Design for Serviceability

The objective of Design for Serviceability is to maximize the ease with which maintenance can be performed on a product (adapted from Dieter, 2000). According to Bralla (1996), the optimal design is the one that considers both manufacturing costs and lifetime maintenance costs. In addition to Bralla, Moss (1985) and Ishii et al. (1998) provide detailed discussions related to maintenance and design. In addition, Bralla (1985) and Gershenson & Ishii (1992) provide examples of specific Design for Serviceability methodologies.

1.4.2. Adapting LCMD for DFX

Within LCMD, there are two levels of models necessary for evaluating design uncertainty: (1) attribute estimation models and (2) system evaluation models. Specifically, as shown in Figure 1.3, LCMD uses *system evaluation models* (e.g., environmental life cycle inventory or material and energy use and emissions estimation models) to evaluate environmental metrics (such as life cycle energy use) based on the materials and masses of individual component design scenarios, which combine to form vehicle design scenarios. LCMD uses *attribute estimation models* to estimate unknown data (such as the final mass of a specific component).

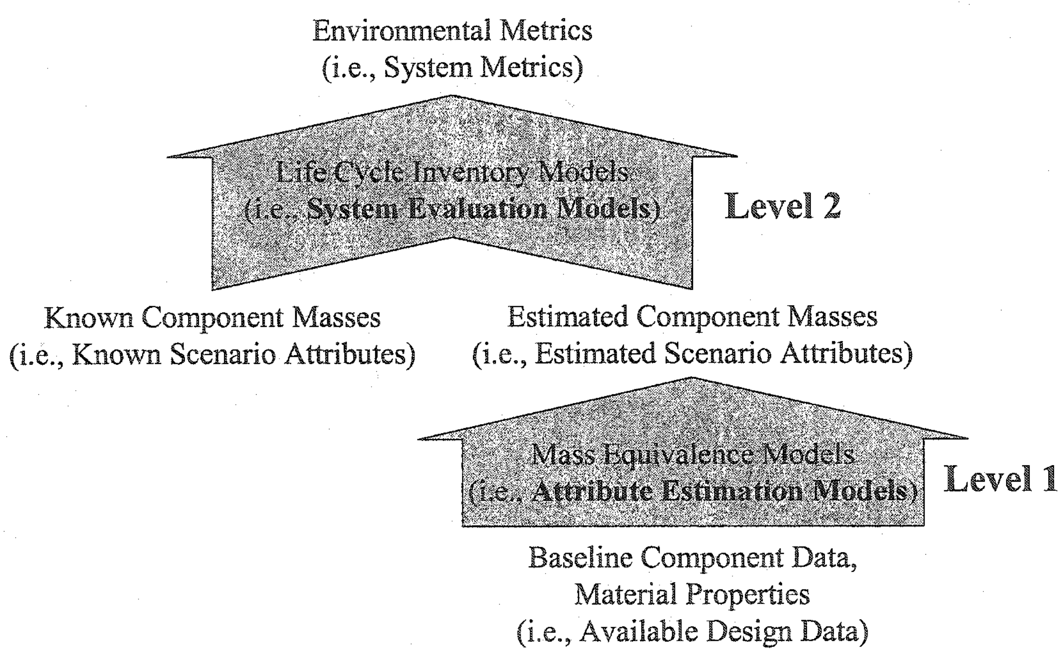

Figure 1.3. Estimating Scenario Attributes and System Metrics Using LCMD

In order to isolate a general methodology applicable to a variety of DFX domains, the DFE-specific information was eliminated from Figure 1.3. The results are presented in Figure 1.4. The distilled modeling structure shown in Figure 1.4 uses known and estimated design attributes with system evaluation models to estimate system metrics.

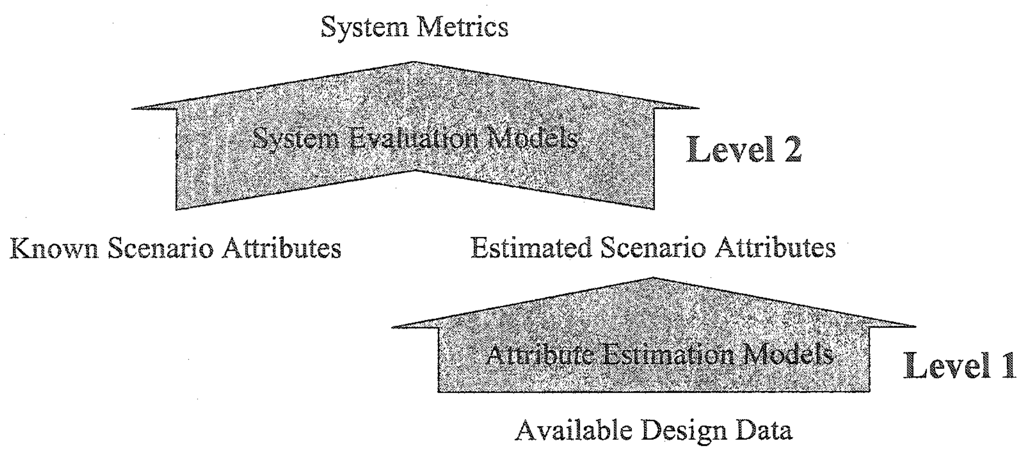

Figure 1.4. Basic Modeling Structure Distilled from LCMD

This basic modeling structure and the outline of LCMD presented in Figure 1.2 provide the basis for *Design Forecasting* (Chapter 2) – a broadly applicable framework for performing detailed DFX analyses earlier in complex product design.

Chapter 2 – Design Forecasting

This chapter presents *Design Forecasting* as a broadly applicable framework for considering design uncertainty during product design. The motivation for developing Design Forecasting was to allow the design uncertainty concepts embodied in LCMD to be applied to more DFX domains than just DFE. Based on the modeling structure and outline of LCMD (Figures 1.4 and 1.2, respectively), Figure 2.1 presents the methodological outline for Design Forecasting. Like LCMD, Design Forecasting has three phases. The first and the third phases of Design Forecasting are nearly identical to those of LCMD, while the second phase is more general and allows for the use of a broad range of DFX models.

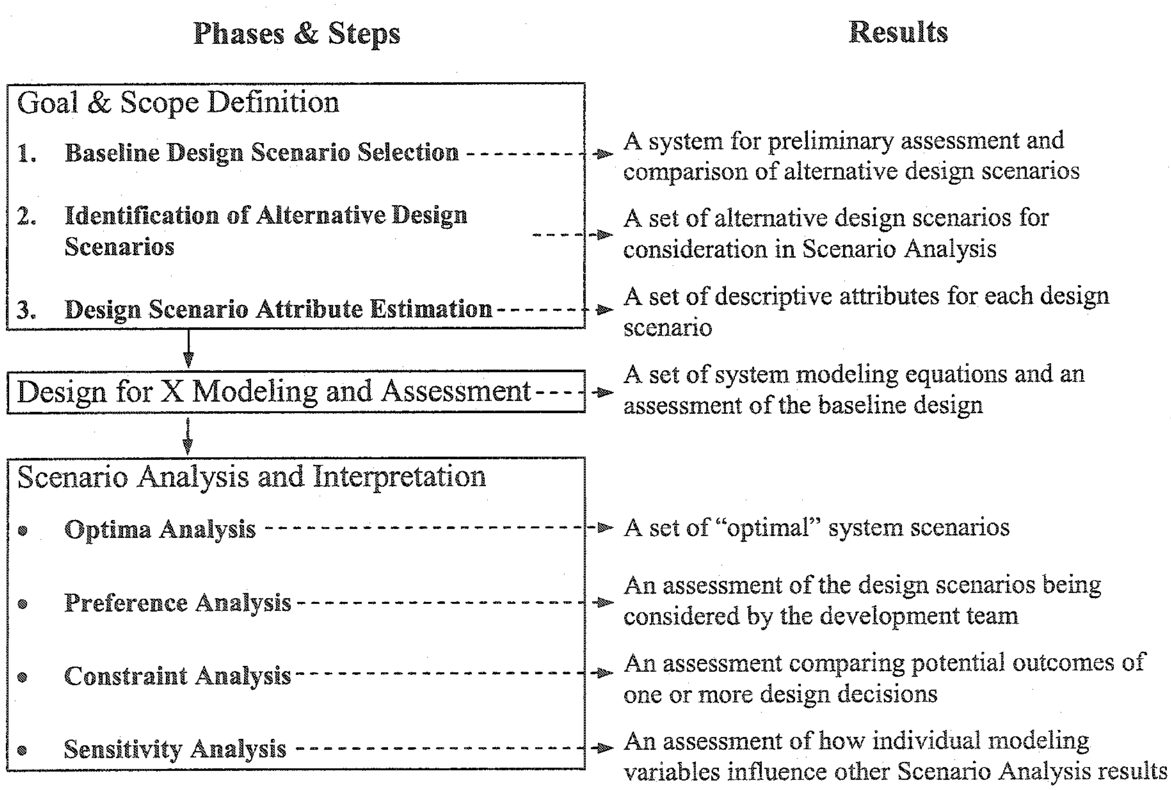

Figure 2.1. Design Forecasting Methodology

2.1. PHASE 1: Goal and Scope Definition

In this phase, the goal and scope of the case study are defined for the product of interest.

Goal and Scope Definition is a critical phase of Design Forecasting, and is based primarily on the protocols provided for Life Cycle Assessment (ISO, 1997 and 1998). If the goal (including objectives and intended audience) of a study is not clearly identified at the beginning, the results may provide little or no value to the modeler or the eventual audience. The same is also true if the scope of a study is not properly defined. In addition, an improperly defined scope can significantly and unnecessarily complicate a study.

To define the goal and scope of a Design Forecasting case study properly, the following items must be defined:

- *Objectives* – The primary objective of any Design Forecasting case study is to identify design scenarios that will likely improve the product or system of interest. However, each study has its own specific objectives for improvement. For example, the primary objective of the Design Forecasting for Environment (DFFE) case study in Chapter 3 is to identify material substitutions that will improve the environmental performance of a Ford C-class sedan, whereas the primary objective of the Design Forecasting for Assembly (DFFA) case study in Chapter 4 is to identify design scenarios that will make the washer and wiper systems for the C-class sedan easier to assemble. In addition, each study may have its own secondary objectives. A secondary objective for the DFFE study is to demonstrate a DFFE methodology (specifically, LCMD). The secondary objectives for the DFFA study are to identify specific washer and wiper design scenarios likely to improve the environmental performance of the sedan and to demonstrate Design Forecasting. The number of secondary objectives for these studies result from the multiple intended audiences for this research.

- *Intended audience* – The primary intended audience for any Design Forecasting case study should be product managers and designers. However, intended audiences can also include manufacturing decision-makers, suppliers, and those who recycle, treat, and dispose of materials at the end of a product's life. The intended audience most directly influences the scope of the study, the specific scenario analyses performed, and the results presented.

- *System metrics* – The primary metrics used to evaluate the products and systems of interest for the two case studies presented in this dissertation are DFE metrics (e.g., life cycle energy consumption, life cycle particulate emissions, and recyclability) and DFA metrics (e.g., number of assembly operations, total assembly time, and assembly defect rate). However, system metrics from other DFX domains can also be evaluated. The objectives and intended audience for a particular case study strongly influence the choice of system metrics. In turn, the choice of system metrics strongly influences the functional units and the system models used in the study.

- *Functional units* – Functional units are measures of the functional output of the product system (ISO, 1998) and are used to ensure a fair comparison of design scenarios. For example, the functional unit for the DFFE case study is "one complete service life time distance (120,000 miles)" (Sullivan et al., 1998) for a Ford C-class sedan. In this case, the lifetime driving distance and type of car are important because a heavy-duty pickup truck with an exceptionally long lifetime driving distance does not provide the same functionality as a C-class sedan. Comparing the two would be "like comparing apples to oranges." As another example, the functional unit for the DFFA case study is one complete service lifetime distance (120,000 miles) for a washer/wiper system on a Ford C-class sedan.

- *System models* – In Design Forecasting, quantitative system models are necessary to estimate DFX metrics for the product or system of interest. Therefore, one or more system models must be selected to estimate the array of chosen system metrics. The selection of system models affects the type, amount, and availability of information needed for analysis during design. Poorly chosen system models can produce highly uncertain results, thus limiting the value of modeling. For selecting from an array of quantitative, system models, the following three questions may be used:

    1. *How well does the model represent the true nature of the system?* In other words, how accurate and unbiased is the model? An ideal system model is completely accurate and unbiased. However, most models are neither. Preferable system models have high accuracy and low bias.

    2. *How many input variables are required for modeling?* Preferable system models require minimal input variables (i.e., less is better and one input variable is ideal).

    3. *What percentage of input variables are likely to be known during conceptual or embodiment design?* Preferable system models have a high percentage of input variables that are likely to be known (i.e., higher is better and 100% is ideal).

  Although some methods for selecting system models have been presented here, refer to Section 4.2.1 for a thorough example of model selection. An opportunity exists for future research investigating the suitability of models for Design Forecasting (e.g., focusing on the sensitivity of selection on the results).

The scope of a Design Forecasting case study is further defined by the array of design scenarios evaluated. This array should include the full range of design scenarios being considered by the design team. In Design Forecasting, arrays of design scenarios are generated using three steps:

Step 1. Baseline Design Scenario Selection

Step 2. Identification of Alternative Design Scenarios

Step 3. Design Scenario Attribute Estimation

The following subsections describe each of these steps for the case study in detail.

2.1.1. STEP 1: Baseline Design Scenario Selection

In this step, a baseline design is chosen for the product of interest.

This step defines Design Forecasting as applicable to variant and adaptive design, as opposed to original design or invention (Otto and Wood, 2001). As provided in adaptive and variant design, an existing design with similar architecture, similar functional requirements, and a considerable number of shared parts with the new design is most appropriate for this step. However, if no single, existing product is available or appropriate, a hybrid of multiple products or a superior concept developed as part of the original design process may be preferred.

Given a physical decomposition of a system (Figure 2.2), existing subsystem and component designs can be used as baseline subsystem and component design scenarios. For example, the body design of an existing C-class sedan may be selected as a baseline subsystem scenario. Alternatively, existing designs for components such as reinforcing beams and energy absorbers can be selected from multiple body designs to be baseline component scenarios.

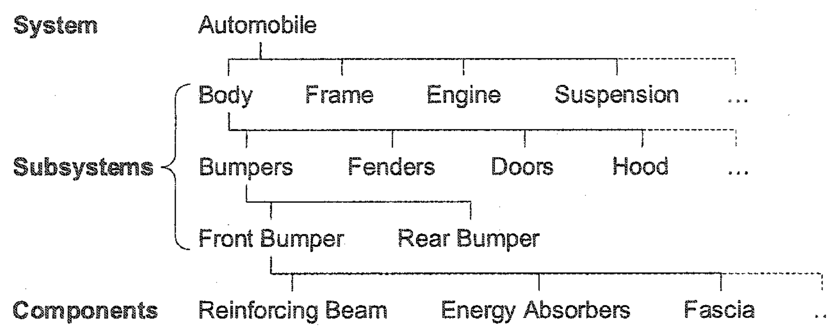

Figure 2.2. Partial Physical Decompositions of an Example System

2.1.2. STEP 2: Identification of Alternative Design Scenarios

This step involves compiling a list of alternative design scenarios being considered by the design team.

In many ways, this step is similar to concept generation in design. The baseline design scenario selected in the previous step represents one collection of concepts, and this step identifies additional concepts for evaluation. Minimally, this step documents design scenarios (i.e., concepts) that already exist:

1. Features of existing products, systems, or components that differ from the baseline
2. Concepts and alternatives currently under consideration by the design team

This step may also be extended to generate entirely new design scenarios. The only requirement is that a set of alternatives or changes to the baseline design be identified.

<u>Documenting Existing Design Scenarios</u>

Ulrich & Eppinger (2000) identify five ways to gather information from external sources (i.e., sources outside the design team) during concept generation:

1. Interview lead users
2. Expert consultation

3. Patent searches

4. Literature searches

5. Competitive benchmarking

These methods for gathering information also work well for documenting existing design scenarios. For both the DFFE case study in Chapter 3 and the DFFA case study in Chapter 4, competitive benchmarking, expert consultation (both internal and external to the design team), and literature searches were most beneficial for documenting existing design scenarios. Much of the benchmarking information for both studies came from Ford benchmarking and teardown reports. At Ford, benchmarking reports compare component masses and costs for two different vehicles, and teardown reports document the material composition and recyclability of components for a single vehicle.

When identifying alternative design scenarios, methods are needed describe and organize design scenarios. Though other methods may also be used to describe and organize design scenarios, the following two options are used in this research:

Option 1. *Design Scenario Arrays* – Table 2.1 illustrates an array of baseline and alternative design scenarios for a single component. The array of scenarios are listed in columns to the right of the table, with rows containing descriptive information used to differentiate each scenario. Collectively, the information used to differentiate scenarios is called the *scenario key*. In Table 2.1, materials and manufacturing processes are used to differentiate design scenarios. However, other design variables (e.g., shape and fit) may be used to differentiate between design scenarios. Using arrays to describe and organize design scenarios is most appropriate when the design team is considering a small number of concepts (i.e., scenarios).

Table 2.1. Example Array of Component Scenarios

COMPONENT A		Baseline Scenario	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Scenario Key	Material(s)	Material A	Material B	Material C	Material D	Material E
	Manufacturing Plan	Process A	Process A	Process A	Process B	Process B

Option 2. *Design Scenario Matrices* – For instances when the design team is considering multiple options for several types of design variables independently, a design scenario matrix (e.g., Table 2.2) may be used to describe and organize design scenarios. The following column headings, prescribed for design scenario matrices, offer a robust method for categorizing design scenarios: function, form (architecture and shape), material, fit, and production (manufacturing and assembly). However, design scenario matrices do have a deficiency. Design scenario matrices do not illustrate dependencies between scenarios. For example, Table 2.2 does not illustrate that Material A and Process B would not be used in conjunction for the design of Component A. Despite this deficiency, design scenario matrices are sometimes necessary to succinctly describe a large number of design scenarios.

Table 2.2. Example Component Design Scenario Matrix

Component	Function	Form		Material	Fit	Production	
		Architecture	Shape			Manufacturing	Assembly
Component A			Shape A Shape B	Material A Material B …	Fastener A Fastener B	Manuf. Plan A Manuf. Plan B (i.e., Processes A and B)	

In addition to using a design scenario matrix to describe design scenarios for a single component, a design scenario matrix can also be used to describe design scenarios for an entire system. The design scenario matrix shown in Table 2.3 represents an extended Morphological Chart (Dieter, 2000) for an example, hierarchical system. The extension includes a classification of solutions on the basis of function, form, material, fit (e.g., joining method), and production process. At the subsystem level, architecture (i.e., form) and assembly (i.e., production) are commonly used to differentiate between design scenarios. At the component level, shape (i.e., form), material, fit, and manufacturing (i.e., production) are commonly used to differentiate between design scenarios. However, to facilitate a higher level of innovation, design scenarios may also be differentiated by function. Component C in Table 2.3 exemplifies this. Rather than identifying individual alternatives for the shape, material, fit, and manufacturing of Component C, a design team can identify another component, Component I, as an alternative design with a predefined function, shape, material, fit, and manufacture.

Table 2.3. Example System Design Scenario Matrix

Component	Function	Form		Material	Fit	Production	
		Architecture	Shape			Manufacturing	Assembly
1 Subsystem A		Architecture A Architecture B					Assembly Plan A
1.1 Component A			Shape A Shape B	Material A Material B ...	Fastener A Fastener B	Manuf. Plan A Manuf. Plan B	
1.2 Component B			Shape C Shape D ...	Material A Material B	Fastener C	Manuf. Plan A Manuf. Plan B	
1.3 Component C	Component C Component I ...						
1.4 Component D			Length A Length B ...	Material C Material D Material E	Fastener D	Manuf. Plan C	
1.5 Component E			Shape E Shape F ...	Material B Material D Material F	Fastener E	Manuf. Plan A	
2 Subsystem B		Architecture C					Assembly Plan B
2.1 Component F		Architecture D Architecture E ...		Material G Material H Material I	Fastener A Fastener B ...	Supplier A	
2.2 Component G			Shape G	Material G Material H Material J	Fastener F	Supplier B	
2.3 Component H			Shape H	Material G	Fastener E	Supplier C	

Generating New Design Scenarios

When performed during the design of a new product, the range of design scenarios chosen should reflect the range of design alternatives being considered by the design team. Therefore, during design, generating new design scenarios is not mandatory. However, in some cases, generating additional design scenarios may be desirable. For example, if the design team knows the current design scenarios are not capable of meeting one or more targets, the team may take this opportunity to supplement the list of existing design scenarios.

The following list describes several options for generating new design scenarios:

Option 1. *Scenario generation using the design scenario matrix* – The design scenario matrix (an extension of the Morphological Chart as illustrated by Table 2.3) may be used to brainstorm and organize new design scenarios. For each cell in the matrix, one or more questions may be asked to inspire new scenarios. Using the design scenario matrix to generate new scenarios is desirable because it is simple and organized. In addition, the use of published Morphological Charts and material and process selection tools (Dieter, 2000) to create the design scenario matrix offer an improvement over brainstorming.

Option 2. *Scenario generation using properties, indices, guidelines, and knowledge-based-systems* – Various properties, indices, guidelines, and knowledge-based-systems may be used to generate new and potentially beneficial design scenarios. This is especially clear for identifying potentially beneficial material options, since properties, indices, guidelines, and knowledge-based-systems are commonly used for material selection in design (Dieter, 2000). For example, Fitch & Cooper (2003; Appendix C) present a detailed example of using indices to identify material options likely to minimize the life cycle energy consumption of a product. Identifying the appropriate properties, indices, guidelines, and knowledge-based systems for use in Design Forecasting offers an opportunity for further research.

Option 3. *Scenario generation using physical or functional decomposition* – Another option for generating new design scenarios is to decompose the baseline system, either physically or functionally. To generate new design scenarios, the design team should ask thought provoking questions at each branch in the decomposition. For a physical decomposition, the team should ask: 1) "Can this component or subsystem be eliminated?" and 2) "Is there a different component or subsystem that can be substituted for this one?" For a functional decomposition, the team should ask: "How can this function be performed differently than it is for the baseline design?" Of the options presented here, this one is most likely to lead to divergent and original design scenarios. In some instances, this can be extremely beneficial. In others, it can be an ineffective use of time.

Regardless of the method chosen for generating design scenarios, the design team should review the new scenarios and find them to be reasonable before adding them to the set of existing design scenarios. In addition, once the array of alternative design scenarios has been collected, the design team provides appropriate, available data for each scenario. Early in design, data for scenario attributes may only be available for the baseline scenario. However, as design scenarios are developed, the design team may determine values for some attributes. During this step, the design team only provides attributes known by the team at that time.

Table 2.4 illustrates the type of results produced in this step. In addition to presenting each scenario along with the descriptive information contained in the scenario key, Table 2.4 also presents a list of attributes for each component scenario (e.g., mass, thickness, and assembly time). These attributes will later be required in later phases of Design Forecasting to estimate system metrics (e.g., total system mass, life cycle energy consumption, and total assembly time). Once again, the design team only provides values for known attributes during this step.

Table 2.4. Example Component Scenarios with Baseline Attributes

Component A		Baseline Scenario	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Scenario Key	Material(s)	Material A	Material B	Material C	Material D	Material E
	Manufacturing Plan	Process A	Process A	Process A	Process B	Process B
Scenario Attributes	Attribute X	X_b	Information not provided by product design team			
	Attribute Y	Y_b				

2.1.3. STEP 3: Design Scenario Attribute Estimation

This step involves estimating missing data for each new scenario.

Once the array of design scenarios has been compiled for each component or subsystem considered for redesign, missing data for each new scenario must be estimated. The most accurate and time-consuming method for doing this is to completely redesign components and subsystems for each design scenario. However, performing this method for every design scenario is usually impractical early in the design process. As an alternative, the following methods are suggested for Design Forecasting:

1. *Equivalence Models* – Mathematical models that use physical relationships to ensure the functional equivalence (i.e., equivalent strength, stiffness, fatigue life, etc.) of two or more competing design scenarios. For example, Cooper's (2003) mass equivalence method uses a mathematical model to estimate the mass required to provide equivalent mechanical performance between a baseline material and a substitute for a certain aircraft component. Section 3.1.3 illustrates how this type of equivalence model can be used to estimate unknown scenario attributes. The primary benefit of equivalence models is that they can be applied to design scenarios for which little or no previous design experience exists. The disadvantage of equivalence models is that they require specific information about the function of component or subsystem being analyzed.

2. *Anecdotal Models* – Simple models and distributions based entirely on anecdotal data. For example, anecdotal data can be used to estimate the relative mass of two components, the first made of aluminum and the second made of magnesium. Davis (1991) provides a set of actual material substitution data for five vehicles: a small, front wheel drive (FWD) car; an intermediate, FWD car; a sporty, rear wheel drive car; a large, FWD car; and a luxury, FWD car. Figure 2.3 presents a histogram of the Davis data. The histogram suggests that magnesium components typically had 30-40% less mass than functionally equivalent aluminum components. An anecdotal model based solely on a normal approximation of this data would estimate the mass of a magnesium component to be 66.9% of the aluminum mass, with a standard deviation of σ = 10.2%. The advantage of such an anecdotal model is that it requires very little information (only mass) about the specific component being analyzed. The disadvantage is that the model may only be applied to materials for which anecdotal data exist.

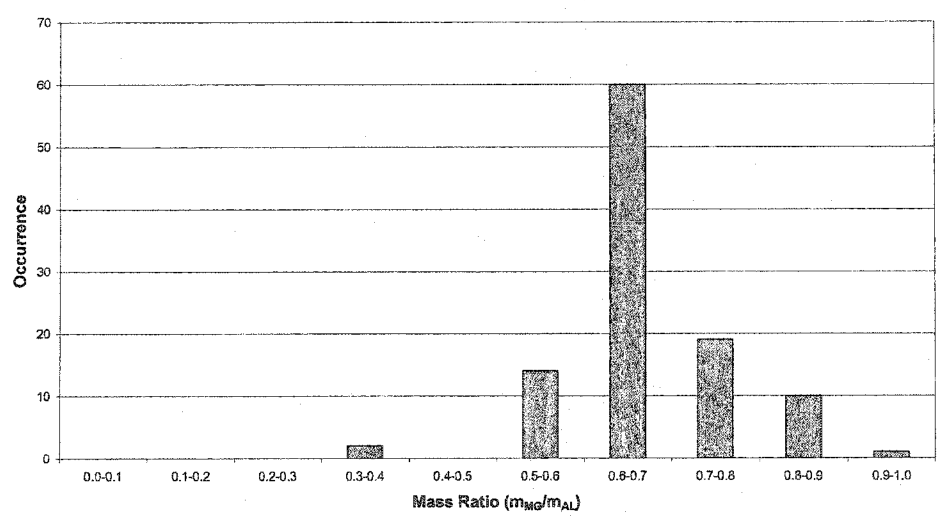

Figure 2.3. Relative Mass Histogram for Magnesium and Aluminum Components (data from Davis, 1991)

3. *Constraints* – Limits and other restrictions imposed on one or more design scenarios. For example, selecting a material for a given component often constrains the options (i.e., scenarios) available for fastening that component to another. Constraints can be imposed on entire scenarios, or just on individual scenario attributes. For estimating scenario attributes, constraints can be full or partial (i.e., fully constraining to a single value or partially constraining to more than one value), absolute or conditional, theoretical or practical. In addition, constraints can be imposed by design decisions related to form (shape or architecture), material, fit, and manufacturing, or by other decisions not made by the design team. By incorporating these and other types of constraints into Design Forecasting, the method is better able to estimate design uncertainty. For further illustration of constraints, refer to Section 4.1.3 of the DFFA case study.

4. *Design Preferences* – Preferences the design team has toward one or more design scenarios or toward controllable scenario attributes. For both case studies presented in this dissertation, preference is described using a 1/3/9 (i.e., low/medium/high) rating system. Preferences help identify the scenarios and values of controllable scenario attributes likely to be selected by the design team. By knowing which scenarios and attributes values are most likely to be chosen, the validity of later scenario analyses can be increased. Section 2.3.1 further illustrates this benefit and discusses the collection of preference data.

Estimating Model Uncertainty

Design Forecasting can be performed using deterministic values for estimated attributes. However, doing so underestimates design uncertainty. In other words, using deterministic values for estimated scenario attributes suggests that the design team knows precisely the final attributes for each potential component design. By estimating the uncertainty associated with each model (i.e., model uncertainty) used to estimate missing scenario attributes, Design Forecasting can better capture the amount of uncertainty the design team has in the attributes of the final design (i.e., design uncertainty). Capturing design uncertainty in Design Forecasting can help the design team better understand the influence it has over the product's final attributes and performance. Table 2.5 presents the type of results produced during this step. In the table, each previously missing piece of data has been replaced by estimated values: either deterministic (i.e., single values) or stochastic (i.e., ranges or distributions). For a detailed example of estimating model uncertainty, refer to Section 3.1.3.

Table 2.5. Example Component Scenarios with Estimated Attributes

COMPONENT A		Baseline Scenario	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Scenario Key	Material(s)	Material A	Material B	Material C	Material D	Material E
	Manufacturing Plan	Process A	Process A	Process A	Process B	Process B
Scenario Attributes	Attribute X	X_b	X_1 [Single Value, Range, or Distribution]	X_2 [Single Value, Range, or Distribution]	X_3 [Single Value, Range, or Distribution]	X_4 [Single Value, Range, or Distribution]
	Attribute Y	Y_b	Y_1 [Single Value, Range, or Distribution]	Y_2 [Single Value, Range, or Distribution]	Y_3 [Single Value, Range, or Distribution]	Y_4 [Single Value, Range, or Distribution]

2.2. PHASE 2: Design for X Modeling and Assessment

This phase consists of identifying appropriate system modeling equations and performing an assessment of the baseline design.

Phase 2 of Design Forecasting (Design for X Analysis) corresponds to Phase 2 of LCMD (Inventory Analysis and Impact Assessment). The primary product of Design for X Analysis is a set of system evaluation equations/models that may be:

1. used to assess the baseline design,
2. used to assess alternative system design scenarios for Scenario Analysis and Interpretation (Phase 3), and
3. adapted for reuse in future Design Forecasting case studies.

Explicit statements of system modeling equations are presented in Sections 3.2 and 4.2.

2.3. PHASE 3: Scenario Analysis and Interpretation

In this phase, the product or system of interest is evaluated relative to the system metrics defined during Goal and Scope Definition. Specifically, the analyses in this phase evaluate optimal system scenarios, likely system characteristics, and the sensitivity of system characteristics to individual design decisions.

Phase 3 of Design Forecasting (Scenario Analysis and Interpretation) is the process of evaluating the range of product design scenarios being considered by the design team. For this phase, four types of analyses are were developed for this research (each may be performed individually or in conjunction with one another):

- *Preference Analysis* – the process of estimating the probable characteristics of a design (in terms of system metrics), given the design preferences of the design team and other stakeholders
- *Sensitivity Analysis* – the process of identifying the scenario attributes and other modeling variables that most significantly influence individual system metrics
- *Constraint Analysis* – an extension of preference analysis used to estimate the influence of specific design decisions on individual system metrics
- *Optima Analysis* – the process for identifying optimal system scenarios

As with Life Cycle Modeling for Design, this phase of Design Forecasting requires interpretation. Specifically, the design team and other stakeholders should review the results of each analysis to make sure they are reasonable and consistent. Interpretation is also necessary to determine whether specific design decisions or changes need to be made to meet system objectives. The following subsections describe each analysis for Phase 3 further.

2.3.1. Preference Analysis

Preference Analysis is the process of estimating the probable characteristics of a design (in terms of system metrics), given the design preferences of the design team and other stakeholders.

Using stochastic modeling such as Monte Carlo simulation, preference analysis allows the design team to assess how the design is progressing relative to system objectives. Specifically, this analysis allows the design team to answer the following questions:

- Given the design scenarios under consideration, is it possible to meet the design program's objectives?
- Is the most preferred system scenario likely to meet the design program's objectives?
- Do the design scenarios under consideration offer realistic opportunities for improvement over the baseline?

The primary outputs of preference analysis are histograms or probability density plots for system metrics such as vehicle mass. The method proposed here is an adaptation of that proposed in SAWE (1996) for aircraft mass estimation. Whereas SAWE's method relies heavily on data from past aircraft development programs to predict the outcome of future configurations, the method proposed here uses design preferences of the current design team. When significant historical design data is available, such a method is appropriate and, in certain situations, may even be used for Design Forecasting. However, preference analysis may be used in the absence of such data. In addition, preference analysis is used for a range of metrics beyond just mass.

For both case studies presented in this dissertation, design preference was described using a 1/3/9 rating system. For each component scenario category, the design team rated the preferred scenario with a nine. Any other seriously considered scenario received a rating of three. The remaining scenarios received a rating of one. Note that scenarios ruled out by a design team should not be considered for modeling.

To simulate the affect design preference has on the final product design, Monte Carlo simulation was used in both case studies to generate an array of design scenarios and estimate system metrics. To generate each system scenario, component scenarios were created by selecting a shape, material, fit, and manufacturing scenario for each component based on an approximation of the likelihood that a particular shape, material, fit, or manufacturing scenario would be chosen. Specifically, Equation 3.11 in Section 3.3.2 is used in both case studies to approximate likelihood. However, Equation 3.11 is just one example of a preference model. As discussed in Section 5.2.2, opportunities exist to develop and validate preference models for a range of industries or complex products.

The Importance of Preference

Why is preference important? Why not model design scenarios randomly? These are important questions. Preference is important because design teams do not make decisions randomly. Instead, design teams choose design scenarios (i.e., concepts) based on preferences for one scenario over another.

The Preference Analysis results presented in Figure 2.4 illustrate differences between results obtained using preferentially selected scenarios and those obtained using randomly selected scenarios. The left distribution in Figure 2.4 (generated as part of the DFFA case study) represents the range of scenarios likely to be chosen by the design team, based on the team's preferences. However, by assuming no design preferences and choosing scenarios randomly, the right distribution was generated. Together, the two distributions demonstrate the general preference toward easy-to-assemble design scenarios. In addition, the baseline assembly time shown in Figure 2.4 demonstrates the previous design team's selection of relatively easy-to-assemble scenarios.

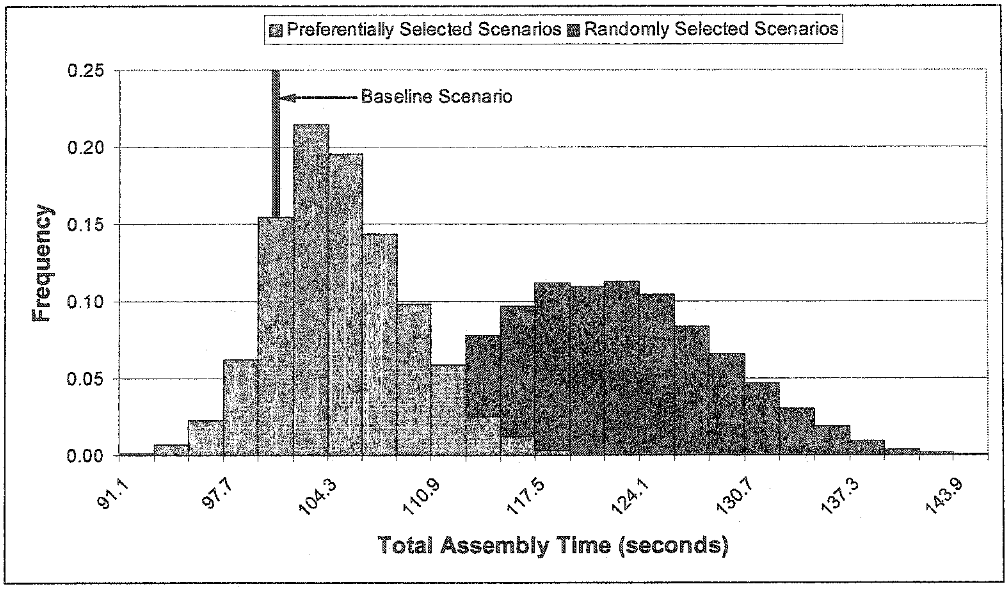

Figure 2.4. Influence of Preference on Modeling Results

Not only do the preferentially obtained results in Figure 2.4 suggest shorter total assembly times than randomly obtained results; the preferentially obtained results are also skewed, with a long tail. Hinckley (1993) observed similar results when he compared the observed times for 3782 assembly operations to random selections of Design for Assembly handling and insertion times.

2.3.2. Sensitivity Analysis

Sensitivity Analysis is the process of identifying the scenario attributes and other modeling variables that most significantly influence individual system metrics.

Sensitivity Analysis is the process of identifying the scenario attributes and other modeling variables that most significantly influence individual system metrics. Sensitivity analysis is not unique to Design Forecasting. In fact, it is used extensively for mathematical and statistical modeling. For more information on sensitivity analysis, refer to Saltelli et al. (2000) and Cacuci (2003). In addition, Section 4.3.2 demonstrates the use of sensitivity results for Design Forecasting.

2.3.3. Constraint Analysis

Constraint Analysis is an extension of preference analysis used to estimate the influence of a design decision on system metrics. This analysis involves performing two parallel, constrained preference analyses and comparing the results.

Constraint Analysis is an extension of preference analysis used to estimate the influence of specific design decisions on individual system metrics. This analysis involves performing two parallel, constrained preference analyses and comparing the results. Though Constraint Analysis may be used to evaluate many types of design decisions, it is most beneficial for further evaluating influential decisions and variables identified using sensitivity analysis (as demonstrated in the DFFA case study). For examples of Constraint Analysis results, refer to Sections 3.3.3 and 4.3.3.

2.3.4. Optima Analysis

Optima Analysis is the process of identifying optimal system scenarios relative to one or more system metrics. Optima analysis is appropriate for identifying candidate design scenarios for further consideration, not for choosing a single, "ideal" solution.

Optima Analysis is the process of identifying optimal system scenarios. Optimization methods are used to identify system scenarios that maximize the expected performance using a single metric, minimize expected cost while satisfying performance constraints, or maximize a utility function based on multiple system metrics. Optima analysis is appropriate for identifying candidate design scenarios for further consideration, not for choosing "the ideal solution."

For example, Optima Analysis is used in the DFFE case study (Chapter 3) to identify two "optimal" vehicle designs. The first vehicle design minimizes life cycle carbon dioxide emissions, particulate matter emissions, and energy consumption; while the second vehicle minimizes life cycle carbon monoxide emissions, hydrocarbon emissions, and gasoline consumption. Each vehicle design is optimal relative to certain metrics.

However, neither design is optimal relative to every metric modeled in the case study, let alone metrics outside the scope of the study. Therefore, neither design represents "the ideal solution." For further detail regarding this Optima Analysis example, refer to Section 3.3.1.

Chapter 3 – Design Forecasting for Environment Case Study

This chapter presents a Design Forecasting case study using Design for Environment (DFE) system metrics. As a result, the specific DF methodology used to perform this case study fits a category of methods called Design Forecasting for Environment (DFFE; Figure 3.1). Just as DFE refers to a specific class of Design for X (DFX) methodologies, DFFE refers to a specific class of Design Forecasting methodologies. The specific DFFE methodology used for this case study is called *Life Cycle Modeling for Design* (LCMD; Figure 1.2). Its name comes from the original purpose of its development. Specifically, LCMD was developed in an effort to make life cycle models easier to use during the design of complex products.

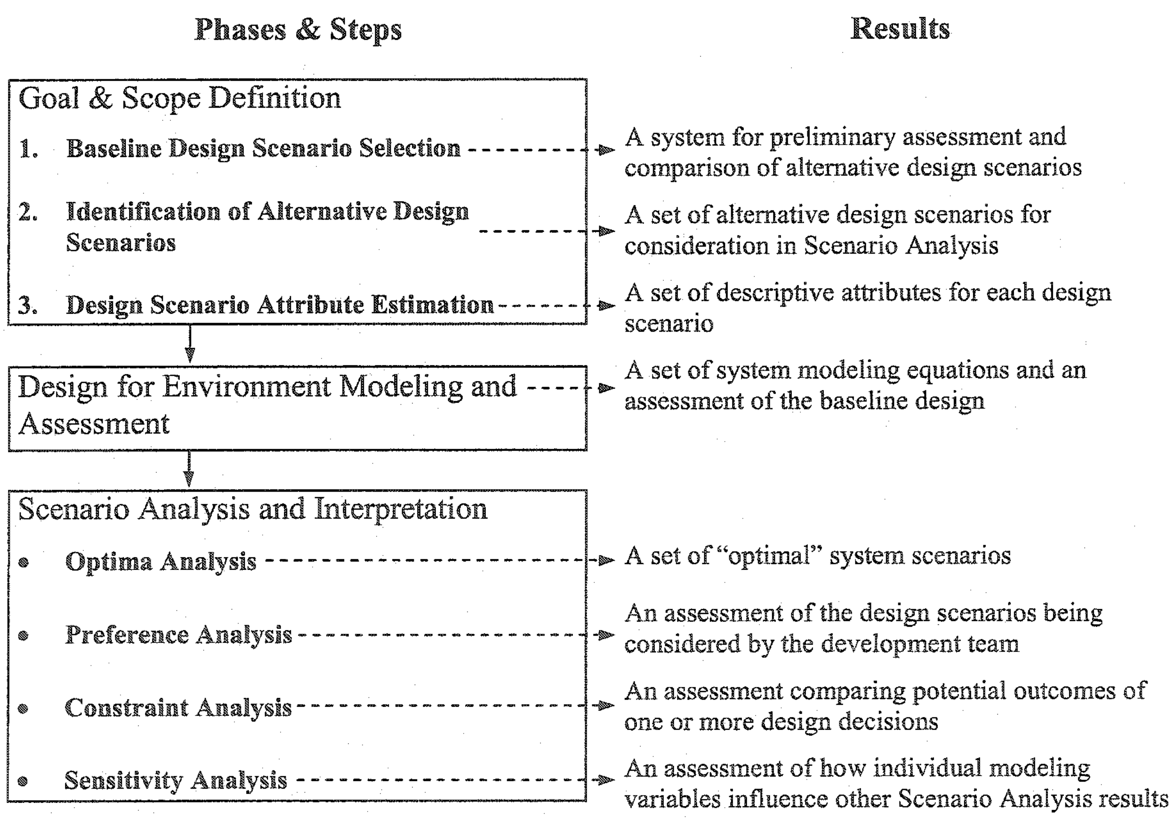

Figure 3.1. Design Forecasting for Environment Methodology

For this case study, LCMD was used to evaluate material substitution opportunities to cost effectively reduce resource consumption, reduce life cycle air emissions, and increase the recyclable mass for a Ford C-class sedan. Component data for the baseline sedan were obtained from Ford benchmarking and teardown reports. A total of 786 components (including some fasteners and subassemblies) were considered for redesign by material substitution. This set of components had a total mass of 608 kg (approximately 51% of the baseline vehicle mass). The remaining components were not considered for redesign and were assumed to remain unchanged. In total, nine materials were considered as potential substitutes for the redesign of the vehicle's components. Specifically, aluminum (ALU), iron (FE), magnesium (MG), and steel (S) were considered for the redesign of metallic components and acrylonitrile butadiene styrene (ABS), polyamide (PA), polycarbonate (PC), polyethylene (PE), and polypropylene (PP) were considered for plastic components. In addition, no subsystem scenarios, manufacturing plan changes, or high-strength steel options were considered. The remainder of this chapter describes the methods used and results obtained for the case study in detail.

3.1. PHASE 1: Goal and Scope Definition

In this phase, the goal and scope of the case study are defined for the product of interest.

Goal

Primary Objective: To identify design scenarios that will likely improve the environmental performance of a Ford C-class sedan

Intended Audience: Designers and manufacturers, their suppliers, and those who recycle, treat, and dispose of materials at the end of a product's life

<u>Scope</u>

Functional Unit: "One complete service life time distance (120,000 miles)" (Sullivan et al., 1998) for a Ford C-class sedan

Life Cycle Stages: Cradle-to-grave

System Metrics: Environmental performance was measured in terms of: (1) *reductions* in vehicle mass, vehicle fuel consumption, drive cycle tailpipe emissions, and resource use and emissions in material production, operation, and for the life cycle, and (2) *increases* in the recyclability of materials in the vehicle.

System Models: System metrics were estimated using life cycle inventory and recyclability models (as described in Section 3.2).

The scope of the case study is further defined by the array of design scenarios evaluated. This array should include the full range of design scenarios being considered by the design team. For this case study, arrays of design scenarios were generated using three steps:

Step 1. Baseline Design Scenario Selection

Step 2. Identification of Alternative Design Scenarios

Step 3. Design Scenario Attribute Estimation

The following subsections describe each of these steps for the case study in detail.

3.1.1. STEP 1: Baseline Design Scenario Selection

In this step, a baseline design is chosen for the product of interest.

For this case study, the baseline product was an existing Ford C-class sedan. Component data for the sedan were obtained from Ford benchmarking and teardown reports. At Ford, benchmarking reports compare component costs for two different vehicles and teardown reports document the material composition and recyclability of components for a single vehicle. Table 3.1 provides a sample of the component data used for the baseline design scenario. In the table, reference flows are the amount of product materials necessary for the functional unit and the manufacturing plan includes the processes used to manufacture each component.

Table 3.1. Sample Components for the Baseline Scenario

	Reference Flows			Manufacturing Plan	
Component Name	**Mat'l**	**Part mass (kg)**	**Quantity in vehicle**	**Process1**	**Process2**
DOOR FUEL FILLER OPENING	PA	0.12	1	injection molding	painting
DUCT ASY REGISTER RH	PE	0.155	1	blow molding	
MOULDING FRONT DOOR OUTSIDE FIN PANEL RH/LH	ALU	0.07	2	stamping	painting
PLATE TRANS GEARSHIFT SELECTOR	FE	0.13	1	sintering	
REINFORCEMENT PASSENGER AIRBAG SUPPORT	PP	0.49	1	injection molding	sonic welding
SUPPORT TRANSAXLE MOUNTING	ALU	0.795	1	die casting	
TRAY ASY BATTERY	PP	0.7	1	Stamping	painting
Etc.					

3.1.2. STEP 2: Identification of Alternative Design Scenarios

This step involves compiling a list of alternative design scenarios being considered by the design team.

For this case study, vehicle components were considered for redesign by material substitution. Table 3.2 contains an example set of component scenarios for the design of a battery tray assembly. As shown, the baseline battery tray assembly was originally made from polypropylene (PP) at a mass of 0.7 kg; and acrylonitrile butadiene styrene (ABS), polyamide (PA), polycarbonate (PC), and polyethylene (PE) were considered as possible alternatives. For this example, the scenario key included the type of materials and manufacturing plan and was used to distinguish between scenarios.

Table 3.2. Component Scenarios for Battery Tray Assembly

TRAY ASY BATTERY		Baseline Scenario	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Scenario Key	Type of Materials	PP	ABS	PA	PC	PE
	Manufacturing Plan	Injection molding, painting	Injection molding, painting	Injection molding, painting	Injection molding, painting	Injection molding, painting
Scenario Attributes	Mass	0.7 kg	Information not provided by product design team			
	Recyclability Category[1]	1				

In addition to the information contained in the scenario key, each scenario was also described by a list of attributes that were used later in the case study (specifically, life cycle inventory models) to estimate system level metrics. During this step, the design team only provided information for attributes known by the team at that time. No additional information was provided.

3.1.3. STEP 3: Design Scenario Attribute Estimation

This step involves estimating missing data for each new scenario.

Once the list of design scenarios was compiled for each component being considered for redesign, missing data for each new scenario had to be estimated. The most accurate and time consuming method for doing so would have been to redesign each component, solicit quotes from in-house manufacturing representatives and suppliers, and test prototypes to determine performance attributes. Doing so would have significantly decreased design uncertainty. However, performing this method for every design scenario would be impractical during product development. Therefore, for this case study, alternative methods for estimating scenario attributes had to be identified. The remainder of this subsection describes the specific methods used in this case study to estimate:

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[1] Recyclability categories are used by automotive companies to classify components by their potential for recycling or energy recovery after use.

- missing recyclability categories and mass data, and
- *model uncertainty* – lack of knowledge about how well a model represents the true nature of a system.

Recyclability Categories

For each component considered for the redesign of the sedan, recyclability categories were determined using corporate recyclability criteria. Specifically, four categories were used: Category 1 components were commonly recycled at the time of the study; Category 2 components showed potential for economical recycling in the future; Category 3 components were made of organic materials and had sufficient energy density for potential energy recovery; and Category 4 was the category used for all remaining components and assumed landfill disposal after use.

Mass Estimation

For this case study, engineering models were used to estimate missing mass attributes based on anecdotal data and fundamental relationships. Constraining each alternative scenario to be functionally equivalent to its associated baseline scenario simplified this estimation. Specifically, functional equivalence allowed the use of relative modeling methods such as Cooper's (2003) "mass equivalents" methodology (described below) in addition to absolute modeling methods. Though estimating missing attributes using engineering models introduced model uncertainty (hence, design uncertainty was not eliminated), it allowed LCMD to be performed earlier in product design while reducing the need for a large data collection effort.

To determine the relative mass of functionally equivalent components, Cooper (2003) provides a methodology based on the material selection performance indices presented by Ashby (1999). Cooper's mass equivalence method estimates the mass required to provide equivalent mechanical performance between a baseline material and a substitute for a certain component. For example, supposing the component of interest is a tie in tension, the mass (or "mass equivalent") of each material is the mass required to carry the same tensile load, at the same length, for the same factor of safety. Thus, when comparing two materials (e.g., material *j* and baseline material *b*) for the design of the tie, the following relationship may be derived:

$$m_j = \frac{\left(\frac{\sigma_b}{\rho_b}\right)}{\left(\frac{\sigma_j}{\rho_j}\right)} m_b = \frac{\sigma_b \rho_j}{\rho_b \sigma_j} m_b$$ <Equation 3.1>

where: m_b = mass of tie made of material *b* (kg)

m_j = mass of tie made of material *j* (kg)

σ_b = failure strength of material *b* (Pa)

σ_j = failure strength of material *j* (Pa)

ρ_b = density of material *b* (kg/m^3)

ρ_j = density of material *j* (kg/m^3)

Equation 3.1 allows the mass of a functionally equivalent substitute material, m_j, to be estimated given the mass of the baseline material, m_b, for a tie in tension. Equation 3.1 also applies to numerous other components and loading conditions, including any components for which specific strength, σ/ρ, is an important criterion for material selection. According to Anon (1991) and Faller (2001), specific strength is an important material property within the context of automotive components because of the drive for vehicle weight reduction. Table 3.3 contains material properties and mass equivalence values (based on Equation 3.1) for the materials considered in this example. For components for which specific strength is not an appropriate criterion for material selection (e.g., torsion bars with torque, stiffness, and length specified), Cooper's (2003) mass equivalence method may be used to derive relationships similar to Equation 3.1.

Table 3.3. Material Properties and Mass Equivalence Data

	Metals				Plastics				
	Low Carbon Steel	Ductile Cast Iron	Wrought Aluminum	Wrought Magnesium	ABS	PA	PC	HDPE	PP
Tensile Strength (MPA)	463	675	327	330	46.5	63	65.5	35	32.5
Density (kg/m^3)	7850	7150	2680	1850	1050	1085	1230	958	905
Specific Strength (kN*m/kg)	59.0	94.4	122	178	44.3	58.1	53.3	36.5	35.9
Mass Equivalence Relative to Low Carbon Steel (based on Equation 1)	1.00	0.63	0.48	0.33	1.33	1.02	1.11	1.62	1.64

The primary benefit of using mass equivalence models for estimating missing data for alternative component scenarios was that no material-specific, anecdotal, design data was required. In other words, component mass could have been estimated for any material with known physical properties. Therefore, previous design experience using the material of interest was not necessary.

Estimating Model Uncertainty

Table 3.4 presents the component scenarios for the battery tray assembly without any consideration for the uncertainty of estimated scenario attributes. LCMD and other Design Forecasting methods can be performed using deterministic values, however, doing so underestimates design uncertainty. In other words, using the values presented in Table 3.4 suggests that design team knows precisely the final mass for each potential design of the battery tray assembly. By estimating the uncertainty associated with each model (i.e., model uncertainty) used to estimate missing scenario attributes, LCMD can better capture the amount of uncertainty the design team has in the attributes of the final design (i.e., design uncertainty). Capturing design uncertainty in LCMD can help the design team better understand the influence it has over the product's final attributes and environmental performance.

Table 3.4. Deterministic Component Scenarios for Battery Tray Assembly

BATTERY TRAY ASSEMBLY		Baseline Scenario	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Scenario Key	Type of Materials	PP	ABS	PA	PC	PE
	Manufacturing Plan	Injection molding, painting	Injection molding, painting	Injection molding, painting	Injection molding, painting	Injection molding, painting
Scenario Attributes	Mass	0.7 kg	0.57 kg	0.44 kg	0.47 kg	0.69 kg
	Recyclability Category	3	3	3	3	3

Referring to the two attributes shown for each scenario in Table 3.4, model uncertainty was only estimated for mass. The discrete categorization of recyclability based on simple corporate criteria made the recyclability categories estimated for each scenario highly reliable. As a result, the recyclability categories for each scenario were assumed to be correct.

As for mass, the purpose of estimating model uncertainty was to determine approximately how accurate the mass estimates were for each of the batter tray assembly's design scenarios. To estimate model uncertainty for the mass equivalence model based on specific strength, anecdotal material substitution data was collected from Society of Automotive Engineers (SAE) literature and compared to estimates using Equation 3.1 (comparison shown in Figure 3.2). Though a review of SAE literature identified 411 material substitution examples in 14 articles, only 13 data points in four articles (Nassar, 1991; Sindrey, 1999; Shim et al., 2000; Koike et al., 2000) included sufficient information for the analysis.

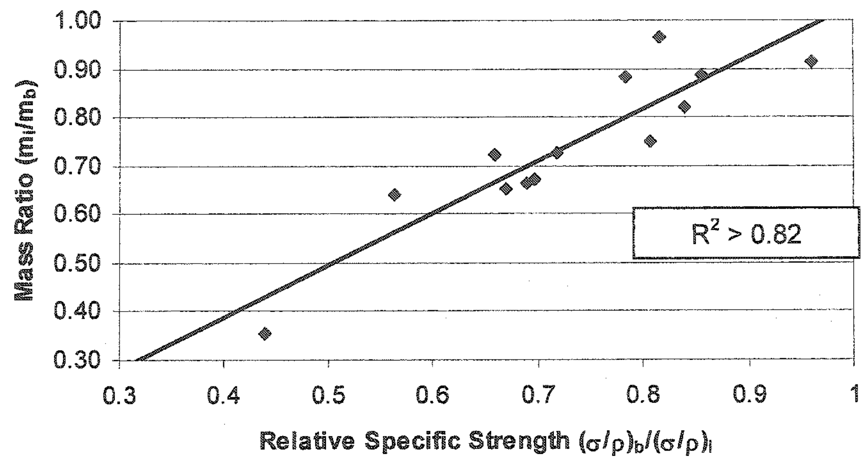

Figure 3.2. Relative Mass vs. Specific Strength for Example Automotive Components

By defining error for the mass equivalence model based on specific strength as

$$e \equiv \frac{m_{j(\text{actual})}}{m_{b(\text{actual})}} - \frac{m_{j(\text{predicted})}}{m_{b(\text{predicted})}} = \frac{m_{j(\text{actual})}}{m_{b(\text{actual})}} - \frac{\sigma_b \rho_j}{\rho_b \sigma_j} \qquad \text{<Equation 3.2>}$$

and using the previous set of sample data to calculate a set of error values, the distribution shown in Figure 3.3 was generated. Though the sample data set was too small to make precise conclusions about the uncertainty of using this mass equivalence model to estimate missing data, it did provide an approximation of model uncertainty. To put this uncertainty into perspective: If modeling error was assumed random and the error distribution was normally distributed, the standard deviation of the distribution would be 0.068. Regardless, the largest error calculated using the sample data set was less than 14%.

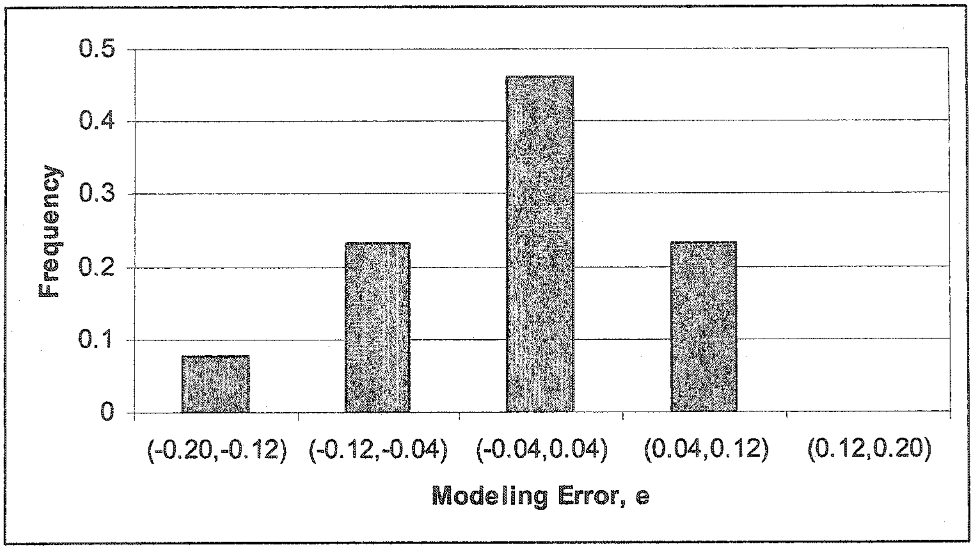

Figure 3.3. Modeling Error Distribution for Example Automotive Components

A more comprehensive survey of functionally equivalent component designs would undoubtedly reveal numerous exceptions to the trend show in Figure 3.2, especially if a review of plastic components was included (this is left for future research). However, this correlation along with Faller's (2001) (also Anon, 1991) identification of specific strength as an important material property within the context of automotive components (because of the drive for vehicle weight reduction) suggest that, in many cases, relative specific strength may reasonably be used to estimate the relative masses of two functionally equivalent, mechanical, automotive component designs.

After estimating model uncertainty, the mass estimates in Table 3.4 were revised to reflect this uncertainty. Though normally distributed values were used in this case study, Table 3.5 presents a range for each scenario's mass attribute. Also for this case study, similar information was developed for each of the components considered for redesign, using the original material as the baseline for each component.

Table 3.5. Stochastic Component Scenarios for Battery Tray Assembly

BATTERY TRAY ASSEMBLY		Baseline Scenario	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Scenario Key	Type of Materials	PP	ABS	PA	PC	PE
	Manufacturing Plan	Injection molding, painting	Injection molding, painting	Injection molding, painting	Injection molding, painting	Injection molding, painting
Scenario Attributes	Mass	0.7 kg	0.47 - 0.67 kg	0.34 - 0.53 kg	0.38 - 0.57 kg	0.59 - 0.79 kg
	Recyclability Category	3	3	3	3	3

3.2. PHASE 2: Inventory Analysis and Impact Assessment

This phase consists of identifying appropriate system modeling equations and performing an assessment of the baseline design. Specifically, for LCMD, material and energy use, recovery, and waste for the baseline product and the processes of the life cycle are estimated. In addition, the contribution of material and energy use, recovery, and waste to select impacts to the environment, economy, or society may be analyzed.

For this case study, an inventory analysis was performed to estimate resource consumption and air emissions throughout the life cycle for the baseline vehicle and the alternative design scenarios. Resource consumption data captured the use of energy (i.e., total energy consumed during the product life cycle, including the available energy content of consumed energy resources such as coal and natural gas), bauxite, coal, gasoline, iron ore, and natural gas. Air emissions data captured carbon dioxide, carbon monoxide, nitrogen oxides, particulate matter, sulfur oxides, and hydrocarbons. Each vector of resource use and air emissions presented in the equations below includes each of these twelve inventory items. The estimation methods used for each stage of the life cycle are described below.

- **Material Production and Component Manufacture** – For each of the nine materials evaluated, data for resource consumption and air emissions for material production and component manufacture were obtained from Franklin Associates (1993). For each component's baseline and associated scenarios, resource consumption and air emissions incurred during material production and component manufacturing for a vehicle were assumed equal to the sum of the material and energy use and waste required to produce each component:

$$\vec{b}_{PR} = \sum_{i} \vec{b}_i \qquad \text{<Equation 3.3>}$$

where: $\vec{b}_{PR}$ = vector of resource use and air emissions incurred during material production and component manufacturing for the vehicle (kg & MJ)

$\vec{b}_i$ = vector of resource use and air emissions incurred during material production and component manufacturing for component i (kg & MJ)

Also, resource consumption and air emissions were assumed to be linearly related to that needed to produce one kilogram of the component's primary material:

$$\vec{b}_i \approx m_i \vec{B}_i \qquad \text{<Equation 3.4>}$$

where: m_i = mass of component i (kg)

$\vec{B}_i$ = vector of resource use and air emissions incurred during production of one kg of the primary material used to make component i (kg/kg & MJ/kg)

- **Vehicle Assembly** – Data for resource consumption and air emissions incurred in the assembly of a generic, 1530-kg, family sedan were obtained from Sullivan et al. (1998) and assumed to be representative of those incurred in the assembly of the baseline vehicle and all design scenarios. Both resource consumption and air emissions are functions of the mass of the vehicle (M) which was estimated for each system scenario as the sum of the mass of the components for the scenario and 577 kg (which represents the remainder, or 49%, of the mass of the baseline vehicle).
- **Vehicle Use** – Resource consumption and air emissions incurred during vehicle use were taken to be from fuel consumption and vehicle tailpipe emissions and therefore

related to the lifetime driving distance of the vehicle. Equation 3.5 approximates the relationship between tailpipe emissions, fuel economy, resource consumption, and air emissions incurred during fuel production and vehicle use:

$$\vec{b}_{OP} \approx d_{OP}\left(\vec{b}_{DC} + \frac{\rho_F}{e}\vec{B}_{FC}\right) \qquad \text{<Equation 3.5>}$$

where: $\vec{b}_{OP}$ = resource use and air emissions incurred during vehicle operation (kg & MG)

d_{OP} = distance traveled during lifetime of vehicle (120,000 miles assumed)

$\vec{b}_{DC}$ = tailpipe emissions produced per mile traveled (kg/mile)

ρ_F = fuel density (kg/gal)

e = fuel economy (miles/gal)

$\vec{B}_{FC}$ = burdens incurred to produce one kg of fuel (kg/kg & MJ/kg)

The following fuel economy relationship is based on algorithms used for the baseline vehicle in Ford's Corporate Vehicle Simulation Program (CVSP):

$$e \approx \frac{1}{1.289(10^{-5})M + 1.769(10^{-2})} \qquad \text{<Equation 3.6>}$$

where: e = fuel economy (miles/gal)

M = mass of vehicle (kg) as defined for vehicle assembly

For tailpipe emissions, carbon monoxide, nitrogen oxides, particulate matter, and hydrocarbon emissions were assumed directly proportional to vehicle miles driven. The values presented in Equation 3.7 for these emissions were based on Statutory Tier II Limits (EPA, 1998). Alternatively, carbon dioxide and sulfur oxides were assumed indirectly proportional to vehicle miles driven by their correlation to fuel consumption. The carbon dioxide relationship presented in Equation 3.7 was computed stoichiometrically using data from A.D. Little (undated). Whereas, the sulfur oxide relationship is based on AAMA (1993).

$$\vec{b}_{DC} \approx \begin{bmatrix} 3.14\frac{\rho_F}{e} & kgCO_2 / mile \\ 0.0156 & kgCO / mile \\ 0.0013 & kgNO_x / mile \\ 0.00008 & kgPM / mile \\ 0.00058\frac{\rho_F}{e} & kgSO_x / mile \\ 0.000845 & kgHCs / mile \end{bmatrix}$$ <Equation 3.7>

- **Maintenance and End-of-Life** – Data for resource consumption and air emissions incurred through the maintenance and at the end-of-life was again based on Sullivan et al. (1998) and assumed to be representative for the baseline vehicle and all design scenarios. Again both are based on the mass of the vehicle as defined for vehicle assembly.

The resource consumption and air emissions incurred during the vehicle life cycle is therefore:

$$\vec{b}_{LC} \approx \vec{b}_{PR} + \vec{B}_{AS} + \vec{b}_{OP} + \vec{B}_{MA} + \vec{B}_{EOL}$$ <Equation 3.8>

where: $\vec{b}_{LC}$ = the vector of resource use and air emissions incurred during the life cycle of the vehicle (kg & MJ)

$\vec{b}_{PR}$ = the vector of resource use and air emissions incurred during material production and component manufacturing for the vehicle (kg & MJ)

$\vec{B}_{AS}$ = the vector of resource use and air emissions incurred during the assembly of a generic family sedan (kg & MJ)

$\vec{b}_{OP}$ = the vector of resource use and air emissions incurred during the operation of the vehicle (kg & MJ)

$\vec{B}_{MA}$ = the vector of resource use and air emissions incurred during the maintenance of a generic family sedan (kg & MJ)

$\vec{B}_{EOL}$ = the vector of resource use and air emissions incurred at the end-of-life of a generic family sedan (kg & MJ)

Equation 3.9 presents the results of the baseline inventory analysis using Equation 3.8 and a 120,000-mile lifetime driving distance.

$$\left(\vec{b}_{LC}\right)_{baseline} \approx \begin{bmatrix} energy\ consumption \\ carbon\ dioxide\ emissions \\ carbon\ monoxide\ emissions \\ nitrogen\ oxide\ emissions \\ particulate\ matter\ emissions \\ sulfur\ oxide\ emissions \\ hydrocarbon\ emissions \\ bauxite\ consumption \\ coal\ consumption \\ gasoline\ consumption \\ iron\ ore\ consumption \\ natural\ gas\ consumption \end{bmatrix} \approx \begin{bmatrix} 690\,GJ \\ 44200kg \\ 1950kg \\ 197kg \\ 42kg \\ 55.6kg \\ 165kg \\ 98.9kg \\ 1480kg \\ 9860kg \\ 563kg \\ 788kg \end{bmatrix}$$ <Equation 3.9>

An additional metric related to vehicle end-of-life, recyclability rating, was also assessed for this case study. *Recyclability rating* – an estimate of the percentage of the vehicle's mass likely to be recycled at the end-of-life – is equivalent to the total mass of all vehicle components in recyclability categories 1 or 2 divided by the total mass of the vehicle:

$$r = \frac{\sum_i m_i f(R_i - 1,2)}{M}$$ <Equation 3.10>

where: r = recyclability rating

m_i = mass of component i (kg)

R_i = recyclability category for component i

$f(R_i - 1,2) = \begin{Bmatrix} 1 & R_i = 1,2 \\ 0 & R_i = 3,4 \end{Bmatrix}$ = unit function with nonzero value when R_i = 1or2

M = mass of vehicle (kg)

Based on Equation 3.10, the recyclability rating of the baseline vehicle was 80.15%.

3.3. PHASE 3: Scenario Analysis and Interpretation

In this phase, the product or system of interest is evaluated relative to the system metrics defined during Goal and Scope Definition. Specifically, the analyses in this phase evaluate optimal system scenarios, likely system characteristics, and the sensitivity of system characteristics to individual design decisions.

For this case study, three scenario analyses were used to estimate material and energy use, recovery, and waste for alternative, product design scenarios: Optima Analysis, Preference Analysis, and Constraint Analysis. As with LCA, the results of these analyses required interpretation. The following sections describe the results of this case study in detail.

3.3.1. Optima Analysis

Optima Analysis is the process of identifying optimal system scenarios relative to one or more system metrics. Optima analysis is appropriate for identifying candidate design scenarios for further consideration, not for choosing a single, "ideal" solution.

In this case study, performance was optimized relative to a single inventory item when one of the twelve inventory metrics within $(\vec{b}_{LC})_{baseline}$ (Equation 3.9) was minimized or when the recyclability rating (Equation 3.10) was maximized. For example, when no other constraints were imposed, the optimal design scenario in terms of carbon dioxide was the one that minimized the expected life cycle carbon dioxide emissions for the vehicle. For this case study, optima analysis was used to identify an optimal vehicle design scenario for each performance metric, given uncertainty in component attributes (component mass and recyclability category). As a result, design uncertainty was limited to uncertainty in attributes for each component scenario and did not include uncertainty related to the selection of component scenarios.

Table 3.6 and Figure 3.4 present two optimized system scenarios. The first scenario, Optimum 1, represents best performance relative to six inventory metrics. The second scenario, Optimum 2, demonstrated the best performance relative to three other inventory metrics. As shown in Figure 3.4, besides reduced iron ore consumption, both scenarios provide only small improvements relative to several inventory metrics. Optimum 2 achieves these small improvements at the cost of coal consumption and sulfur oxide emissions. Similarly, Optimum 1 achieves improvements at the cost of bauxite consumption. Both system scenarios are expected to increase direct material costs by more than $100 per vehicle and may require additional costs as well. This analysis may also be repeated using constraints to avoid unacceptable design scenarios (e.g., too costly, too massive, or too energy intensive scenarios).

Table 3.6. Example Profiles from Optima Analysis

		Optimum 1	Optimum 2
Best Performance Relative to:		1. Carbon Dioxide Emissions 2. Particulate Matter Emissions 3. Energy Consumption	1. Carbon Monoxide Emissions 2. Hydrocarbon Emissions 3. Gasoline Consumption
Materials (net values are relative to baseline)	Aluminum	+110 components (+143.4 ± 11.9 kg)	+101 components (+5.4 ± 0.04 kg)
	Iron	-14 components (-34.6 ± 1.5 kg)	-24 components (-29.9 ± 1.4 kg)
	Magnesium	+50 components (+8.7 ± 0.3 kg)	+59 components (+106.9 ± 8.6 kg)
	Steel	-146 components (-286.8 ± 18.2 kg)	-136 components (-287.6 ± 16.9 kg)
	Acrylonitrile Butadiene Styrene	-1 component (-0.7 ± 0.01 kg)	+7 components (+0.4 ± 0.03 kg)
	Polyamide	-6 component (+0.5 ± 0.01 kg)	-13 components (-0.4 ± 0.01 kg)
	Polycarbonate	+7 components (+0.0 ± 0.01 kg)	+6 components (+0.1 ± 0.02 kg)
	Polyethylene	+6 components (+2.8 ± 0.05 kg)	+2 component (+0.5 ± 0.05 kg)
	Polypropylene	-6 components (-2.8 ± 0.05 kg)	-2 component (-0.5 ± 0.05 kg)
Vehicle Mass		1015 ± 22 kg	980 ± 19 kg
Vehicle Fuel Consumption		32.5 ± 0.3 mpg	33.0 ± 0.2 mpg
Recyclability Rating for the Vehicle		76.9 ± 0.5 %	76.0 ± 0.4 %

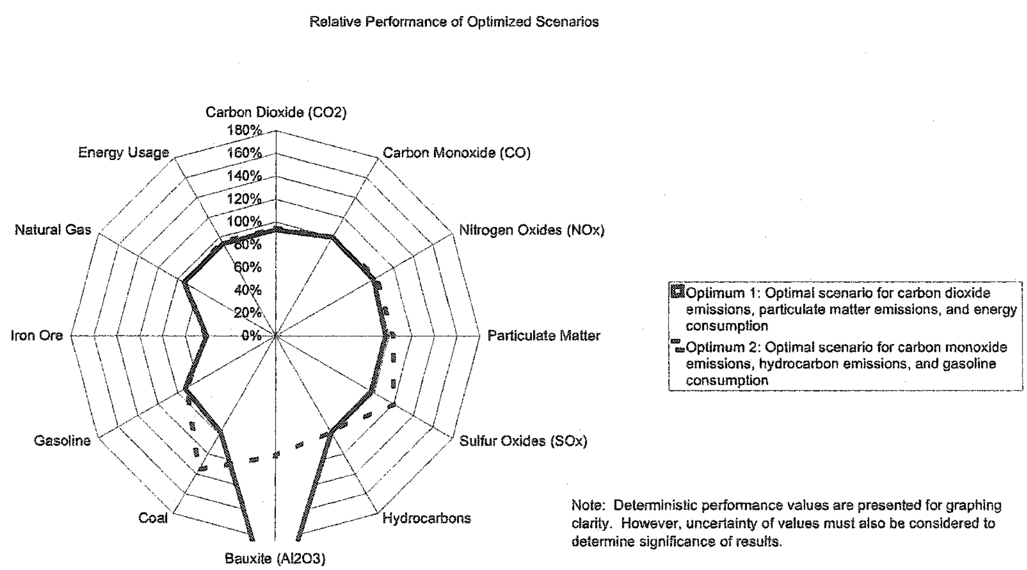

Figure 3.4. Example Results from Optima Analysis

3.3.2. Preference Analysis

Preference Analysis is the process of estimating the probable characteristics of a design (in terms of system metrics), given the design preferences of the design team and other stakeholders.

For this case study, *design preference*, p_{ij} in Equation 3.11, was described using a 1/3/9 rating system. For each component, the design team rated the preferred material with a nine. Any other seriously considered material received a rating of three. The remaining materials received a rating of one. Note that any material ruled out by the design team was never considered in the example.

To simulate the affect design preference would have on inventory metrics for the final product design, Monte Carlo simulation was used to generate an array of design scenarios and estimate the twelve inventory metrics. To generate each system scenario, component scenarios were created by selecting a material for each component based on an approximation of the likelihood of use, l_{ij}:

$$l_{ij} \approx \frac{p_{ij}}{\sum_{j} p_{ij}} \quad \text{<Equation 3.11>}$$

where: l_{ij} = the likelihood material j will be used for component i

p_{ij} = the design preference (1, 3, or 9) of material j for component i

For each resulting system scenario, the twelve inventory performance metrics were estimated using Equations 3.3–3.8. Figure 3.5 illustrates the maximum, median, and minimum life cycle inventory metric estimates for the array of system scenarios generated. The values presented are normalized relative to the performance of baseline design scenario. Though several of the inventory metrics illustrated in Figure 3.5 show potential for substantial change (mostly in a worsening direction), the median values suggest that the likelihood for significant change relative to the baseline scenario is low. Only median values for bauxite and iron ore consumption are greater than 10% more or less than baseline performance. These potential changes in bauxite and iron ore consumption reflect the likely replacement of numerous steel components with aluminum components.

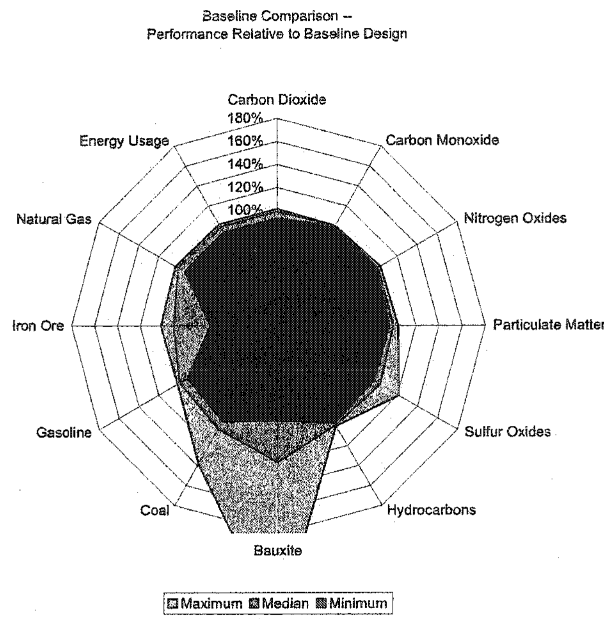

Figure 3.5. Summary Results of Preference Analysis

The histograms in Figures 3.6-3.17 illustrate the frequency of occurrence of different inventory metric estimates resulting from the preference analysis. For the metrics analyzed, the results take the form of a single, double, or triple mode. When a single mode is formed, no single design decision has dominant influence over the performance of the vehicle, relative to the given metric. In other words, no single design decision alone will ensure improved performance relative to the given metric. In these cases, the preferences of individual designers have only small influence on performance and a combination of multiple design decisions is necessary to ensure improved performance relative to the given metric. However, in the case of metrics with double and triple modes, a small number of design decisions (one or two) have dominant influence over the performance of the vehicle. In these cases, the dominating design decisions may be identified and made early in design to ensure preferred results.

As an example of multimodal results, the first histogram illustrates the probable range of life cycle carbon dioxide emissions for the array of design scenarios being considered by the design team. The multimodal distribution is primarily the result of multiple materials (steel, aluminum, and magnesium) being considered for the design of the vehicle frame. According to this histogram, the most likely amount of life cycle carbon dioxide emissions is approximately 44,100 kg; only about 0.2% lower than the life cycle emissions for the baseline vehicle. The histogram also suggests that there is a low likelihood (~35%) that carbon dioxide emissions will be cut by more than 1%.

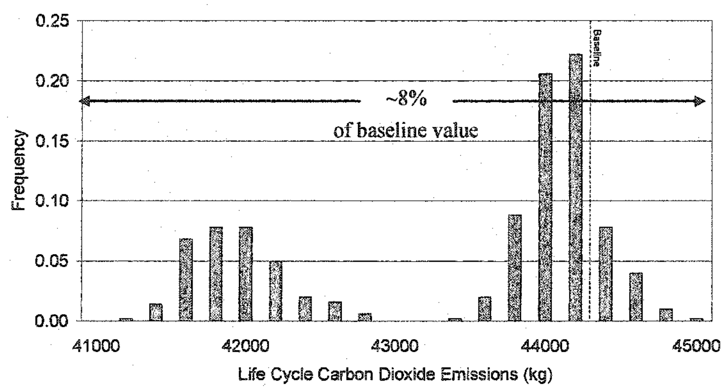

Figure 3.6. Monte Carlo Preference Results – Carbon Dioxide Emissions

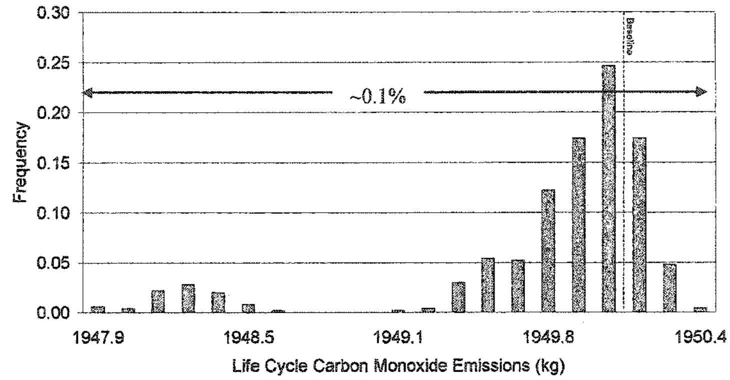

Figure 3.7. Monte Carlo Preference Results – Carbon Monoxide Emissions

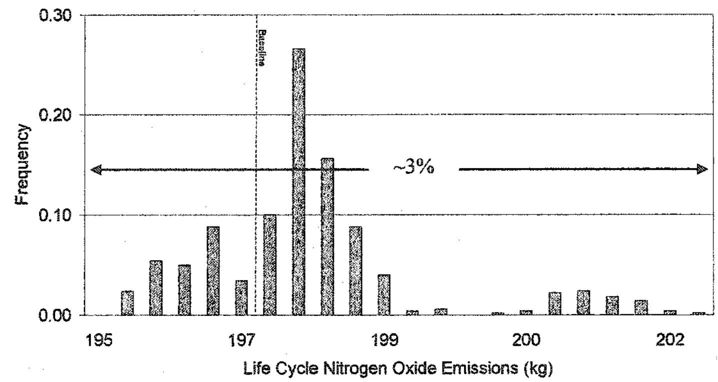

Figure 3.8. Monte Carlo Preference Results – Nitrogen Oxide Emissions

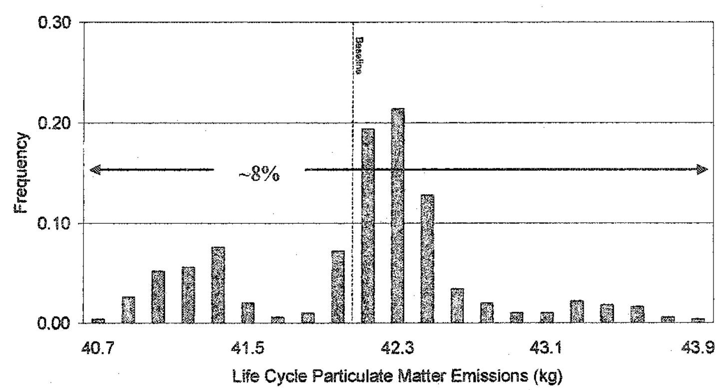

Figure 3.9. Monte Carlo Preference Results – Particulate Emissions

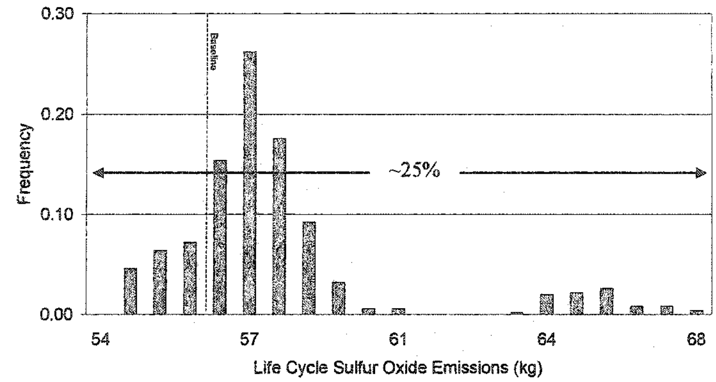

Figure 3.10. Monte Carlo Preference Results – Sulfur Oxide Emissions

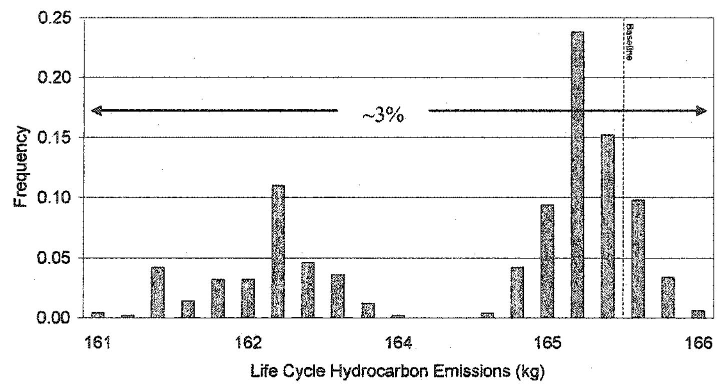

Figure 3.11. Monte Carlo Preference Results – Hydrocarbon Emissions

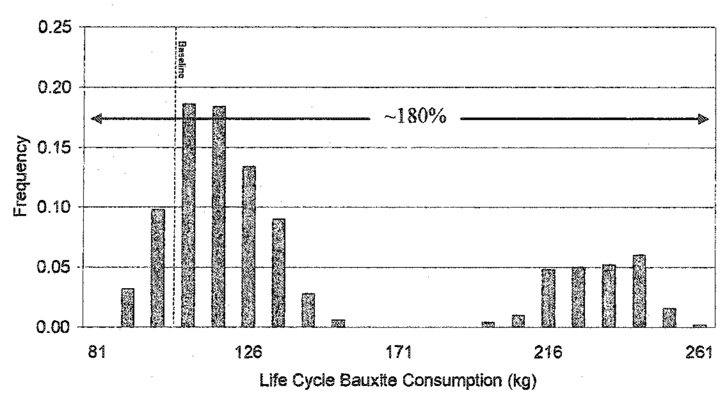

Figure 3.12. Monte Carlo Preference Results – Bauxite Consumption

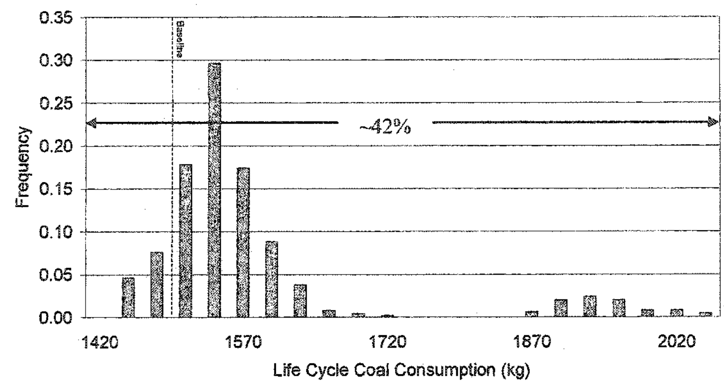

Figure 3.13. Monte Carlo Preference Results – Coal Consumption

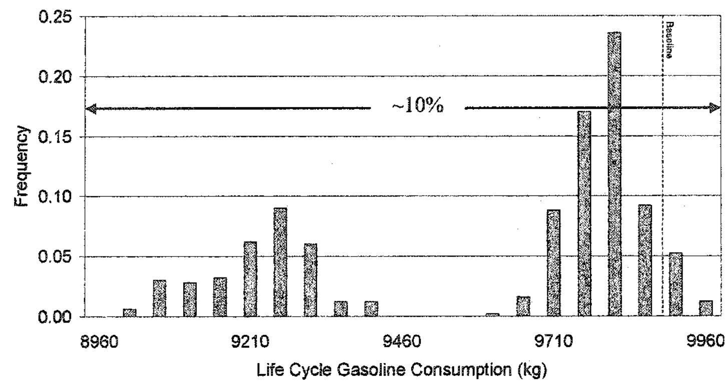

Figure 3.14. Monte Carlo Preference Results – Gasoline Consumption

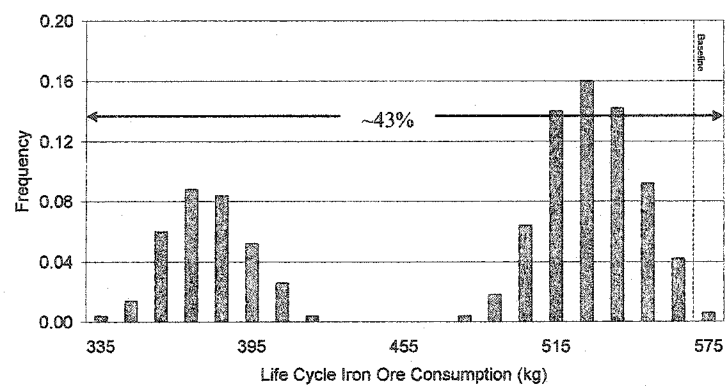

Figure 3.15. Monte Carlo Preference Results – Iron Ore Consumption

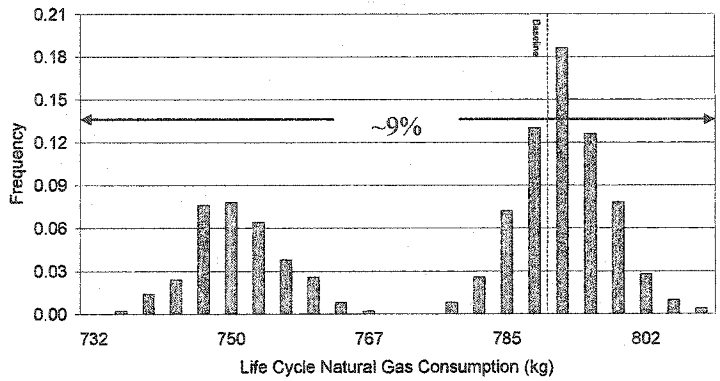

Figure 3.16. Monte Carlo Preference Results – Natural Gas Consumption

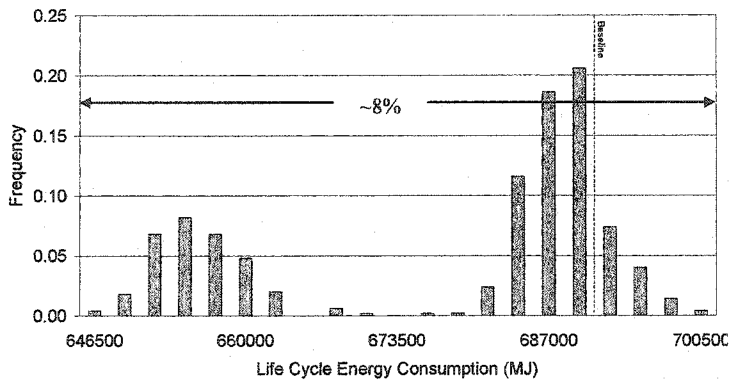

Figure 3.17. Monte Carlo Preference Results – Energy Consumption

3.3.3. Constraint Analysis

Constraint Analysis is an extension of preference analysis used to estimate the influence of a design decision on system metrics. This analysis involves performing two parallel, constrained preference analyses and comparing the results.

Constraint analyses can be used to demonstrate the influence of one or more design decisions. For example, in this case study, the design team considered switching from a steel frame design to an aluminum frame design. As a result, two preference analyses were performed and compared: one with all frame components constrained to steel scenarios, and one with all frame components constrained to aluminum scenarios. Figures 3.18-3.29 present the results of these two, constrained preference analyses. A cursory review of the histograms in Figures 3.18-3.29 suggests:

- An aluminum frame offers clear advantages in carbon dioxide emissions, hydrocarbon emissions, gasoline consumption, iron ore consumption, natural gas consumption, and energy consumption;
- A standard steel frame offers clear advantages in carbon monoxide emissions and bauxite consumption; and
- These two frame options are expected to perform similarly relative to nitrogen oxide emissions, particulate matter emissions, sulfur oxide emissions, and coal consumption.

A more thorough review is necessary to understand the significance of the advantages for each frame design. For example, aside from consuming about 30% less iron ore than a standard steel frame design, the aluminum frame design offers less than 3% advantage relative to other metrics. Conversely, aside from consuming about 60% less bauxite than an aluminum frame design, the standard steel frame design offers no significant advantages. The carbon monoxide advantage noted previously is only about 0.05%.

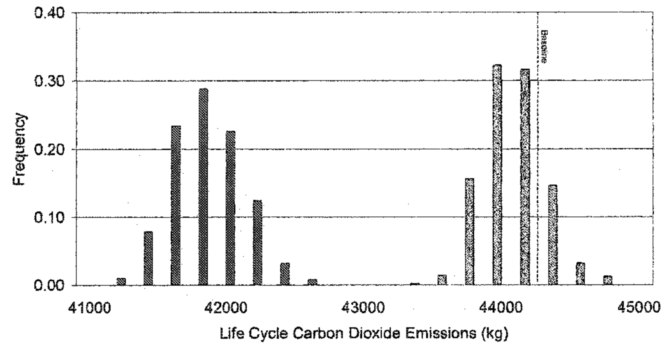

Figure 3.18. Monte Carlo Constraint Results – Carbon Dioxide Emissions[2]

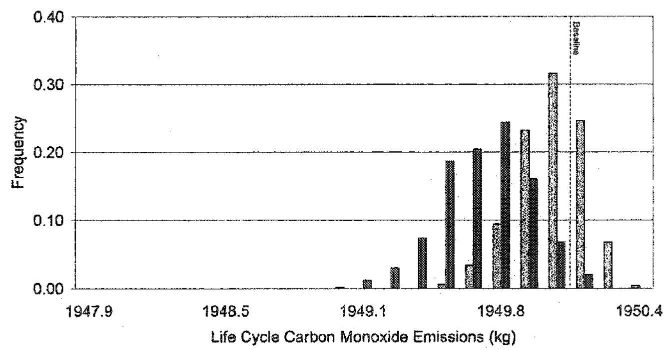

Figure 3.19. Monte Carlo Constraint Results – Carbon Monoxide Emissions[2]

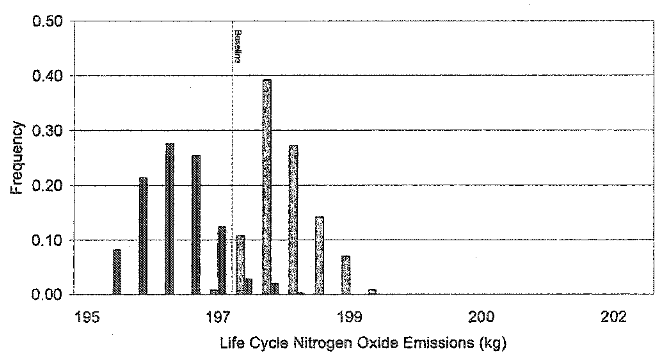

Figure 3.20. Monte Carlo Constraint Results – Nitrogen Oxide Emissions[2]

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[2] Light bars represent Monte Carlo results for a steel frame vehicle. Dark bars represent results for an aluminum frame vehicle.

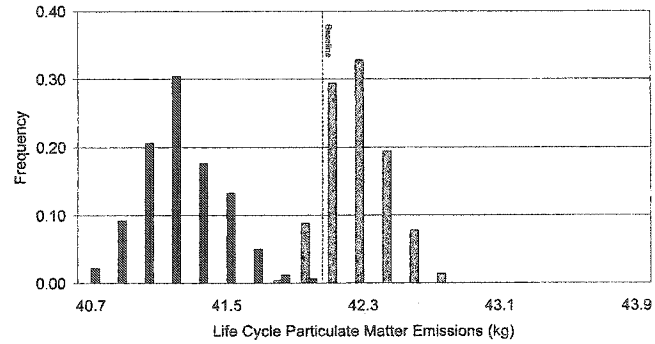

Figure 3.21. Monte Carlo Constraint Results – Particulate Emissions[3]

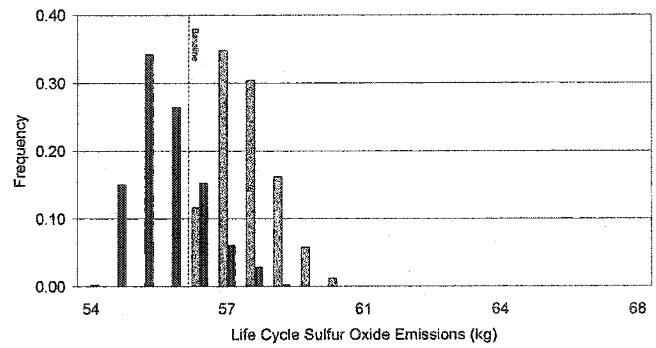

Figure 3.22. Monte Carlo Constraint Results – Sulfur Oxide Emissions[3]

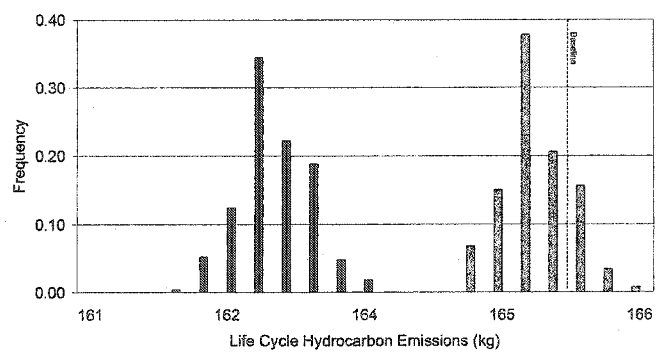

Figure 3.23. Monte Carlo Constraint Results – Hydrocarbon Emissions[3]

[3] Light bars represent Monte Carlo results for a steel frame vehicle. Dark bars represent results for an aluminum frame vehicle.

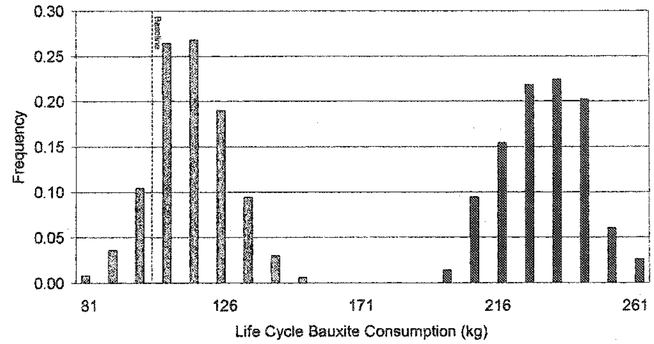

Figure 3.24. Monte Carlo Constraint Results – Bauxite Consumption[4]

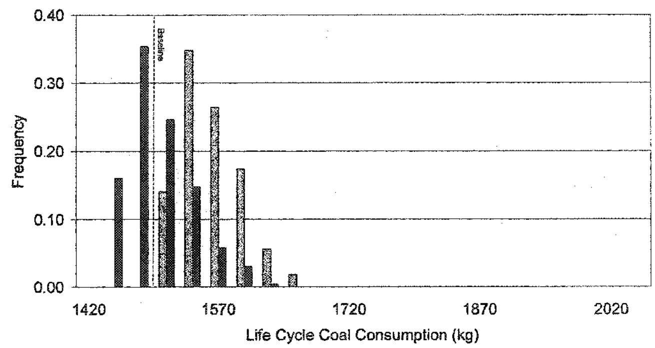

Figure 3.25. Monte Carlo Constraint Results – Coal Consumption[4]

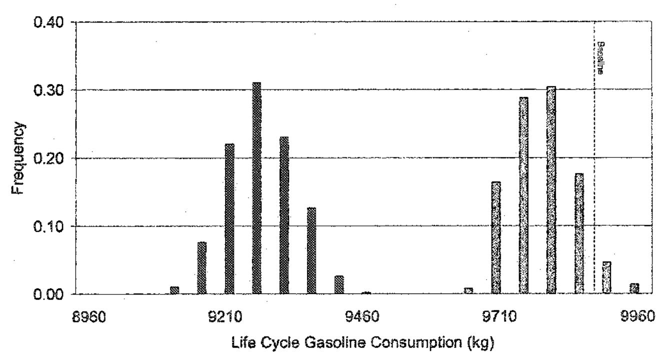

Figure 3.26. Monte Carlo Constraint Results – Gasoline Consumption[4]

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[4] Light bars represent Monte Carlo results for a steel frame vehicle. Dark bars represent results for an aluminum frame vehicle.

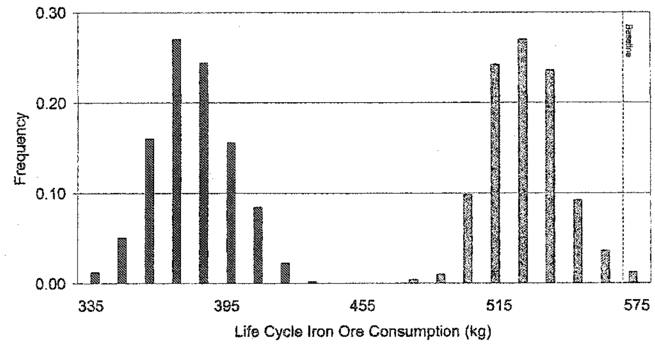

Figure 3.27. Monte Carlo Constraint Results – Iron Ore Consumption[5]

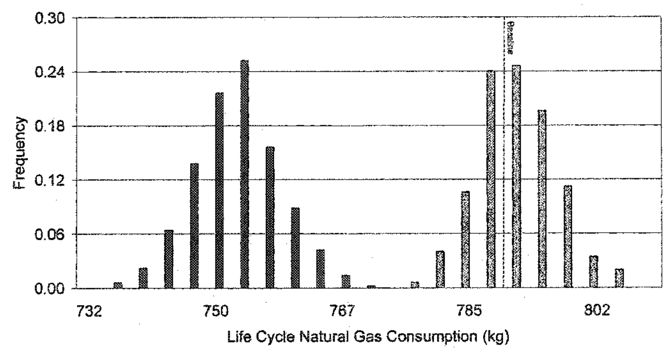

Figure 3.28. Monte Carlo Constraint Results – Natural Gas Consumption[5]

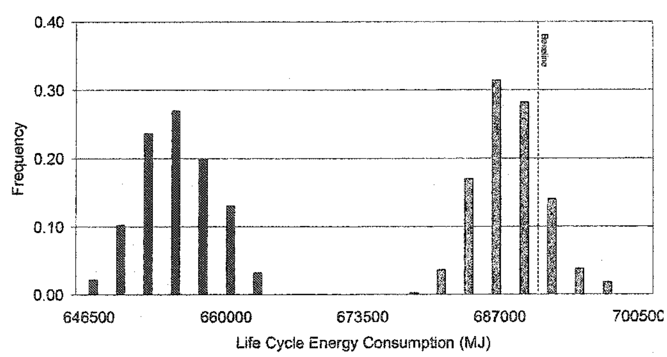

Figure 3.29. Monte Carlo Constraint Results – Energy Consumption[5]

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[5] Light bars represent Monte Carlo results for a steel frame vehicle. Dark bars represent results for an aluminum frame vehicle.

3.3.4. Interpretation of Results

All three scenario analyses suggest that a small number of design decisions have a dominating influence on critical resource use, waste, and emissions; the most notable being the choice of material for the frame of the vehicle. Under the original assumptions made in this example, an aluminum frame design offers advantages in carbon dioxide emissions, hydrocarbon emissions, gasoline consumption, iron ore consumption, natural gas consumption, and energy consumption over a standard steel frame design. Despite some clear disadvantages resulting from vehicle weight, a standard steel frame design still performs competitively and is currently the most likely to be used by automotive manufacturers.

As discussed previously, the results of this case study do not include high-strength steel frame options. As shown by Sullivan (2001), from an energy perspective, high-strength steel frame vehicles compete favorably with aluminum frame vehicles, especially when the lifetime of the vehicle is less than 135,000 miles. Also, the numbers used here may reflect the current levels of recycled material content used (70% or steel and 80% for aluminum); however, significant changes in automotive material use could potentially influence future levels of recycled material content. Any conclusions drawn from the results presented here should consider uncertainty in the assumptions. For example, reducing the assumed content of recycled aluminum to 50%, instead of 80%, significantly decreased the advantages of the aluminum frame design. Hydrocarbon emissions, iron ore consumption, and energy consumption for the aluminum frame design did not change significantly, however, performance relative to other metrics decreased noticeably when recycled content was reduced. Using this new assumption, the aluminum frame design performed poorly relative to most metrics when compared to the standard steel frame design.

A second issue is related to the use of lightweight vehicle materials and *weight compounding*. Weight compounding refers to the fact that the use of lighter components facilitates the use of other lighter components in the balance of the vehicle. For example, if the vehicle is lighter, a smaller (and therefore lighter) powertrain will move the vehicle. Because weight compounding was not considered in this example, any improvements that might be concluded would be conservative.

A third issue is related to the use of a single mass equivalence model (based on the specific strength performance index, σ_y/ρ) for the entire analysis. Despite the assumption that choosing appropriate equivalent mass models for each component during design will be practical during embodiment and detailed design, doing so can be impractical for a very large number of components and during conceptual design. Though this simplification eliminated the need for information regarding the basic shape and loading conditions for 786 components, it decreased the expected accuracy of the mass equivalence modeling and increased the uncertainty of the final design attributes. However, as previously mentioned, because the results of the mass equivalents model compared favorably with anecdotal data for material substitution in automobiles, it has been assumed the method is adequate for use in LCMD during conceptual design.

Finally, the uncertainty of inventory results was understated here because the uncertainty and variation of the inventory data from Franklin Associates (1993) was not available. As a result, some design scenarios may appear to have clear advantages and disadvantages even in situations where no differentiation is truly possible. This lack of knowledge regarding uncertainty and variation in inventory data also made performing a meaningful sensitivity analysis impossible. In the future, a sensitivity analysis should be used to determine the aspects of the design scenarios that most significantly influence performance metrics and cost. Also, assessment of data quality and validation of all analyses should include a peer review of the design scenarios and analysis results by the design team and other stakeholders. Fortunately, efforts similar to the United States Life Cycle Inventory Database Project (Athena, 2002) are expected to simplify these problems for future analyses.

Despite these issues, several recommendations can be made based on the results of the example. First, the design team should investigate the feasibility and cost effectiveness of vehicle design scenarios resembling Optimum 1 presented in Table 3.6. According to the very basic cost analysis performed for this example, Optimum 1 is expected to be somewhat more expensive than the baseline vehicle. If this or a similar design scenario is found to be cost effective enough to develop further, program leadership should provide incentives or requirements for engineers to assure component level decisions are made consistent with the results of the optima analysis.

If none of the "optimal" solutions identified through optima analysis are found to be acceptable, the design team should make the most dominant design decisions (e.g., material selection for the vehicle frame) early in design and reassess the feasibility of finding an acceptable solution given the existing design scenarios being considered. If an acceptable solution is unlikely to be chosen, the design team must either reevaluate the targets for the design project or identify new, superior design scenarios to consider.

Chapter 4 – Design Forecasting for Assembly Case Study

Design Forecasting for Assembly (DFFA; Figure 4.1) is a Design Forecasting methodology used to forecast assembly metrics for adaptive and variant designs during the development of complex products. The methodology combines existing Design for Assembly (DFA) methods with the general Design Forecasting methodology presented in Chapter 2. The remainder of this chapter presents an automotive case study used to illustrate DFFA.

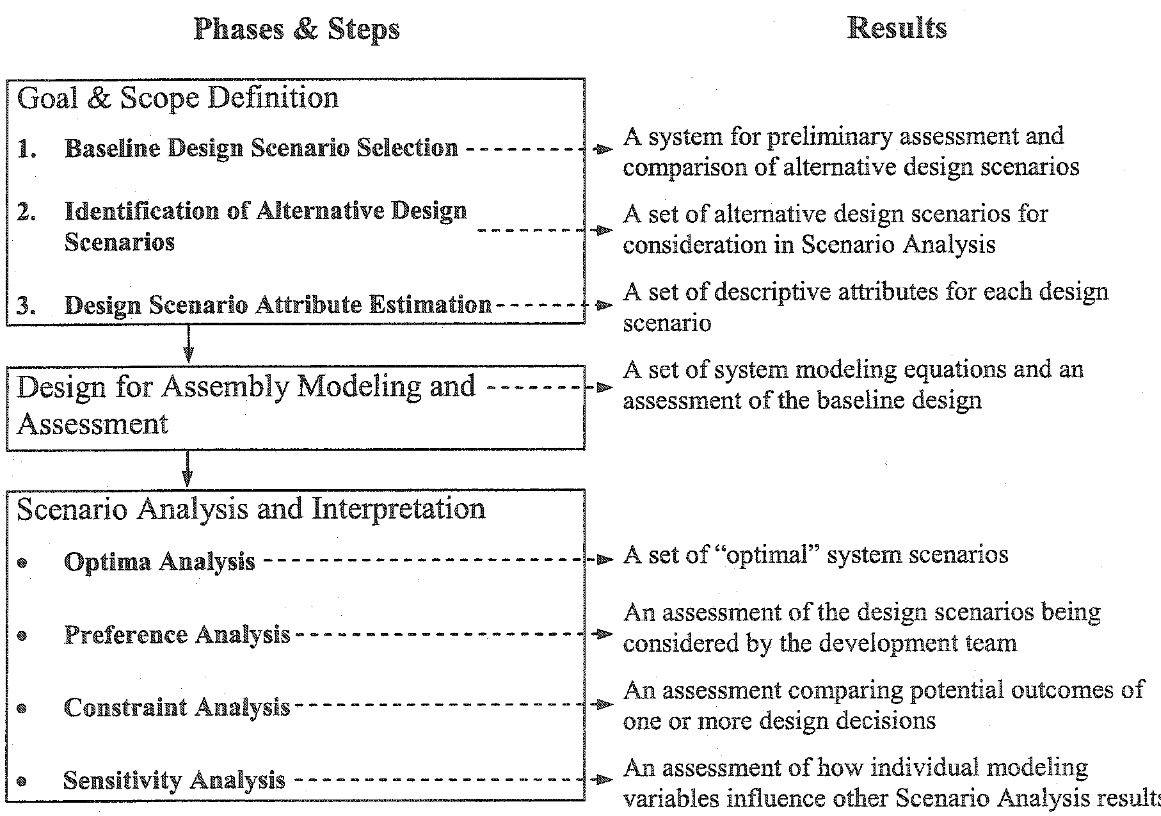


Figure 4.1. Design Forecasting for Assembly Methodology

For this case study, DFFA was used to evaluate opportunities to reduce the total assembly time and assembly defect rate for the wiper and washer systems on a Ford C-class sedan. Component data for the baseline systems were obtained from production components and

Ford benchmarking and teardown reports. Alternatively, detailed engineering drawings and bills-of-materials could have been used. For this study, the systems' eight major components were considered for redesign: the reservoir, spout, pump, hose, nozzles, wiper motor and linkage, arms, and blades.

4.1. PHASE 1: Goal and Scope Definition

In this phase, the goal and scope of the case study are defined for the product of interest.

Goal

Primary Objective: To generate and evaluate opportunities to reduce the total assembly time and assembly defect rate for the wiper and washer systems on a Ford C-class sedan

Intended Audience: Designers, manufacturers, and their suppliers

Scope

Functional Unit: One complete service lifetime distance (120,000 miles) for a washer/wiper system on a Ford C-class sedan

Life Cycle Stage: Assembly

System Metrics: Total assembly time and assembly defect rate

System Models: System metrics were estimated using a model based on the Modified Westinghouse Method (Ishii et al., 1998) and the Barkan & Hinckley conformance quality model (Barkan & Hinckley, 1993; Hinckley, 1993). The selection of these models is discussed in Section 4.2.

The scope of the case study is further defined by the array of design scenarios evaluated. For this case study, arrays of design scenarios were generated using three steps:

Step 1. Baseline Design Scenario Selection

Step 2. Identification of Alternative Design Scenarios

Step 3. Design Scenario Attribute Estimation

The following subsections describe each of these steps for the case study in detail.

4.1.1. STEP 1: Baseline Design Scenario Selection

In this step, a baseline design is chosen for the product of interest.

As with the DFFE case study, an existing Ford C-class sedan was chosen as the baseline product for this study. However, the baseline design scenarios for this study were limited to the washer and wiper systems of the sedan. Figure 4.2 shows a physical decomposition of the major components in the washer and wiper systems.

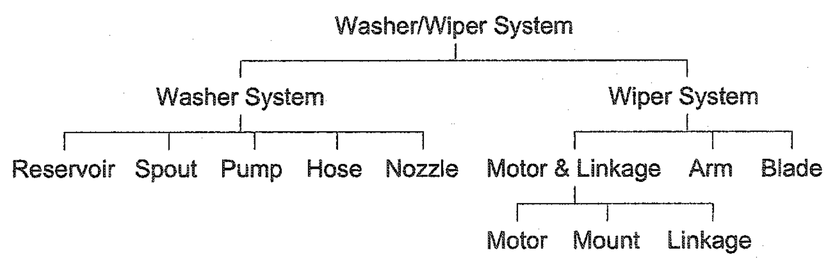


Figure 4.2. Physical Decomposition of the Baseline Washer/Wiper System

Table 4.1 presents an extended Morphological Chart (Dieter, 2000) for the washer/wiper system. The extension includes a classification of the functional solutions on the basis of form, material, fit (e.g., joining method), and production process for each of the major components. Specifically, the first column of Table 4.1 presents a physical decomposition in a hierarchical format, with washer system components separated from wiper system components. The second column provides a brief description of each component's basic function.

Table 4.1. Component Descriptions for the Baseline Washer/Wiper System

Component	Function	Form		Material	Fit	Production	
		Architecture	Shape			Manufacturing	Assembly
1 Washer System	Store and deliver washer fluid to windshield	Architecture A					Manual assembly
1.1 Reservoir	Store washer fluid		Shape A	HDPE	2 bolts w/nuts	Injection molding	
1.2 Spout	Deliver washer fluid to reservoir		Shape A	PP	Snap fit w/washer	Blow molding	
1.3 Pump	Pump washer fluid from reservoir through hoses and nozzles		Shape A	Housing PA Pump ELEC	Snap fit w/washer	Supplier A	
1.4 Hoses	Deliver washer fluid to nozzles		Length A	EPDM	Press fit, 4 snap fits	Molding & Extrusion	
1.5 Nozzles	Direct washer fluid at windshield		Shape A	PP	Snap fit	Injection molding	
2 Wiper System	Clear windshield	Architecture A					Manual assembly
2.1 Motor & Linkage	Rotate arms	Architecture A		Linkage Steel Mount AL Motor ELEC	3 screws	Supplier A	
2.2 Arms	Move blades		Shape A	Head Zinc Arm Steel	Nut	Supplier A	
2.3 Blades	Clear windshield		Shape A	Steel	Snap fit	Supplier A	

The third and fourth columns of Table 4.1 provide names for the baseline form (architecture or shape) of each component. Here, only the names "Architecture A," "Shape A," and "Length A" are used to signify the baseline form of each component. When existing component designs are used as baseline concepts, part numbers may also be used to label the baseline form of each component. For example, the baseline shape for the reservoir may be designated "XXXX-17618-XX," instead of "Shape A." The fifth and sixth columns of Table 4.1 describe the baseline material(s) and fit for each component. Note also that the washer pump and wiper motor contain electrical elements.

Rather than breaking those elements into constituent materials (e.g., copper and steel), those elements are labeled with material type: "ELEC." The final two columns of Table 4.1 describe the basic manufacturing and assembly of the washer and wiper systems. Both systems are assembled manually. As for the basic components in each system, either a manufacturing process or supplier are listed for each. Suppliers are listed in instances where the supplier is responsible for deciding how the component is manufactured.

4.1.2. STEP 2: Identification of Alternative Design Scenarios

This step involves compiling a list of alternative design scenarios being considered by the design team.

For the DFFE case study, only alternative material scenarios were considered. This case study, however, considered a much broader array of scenarios based on the modified Morphological Chart in Table 4.1. The Design Scenario Matrix shown in Table 4.2 was created by adding alternative manufacturing, fit, material, shape, and architecture design scenarios to Table 4.1. As in the development of a Morphological Chart, the alternatives presented in Table 4.2 were identified using expert consultation, competitive benchmarking, and literature searches. However, rather than using the second column to describe the function of each component, as in Table 4.1, the second column in Table 4.2 documents design scenarios at the functional level (the highest level for a particular component) to facilitate a higher level of innovation when assessing each subsystem. Specifically, rather than selecting the shape, material, fit, and manufacturing of the pump, the design team can select a pump design with a predefined function, shape, material, fit, and manufacturing. In addition, in Table 4.2, the lightly shaded cells represent instances where only the baseline scenario was considered for the case study.

Table 4.2. Design Scenario Matrix for the Washer and Wiper Systems (including baseline and alternative scenarios)

Component	Function	Form		Material	Fit	Production	
		Architecture	Shape			Manufacturing	Assembly
1 Washer System		Architecture A Architecture B					Manual assembly
1.1 Reservoir			Shape A Shape B Shape C ...	HDPE PP	2 screws & nuts 3 x screws & nuts ...	Injection molding Blow molding	
1.2 Spout			Shape A Shape B Shape C ...	PP HDPE	Snap fit w/washer	Blow molding Injection molding	
1.3 Pump	Pump A Pump B Pump C ...						
1.4 Hoses			Length A Length B Length C ...	EPDM PA PVC	Press fit w/snap fits	Molding & Extrusion	
1.5 Nozzles			Shape A Shape B Shape C ...	PP PA PET	Snap fit	Injection molding	
2 Wiper System		Architecture A					Manual assembly
2.1 Motor & Linkage		Architecture A Architecture B Architecture C ...		<u>Linkage</u> Steel <u>Mount</u> AL MG	3 screws 3 screws w/nuts 4 screws ...	Supplier A	
2.2 Arms			Shape A	<u>Head</u> Zinc AL <u>Arm</u> Steel	Nut	Supplier A	
2.3 Blades			Shape A	Steel	Snap fit	Supplier A	

Having identified alternative design scenarios for the washer/wiper system, available data was collected for each of the input variables (i.e., attributes) listed in Table 4.3. The list of variables is substantial, but necessary for using the system models presented in Section 4.2. To provide some description of these variables, each is classified into one of five categories (as described by Otto & Wood, 2001):

- *Yes/No* – User specifies whether a certain condition exists in an assembly operation or part (e.g., Are two hands required?)
- *Options* – User chooses one or more of a few options to describe an assembly or part property (e.g., fastening procedure: snap, weld, screw, etc.)
- *Levels* – User picks one out of a few discrete ranges or options of a certain variable (e.g., handling distance: <500 mm, 500-1000 mm, 1000-2000 mm, >2000 mm)
- *Number* – User enters a figure for a certain assembly or part attribute (e.g., part length in mm)
- *Formula* – User enters a formula or index to specify a custom-defined operation

Table 4.3. Detailed List of Input Variables for the DFFA Case Study

Input Variables for Washer/Wiper Case Study	Variable Class	Detail
Material	Option	Aluminum (AL), magnesium (MG), polypropylene (PP), high density polyethylene (HDPE), polyethylene terephthalate (PET), nylon (PA), polyvinyl chloride (PVC), Ethylene Propylene Rubber (EPDM), steel, zinc, etc.
Mass	Number	kg
Handling conditions		
Weight / mass problems	Yes/No	Is the mass of the component greater than 4.5 kg?
Fragility / durability problems	Yes/No	Is the component prone to break, scratch, bend, dent, or crinkle?
Nesting / tangling problems	Options	no nesting/tangling, nesting/tangling, severe nesting/tangling
Tool requirements	Options	no tool, tweezers, other tool
Part size	Levels	<2 mm, 2-6 mm, 6-12 mm, >12 mm
Part thickness	Levels	<0.5 mm, 0.5-2 mm, >2 mm
Orientation about insertion axis	Options	1 subtle, 1 obvious, 2 or more
End-to-end alignment	Options	1 subtle, 1 obvious, 2 or more
Insertion direction	Options	down, side, diagonal, twist/turn/tilt, up
Insertion conditions		
Constrained motion	Yes/No	Is operator access limited by fixturing or other components?
Temporary hold down required	Yes/No	Will component stay in place only if supported until another subsequent component is added?
Two hands required	Yes/No	Are two hands required to insert component?
Rotation required	Yes/No	Is reorientation required before inserting component?
Fixturing required	Yes/No	Is fixturing required before inserting component?
Flexible part	Yes/No	Does the component require extra manipulation during insertion? or does it not stay in place when released?
Insertion clearance	Levels	<1%, 1-10%, 10-50%, >50%
Fastener type	Options	washer, pin, retaining ring, screw, nut, rivet
Fastening process	Options	snap fit, press fit, bending, crimping, screwing, polymer weld or stake, solder, metal weld, braze, adhesive

The following subsection describes the methods used in the study to estimate unavailable data.

4.1.3. STEP 3: Design Scenario Attribute Estimation

This step involves estimating missing data for each new scenario.

For each washer/wiper component, an evaluation matrix like the one in Table 4.4 was generated using the design scenario matrix and the detailed list of input variables for the study (Tables 4.2 and 4.3, respectively). The first three columns of Table 4.4 describe the input variables (i.e., attributes) for the baseline reservoir. The last six columns of the table both describe the reservoir design scenarios for the study and provide a format for the design team to make a preliminary evaluation of alternative design scenarios.

Table 4.5 shows the preliminary evaluation made for the reservoir in this case study. According to the evaluation, eleven of the eighteen attributes for the new reservoir design were known and identical to the reservoir's baseline attributes, regardless of the design scenarios chosen for the final design. The other seven attributes were uncertain during the design process: mass, end-to-end alignment, insertion direction, constrained motion, two hands required for insertion, insertion clearance, and separate fasteners. For these attributes, the evaluation shows preliminary values and descriptions of why these attributes were uncertain. The last five columns of the table aid in this description by identifying categorical sources of design uncertainty: shape (or architecture), material, fit, manufacture, and other. The first four categories are types of design scenarios. The "other" category is a catchall category, and is most useful for identifying design uncertainty outside the control of the design team. For example, the components of most products can be assembled in multiple different sequences. Unless the design team over designs the product to assure only one possible assembly sequence, some of the product attributes that depend on assembly sequence will remain outside the control of the design team.

Table 4.4. Evaluation Matrix for the DFFA Case Study Reservoir

		Baseline Design	New Design	Sources of Design Uncertainty (Design Scenarios)				
				Shape	Material	Fit	Manufacturing	Other
Attributes (i.e., Input Variables)	Variable Class	Shape A HDPE 2 x screw & nut Injection molding	Unknown	Shape A Shape B Shape C …	HDPE PP	2 x screw & nut 3 x screw & nut …	Injection molding Blow molding	
Mass	Number	0.554						
Kg								
Fragility / durability problems	Yes/No	No						
Is the component prone to break, scratch, bend, dent, or crinkle?								
Nesting / tangling problems	Options	No nesting/ tangling						
No nesting/ tangling, nesting/ tangling, severe nesting/ tangling								
Tool requirements	Options	No tool						
No tool, tweezers, other tool								
Part size	Levels	>12 mm						
<2 mm, 2-6 mm, 6-12 mm, >12 mm								
Part thickness	Levels	>2 mm						
<0.5 mm, 0.5-2 mm, >2 mm								
Orientation about insertion axis	Options	1 obvious						
1 subtle, 1 obvious, 2 or more								
End-to-end alignment	Options	1 obvious						
1 subtle, 1 obvious, 2 or more								
Insertion direction	Options	Down						
Down, side, diagonal, twist/turn/tilt, up								
Constrained motion	Yes/No	No						
Is operator access limited by fixturing or other components?								
Temporary hold down required	Yes/No	No						
Will component stay in place only if supported until another subsequent component is added?								
Two hands required	Yes/No	No						
Are two hands required to insert component?								
Rotation required	Yes/No	No						
Is reorientation required before inserting component?								
Fixturing required	Yes/No	No						
Is fixturing required before inserting component?								
Flexible part	Yes/No	No						
Does the component require extra manipulation during insertion? or does it not stay in place when released?								
Insertion clearance	Levels	1-10%						
<1%, 1-10%, 10-50%, >50%								
Fastening process	Options	Separate fasteners						
Snap fit, press fit, bending, crimping, screwing, polymer weld or stake, solder, metal weld, braze, adhesive, separate fasteners								
Separate fasteners	Options	2 x screws & nuts						
Washer, snap fit, pin, retaining ring, screw, nut, rivet								

Table 4.5. Example Evaluation of New Reservoir Design for DFFA Case Study

		Baseline Design	New Design	Sources of Design Uncertainty (Design Scenarios)				
				Shape	Material	Fit	Manufacturing	Other
Attributes (i.e., Input Variables)	Variable Class	Shape A HDPE 2 x screw & nut Injection molding	Unknown	Shape A Shape B Shape C …	HDPE PP	2 x screw & nut 3 x screw & nut …	Injection molding Blow molding	
Mass	Number	0.554	Unknown	X	X			
Kg				The mass of the new design depends on its shape and material.				
Fragility / durability problems	Yes/No	No	No					
Is the component prone to break, scratch, bend, dent, or crinkle?								
Nesting / tangling problems	Options	No nesting/ tangling	No nesting/ tangling					
No nesting/ tangling, nesting/ tangling, severe nesting/ tangling								
Tool requirements	Options	No tool	No tool					
No tool, tweezers, other tool								
Part size	Levels	>12 mm	>12 mm					
<2 mm, 2-6 mm, 6-12 mm, >12 mm								
Part thickness	Levels	>2 mm	>2 mm					
<0.5 mm, 0.5-2 mm, >2 mm								
Orientation about insertion axis	Options	1 obvious	1 obvious					
1 subtle, 1 obvious, 2 or more								
End-to-end alignment	Options	1 obvious	1 obvious 2 or more	X				
1 subtle, 1 obvious, 2 or more				The shape may be changed to allow for 2 acceptable alignments.				
Insertion direction	Options	Down	Down Side					X
Down, side, diagonal, twist/turn/tilt, up				The design does not fully constrain the insertion direction.				
Constrained motion	Yes/No	No	Yes No					X
Is operator access limited by fixturing or other components?				Changes to other components outside this system may limit operator access.				
Temporary hold down required	Yes/No	No	No					
Will component stay in place only if supported until another subsequent component is added?								
Two hands required	Yes/No	No	Yes No					X
Are two hands required to insert component?				Changes to components outside this system may make two hands necessary.				
Rotation required	Yes/No	No	No					
Is reorientation required before inserting component?								
Fixturing required	Yes/No	No	No					
Is fixturing required before inserting component?								
Flexible part	Yes/No	No	No					
Does the component require extra manipulation during insertion? or does it not stay in place when released?								
Insertion clearance	Levels	1-10%	1-10% 10-50%			X		
<1%, 1-10%, 10-50%, >50%				The fit may be changed to allow for more insertion clearance.				
Fastening process	Options	Separate fasteners	Separate fasteners					
Snap fit, press fit, bending, crimping, screwing, polymer weld or stake, solder, metal weld, braze, adhesive, separate fasteners								
Separate fasteners	Options	2 x screws & nuts	2 x screws & nuts 3 x screws & nuts …			X		
Washer, snap fit, pin, retaining ring, screw, nut, rivet				The choice of separate fasteners corresponds directly to a selection of fit.				

Despite containing considerable useful information, the data in Table 4.5 and in the other evaluation matrices for this study (Appendix D) are incomplete. In the DFFE case study, equivalence models were chosen over anecdotal models as the preferred method for estimating missing mass data without redesigning every component. However, this case study demonstrates that those estimation methods are not always sufficient for Design Forecasting. Other methods for refining data are necessary for DFFA. As shown in Table 4.5, seven attributes of the new reservoir design for this case study were uncertain: mass, end-to-end alignment, insertion direction, constrained motion, two hands required for insertion, insertion clearance, and separate fasteners. The following subsections discuss the methods used to refine these uncertain data for the new reservoir design.

Mass

According to Table 4.5, the mass of the new reservoir design depended primarily on its shape and material. Section 3.1.3 of the DFFE case study demonstrated how to use an equivalence model to estimate the mass of a component made out of a certain material; given the mass of the same component made out of a different material, the component's basic function, and the component's basic shape. However, estimating the mass of the new reservoir design for this case study allowed alternative shapes to be considered, whereas the DFFE case study only allowed alternative materials and component thickness as variables. Here, in addition to estimating mass for multiple material scenarios, the mass of the new reservoir was estimated for multiple shape scenarios (all dimensions are variable instead of simply material thickness). Fortunately, the shape scenarios for the new reservoir were all based on existing reservoir designs. As a result, a single mass data point was available for each shape scenario. By knowing the mass of each reservoir shape for a certain material, the mass of the same reservoir shape could be estimated for any other suitable material.

End-to-end Alignment

According to Table 4.5, the number of correct end-to-end alignments for the new reservoir design depended on its basic shape. In this study, since one shape allowed for two or more correct alignments and the others did not, the end-to-end alignment attribute for the new reservoir design could be constrained to correspond directly to the design team's choice of basic shape. The following statement illustrates the conditional nature of this constraint: If "shape" = X, then "end-to-end alignment" = Y.

Insertion Direction

According to Table 4.5, all of the new reservoir design scenarios allowed for both downward and sideways insertion. Having assumed that the design team would not choose to create a constraint to ensure the new reservoir would be inserted from a certain direction, two options existed for modeling:

Option 1. Treat the two insertion direction options as random (i.e., equally likely)

Option 2. Assign preference to one option (i.e., assume that a preferred option is more likely to be used/chosen because it is preferred by the design team)

In this case, downward insertion was preferred both because the baseline reservoir was inserted downward during assembly and because downward insertion requires less assembly time than sideways insertion. Preference and the benefits of assigning it in this and other situations were discussed in Section 2.3.1.

Constrained Motion

According to Table 4.5, changes to other components outside of the washer system could limit operator access during insertion of the new reservoir. For this study, three options were identified for modeling:

Option 1. Constrain this attribute to equal "no." In other words, constrain the design so that operator access will not be limited during insertion of the new reservoir.

At least two possible justifications exist for this constraint: 1) a *design decision* could be made to constrain the new vehicle design in a way that ensures operator access will not be limited in this situation, or 2) an *assumption* could be made that the new vehicle design will be close enough to the baseline design that this attribute will not change.

Option 2. Assign preference to "no" for this attribute. For example, give "yes" a preference rating of "1" and give "no" a preference rating of "9" (refer to Section 2.3.1 for a discussion of using a 1/3/9 rating system to describe preference). The possible justification being that operator access is not likely to be limited in this situation, both because limited access is undesirable and because access is not limited in the baseline design.

Option 3. Assign no preference or constraint and treat this attribute as random. If the design team has no design influence over components outside of the washer and wiper systems and if the new vehicle design is likely to be considerably different from the baseline, this option may be appropriate.

For this case study, Option 2 was chosen because it acknowledged that operator access could be limited during insertion of the new reservoir, but it was unlikely.

Two Hands Required for Insertion

According to Table 4.5, changes to other components outside of the washer system could have caused two hands to be required for insertion of the new reservoir. The three options identified for "constrained motion" also exist for this attribute. The same justifications for each option are also valid here. As a result, for this study, preference was assigned to "no" for this attribute. Doing so acknowledged that two hands could be required for insertion of the new reservoir design, but that needing two hands was unlikely.

Insertion Clearance

According to Table 4.5, the fit of the new reservoir design could have been changed to allow for more insertion clearance. Again, three options were identified for the case study:

Option 1. Fully constrain this attribute to equal either "1-10%" or "10-50%." A constrained insertion clearance of "1-10%" might be justified by an assumption that the new design would remain very similar to the baseline. However, a constrained insertion clearance of "10-50%" might be justified by a design decision to improve ease of assembly.

Option 2. Assign preference to one of the levels for this attribute. Assigning preference to "1-10%" might be justified by an assumption that the new design would likely remain similar to the baseline. However, assigning preference to "10-50%" might be justified because having a larger insertion clearance is desirable from a Design for Assembly perspective.

Option 3. Assign no preference or constraint and treat this attribute as random. If neither of the other two options is clearly justified, this option may be appropriate.

For this study, the new design was likely to remain similar to the baseline. However, preference was shown to "1-10%," rather than assigning a constraint, because loosening the insertion clearance to "10-50%" was acknowledged as a potentially viable design option.

Separate Fasteners

According to Table 4.5, the "separate fasteners" attribute for the new reservoir design corresponded directly to the design team's choice of fit. Therefore, until the design team was prepared to define the fit of the new reservoir design (or at least for one or more of its shape concepts), the most appropriate modeling option was to assign design preferences for the array of fastening options.

The methods described above were used to estimate and refine data for each component in this DFFA case study. Doing so was necessary to make Scenario Analysis and Interpretation possible, as follows.

4.2. PHASE 2: Design for Assembly Modeling and Assessment

This phase consists of identifying appropriate system modeling equations and performing an assessment of the baseline design.

For this case study, assembly models were selected to estimate total assembly time and assembly defect rate for the washer/wiper system. The following subsections describe the selection of these models and provide an assessment of the baseline system.

4.2.1. Modeling Total Assembly Time

Numerous quantitative evaluation methods exist for DFA. Of the methods identified by Redford & Chal (1994), English (1995), Gonzales-Zugasti et al. (1997), Ishii et al. (1998), and Das et al. (2000), six estimate total assembly time:

- Boothroyd-Dewhurst DFA Method (BDI) (Boothroyd & Dewhurst, 1983)
- GE Method (English, 1995)
- LASeR (Ishii et al, 1994)
- Lucas Engineering and Systems DFA (Gonzales-Zugasti et al., 1997)
- Modified Westinghouse Method (Ishii et al. 1998)
- SEER DFM (Galorath, 1996)

Table 4.6 (adapted from Gonzales-Zugasti et al., 1997) summarizes the input and output variables associated with each of the assembly time estimation methods. The input variables for each method presented in Table 4.6 are classified into the five categories described by Otto & Wood (2001): Yes/No, Options, Levels, Number, Formula.

Table 4.6. Summary of Input & Output Variables for Quantitative DFA Methods[1,2]

	BDI	Lucas	SEER	LASeR	Modified Westinghouse	GE
Assembly analysis [output variables]						
Estimated assembly time	Yes	Yes	Yes	Yes	Yes	Yes
Assembly efficiency metric	Design Efficiency	Unknown	Unknown	Unknown	Assembly Rating	Assemblability Rating
Additional metrics		Unknown	Unknown	Unknown	Part Efficiency	
Functional analysis [input variables]						
Theoretical part count	Yes/No	Yes/No		Yes/No	Yes/No	
Handling analysis [input variables]						
Part attributes						
Standard part						
Part size	Levels + Number	Levels			Levels	
Part weight (heavy?)	Yes/No	Yes/No			Yes/No	
Part shape/symmetry	Options + Levels	Options			Options	
Handling distance	Levels					
Handling method						
More than one hand	Yes/No	Yes/No			Yes/No	
More than one person	Yes/No	Yes/No				
Tool requirements	Options	Yes/No			Yes/No	
Aids requirements	Options	Yes/No				
Handling difficulties						
Handling conditions	Options	Options			Options	Options
Orienting ease		Levels			Options	
Insertion analysis [input variables]						
Wrong insertion possibility		Yes/No				
Insertion method						
Holding requirement	Yes/No	Yes/No		Options	Options	Options
Fastening method	Options	Options		Options	Options	Options
Insertion direction		Options		Options	Options	Options
Multiple/simultaneous processes	Options + Number	Options		Options + Number		Options
Tool acquisition	Levels					
Number of fasteners	[1]	[1]	Number	[1]	[1]	
Mechanization	[2]	[2]	Levels			
Insertion difficulties:						
Access/vision restrictions	Yes/No	Yes/No				
Alignment ease	Yes/No	Yes/No			Levels	
Resistance to insertion	Yes/No	Yes/No			Levels	
Large-part difficulties	Options					
Installation difficulty			Levels			
Whole-assembly difficulty			Levels			
Special problems						
Assembly environment requirements						
Secondary assembly						
Standard operations	Options	Options		Options		
Explicit user-defined	Formula	Formula				

[1] Fasteners are considered in the same manner as regular parts by all methods except SEER and GE.

[2] Boothroyd-Dewhurst and Lucas have separate analysis modules to model assembly automation.

Though any of the six methods listed in Table 4.6 could have been used for the DFFA case study, some methods were more appropriate than others because of the amount and types of data required for modeling. Since each method has been shown to be reasonably accurate,[3] there were two key criteria for selecting a method for the study:

1. Total number of input variables
2. Whether or not the input variables that are likely to be known during conceptual or embodiment design

Using Table 4.6 and these two criteria, Table 4.7 compares each of the previously mentioned methods for estimating total assembly time. Noting that, as discussed by Otto & Wood (2001), design processes, standards, and thus information availability vary from industry to industry and from company to company. As a result, without very specific knowledge of a particular product design process, whether or not input variables are likely to be known for a specific estimation method is not universal. Thus, in Table 4.7, information availability for each model was determined using Dieter's (2000) engineering design process as a reference.

Table 4.7. Comparison of Quantitative DFA Methods for System Model Selection

Modeling Methodology	Total Number of Input Variables	% of Input Variables Known
BDI	22	45%
Lucas	19	42%
Modified Westinghouse	13	54%
LASeR	6	17%
GE	5	20%
SEER	4	25%

[3] Each of these methods has passed at least some minimal form of validation. Based on the evaluation of a disposable camera, BDI, Lucas, SEER, and LASeR all provide reasonable overall assembly time estimates (Otto & Wood, 2001). Based on evaluations performed on two desktop printers by English (1995), the same can also be concluded about the Modified Westinghouse and GE methods. Also, in some instances, a scaling factor can be used to improve modeling accuracy.

Preferable system models require minimal input variables (less is better; ideal = 1) with a high percentage of input variables likely to known (i.e., have data available) during design (higher is better; ideal = 100%). As shown in Table 4.7, the LASeR, GE, and SEER methods, require minimal input variables, between four and six. However, less than 25% of the input variables are likely to be known during conceptual or embodiment design. In other words, though requiring very little data for modeling, the LASeR, GE, and SEER methods mostly require data that may not be known during design. Conversely, the BDI, Lucas, and Modified Westinghouse methods require much more data for modeling, but a higher percentage of the data is likely to be known during design. Of these last three methods, the Modified Westinghouse Method both required the least number of input variables and had the highest design knowledge factor. As a result, the Modified Westinghouse Method was chosen to model total assembly time for this case study.

The Modified Westinghouse Method

The Modified Westinghouse Method (Ishii et al., 1998) was adapted from the original Westinghouse Method (Sturges & Kilani, 1992) in an attempt to decrease complexity and the time necessary to evaluate assembly concepts. In addition to total assembly time, the Modified Westinghouse Method evaluates assembly concepts using number of assembly operations, *assembly rating* – a normalized measure that compares the total assembly time with a reference time of 2.35 seconds per part – and *part efficiency* – the ratio of the number of parts in the assembly concept to the theoretical minimum number of parts. The method uses ten handling, insertion, component, and fastener characteristics to evaluate assembly times for each component:

1. Handling conditions
2. Part size
3. Part thickness
4. Orientation about insertion axis
5. End-to-end alignment
6. Insertion direction

7. Insertion conditions
8. Insertion clearance
9. Fastener type
10. Fastening process

Each characteristic has an array of descriptive options and each option has its own time penalty. The total assembly time for the system is calculated by summing all of the time penalties for every component in the system. The following subsections present the descriptive options and time penalties for each modeling characteristic as described by Ishii et al. (1998). However, additional detail has been added where appropriate.

Handling Conditions

Handling conditions apply to special cases (default = 0 seconds). These times can be added when more than one condition applies.

Penalty	Option	Description
0.5	heavy	More than 4.5 kg (10 lbs)
1.0	delicate	Parts prone to break, scratch, bend, crinkle, parts with sharp edges (e.g., shims, foils, and brittle materials)
1.5	nests/tangles	Parts supplied to operator in bulk and requires simple manipulation to separate it from other parts in the container (e.g., retaining ring or sticky parts)
2.0	tweezers required	
3.5	other tool required	Part cannot be inserted without the use of other tools (e.g., pliers or wrenches)
6.0	severe nest/tangle	Parts supplied to operator in bulk and requires considerable manipulation to separate it from other parts in the container (e.g., cable or coil springs)

Since handling condition penalties are additive, each option may be considered individually. One alternative to treating handling condition as a single characteristic is to subdivide it into four, more specific characteristics (i.e., weight/mass, fragility/durability, nesting/tangling, and tool requirements).

Size

Size is the largest dimension of the rectangular solid that can enclose the part (default = 0 seconds).

Penalty	Option	Description
0.6	< 2 mm	(< 0.08 in)
0.4	2 – 6 mm	(0.08 – 0.25 in)
0.1	6 – 12 mm	(0.25 – 0.5 in)
time x2	insertion orientation < 4	If there are less than four possible orientations about the axis of insertion, then multiply the time penalty by two.

Thickness

Thickness is the smallest dimension of the rectangular solid that can enclose the part (default = 0 seconds).

Penalty	Option	Description
0.5	< 0.5 mm	(< 0.02 in)
0.2	0.5 – 2 mm	(0.02 – 0.08 in)
time x2	insertion orientation < 4	If there are less than four possible orientations about the axis of insertion, then multiply the time penalty by two.

Orientation about Insertion Axis

This characteristic reflects the number of orientations about the axis of insertion where a part may be correctly inserted.

Penalty	Option	Description
1.50	1 (subtle feature)	There is only one correct orientation and the asymmetric feature is not very noticeable.
1.00	1 (obvious feature)	There is one easily recognizable, correct orientation.
0.25	2 or more	There is more than one correct insertion orientation (e.g., screws, pins, and rectangular pieces).

End-to-end Alignment

This characteristic reflects the number of end-to-end orientations where a part may be correctly inserted. A part with two end-to-end orientations can be inserted upside down.

Penalty	Option	Description
1.50	1 (subtle feature)	There is only one correct orientation and the asymmetric feature is not very noticeable.
1.00	1 (obvious feature)	There is one easily recognizable, correct orientation.
0.25	2 or more	There is more than one correct insertion orientation.

Insertion Direction

The insertion direction refers to the direction the part will be inserted. If more than one direction applies, the times may be added.

Penalty	Option
0.6	down
1.4	from the side
1.7	diagonally or twist/turn/tilt
2.0	up

Insertion Conditions

Insertion conditions apply to special cases (default = 0 seconds). Though Ishii et al. (1998) do not state that these penalties can be added when more than one condition applies, being able to do so would be consistent with the treatment of the handling condition characteristic described previously.

Penalty	Option	Description
1.25	constrained motion	Operators access limited by fixturing or other parts
1.35	temporary hold down	Part will stay in place only if supported until another subsequent part is added
1.50	two hands	
2.25	rotate or fixture	Fixture: fixturing operation precedes insertion of part Rotate: re-orientation precedes insertion of part
6.00	flexible	Requires extra manipulation during insertion, or does not stay in place when released

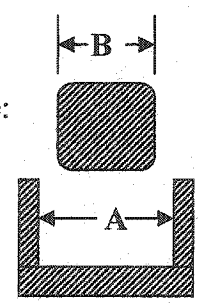
Assuming the penalties are additive, each option may be considered individually.

Insertion Clearance

This characteristic is a relative measure of the clearance between the base assembly and the component being inserted. Insertion clearance is described using the following equation:

$$IC = 100\% \, (A - B) / B$$

where:



Penalty	Option
0.25	large (10-50%)
0.90	small (1-10%)
1.60	very small (<1%)

Fastener Type

Fastener type applies to cases where a separate fastener is used (default = 0 seconds). Though Ishii et al. (1998) do not state that these penalties can be added when more than one fastener is used, being able to do so would be consistent with previously described characteristics.

Penalty	Option
0.0	washer
1.0	pin
2.5	retaining ring
4.0	screw
5.0	nut
6.0	rivet

Fastening Process

This characteristic is a measure of the time required to fasten a component to the base subassembly. Though Ishii et al. (1998) do not state that these penalties can be added when more than one fastening process is used, being able to do so would be consistent with previously described characteristics.

Penalty	Option
1.0	snap or press fit
3.0	bending or crimping
4.0	screwing
5.0	polymer weld or polymer stake
7.0	solder
9.0	weld or braze
11.0	adhesive

4.2.2. Modeling Assembly Defect Rate

Of the methods identified by Redford & Chal (1994), English (1995), Gonzales-Zugasti et al. (1997), Ishii et al. (1998), and Das et al. (2000), two could have been used to estimate defect rates: DFQM (Das et al. 2000) and the Barkan & Hinckley (1993) conformance quality model. Of these two methods, DFQM requires far more input data. Specifically, DFQM uses nearly 50 input variables to estimate assembly defect rates, whereas the Barkan & Hinckley global conformance quality model requires only two input variables: number of assembly operations and total assembly time (both output variables of the Modified Westinghouse Method). As a result, the Barkan & Hinckley conformance quality model was chosen to model assembly defect rate for this case study.

Barkan & Hinckley Conformance Quality Model

For the Barkan & Hinckley conformance quality model, Hinckley (1993) defines a complexity metric based on product assembly time and uses empirical observations from Motorola to relate complexity to the probability of assembly related defects. The key relationship identified by Hinckley is:

$$DPU = \frac{(TM - t_0 \cdot N_a)^{\bar{k}}}{c_3} \qquad \text{<Equation 4.1>}$$

where: DPU = defects per unit;

TM = DFA manual assembly time;

N_a = number of assembly operations;

t_0 = constant = assembly time below which defects are not defined;

$\bar{k}$ = constant denoting sensitivity of defects to assembly complexity; and

c_3 = constant.

The constants in Equation 4.1 may be determined by fitting the relationship to defect data for existing products. However, by using typical values for t_0 and $\bar{k}$, relative defect rates may be estimated for two product designs without needing actual defect data. Because Hinckley's complexity metric is based on assembly time, the model must be used in conjunction with an assembly time estimation methodology such as the Modified Westinghouse Method.

4.2.3. Baseline Assessment

As stated previously, using the Modified Westinghouse Method, total assembly time is calculated by summing all of the time penalties for every component in a system. For the baseline washer/wiper system, 18 assembly operations were required and the total assembly time was estimated to be 99.9 seconds. By using estimates from the Modified Westinghouse Method and representative values for the constants in Equation 4.1 (e.g., t_0 = 1.68 seconds/operation, $\bar{k}$ = 1.316, and c_3 = 112370), assembly defect rate for the baseline washer/wiper system was estimated to be approximately 0.0024 defects per unit.

4.3. PHASE 3: Scenario Analysis and Interpretation

In this phase, the product or system of interest is evaluated relative to the system metrics defined during Goal and Scope Definition. Specifically, the analyses in this phase evaluate optimal system scenarios, likely system characteristics, and the sensitivity of system characteristics to individual design decisions.

For this case study, four scenario analyses were used to estimate material and energy use, recovery, and waste for alternative, product design scenarios: Preference Analysis, Sensitivity Analysis, Constraint Analysis, and Optima Analysis. As with the results of the DFFE case study, the results of these analyses required interpretation. The following sections describe the results of this case study in detail.

4.3.1. Preference Analysis

Preference Analysis is the process of estimating the probable characteristics of a design (in terms of system metrics), given the design preferences of the design team and other stakeholders.

Preference Analysis was used in this study to estimate the probable characteristics of the new washer and wiper systems (in terms of total assembly time and assembly defect rate), given the design preferences of the design team and other stakeholders. As with the

DFFE case study, *design preference*, p_{ij} in Equation 4.2, was described using a 1/3/9 rating system. For each component scenario category, the design team rated the preferred scenario with a nine. Any other seriously considered scenario received a rating of three. The remaining scenarios received a rating of one. Note that any scenario ruled out by the design team was never considered for the study.

To simulate the affect design preference has on the final product design, Monte Carlo simulation was used to generate an array of design scenarios and estimate system metrics. To generate each system scenario, component scenarios were created by selecting a shape, material, fit, and manufacturing scenario for each component based on an approximation of the likelihood of use, l_{ij}:

$$l_{ij} \approx \frac{p_{ij}}{\sum_j p_{ij}} \qquad \text{<Equation 4.2>}$$

where: l_{ij} = the likelihood scenario j will be used for component i

p_{ij} = the design preference (1, 3, or 9) of scenario j for component i

Figures 4.3 and 4.4 show example Preference Analysis results from this case study. Specifically, Figure 4.3 presents the results for the total assembly time of the washer and wiper systems. The results suggest that the new washer and wiper systems will likely take longer to assemble than the baseline design. However, the results also show that opportunities do still exist for improving the total assembly time of the washer/wiper system over the baseline.

Figure 4.4 presents similar results for the relative defect rate of the new washer and wiper systems. These results show that at least a 15% improvement in assembly defect rate may be realized, relative to the baseline system. However, the defect rate of the new washer and wiper systems is likely to be higher than baseline system, possibly more than 30% higher.

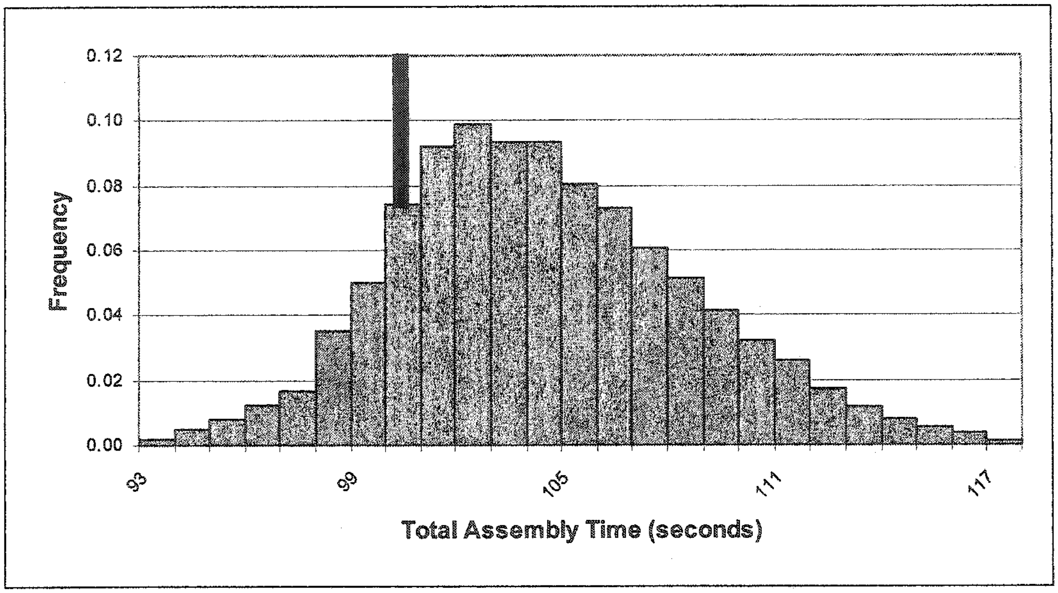


Figure 4.3. Preference Analysis Results for Total Assembly Time

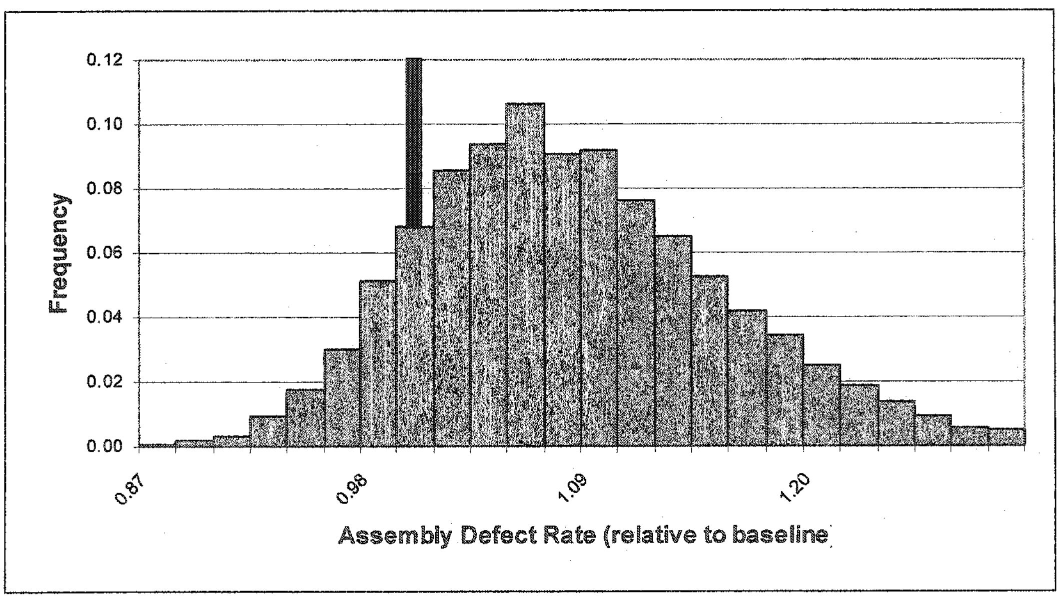


Figure 4.4. Preference Analysis Results for Relative Assembly Defect Rate

4.3.2. Sensitivity Analysis

Sensitivity Analysis is the process of identifying the scenario attributes and other modeling variables that most significantly influence individual system metrics.

For this case study, sensitivity analysis was used to identify the components and input variables that most significantly influenced the estimated assembly time and defect rates for the washer and wiper systems. Table 4.8 shows the four different methods used to rank the components in the study (1 = highest priority/ranking for reducing assembly time; 8 = lowest priority/ranking). The first method used the baseline assembly times for each component to identify components of interest (the higher the assembly time, the higher the ranking). The second method used the sensitivity of the total assembly time model to input variables that the design team controlled for each component (e.g., the separate fasteners and insertion clearance for the reservoir). The third method used the sensitivity of the model to input variables that the design team did have complete control over for each component (e.g., the insertion direction and rotation requirements for the pump). The last method used the sensitivity of the model to all input variables for each component.

Table 4.8. Rankings of Components by Assembly Time and Model Sensitivity

Component	Rank Based on Baseline Assembly Time	Rank Based on Model Sensitivity to Design Variables	Rank Based on Model Sensitivity to Other Variables	Rank Based on Model Sensitivity to All Variables
Hose	1	3	5	6
Motor and Linkage	2	2	8	3
Reservoir	3	1	7	1
Arms	4	4	3	5
Blades	5	8	2	4
Spout	6	6	4	7
Pump	6	7	6	8
Nozzles	8	5	1	2

The logic of the first ranking method is that DFA should begin with the components that take longest to assemble. For example, Otto & Wood (2001) identify candidates for redesign using assembly cost, which in their coffee mill example is directly proportional to assembly time. However, the three ranking methods based on sensitivity analysis show that "longest to assemble" rule-of-thumb is not always correct. For example, though the hose takes the longest to assemble to the vehicle, the second ranking shows that the design of the hose is less influential on total assembly time than the designs of both the reservoir and the motor and linkage.

In addition to identifying influential components, sensitivity analysis was used to identify influential input variables. Identifying the most influential input variables provided additional insight into product or system of choice. For the washer and wiper systems, Table 4.9 shows that the most influential input variables were not always the variables with the largest time penalties. For example, "constrained motion" and "two hands required for insertion" were the third and fourth most influential input variables in the study, despite the fact that eleven other variables had larger maximum time penalties than they did.

Table 4.9. Rankings of Six Most Influential Assembly Input Variables (of Eighteen)

Input Variable	**Rank Based on Model Sensitivity**	**Rank Based on Maximum Time Penalty**
Fastener Type	1	2
Rotation Required	2	6
Constrained Motion	3	14
Two Hands Required for Insertion	4	12
Insertion Direction	5	8
Insertion Clearance	6	9

4.3.3. Constraint Analysis

Constraint Analysis is an extension of preference analysis used to estimate the influence of a design decision on system metrics. This analysis involves performing two parallel, constrained preference analyses and comparing the results.

Sensitivity Analysis showed that "fastener type" was an influential input variable. However, sensitivity did not fully illustrate the influence of "fastener type." Constraint Analysis was used in this case study to better illustrate this type of influence. The constraint analysis shown in Figure 4.5 illustrates how choosing the quickest fastener proposed by the design team for each component can reduce the expected assembly time for the washer and wiper systems from 104 seconds (the mean of the right distribution) down to 96.5 seconds (the mean of the left distribution). In addition, the constraint analysis shows that making this decision about fasteners would noticeably reduce design uncertainty (variance down to 11.8 sec^2 from 19.1 sec^2) and would significantly increase the likelihood of the new washer and wiper systems taking less time to assemble than the baseline systems (approximate likelihood up to >80% from <20%).

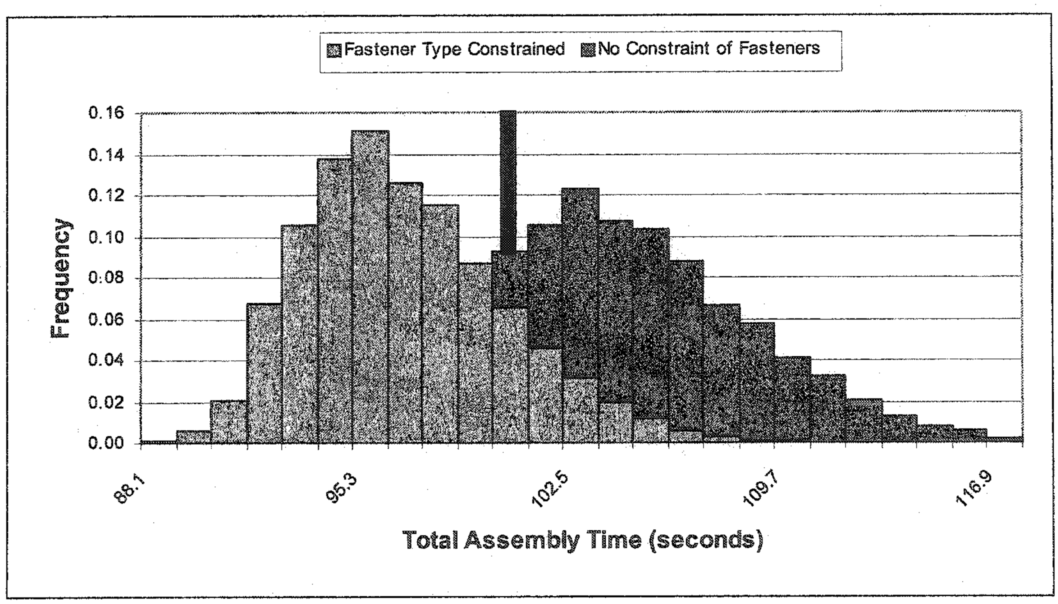


Figure 4.5. Influence of Selecting Easy to Assemble Fasteners

Sensitivity analysis also showed that the model was sensitive to the design of the new reservoir. Figure 4.6 shows the influence of choosing the quickest fastener proposed by the design team for the reservoir (i.e., a single screw/bolt). Note the similarity between

Figures 4.5 and 4.6. Both figures show a clear shift caused by a design decision regarding fasteners.

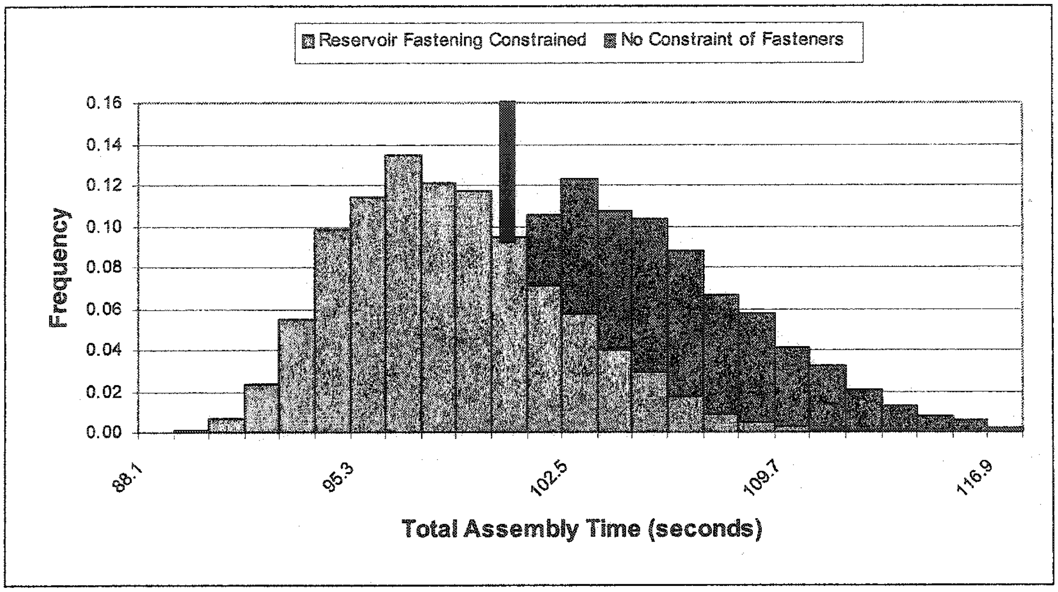


Figure 4.6. Influence of Selecting Easy to Assemble Reservoir Fasteners

However, not all design decisions resulted in an obvious shift. For example, the constraint analysis shown in Figure 4.7 illustrates the change in results caused by having the design team commit to using the preferred fasteners. Committing to those fasteners did not change the expected assembly time of the washer and wiper systems significantly, but it did decrease design uncertainty (variance down to 11.8 sec^2 from 19.1 sec^2).

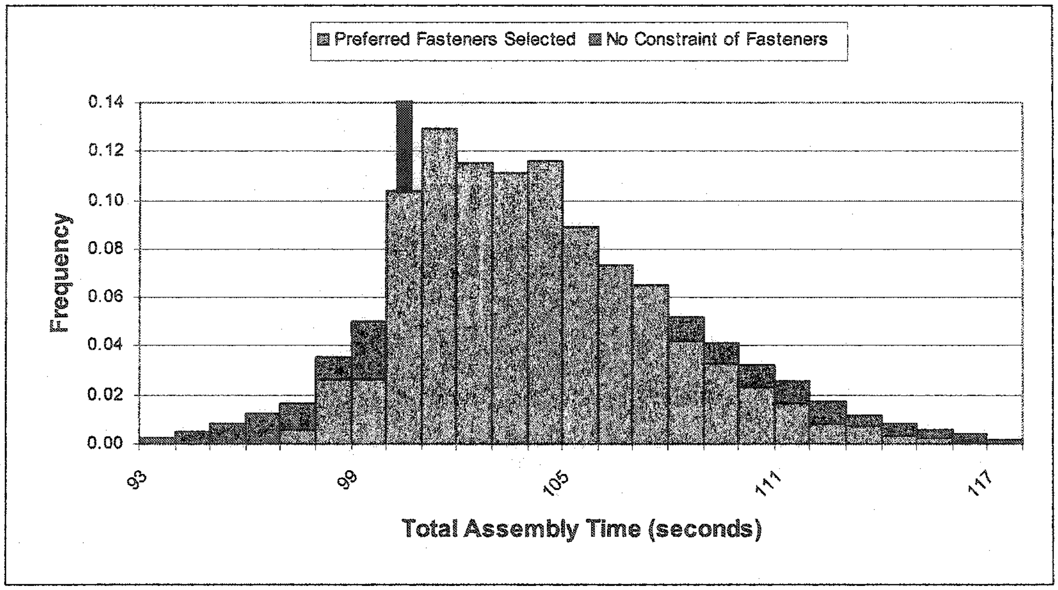


Figure 4.7. Influence of Selecting Baseline Fasteners on Modeling Results

4.3.4. Optima Analysis

Optima Analysis is the process of identifying optimal system scenarios relative to one or more system metrics. Optima analysis is appropriate for identifying candidate design scenarios for further consideration, not for choosing a single, "ideal" solution.

Optima Analysis was used in this case study to identify washer and wiper system scenarios that minimize total assembly time, number of assembly operations, and assembly defect rate. The purpose of doing so was to identify candidate design scenarios for further consideration, not for choosing "the ideal solution." For this case study, identifying optimal system scenarios for total assembly time and the number of assembly operations was very simple. The study did not consider the possibility of eliminating components from the system. As a result, minimizing assembly time and the number of assembly operations for each component minimized both total assembly time and the number of assembly operations at the system level. However, minimizing total assembly time and the number of assembly operations for the washer and wiper systems did not minimize the assembly defect rate predicted by the Barkan & Hinkley conformance quality model. Counterintuitively, results from using the Barkan & Hinckley model suggested that adding two snap fit fasteners to the hose would reduce the assembly defect rate for the system, despite an increase in total assembly time.

Ultimately, the two optima identified for this case study were almost identical, and the differences between the two (i.e., the snap fit fasteners that do not replace any other fasteners) were unlikely to affect the system's assembly defect rate significantly. As a result, there appeared to be one optimal solution. However, this "optimal" system scenario was not observed once in 250,000 Monte Carlo trials generated as part of an extended Preference Analysis. The results of the extended Preference Analysis suggested that this "optimal" system scenario was certainly not optimal from the design team's perspective.

4.3.5. Interpretation of Results

As stated previously, given the scenarios under consideration and stated design preferences, the new washer and wiper systems were likely to take longer to assemble and have more assembly defects than the baseline system. However, opportunities existed for improvement over the baseline. The best opportunities related to reservoir design and fasteners.

The most useful information provided by these analyses was not necessarily a list of all the ways assembly time and assembly defects could be reduced for the washer and wiper systems. That information can be obtained directly from the Modified Westinghouse Method itself. Rather, these analyses were most helpful for identifying the best ways (i.e., the most effective and preferable ways) to reduce assembly time and assembly defects. Sensitivity Analysis highlighted the components and design attributes most able to reduce the expected assembly time of the system, while Constraint Analysis demonstrated how much those components and attributes were likely to reduce the expected assembly time of the system. Also, though Optima Analysis demonstrated that the expected assembly time and defect rates could be reduced as much as 18% and 28%, respectively; Preference Analysis showed that such large improvements were highly unrealistic. Together, these four analyses contributed to a better understanding of how best to improve the design of the system.

Despite the added insight provided by these analyses, opportunities still existed for misinterpreting the results presented here. For example, Sensitivity Analysis showed that total assembly time was very sensitive to the nozzles' input variables. Without further investigation, it might have been assumed that extra effort should have been devoted to the proper design of the nozzles. However, it turns out that the nozzles' location in the assembly sequence of the vehicle was much more important than changing their design. Fortunately, the third and fourth columns of Table 4.8 suggested that modeling results were much less sensitive to the design of the nozzles than to other factors.

Regardless, several recommendations can be made based on the results of this case study. First, any attempts to reduce total assembly time and assembly defects for the washer/wiper system should begin with efforts to: (1) reduce fasteners while ensuring functional equivalence within the context of vibration during vehicle operation and (2) ease the insertion of the reservoir, motor and linkage, and hoses. Second, if assembly improvements over the baseline system are critical, attempts to reduce assembly time and defects for the new washer/wiper system should be considered early in design. Though design teams tend to prefer design scenarios that lead to relatively fast and correct assembly, without early attention to assembly, the new design is likely to take longer to assemble and have more defects than the previous design. Finally, any attempts to reduce assembly time and defects for the washer/wiper system should be analyzed carefully before making a final decision. In general, the automotive industry tends to focus heavily on ease of assembly while ensuring the robustness of the system during vehicle operation.

As a result, when automotive design teams prefer a design that is not easy to assemble, there is often a clear disadvantage to the easy to assemble design.

Chapter 5 – Conclusions and Recommendations

5.1. Discussion

The Design Forecasting methodology presented in Chapter 2 builds on the design uncertainty concepts of LCMD to effectively facilitate the use of DFX analyses earlier in the design of automobiles and other complex products. This is demonstrated by the DFFA and DFFE case studies presented in Chapters 3 and 4, respectively. This discussion begins by comparing the two case studies, emphasizing their differences and the conclusions drawn from those differences. It concludes with an evaluation of the Design Forecasting methodology (as presented in this dissertation) based on the design method evaluation criteria presented by Bras (1997).

5.1.1. Case Studies

In many ways, the DFFE case study in Chapter 3 and the DFFA case study in Chapter 4 are very similar. Both studies use design uncertainty methods to perform DFX analyses for a Ford C-class sedan. Both studies used mass equivalence models to estimate missing mass data. In addition, both studies use preference, constraint, and optima analyses to evaluate arrays of proposed design scenarios. However, in many ways the two studies are very different.

The driving force behind the case studies' differences is the use of DFA models (i.e., Modified Westinghouse and Barkan & Hinckley models) in the DFFA case study, rather than the DFE models (i.e., life cycle inventory and recyclability models) in the DFFE case study. As shown in Table 5.1, the DFA models used in the DFFA study required considerably more design data (in the form of input variables) than the DFE models in the DFFE study. Consequently, data collection and modeling for the DFFA study was more complex and time consuming.

The different types of models used in the case studies also caused the dominant sources of design uncertainty to be different in each case. Since the DFFE case study only considered material scenarios, choice of material was the dominant source of uncertainty. If other types of design scenarios had also been considered for the study, choice of shape would likely have been a dominant source of design uncertainty as well. For the DFFA study, choices of fit and assembly sequence were dominant sources of design uncertainty. Consequently, uncertainty in DFE metrics would likely decrease earlier in product development than uncertainty in the DFA metrics, since assembly sequence and fit are often determined late in design.

Table 5.1. Comparison of DFE and DFA Models Using Design Forecasting

Notable Differences	**DFE Models** Life Cycle Inventory and Recyclability Models	**DFA Models** Modified Westinghouse and Barkan & Hinckley Models	**Consequence**
Data Requirements – the amount of design data required to use models should, ideally, be low	Low	High	The higher the data requirements, the higher the complexity and cost of using the method.
Dominant Source(s) of Uncertainty – function, form (shape or architecture), material, fit, manufacture, other	Material	Fit, Other (Assembly Sequence)	The dominant source of uncertainty can greatly influence the times and rate at which design uncertainty decreases during product development.
Forecasting – uncertain data should, ideally, be *estimated*; however, sometimes uncertain data must be *refined* (i.e., constrained or shown preference)	Estimation	Refinement	Not having to identify estimation models for every attribute reduces the burden placed on the modeler, but increases the burden placed on the design team.

Finally, the larger data requirements for the DFA models used in the DFFA study made forecasting for that study more difficult than for the DFFE case study. Specifically, some of the input variables required for the DFA models could not be estimated using the equivalence and anecdotal models that had been sufficient for the DFFE case study. As a result, unknown data for the DFFA study often had to be refined (e.g., constrained or shown preference). Though refinement reduces modeling needs, it often requires the design team to provide additional information.

5.1.2. Evaluation

In this subsection, Bras' (1997) criteria are used to evaluate the strengths and weaknesses of Design Forecasting as a method for performing detailed DFX analyses earlier in complex product design:

- **Simple** – *the method should be easy to use.* The simplicity of using Design Forecasting is dependent upon the DFX domain of interest. As shown in the DFFE and DFFA case studies, the complexity of each activity depends on the amount and availability of information needed for the domain-specific assessment. From a modeling perspective, Design Forecasting is not very complex. However, performing scenario analyses without complete and certain scenario data from the design team can require the modeler to use models, anecdotal data, constraints, and design preferences to refine the data provided by the design team. Unfortunately, for automobiles and other products with hundreds or thousands of components, some complexity is unavoidable. Regardless, Design Forecasting is relatively simple for design teams to use.

- **Easily obtainable** – *the method should be available at a reasonable cost.* The identification of appropriate DFX models and data for Design Forecasting can be somewhat challenging. As a result, the initial cost of using Design Forecasting for a new product or domain is not zero. However, since models, data, and constraints can often be reused from one study to the next, the cost of using Design Forecasting quickly drops after the initial investment of time and effort.

- **Precisely definable** – *it is clear how the information can be evaluated.* From a design perspective, the ability to account for design uncertainty reduces ambiguity. Without recognizing design uncertainty, the design team has to evaluate its new design using assumptions and conjecture. Using Design Forecasting, if an attribute for a new design is uncertain, the design team has the ability to state: "that depends" or "that is uncertain." The design team is able to define information as precisely as appropriate for the product's stage of development. This is one of the major contributions of Design Forecasting to DFX.

- **Objective** – *two or more qualified observers should arrive at the same result.* By reducing ambiguity for the design team, it is more likely two separate teams will provide similar or identical evaluations of a new design. This is a clear benefit of Design Forecasting. However, since the method does provide some flexibility by accommodating a variety of data estimation methods, some variation in results can be expected. For example, the choice of using equivalence or anecdotal models to estimate missing mass data can affect the amount of uncertainty reflected in the results. Though Design Forecasting prescribes using the most accurate models, data, and constraints for a given situation, the method is inherently flexible.

- **Valid** – *the method should measure, indicate, or predict correctly what it is intended to measure, indicate, or predict.* The validity of Design Forecasting depends greatly on the validity of the underlying models used for an analysis. However, through the explicit inclusion of design uncertainty (including model uncertainty) in an analysis, the validity of the results is increased. In other words, it is an important finding of this research that during product development, the validity of any method that does not account for design uncertainty should be questioned.

- **Robust** – *the method should be relatively insensitive to changes in the domain of application.* Design Forecasting is proven robust in this research to estimate a range of uncertain DFE and DFA metrics for new automotive designs. However, the full robustness of the methodology is yet to be tested for a wide variety of DFX domains and is left for future research.

- **Enhancement of understanding and prediction** – *good metrics, models, and decision support tools should foster insight and assist in predicting process and product parameters*. The case studies presented in this dissertation demonstrate how Design Forecasting enhances understanding and prediction. The scenario analyses in both case studies offered insights into how much influence design teams have on the predicted performance of systems, relative to both DFE and DFA metrics. In addition, the sensitivity results presented in the DFFA study demonstrated how Design Forecasting offers additional insight for determining design priorities.

In conclusion, the Design Forecasting methodology developed in this research effectively facilitates the use of detailed DFX analyses earlier in complex product design. The method uses probabilistic design methods to supplement DFX analyses in a systematic, yet flexible, manner that allows rigorous review, improvement, and customization of individual, underlying models. In addition to benefits and contributions described to this point, the methodology developed here provides a sound framework for future, scholarly research.

5.2. Opportunities for Future Research

Numerous opportunities exist for refining and extending the research presented in this dissertation. Specifically, the ease and validity of using Design Forecasting may be improved:

- Additional case studies for a range of systems, industries, and DFX domains may be developed as a resource for Model Definition and Scenario Attribute Estimation.

- Additional preference data may be collected for complex product design to develop or validate preference models.

In addition, the benefits of using Design Forecasting may be increased:

- Additional methods may be developed to generate, constrain, and eliminate potential design scenarios.
- Additional DFX metrics may be estimated.
- Additional methods may be developed to use and communicate the information needed for Design Forecasting.

Many of these opportunities stem directly from the observations, strengths, and weaknesses of Design Forecasting identified in the previous section. Others presented in the following subsections are inspired by Ullman (2002).

5.2.1. Developing Additional Case Studies

Opportunities exist for developing new case studies for a range of systems, industries, and DFX domains; the objective being to amass a collection of methods, models, constraints, and data that can be reused in future studies. Such a collection would make Scenario Attribute Estimation and DFX Modeling and Assessment less time consuming by reducing the likelihood of having to identify new models, constraints, and data (the biggest hindrance of using the methodology). The best way to reduce this hurdle is to perform case studies designed to extend the bounds of experience using Design Forecasting.

Developing additional case studies provides additional opportunities as well. First, additional studies provide the opportunity to investigate the suitability of particular system models for Design Forecasting. For example, using two or more system models to estimate the same metric for the same system would provide insight into the sensitivity of modeling results to model selection. Second, additional studies provide the opportunity to investigate the compatibility of component and subsystem objectives. In other words, additional studies can focus specifically on identifying situations where "improvements" at the component level work against subsystem and system objectives.

5.2.2. Enhancing Preference Modeling

Preference data may be collected throughout complex product design to develop or validate preference models. For both case studies, the same, static preference model based on a 1/3/9 rating system was used to estimate the likelihood of individual design scenarios being chosen. However, by correlating final design decisions to preferences stated at different times during product development, more accurate preference models can be developed. This will improve prediction and the validity of preference analyses and, ultimately, lead to enhanced insight and understanding from Design Forecasting results.

5.2.3. Generating, Constraining, and Eliminating Design Scenarios

Section 2.1.2 describes options for generating new design scenarios during Goal and Scope Definition. In addition to there being opportunities to identify more and better options for generating new design scenarios, opportunities exist to develop simple evaluation methods to identify design scenarios that should probably be constrained or eliminated by the design team before moving on to Scenario Attribute Estimation and any scenario analyses. For example, any of the three methods identified by Fitch & Cooper (2003) for comparing materials based on energy consumption may be used to identify material scenarios that should probably be eliminated because they are likely to increase the life cycle energy consumption of a system. Eliminating and constraining scenarios early can reduce the wasted effort from collecting data for and evaluating unrealistic or undesirable design scenarios.

5.2.4. Identifying Unnecessary Data

Unnecessary Scenario Attribute Estimation can also be avoided by investigating the importance of missing data. By evaluating the sensitivity of modeling results to missing data, some data might prove to be unnecessary. In such situations, the unnecessary data may be ignored, eliminating some of the need for data estimation.

5.2.5. Estimating Additional Metrics

Thus far, Design Forecasting has been used to estimate DFE and DFA metrics for a product during design. However, the method may be extended to assess any metrics based on component or subsystem attributes such as mass, cost, material, fabrication methods, reliability, etc. For example, Booker (2001) prescribes methods for estimating product reliability using component and subsystem attributes. As shown by this research, an effective way to adapt the methodology for assessing additional metrics is to perform case studies for new DFX domains.

5.2.6. Using and Communicating Information

Even metrics or analyses for which Design Forecasting is an inappropriate modeling methodology may benefit from the availability of information collected as part of a study. For example, part deployment and manufacturing planning using Quality Function Deployment (Hauser & Clausing, 1988), Cost-Worth Analysis (Ishii et al., 1998), and concept selection methods (Pugh, 1991, 1996; Saaty, 1980, 1995; Ullman, 2003) can benefit from Design Forecasting data. Opportunity also exists for facilitating Failure Modes and Effects Analysis with Design Forecasting. By treating potential failure modes as component and subsystem attributes, failure modes may be communicated across generations of products and engineers may evaluate risk associated with individual design scenarios.

5.3. Conclusions

The Design Forecasting methodology presented here builds on the design uncertainty concepts of LCMD to effectively facilitate the use of DFX analyses earlier in the design of automobiles and other complex products. Specifically, Design Forecasting uses probabilistic design methods to supplement DFX analyses in a systematic, yet flexible, manner that allows rigorous review, improvement, and customization of individual, underlying models. Specifically, the method:

1. provides systematic techniques for modeling design uncertainty,
2. allows design teams to define information as precisely as appropriate for the product's stage of development,
3. reduces the effort required to collect data for models of complex products, and
4. offers benefits to product design beyond environmental assessment.

Further, the case studies presented in this dissertation:

1. demonstrate the applicability of design uncertainty to both DFE and DFA,
2. begin a collection of methods, models, constraints, and data that can be reused in future studies, and
3. provide a blue print for the future development of additional design uncertainty models.

The research described in this dissertation is significant because it:

1. defines a previously informal or even nonexistent process within design decision-making, and
2. provides a sound framework for future, scholarly research.

Glossary

Anecdotal models – Simple models and distributions based entirely on anecdotal data; refer to Section 2.1.3 for further description and illustration

Assembly rating – from the Modified Westinghouse Method, a normalized measure that compares the total assembly time with a reference time of 2.35 seconds per part

Attribute estimation models – models used to estimate uncertain or missing attributes for individual design scenarios

Constraint – a limit or other restriction imposed on one or more design scenarios; refer to Sections 2.1.3 and 4.1.3 for further description and illustration

Constraint Analysis – an extension of preference analysis used to estimate the influence of specific design decisions on individual system metrics; refer to Sections 2.3.3, 3.3.3, and 4.3.3 for further description and illustration

Design for X (DFX) – the process where the full life cycle needs of a product are addressed during the product's design; the goal being greater customer satisfaction through improved quality and reduced life cycle costs (Layendecker & Kim, 1993)

Design Forecasting – a broadly applicable framework for performing detailed DFX analyses earlier in complex product design

Design Forecasting for Assembly (DFFA) – a Design Forecasting methodology used to forecast assembly metrics for adaptive and variant designs during the development of complex products

Design Forecasting for Environment (DFFE) – a Design Forecasting methodology used to forecast environmental metrics for adaptive and variant designs during the development of complex products

Design preferences – preferences the design team has toward one or more design scenarios or toward controllable scenario attributes; refer to Sections 2.1.3 and 2.3.1 for further description and illustration

Design scenario – a potential design outcome pending one or more future design decisions; also known as a design concept

Design scenario matrix – a matrix used identify, organize, and illustrate alternative design scenarios for a component or system; refer to Section 2.1.2 for further description and illustration

Design uncertainty – uncertainty related to knowledge of a product design's final attributes (e.g., materials, geometries, manufacturing processes)

Equivalence models – mathematical models that use physical relationships to ensure the functional equivalence (i.e., equivalent strength, stiffness, fatigue life, etc.) of two or more competing design scenarios; refer to Sections 2.1.3 and 3.1.3 for further description and illustration

Functional units – measures of the functional output of the product system (ISO, 1998) used to ensure a fair comparison of design scenarios

Life cycle modeling – the use of quantitative or qualitative models to evaluate the life cycle performance or cost of a product or system

Life Cycle Modeling for Design (LCMD) – a systematic life cycle modeling methodology that may be used to forecast the potential life cycle environmental impacts of an adaptive or variant design during the conceptual, embodiment, and detailed design of a complex product

Model uncertainty – uncertainty related to how well a model represents the true nature of a system

Modified Westinghouse Method – a Design for Assembly methodology adapted from the original Westinghouse Method (Sturges & Kilani, 1992) in an attempt to decrease complexity and the time necessary to evaluate assembly concepts

Optima Analysis – the process for identifying optimal system scenarios; refer to Sections 2.3.4 and 3.3.1 for further description and illustration

Part efficiency – from the Modified Westinghouse Method, the ratio of the number of parts in the assembly concept to the theoretical minimum number of parts

Preference Analysis – the process of estimating the probable characteristics of a design (in terms of system metrics), given the design preferences of the design team and other stakeholders; refer to Section 2.3.1 for further description

Recyclability rating – an estimate of the percentage of a vehicle's mass likely to be recycled at its end-of-life

Scenario key – the minimal set of design attributes necessary to differentiate between design scenarios; refer to Section 2.1.2 for further description and illustration

Sensitivity Analysis – the process of identifying the scenario attributes and other modeling variables that most significantly influence individual system metrics; refer to Sections 2.3.2 and 4.3.2 for further description and illustration

System evaluation models – models used to estimate system level metrics (e.g., life cycle inventory models or the Barkan & Hinckley conformance quality model)

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Appendix A

Life Cycle Modeling for Adaptive and Variant Design

Part 1: Methodology[1]

List of Figures

List of Tables

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[1] This article has been accepted for publication in Research in Engineering Design (Springer-Verlag, Berlin, Germany), pending final edits. Refer to the journal for the final version of this article.

Life Cycle Modeling for Adaptive and Variant Design

Part 1: Methodology[2]

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Abstract

Life Cycle Modeling for Design (LCMD) facilitates the incorporation of life cycle modeling into product design by including consideration of uncertainty in a product's final specifications. The methodology combines Life Cycle Assessment with probabilistic design methods in a way that reduces information needs. Specifically, this paper presents steps for: 1) generating arrays of design scenarios that communicate the range of designs being considered by a design team, and 2) using attribute estimation models to estimate missing data for those design scenarios. This paper also suggests several analyses for evaluating these arrays of design scenarios using life cycle inventory models. The automotive case study presented in Part 2 of this article develops these

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scenario analyses (Optima Analysis, Preference Analysis, and Constraint Analysis) further and demonstrates one application of LCMD.

Keywords: Design Uncertainty, Scenario Analysis, Probabilistic Design, Life Cycle Assessment, Design for Environment, Adaptive Design

1. Introduction

Life cycle modeling is the use of quantitative or qualitative models to evaluate the life cycle performance or cost of a product or system. Typically, life cycle models are used to create inventories of material and energy flows in terms of physical units such as kilograms and joules. Life cycle modeling may also quantify cost, manufacturing or environmental impact, or other consequences resulting from the extraction, production, transformation, consumption, recycling, and disposal of materials and energy within a system. Some examples of life cycle modeling include the use of mass and energy flow models for a product in Life Cycle Assessment (LCA) (SETAC, 1991; ISO, 1997) and the use of production and service models in Life Cycle Costing (Brown & Yanuck, 1985; Fabrycky & Blanchard, 1991). Life cycle models may also be used to support quality and risk analyses such as Failure Modes and Effects Analysis (FMEA) (Ford, 1988; Stamatis, 1995). Life cycle modeling is an important Design for Environment (DFE) tool because it facilitates consideration of impacts to health, natural resources, and the Environment in the design process.

Despite its importance as a DFE tool, life cycle modeling still finds limited use during the design of complex products such as automobiles. Data collection and modeling complexity are primary reasons for this lack of use in all different types of design: variant design, adaptive design, and original design (Pahl & Beitz, 2001; as defined by Otto & Wood, 2001). One specific reason, related to data collection, stems from the existence of *design uncertainty* – uncertainty related to knowledge of a product design's final attributes (e.g., materials, geometries, manufacturing processes). As shown in Figure A1, design uncertainty decreases during product design and is largest for entirely original designs. This research focuses on adaptive and variant design because complex system designs, especially those for automobiles, are most often adaptations or variants of previous designs.

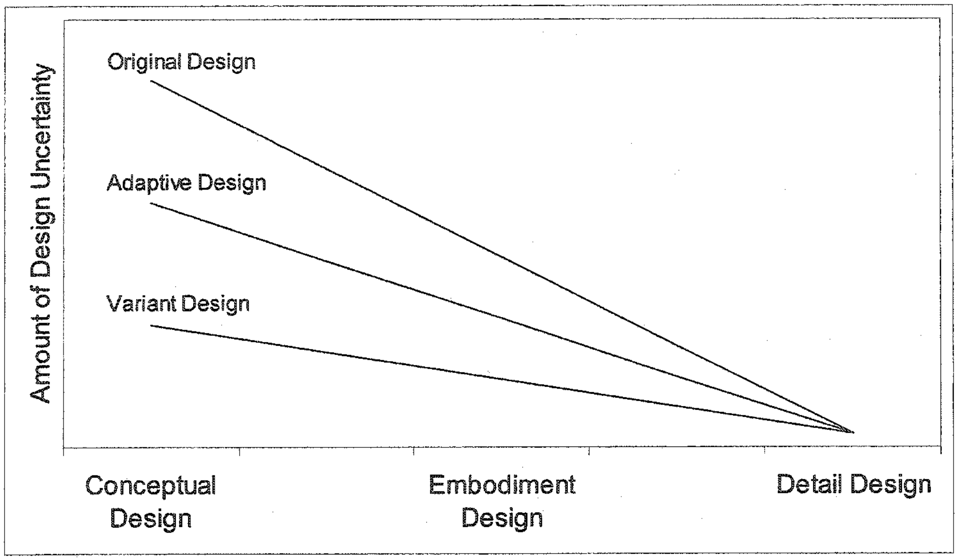

Figure A1. Decreasing Design Uncertainty through Product Design

Existing Methods

Numerous authors have proposed methodologies for incorporating life cycle modeling into product design. Table A1 compares eleven existing methods identified in engineering and scientific literature. The methods differ in the motivation for modeling, the scope of the life cycle analyzed, the type of models used, the phase(s) of design they support, and the treatment of uncertainty. Specifically, environmental assessment is the primary impetus for many of the design methodologies in Table A1, while analysis of production efficiency and cost, and concurrent design motivate others. When environmental assessment is the motivation for modeling, one or more of five levels of appraisal are included:

1. creating an *inventory* of material and energy use and waste,

2. *classifying* material and energy use and waste in relation to the damage or costs they might cause,

3. *characterization* of the amount of damage or costs,

4. *normalization* or comparing the amount of damage or cost to that at the corporate, regional, national, or global levels, and

5. *weighting* or rating of the importance of the potential damage or costs.

When concurrent design is the motivation for life cycle modeling, the results can be used at the same time for environmental, economic, and other assessments (Kalyan-Seshu et al., 1998; Borg et al., 2000).

In addition to different motivations, the methodologies presented in Table A1 vary in recommended and applied scope. Most may be applied to the entire life cycle of a product. However, the scope of the methodology presented by Barton & Love (2000) is limited to production and distribution activities, from gate to gate. Also, although the majority of methodologies may be used for cradle-to-grave analyses, some of the examples used to demonstrate these methodologies in their respective papers are limited to simpler, cradle-to-gate analyses.

In addition to scope, it is important to consider the types of models and results proposed for each methodology. Most of the life cycle modeling methodologies presented in Table A1 use analytic modeling to simulate material, energy, and economic flows throughout a system's life cycle. Some, however, use parametric and knowledge-based modeling to produce results without simulating flows.

Also, most of the methodologies in Table A1 do not allow for easy assessment of numerous design scenarios. Within this context, a *design scenario* represents the outcome of a series of design decisions. For example, during conceptual design, product developers must evaluate and select from numerous design concepts such as steel vs.

aluminum vehicle frames and gasoline vs. electric powertrains. Each legitimate concept, or combination of concepts, is a potential design scenario.

Table A1. Life Cycle Modeling in Product Design

Authors	Title	Goal	Treatment of Uncertainty	LC Scope LC Example	Modeling Techniques	Simulated LC Flows	Environmental Impact Quantification	Appropriate Stage(s) of Design
Azapagic & Clift (1999)	Life Cycle Assessment and Multiobjective Optimisation	Process Parameter Optimization	N/A	Cradle to Grave Cradle to Gate	Analytic Modeling	Economic, Energy, Material	Characterization	Detail Design
Barton & Love (2000)	Design Decision Chains as a Basis for Design Analysis	Whole Business Simulation	N/A	Gate to Gate Gate to Gate	Analytic Modeling	Economic	N/A	Embodiment Design, Detail Design
Borg et al. (2000)	Exploring Decisions' Influence on Life-Cycle Performance to Aid "Design for Multi-X"	Consequence Identification for Design Decisions	N/A	Cradle to Grave No Example	Knowledge-Based Modeling	N/A	N/A	Embodiment Design, Detail Design
Borland et al. (1998)	Integrating Environmental Impact Assessment into Product Design	Quantitative Environmental Assessment	Data Uncertainty & Variability	Cradle to Grave Cradle to Gate	Analytic Modeling with Monte Carlo Simulation	Energy, Material	Characterization	Embodiment Design, Detail Design
Eisenhard et al. (2000)	Approximate Life-Cycle Assessment in Conceptual Product Design	Approximate, Quantitative Environmental Assessment	N/A	Cradle to Grave Cradle to Grave	Automated Neural Networks	N/A	Characterization	Conceptual Design
Graedel & Allenby (1996)	Design for Environment: Section 9.2 – Efficient Assessment Tools	"Semi-qualitative" Environmental Assessment	N/A	Cradle to Grave No Example	N/A	N/A	Weighting	Conceptual Design
Jackson & Wallace (1997)	A Modular Method for Representing Product Life-Cycles	Time-Dependent, Quantitative Environmental Assessment	N/A	Cradle to Grave Cradle to Grave	Analytic & Parametric Modeling	Energy, Material	Characterization	Detail Design
Kalyan-Seshu et al. (1998)	Integrating DFX Tools with Computer-Aided Design Systems	Integration of DFX and CAD	Unspecific Recognition of Uncertainty	Cradle to Grave Cradle to Grave	Unclear	N/A	Weighting	Detail Design
Nielsen & Wenzel (2002)	Integration of Environmental Aspects in Product Development: A Stepwise Procedure Based on Quantitative Life Cycle Assessment	Quantitative Environmental Assessment	Design Uncertainty	Cradle to Grave Cradle to Grave	Analytic Modeling	Energy, Material	Normalization	Embodiment Design, Detail Design
Regnier & Hoffman (1998)	Uncertainty Model for Product Environmental Performance Scoring	Probabilistic, Quantitative Environmental Assessment	Data Uncertainty & Variability, Model Uncertainty	Cradle to Grave Cradle to Grave	Monte Carlo Simulation	N/A	Weighting	Embodiment Design
Umeda et al. (2000)	Study on Life-Cycle Design for the Post Mass Production Paradigm	Optimal Life Cycle Selection	Unspecific Recognition of Uncertainty	Cradle to Grave Cradle to Grave	Analytic Modeling	Economic, Energy, Material	Inventory	Detail Design

When multiple design scenarios are not assessed, the use of life cycle modeling in conceptual design may not only be difficult but also inappropriate. In fact, only the methodologies presented by Eisenhard et al. (2000) and Graedel & Allenby (1996) are expressly targeted for use in conceptual design. Specifically, the limited number of design variables used by Eisenhard et al.'s automated neural network model allows for quick evaluation of numerous, divergent concepts. However, as concepts converge during design, the effectiveness of the methodology decreases because the model is unable to reliably differentiate between design alternatives. Thus, the methodology presented by Eisenhard et al. is not appropriate for use during embodiment and detail design. Also, the matrix method presented by Graedel & Allenby is not detailed enough to reliably differentiate between similar design alternatives (e.g., among metals or among thermoplastics) and is not appropriate for use during embodiment and detail design.

Of the articles presented in Table A1, only five cite the need to accommodate uncertainty in life cycle modeling. Most generally, Umeda et al. (2000) and Kalyan-Seshu et al. (1998) state that there is a need to handle uncertainty and to understand its effects. Others provide more particular instruction related to data uncertainty (related to the true values of input data), data variability (related to the heterogeneity of data values over time, space, or different members of a population), model uncertainty (related to how well a model represents the true nature of a system), and design uncertainty (related to knowledge about the final product design such as what materials will be used).

Specifically, Borland et al. (1998) allows the use of both discrete and continuous input variables to accommodate both data uncertainty and variability. Regnier & Hoffman (1998) progress one step further by also incorporating model uncertainty. Finally, among the methodologies characterized in Table A1, only Nielsen & Wenzer (2002) addresses the issue of design uncertainty. The authors propose an iterative series of analyses that become increasingly focused and detailed as information becomes available. This allows assessments to be performed throughout the product design process. However, Nielsen & Wenzer provide no specific methods for estimating missing design information or for capturing design uncertainty; making assessment during conceptual design difficult.

Difficulty in capturing design uncertainty is one reason detailed life cycle models are rarely used in the design of complex systems such as automobiles. Under design uncertainty, the exact materials, geometries, and other features of the product are unknown. As a result, the exact material flows and life cycle processes to be analyzed are also unknown. Without a systematic method for modeling design uncertainty, the life cycle modeler has two choices:

1. wait until the new design is nearly complete, thus significantly reducing the usefulness of the modeling results; or
2. make numerous assumptions about the final product design, thereby disguising the amount of influence design decisions may have on the final cost and performance of the system.

Both options are reasonable, but being able to perform analyses throughout product design with a minimal number of hidden assumptions is preferable for effective decision-making.

This research seeks to develop a systematic life cycle modeling methodology that may be used effectively within the basic framework presented by Nielsen & Wenzel (2002). For effective use during conceptual design, life cycle modeling must allow for easy assessment of numerous design scenarios (e.g., scenarios such as steel vs. aluminum vehicle frames and gasoline vs. electric powertrains). Following conceptual design, evaluation of multiple design scenarios is still necessary during embodiment design; however, the scenarios under consideration are typically less numerous and varied (e.g., extruded vs. cold-rolled reinforcing beams and steel vs. aluminum oil pans). As a result, design uncertainty is smaller and higher accuracy is required for modeling results. Finally, during detail design, design uncertainty is minimal and modeling accuracy is of greatest importance.

Parts 1 and 2 of this article, together, present a systematic life cycle modeling methodology that accommodates design uncertainty while curtailing the information required from product designers during conceptual design. Specifically, Part 1 presents steps for developing arrays of design scenarios that communicate the range of designs being considered by a design team, and Part 2 presents several analyses for evaluating these arrays of design scenarios using life cycle models. Automotive examples are used throughout the article to illustrate the methodology.

2. Methodology

Life Cycle Modeling for Design (LCMD; Figure A2) is a methodology proposed here to forecast the potential life cycle cost and/or environmental impact of an adaptive or variant design for complex products during conceptual, embodiment, and detailed design. The methodology combines existing product design and LCA methods, and incorporates the four phases recommended by LCA guidelines (ISO, 1997; Curran, 1996; Klöpffer & Hutzinger, 1997): (1) goal and scope definition, (2) inventory analysis, (3) impact assessment, and (4) interpretation.

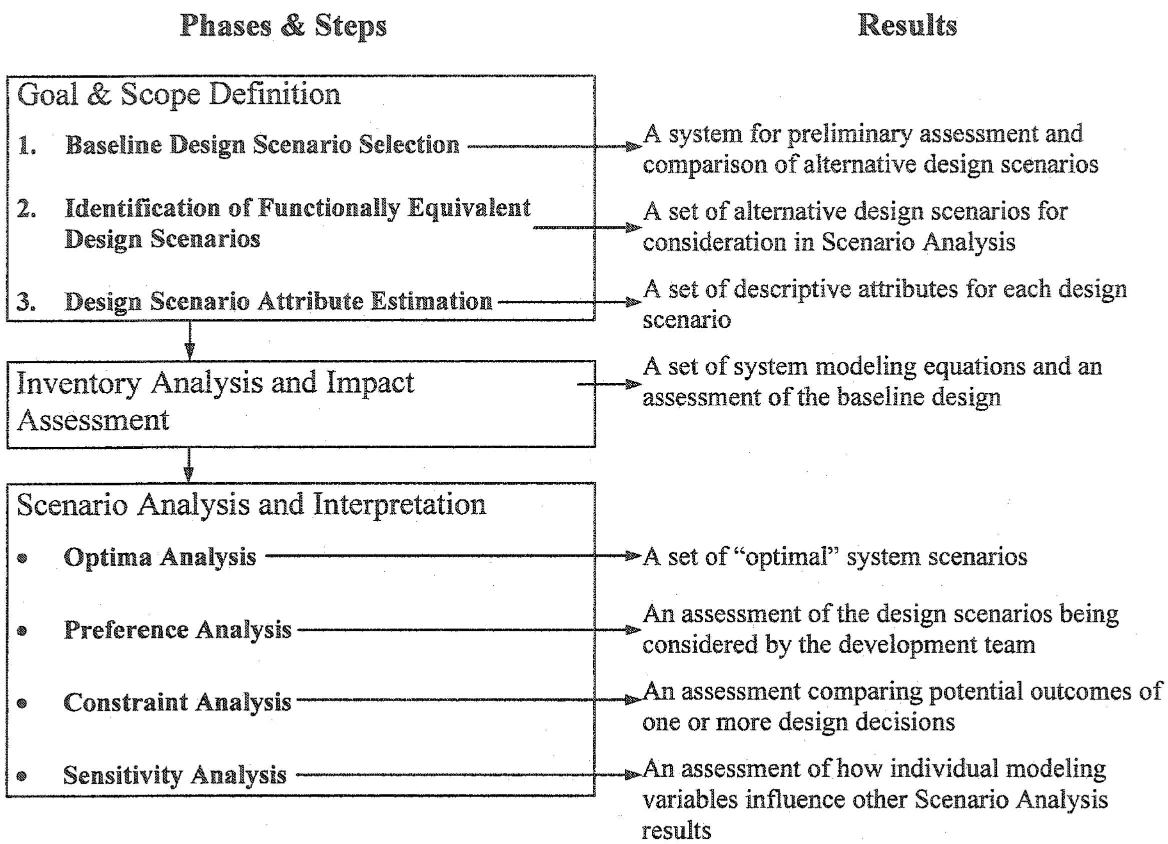

Figure A2. Life Cycle Modeling for Design Methodology

2.1. PHASE 1: Goal and Scope Definition

In this phase, the goal and scope of the life cycle model are defined for the product of interest.

In LCMD, although the goal and scope for each case study will vary, there are several common themes. First, the primary goal of each study is to identify design scenarios that will likely improve cost and environmental performance. Second, the intended audience of analysis results includes designers and manufacturers, their suppliers, and those who recycle, treat, and dispose of materials at the end of a product's life. The reason for carrying out studies using LCMD is to help guide product decision-making towards more cost effective and environmentally conscious results. Finally, the scope of an LCMD analysis is intended to be the life cycle, from cradle-to-grave.

What differ in LCMD case studies are the:

1. *Functional units* – The measures of the functional output of the product system (ISO 1998). For the example used throughout this article, the functional unit is "one complete service life time distance (120,000 miles)" (Sullivan et al., 1998) for a Ford C-class sedan.

2. *Cost and environmental performance measures calculated* – Specifically, costs can include conventional, potentially hidden, contingent, and image/relationship costs (as defined in EPA, 1995). In addition, environmental performance can be measured using inventory metrics (e.g., carbon dioxide emissions, particulate matter emissions, iron ore consumption, and natural gas consumption) and/or impact indicators (e.g., global warming potentials, ozone depletion potentials, and mass percent recycled content). For this article's Ford C-class sedan example, performance is measured in terms of: (1) *reductions* in direct materials and production cost, vehicle mass, vehicle fuel consumption, drive cycle tailpipe emissions, and resource use and emissions in material production, operation, and for the life cycle, and (2) *increases* in the recyclability of materials in the vehicle.

3. *Range of design scenarios modeled* – As stated previously, the goal of each study is to identify design scenarios that will likely improve cost and environmental performance. In LCMD, those scenarios are identified by evaluating the full array of design scenarios being considered by the design team. Generating the array of scenarios to be evaluated involves three steps:

   Step 1. Baseline Design Scenario Selection

   Step 2. Identification of Functionally Equivalent Design Scenarios

   Step 3. Design Scenario Attribute Estimation

The following subsections describe each of these steps in further detail.

2.1.1. STEP 1: Baseline Design Scenario Selection

Typically, for an adaptive or variant design, a baseline product is predetermined. However, if the most appropriate baseline product is not immediately obvious, care should be taken to select a product with similar architecture and functional requirements to the expected new design. An existing design that may share a considerable number of parts with the new design is ideal.

If no single, existing product is available or appropriate, a hybrid of multiple products may be preferred. Given a physical decomposition of a system (e.g., Figure A3), existing subsystem and component designs can be used as baseline subsystem and component design scenarios. For example, the body design of an existing C-class sedan may be selected as a baseline subsystem scenario. Alternatively, existing designs for components such as reinforcing beams and energy absorbers can be selected from multiple body designs to be baseline component scenarios.

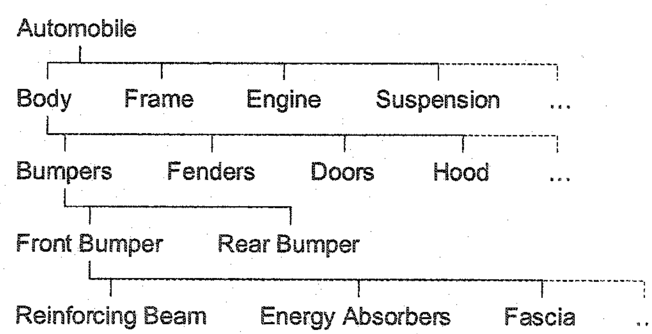

Figure A3. Partial Physical Decomposition of an Automobile

For the example used throughout this article, the baseline product is an existing Ford C-class sedan. Component data for the sedan were obtained from Ford benchmarking and teardown reports. At Ford, benchmarking reports compare component costs for two different vehicles and teardown reports document the material composition and recyclability of components for a single vehicle. Table A2 provides a sample of the component data used for the baseline design scenario (proprietary cost data omitted). In the table, *reference flows* are the amount of product materials necessary for the functional unit and the *manufacturing plan* includes the processes used to manufacture each component.

Table A2. Sample Components for the Baseline Scenario

	Reference Flows			Manufacturing Plan	
Component Name	**Mat'l**	**Part mass (kg)**	**Quantity in vehicle**	**Process1**	**Process2**
DOOR FUEL FILLER OPENING	PA	0.12	1	injection molding	painting
DUCT ASY REGISTER RH	PE	0.155	1	blow molding	
MOULDING FRONT DOOR OUTSIDE FIN PANEL RH/LH	ALU	0.07	2	stamping	painting
PLATE TRANS GEARSHIFT SELECTOR	FE	0.13	1	sintering	
REINFORCEMENT PASSENGER AIRBAG SUPPORT	PP	0.49	1	injection molding	sonic welding
SUPPORT TRANSAXLE MOUNTING	ALU	0.795	1	die casting	
TRAY ASY BATTERY	PP	0.7	1	Stamping	painting
Etc.					

2.1.2. STEP 2: Identification of Functionally Equivalent Design Scenarios

This step involves compiling a list of design scenarios under consideration by the design team. For each component or subsystem being considered for redesign, alternative design scenarios are proposed by the design team that are intended to perform the same function (e.g., move the same load at the same speed under the same conditions) as the baseline scenario but with some potential improvement (e.g., lower cost, lighter weight, or fewer defects).

For the Ford C-class sedan mentioned earlier, vehicle components were considered for redesign by material substitution. Table A3 contains an example set of component scenarios for the design of a battery tray assembly. As shown, the baseline battery tray assembly is made from polypropylene (PP) at a mass of 0.7 kg; and acrylonitrile butadiene styrene (ABS), polyamide (PA), polycarbonate (PC), and polyethylene (PE) are alternatives being considered. For this example, the scenario key includes the type of materials and manufacturing plan and may be used to distinguish between scenarios. The amount of information in the scenario key should reflect the level of detail under consideration by the design team at any given time. For example, early in the design of a component, product developers may be considering different materials without consideration of the fabrication methods. In this situation, each scenario key may only contain the name of a material under consideration for that component. Later, as design of the new product progresses, additional information may be added to the scenario key to more clearly distinguish between competing scenarios.

Table A3. Component Scenarios for Battery Tray Assembly

TRAY ASY BATTERY		Baseline Scenario	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Scenario Key	Type of Materials	PP	ABS	PA	PC	PE
	Manufacturing Plan	Injection molding, painting	Injection molding, painting	Injection molding, painting	Injection molding, painting	Injection molding, painting
Scenario Attributes	Mass	0.7 kg	Information not provided by product design team			
	Recyclability Category[3]	1				

In addition to the information contained in the scenario key, each scenario is also described by a list of attributes that will be used later by system evaluation models (specifically, life cycle inventory models) to estimate system level metrics. When identifying functionally equivalent scenarios, the design team may or may not know values for each scenario's attributes. Early in design, these attributes may only be known for the baseline scenario (as shown in Table A3). However, as design scenarios are developed, the design team may determine some of these attributes. During this step, the design team only provides attributes known by the team at that time.

2.1.3. STEP 3: Design Scenario Attribute Estimation

Once the list of design scenarios has been compiled for each component or subsystem being considered for redesign, missing data for each new scenario must be estimated.

[3] Recyclability categories are used by automotive companies to classify components by their potential for recycling or energy recovery after use.

The most accurate and time consuming method for doing so is to redesign each component and subsystem, solicit quotes from in-house manufacturing representatives and suppliers, and test prototypes to determine performance attributes. Doing so significantly decreases design uncertainty. However, performing this method for every design scenario is impractical.

Another option is to use engineering models to estimate missing attributes based on anecdotal data and fundamental relationships. Constraining each alternative scenario to be functionally equivalent to its associated baseline scenario simplifies this estimation. Specifically, functional equivalence allows the use of relative modeling methods such as Cooper's (2003) "mass equivalents" methodology in addition to absolute modeling methods. Though estimating missing attributes using engineering models introduces model uncertainty (hence, design uncertainty is not eliminated), it allows LCMD to be performed earlier in product design while reducing the need for a large data collection effort.

The remainder of this subsection (2.1.3) describes example methods for estimating:

- missing recyclability categories, mass data, and cost data; and
- model uncertainty.

Recyclability Categories

For each component considered for the redesign of the sedan, recyclability categories were determined using corporate recyclability criteria. There are four categories: Category 1 components are currently recycled today; Category 2 components may potentially be economically recycled in the future; Category 3 components are made of organic materials and have sufficient energy density for potential energy recovery; and Category 4 is the category used for all remaining components and assumes landfill disposal after use.

Mass Estimation

For fair comparison of alternative system scenarios, each component scenario must be functionally equivalent (i.e., equivalent strength, stiffness, fatigue life, etc.) to the associated baseline component. Given the array of materials considered for the redesign of the sedan, three methods were considered for determining the mass of functionally equivalent components made from the substitute materials: (1) redesign each component, (2) use an anecdotal model, or (3) use a mass equivalence or substitution factor model.

Option 1. *Redesign Each Component* – One way to determine the mass of functionally equivalent components is to redesign every component in each of the potential substitute materials, estimate the volume of material in each new design, and estimate the mass given the density of each material. Although this method ensures the accuracy of the mass estimation at the component and vehicle levels, the method requires too much development of each component scenario to be useful during product design.

Option 2. *Use an Anecdotal Model* – As a second mass estimation option, a model based on anecdotal data may be used. Davis (1991) provides a set of actual material substitution data for five vehicles: a small, front wheel drive (FWD) car; an intermediate, FWD car; a sporty, rear wheel drive car; a large, FWD car; and a luxury, FWD car. Figure A4 presents a histogram of the Davis data. The histogram suggests that magnesium components typically had 30-40% less mass than functionally equivalent aluminum components. An anecdotal model based solely on a normal approximation of this data would estimate the mass of a magnesium component to be 66.9% of the aluminum mass, with a standard deviation of □ = 10.2%. The advantage of such an anecdotal model is that it requires very little information (only mass) about the specific component being analyzed. The disadvantage is that the model may only be applied to materials for which anecdotal data exist.

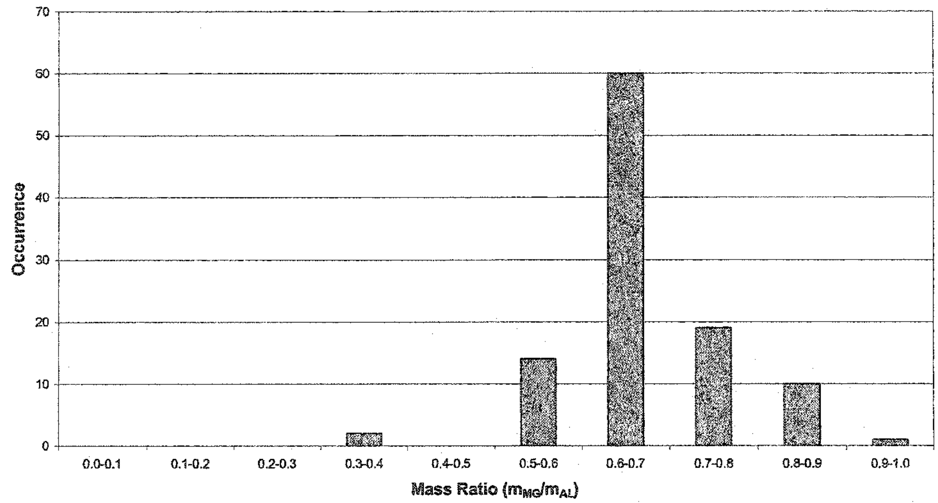

Figure A4. Relative Mass Histogram for Magnesium and Aluminum Components (data from Davis, 1991)

Option 3. *Use a Mass Equivalence or Substitution Factor Model* – As a third option for the determination of the mass of functionally equivalent components, Cooper (2003) provides a methodology based on the material selection performance indices presented by Ashby (1999). Cooper's mass equivalence method estimates the mass required to provide equivalent mechanical performance between a baseline material and a substitute for a certain component. For example, supposing the component of interest is a tie in tension, the mass (or "mass equivalent") of each material is the mass required to carry the same tensile load, at the same length, for the same factor of safety. Thus, when comparing two materials (e.g., material *j* and baseline material *b*) for the design of the tie, the following relationship may be derived:

$$m_j = \frac{\left(\dfrac{\sigma_b}{\rho_b}\right)}{\left(\dfrac{\sigma_j}{\rho_j}\right)} m_b = \frac{\sigma_b \rho_j}{\rho_b \sigma_j} m_b \qquad \text{<Equation 1>}$$

where: m_b = mass of tie made of material *b* (kg)

m_j = mass of tie made of material *j* (kg)

σ_b = failure strength of material *b* (Pa)

σ_j = failure strength of material *j* (Pa)

ρ_b = density of material *b* (kg/m^3)

ρ_j = density of material *j* (kg/m^3)

Equation 1 allows the mass of a functionally equivalent substitute material, m_j, to be estimated given the mass of the baseline material, m_b, for a tie in tension. Equation 1 also applies to numerous other components and loading conditions, including any components for which specific strength, σ/ρ, is an important criterion for material selection. According to Anon (1991) and Faller (2001), specific strength is an important material property within the context of automotive components because of the drive for vehicle weight reduction. Table A4 contains material properties and mass equivalence values (based on Equation 1) for the materials considered in this example. For components for which specific strength is not an appropriate criterion for material selection (e.g., torsion bars with torque, stiffness, and length specified), Cooper's (2003) mass equivalence method may be used to derive relationships similar to Equation 1.

Table A4. Material Properties and Mass Equivalence Data

	Metals				Plastics				
	Low Carbon Steel	Ductile Cast Iron	Wrought Aluminum	Wrought Magnesium	ABS	PA	PC	HDPE	PP
Tensile Strength (MPA)	463	675	327	330	46.5	63	65.5	35	32.5
Density (kg/m^3)	7850	7150	2680	1850	1050	1085	1230	958	905
Specific Strength (kN*m/kg)	59.0	94.4	122	178	44.3	58.1	53.3	36.5	35.9
Mass Equivalence Relative to Low Carbon Steel (based on Equation 1)	1.00	0.63	0.48	0.33	1.33	1.02	1.11	1.62	1.64

The primary benefit of using mass equivalence models for estimating missing data for alternative component scenarios is that no material-specific, anecdotal, design data is required. In other words, component mass may be estimated for any material with known physical properties. Therefore, previous design experience using the material of interest is not necessary.

Cost Estimation

Having estimated mass and recyclability attributes for the new metal and plastic component scenarios, missing cost data were estimated using Equation 2:

$$c_{ij} \approx c_{ib} - C_{ib}m_{ib} + C_{ij}m_{ij} \qquad \text{<Equation 2>}$$

where: c_{ij} = cost of scenario j for baseline component i

c_{ib} = the cost for baseline component i

C_{ib} = per unit cost of the baseline material for baseline component i

m_{ib} = the mass of baseline component i

C_{ij} = per unit cost of the scenario j material for baseline component i

m_{ij} = mass of scenario j for baseline component i

Estimating Model Uncertainty

Table A5 presents the component scenarios for the battery tray assembly without any consideration for the uncertainty of estimated scenario attributes. LCMD can be performed using deterministic values, however, doing so underestimates design uncertainty. In other words, using the values presented in Table A4 suggests that design team knows precisely the final mass for each potential design of the battery tray assembly. By estimating the uncertainty associated with each model (i.e., *model uncertainty* – lack of knowledge about how well a model represents the true nature of a system) used to estimate missing scenario attributes, LCMD can better capture the amount of uncertainty the design team has in the attributes of the final design (i.e., design uncertainty). Capturing design uncertainty in LCMD can help the design team better understand the influence it has over the product's final attributes, environmental performance, and cost.

Table A5. Deterministic Component Scenarios for Battery Tray Assembly[4]

BATTERY TRAY ASSEMBLY		Baseline Scenario	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Scenario Key	Type of Materials	PP	ABS	PA	PC	PE
	Manufacturing Plan	Injection molding, painting	Injection molding, painting	Injection molding, painting	Injection molding, painting	Injection molding, painting
Scenario Attributes	Mass	0.7 kg	0.57 kg	0.44 kg	0.47 kg	0.69 kg
	Recyclability Category	3	3	3	3	3

Referring to the two attributes shown for each scenario in Table A5, model uncertainty was only estimated for mass. The discrete categorization of recyclability based on simple corporate criteria made the recyclability categories estimated for each scenario highly reliable. As a result, the recyclability categories for each scenario were assumed to be correct.

As for mass, the purpose of estimating model uncertainty was to determine approximately how accurate the mass estimates were for each of the batter tray assembly's design scenarios. To estimate model uncertainty for the mass equivalence model based on specific strength, anecdotal material substitution data was collected from Society of Automotive Engineers (SAE) literature and compared to estimates using Equation 1 (comparison shown in Figure A5). Though a review of SAE literature identified 411 material substitution examples in 14 articles, only 13 data points in four articles (Nassar, 1991; Sindrey, 1999; Shim et al., 2000; Koike et al., 2000) included sufficient information for the analysis.

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[4] Cost values omitted due to the proprietary nature of the information.

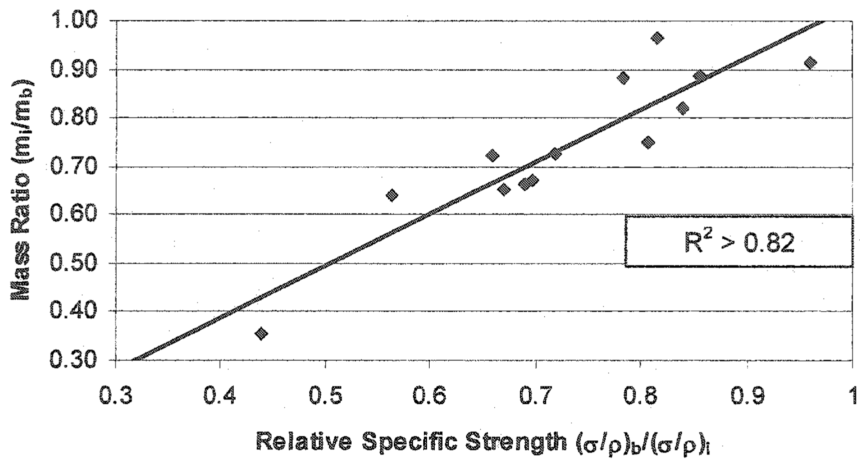

Figure A5. Relative Mass vs. Specific Strength for Example Automotive Components

By defining error for the mass equivalence model based on specific strength as

$$e \equiv \frac{m_{j(\mathrm{actual})}}{m_{b(\mathrm{actual})}} - \frac{m_{j(\mathrm{predicted})}}{m_{b(\mathrm{predicted})}} = \frac{m_{j(\mathrm{actual})}}{m_{b(\mathrm{actual})}} - \frac{\sigma_b \rho_j}{\rho_b \sigma_j} \qquad \text{<Equation 3>}$$

and using the previous set of sample data to calculate a set of error values, the distribution shown in Figure A6 was generated. Though the sample data set is too small to make precise conclusions about the uncertainty of using this mass equivalence model to estimate missing data, it does provide an approximation of model uncertainty. To put this uncertainty into perspective: If modeling error was assumed random and the error distribution was normally distributed, the standard deviation of the distribution would be 0.068. Regardless, the largest error calculated using the sample data set was less than 14%.

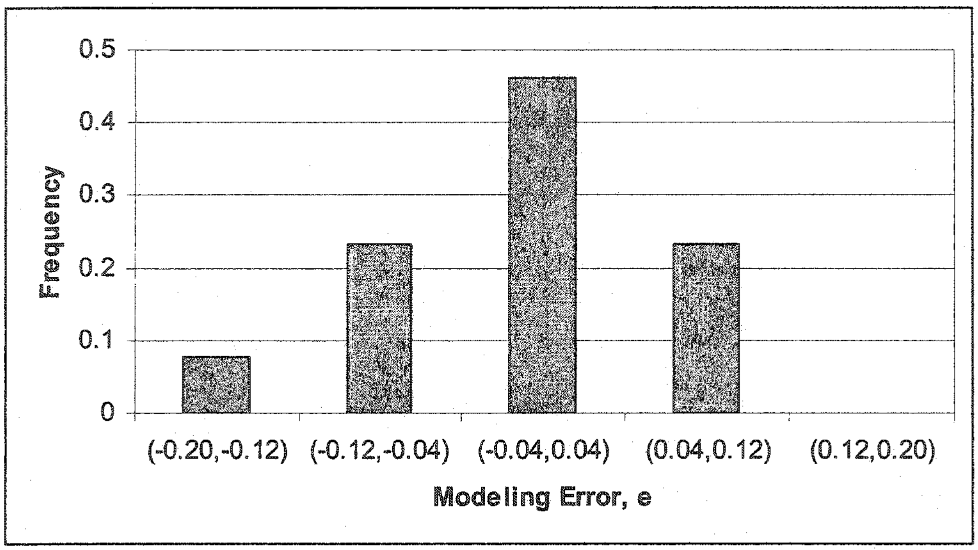

Figure A6. Modeling Error Distribution for Example Automotive Components

A more comprehensive survey of functionally equivalent component designs would undoubtedly reveal numerous exceptions to the trend show in Figure A5, especially if a review of plastic components was included (this is left for future research). However, this correlation along with Faller's (2001) (also Anon, 1991) identification of specific strength as an important material property within the context of automotive components (because of the drive for vehicle weight reduction) suggest that, in many cases, relative specific strength may reasonably be used to estimate the relative masses of two functionally equivalent, mechanical, automotive component designs.

After estimating model uncertainty, the mass estimates in Table A5 were revised to reflect this uncertainty. Though normally distributed values were used in this example, Table A6 presents a range for each scenario's mass attribute. Also, for this example, similar information was developed for each of the components considered for redesign, using the original material as the baseline for each component.

Table A6. Stochastic Component Scenarios for Battery Tray Assembly

BATTERY TRAY ASSEMBLY		Baseline Scenario	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Scenario Key	Type of Materials	PP	ABS	PA	PC	PE
	Manufacturing Plan	Injection molding, painting	Injection molding, painting	Injection molding, painting	Injection molding, painting	Injection molding, painting
Scenario Attributes	Mass	0.7 kg	0.47 - 0.67 kg	0.34 - 0.53 kg	0.38 - 0.57 kg	0.59 - 0.79 kg
	Recyclability Category	3	3	3	3	3

2.2. PHASE 2: Inventory Analysis and Impact Assessment

In this phase, material and energy use, recovery, and waste for the baseline product and the processes of the life cycle are estimated. In addition, the contribution of material and energy use, recovery, and waste to select impacts to the environment, economy, or society may be analyzed.

Phase 2 of LCMD (Inventory Analysis and Impact Assessment) corresponds to Phases 2 and 3 of LCA (as suggested by ISO, 1997; Curran, 1996; Klöpffer & Hutzinger, 1997). The primary product of Inventory Analysis and Impact Assessment is a set of system evaluation models that may be:

1. used to assess the baseline design,
2. used to assess alternative system design scenarios for Scenario Analysis and Interpretation (Phase 3), and
3. adapted for reuse in future LCMD studies.

Like Inventory Analysis and Impact Assessment in LCA, Phase 2 of LCMD should be performed by a knowledgeable practitioner. The design team should not have the burden of developing inventory and impact models for LCMD. Part 2 of this article describes Inventory Analysis and Impact Assessment in more detail and presents the life cycle inventory models used to evaluate the baseline vehicle design and alternative design scenarios for the Ford C-class sedan example.

2.3. PHASE 3: Scenario Analysis and Interpretation

In this phase, material and energy use, recovery, and waste for alternative, product design scenarios are estimated. In addition, the contribution of material and energy use, recovery, and waste to select impacts to the environment, economy, or society may be analyzed.

Phase 3 of LCMD (Scenario Analysis and Interpretation) is the process of evaluating the range of product design scenarios being considered by the design team. For this phase, three types of scenario analyses are proposed (each may be performed individually or in conjunction with one another):

- *Optima Analysis* – the process for identifying optimal system scenarios
- *Preference Analysis* – the process of estimating the probable performance and cost of a design, given the design preferences of the design team and other stakeholders
- *Constraint Analysis* – an extension of preference analysis used to estimate the influence of specific design decisions on performance metrics and cost

Similar to LCA, LCMD also requires interpretation. Specifically, the design team and other stakeholders should review the results of each scenario analysis, and a sensitivity analysis may be used to determine the scenario attributes and other modeling variables that most significantly influence performance and cost. Part 2 of this article describes Scenario Analysis and Interpretation in more detail and presents results for the Ford C-class sedan example.

2.4. Modifications for Original Design

As stated previously, the LCMD methodology presented here is intended for adaptive and variant design. However, with some modification, LCMD may be applied to original product design. The primary modification necessary for original design involves

Baseline Design Scenario Selection (Phase 1, Step 1). Specifically, modifications must overcome the lack of an existing product to serve as the baseline system. When possible, a hybrid system should be developed from multiple existing systems. Otherwise, a function structure (Pahl & Beitz, 2001) for the new product may be used to provide a preliminary "form" for the new design.

Using a functional structure, rather than an existing physical structure, makes LCMD more difficult to perform. More specifically, it makes Design Scenario Attribute Estimation (Phase 1, Step 3) more difficult and results in less certain attribute estimates. Without baseline data, LCMD studies cannot use equivalence models to estimate missing attributes. In addition, when design scenarios are defined in terms of functions, rather than components and subsystems, their form and life cycle tend to be less certain. Consequently, the results of LCMD studies performed on original designs without existing physical structures will tend to be less precise and will not support detailed decision-making.

3. Discussion

Part 1 of this article has presented the steps of LCMD's Phase 1 (Goal and Scope Definition) used to develop arrays of design scenarios that communicate the range of designs being considered by a design team. The purpose of which is to facilitate the use of life cycle models for decision-making during product design. Part 2 of this article further develops the LCMD methodology by presenting the life cycle models and analyses supported by the information developed in Phase 1. The discussion here addresses the following issues related specifically to this presentation of Phase 1 LCMD:

1. The treatment of uncertainty in estimating missing component attributes for the example
2. Opportunities for refining Phase 1 and extending its value to product design activities

An evaluation of the full LCMD methodology is presented in Part 2.

3.1. Treatment of Uncertainty

Like many other engineering quantities, design uncertainty may be evaluated using expert opinion and designer intuition. However, in the battery tray assembly example, design uncertainty was captured through the use of a mass equivalence models. Without this model, the design team would have had to answer the following question: "If an PP component has a mass of 0.7 kilograms, how much mass would a functionally equivalent ABS component have?" In addition, the design team would have had to estimate the certainty of its answer to that question. It would then have to repeat answering these questions for each alternative material. The use of models instead of expert opinion and designer intuition in LCMD reduces the burden of information collection placed on the design team and improves consistency from one analysis to the next.

Substituting models for expert opinion and designer intuition requires consideration of *data uncertainty*, *data variability*, and *model uncertainty* (as defined by Cullen & Frey, 1999). Considerable attention has been devoted to handling data uncertainty and variability in life cycle modeling (Borland et al., 1998; Regnier & Hoffman, 1998). This is most evident in LCA literature (Weidema, 1997; SETAC, 1999; Huijbregts et al., 2001). The example in this paper, however, focused primarily on capturing model uncertainty and ignored data uncertainty and variability.

Specifically, data uncertainty and variability were ignored for mass equivalence modeling because, at Ford, official values for material properties are available in an online database available to all engineers. With such a set of design standards, data uncertainty and variability for mass equivalence modeling is greatly reduced. Considering data uncertainty and variability in mass equivalence modeling is often only necessary if the design team is uncertain about what material grades will be considered for each component. In that situation, one method for modeling the team's uncertainty is to model each potential material grade as a separate design scenario.

To accurately portray the results of life cycle modeling performed during product design, each type of uncertainty must be analyzed for every model. Omitting any form undermines the validity of the results. Specifically, risk of overestimating differences between multiple design scenarios may result from the omission of data uncertainty and variability. Also, omitting model uncertainty and failing to model any form of design uncertainty risks the possibility of distorted results caused by modeling errors and assumptions about the final product design.

3.2. Refining and Extending LCMD Goal and Scope Definition

Opportunities exist for further refining the goal and scope definition process of LCMD to improve the usefulness of the methodology. Specifically, the usefulness of LCMD may be improved by:

- developing methods to propose, constrain, and eliminate potential design scenarios;
- modeling dependencies between design scenarios; and
- estimating metrics beyond environmental and economic performance.

Proposing, Constraining, and Eliminating Design Scenarios

Phase 1 of LCMD may be adapted to suggest that certain design scenarios be considered, constrained, or eliminated. Specifically, a methodology for identifying design scenarios not initially proposed by the design team could be incorporated into LCMD. For example, any of the three methodologies identified by Fitch & Cooper (2003) for comparing materials based on energy consumption may be used to propose materials for decreasing the expected life cycle energy consumption of a system. If accepted for consideration by the design team, the proposed materials may then be evaluated more thoroughly in Phase 3. Similar methods to those proposed by Fitch & Cooper may also be developed for metrics such as life cycle carbon dioxide and particulate matter emissions. Simple evaluation methods may also be developed to identify design scenarios that should probably be constrained or eliminated by the design team before Phases 2 and 3 are performed. This functionality would both improve modeling accuracy and reduce wasted effort considering unrealistic design scenarios.

Modeling Dependencies

As illustrated by the phenomenon of weight compounding, component attributes are sometimes dependent on system attributes as shown by Cooper (2003). In addition, assembly, maintenance, and end-of-life burdens are often dependent on component and system attributes. However, dependencies were not discussed here and many of these dependencies are not modeled in the sedan example. Identifying methods to model these dependencies would increase the validity of modeling results and better inform designers of the consequences of various design decisions.

Estimating Additional Metrics

Finally, though the intent of LCMD is to estimate the likely cost and environmental performance of a product during design, the method may be extended to assess numerous other metrics. Any metric based on component or subsystem attributes such as mass, cost, material, fabrication methods, reliability, etc. may potentially be incorporated into the methodology. Even metrics or analyses for which LCMD is an inappropriate modeling methodology may benefit from the availability of information stored in a detailed life cycle model. For example, part deployment and manufacturing planning using Quality Function Deployment (Hauser & Clausing, 1988), Cost-Worth Analysis (Ishii et al., 1998), and concept selection methods (Pugh, 1991, 1996; Saaty, 1980, 1995; Ullman, 1997) can benefit from LCMD data.

In addition to the attributes used in this paper, several reliability, producibility, assembly, and risk metrics may potentially be incorporated into LCMD. Booker (2001), Hinckley (1994), and Ishii et al. (1998) prescribe methods for estimating product reliability, producibility, and assembly time from component and subsystem attributes. However, incorporating these metrics into LCMD requires models to estimate missing attributes for alternative scenarios during Goal and Scope Definition. Opportunity also exists for facilitating Failure Modes and Effects Analysis with LCMD. By treating potential failure modes as component and subsystem attributes, failure modes may be communicated across generations of products and engineers may evaluate risk associated with individual design scenarios.

4. Conclusion

Part 1 of this article has presented the basic LCMD methodology, focusing on Phase 1: Goal and Scope Definition for adaptive and variant design. Specifically, it presents steps for developing arrays of design scenarios that communicate the range of designs being considered by a design team. The benefit of developing these design scenarios is that they allow life cycle modeling to be performed while design decisions are still being made. The methodology presented here also facilitates the incorporation of life cycle modeling into product design by incorporating methods for estimating missing design data.

Part 2 of this article develops LCMD further by presenting an automotive case study within the context of Phases 2 and 3 of the methodology. The case study explores the redesign of a Ford C-class sedan through material substitution. For the case study, 786 components (including some fasteners and subassemblies) with a total mass of 608 kg (approximately 51% of the baseline vehicle mass) are considered for redesign. The objective of redesigning these components is to cost effectively reduce resource consumption, reduce life cycle air emissions, and increase the recyclable mass of the vehicle. Finally, Part 2 provides an evaluation of LCMD as a design tool.

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Appendix B

Life Cycle Modeling for Adaptive and Variant Design

Part 2: Case Study[1]

List of Figures

List of Tables

[1] This article has been accepted for publication in Research in Engineering Design (Springer-Verlag, Berlin, Germany), pending final edits. Refer to the journal for the final version of this article.

Life Cycle Modeling for Adaptive and Variant Design

Part 2: Case Study[2]

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Abstract

Life Cycle Modeling for Design (LCMD) facilitates the incorporation of life cycle modeling into product design by including consideration of uncertainty in a product's final specifications. The methodology combines Life Cycle Assessment with probabilistic design methods in a way that reduces information needs. Part 1 of this article presents the basic LCMD methodology. Here, in Part 2, LCMD is used to evaluate material substitution opportunities to cost effectively reduce resource consumption, reduce life cycle air emissions, and increase the recyclable mass for a Ford C-class sedan. In addition to further illustrating LCMD, the case study identifies vehicle design scenarios that offer modest improvements in environmental performance (at a higher expected cost, however). When reviewed within the context of the Nielsen &

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[2] This article has been accepted for publication in Research in Engineering Design (Springer-Verlag, Berlin, Germany), pending final edits. Refer to the journal for the final version of this article.

Wenzel (2002) framework for integrating environment into product development, LCMD is found to provide several positive benefits.

Keywords: Design Uncertainty, Scenario Analysis, Probabilistic Design, Life Cycle Assessment, Design for Environment, Adaptive Design

1. Introduction

Part 1 of this article reviewed an array of specific attempts to incorporate life cycle modeling into product design and identified the need to consider design uncertainty when modeling during design. Together, Parts 1 and 2 of this article present a systematic life cycle modeling methodology called Life Cycle Modeling for Design (LCMD) that accommodates design uncertainty while curtailing the information required from product designers by incorporating probabilistic design methods into the basic framework presented by Nielsen & Wenzel (2002). Specifically, Part 1 presented steps for: 1) generating arrays of design scenarios that communicate the range of designs being considered by a design team and 2) using attribute estimation models (Level 1 of Figure B1) to estimate missing data for those design scenarios. Part 2 then goes further by presenting several analyses for evaluating these arrays of design scenarios using system evaluation models (Level 2 of Figure B1). In a stepwise manner, Part 1 presented Phase 1 (Goal and Scope Definition) of LCMD and Part 2 presents Phase 2 (Inventory Analysis and Impact Assessment) and Phase 3 (Scenario Analysis and Interpretation).

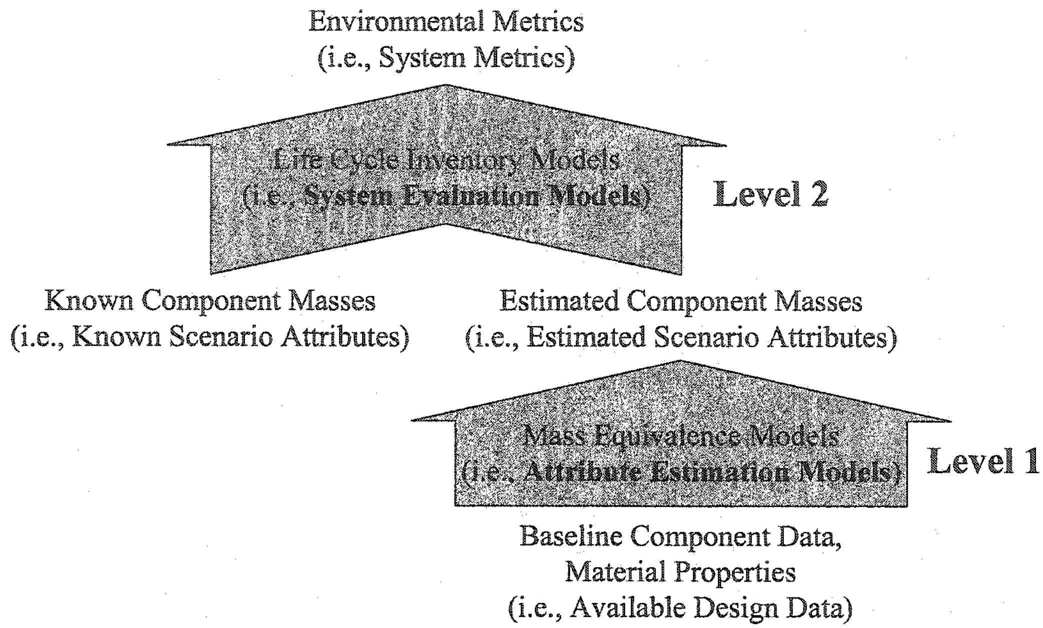

Figure B1. Estimating Scenario Attributes and System Metrics Using LCMD

Throughout this article, a material substitution case study from the automotive industry is used to illustrate LCMD. In addition to illustrating LCMD, the goal of this study is to generate and evaluate opportunities to cost effectively reduce resource consumption, reduce life cycle air emissions, and increase the recyclable mass of a Ford C-class sedan through material substitution. The functional unit for the case study is "one complete service life time distance (120,000 miles)" (Sullivan et al., 1998) for a C-class sedan. Component data for the baseline sedan were obtained from Ford benchmarking and teardown reports. A total of 786 components (including some fasteners and subassemblies) were considered for redesign by material substitution. This set of components had a total mass of 608 kg (approximately 51% of the baseline vehicle mass). The remaining components were not considered for redesign and were assumed to remain unchanged. In total, nine materials were considered as potential substitutes for the redesign of the vehicle's components. Specifically, aluminum (ALU), iron (FE), magnesium (MG), and steel (S) were considered for the redesign of metallic components and acrylonitrile butadiene styrene (ABS), polyamide (PA), polycarbonate (PC), polyethylene (PE), and polypropylene (PP) were considered for plastic components. In addition, no subsystem scenarios, manufacturing plan changes, or high-strength steel options were considered. Finally, for Phases 2 and 3, performance will be measured in terms of: 1) *reductions* in direct materials and production cost, vehicle mass, vehicle fuel consumption, drive cycle tailpipe emissions, and resource use and emissions in material production, operation, and for the life cycle and 2) *increases* in the recyclability of materials in the vehicle.

As stated previously, Part 1 of this article presented Phase 1 of LCMD. The following sections present the remainder of the methodology (i.e., Phases 2 and 3) in detail.

2. PHASE 2: Inventory Analysis and Impact Assessment

In this phase, material and energy use, recovery, and waste for the baseline product and the processes of the life cycle are estimated. In addition, the contribution of material and energy use, recovery, and waste to select impacts to the environment, economy, or society may be analyzed.

Phase 2 of LCMD (Inventory Analysis and Impact Assessment) corresponds to Phases 2 and 3 of LCA (as suggested by ISO, 1997; Curran, 1996; Klöpffer & Hutzinger, 1997). Each design scenario identified in the definition of the goal and scope represents a possible product use and manufacturing alternative for incorporation into life cycle inventory and impact models (i.e., system evaluation models). Given the material composition and manufacturing plan for each component, candidate life cycle processes are identified and used to identify upstream and downstream material and energy use and waste based on LCA inventory analysis as described by the ISO (ISO, 1997 and ISO, 1998). Additionally, inventory analysis may be supplemented with impact assessment when impact indicators (rather than inventory metrics) are desired for the evaluation of system designs. The primary product of Inventory Analysis and Impact Assessment is a set of system evaluation models that may be:

1. used to assess the baseline design,
2. used to assess alternative system design scenarios for Scenario Analysis and Interpretation (Phase 3), and
3. adapted for reuse in future LCMD studies.

Like Inventory Analysis and Impact Assessment in LCA, Phase 2 of LCMD should be performed by a knowledgeable practitioner. The design team should not have the burden of developing inventory and impact models for LCMD.

For the Ford C-class sedan example, an inventory analysis was performed to estimate resource consumption and air emissions throughout the life cycle for the baseline vehicle and the alternative design scenarios. Resource consumption data captured the use of energy (i.e., total energy consumed during the product life cycle, including the available energy content of consumed energy resources such as coal and natural gas), bauxite, coal, gasoline, iron ore, and natural gas. Air emissions data captured carbon dioxide, carbon monoxide, nitrogen oxides, particulate matter, sulfur oxides, and hydrocarbons. Each vector of resource use and air emissions presented in the equations below includes each of these twelve inventory items. The estimation methods used for each stage of the life cycle are described below.

- **Material Production and Component Manufacture** – For each of the nine materials evaluated, data for resource consumption and air emissions for material production and component manufacture were obtained from Franklin Associates (1993). For each component's baseline and associated scenarios, resource consumption and air emissions incurred during material production and component manufacturing for a vehicle were assumed equal to the sum of the material and energy use and waste required to produce each component:

$$\vec{b}_{PR} = \sum_i \vec{b}_i \qquad \text{<Equation 1>}$$

where: $\vec{b}_{PR}$ = vector of resource use and air emissions incurred during material production and component manufacturing for the vehicle (kg & MJ)

$\vec{b}_i$ = vector of resource use and air emissions incurred during material production and component manufacturing for component i (kg & MJ)

Also, resource consumption and air emissions were assumed to be linearly related to that needed to produce one kilogram of the component's primary material:

$$\vec{b}_i \approx m_i \vec{B}_i \qquad \text{<Equation 2>}$$

where: m_i = mass of component i (kg)

$\vec{B}_i$ = vector of resource use and air emissions incurred during production of one kg of the primary material used to make component i (kg/kg & MJ/kg)

- **Vehicle Assembly** – Data for resource consumption and air emissions incurred in the assembly of a generic, 1530-kg, family sedan were obtained from Sullivan, et al. (1998) and assumed to be representative of those incurred in the assembly of the baseline vehicle and all design scenarios. Both resource consumption and air emissions are functions of the mass of the vehicle (M) which was estimated for each system scenario as the sum of the mass of the components for the scenario and 577 kg (which represents the remainder, or 49%, of the mass of the baseline vehicle).

- **Vehicle Use** – Resource consumption and air emissions incurred during vehicle use were taken to be from fuel consumption and vehicle tailpipe emissions and therefore related to the lifetime driving distance of the vehicle. Equation 3 approximates the relationship between tailpipe emissions, fuel economy, resource consumption, and air emissions incurred during fuel production and vehicle use:

$$\vec{b}_{OP} \approx d_{OP}\left(\vec{b}_{DC} + \frac{\rho_F}{e}\vec{B}_{FC}\right) \qquad \text{<Equation 3>}$$

where: $\vec{b}_{OP}$ = resource use and air emissions incurred during vehicle operation (kg & MG)

d_{OP} = distance traveled during lifetime of vehicle (120,000 miles assumed)

$\vec{b}_{DC}$ = tailpipe emissions produced per mile traveled (kg/mile)

ρ_F = fuel density (kg/gal)

e = fuel economy (miles/gal)

$\vec{B}_{FC}$ = burdens incurred to produce one kg of fuel (kg/kg & MJ/kg)

The following fuel economy relationship is based on algorithms used for the baseline vehicle in Ford's Corporate Vehicle Simulation Program (CVSP):

$$e \approx \frac{1}{1.289(10^{-5})M + 1.769(10^{-2})}$$ <Equation 4>

where: e = fuel economy (miles/gal)

M = mass of vehicle (kg) as defined for vehicle assembly

For tailpipe emissions, carbon monoxide, nitrogen oxides, particulate matter, and hydrocarbon emissions were assumed directly proportional to vehicle miles driven. The values presented in Equation 5 for these emissions were based on Statutory Tier II Limits (EPA, 1998). Alternatively, carbon dioxide and sulfur oxides were assumed indirectly proportional to vehicle miles driven by their correlation to fuel consumption. The carbon dioxide relationship presented in Equation 5 was computed stoichiometrically using data from A.D. Little (undated). Whereas, the sulfur oxide relationship is based on AAMA (1993).

$$\vec{b}_{DC} \approx \begin{bmatrix} 3.14\frac{\rho_F}{e} & kgCO_2/mile \\ 0.0156 & kgCO/mile \\ 0.0013 & kgNO_x/mile \\ 0.00008 & kgPM/mile \\ 0.00058\frac{\rho_F}{e} & kgSO_x/mile \\ 0.000845 & kgHCs/mile \end{bmatrix}$$ <Equation 5>

- **Maintenance and End-of-Life** – Data for resource consumption and air emissions incurred through the maintenance and at the end-of-life was again based on Sullivan, et al. (1998) and assumed to be representative for the baseline vehicle and all design scenarios. Again both are based on the mass of the vehicle as defined for vehicle assembly.

The resource consumption and air emissions incurred during the vehicle life cycle is therefore:

$$\vec{b}_{LC} \approx \vec{b}_{PR} + \vec{B}_{AS} + \vec{b}_{OP} + \vec{B}_{MA} + \vec{B}_{EOL}$$ <Equation 6>

where: $\vec{b}_{LC}$ = the vector of resource use and air emissions incurred during the life cycle of the vehicle (kg & MJ)

$\vec{b}_{PR}$ = the vector of resource use and air emissions incurred during material production and component manufacturing for the vehicle (kg & MJ)

$\vec{B}_{AS}$ = the vector of resource use and air emissions incurred during the assembly of a generic family sedan (kg & MJ)

$\vec{b}_{OP}$ = the vector of resource use and air emissions incurred during the operation of the vehicle (kg & MJ)

$\vec{B}_{MA}$ = the vector of resource use and air emissions incurred during the maintenance of a generic family sedan (kg & MJ)

$\vec{B}_{EOL}$ = the vector of resource use and air emissions incurred at the end-of-life of a generic family sedan (kg & MJ)

Equation 7 presents the results of the baseline inventory analysis using Equation 6 and a 120,000-mile lifetime driving distance. Again, cost data have not been included.

$$\left(\vec{b}_{LC}\right)_{baseline} \approx \begin{bmatrix} energy\ consumption \\ carbon\ dioxide\ emissions \\ carbon\ monoxide\ emissions \\ nitrogen\ oxide\ emissions \\ particulate\ matter\ emissions \\ sulfur\ oxide\ emissions \\ hydrocarbon\ emissions \\ bauxite\ consumption \\ coal\ consumption \\ gasoline\ consumption \\ iron\ ore\ consumption \\ natural\ gas\ consumption \end{bmatrix} \approx \begin{bmatrix} 690\,GJ \\ 44200kg \\ 1950kg \\ 197kg \\ 42kg \\ 55.6kg \\ 165kg \\ 98.9kg \\ 1480kg \\ 9860kg \\ 563kg \\ 788kg \end{bmatrix}$$ <Equation 7>

An additional metric related to vehicle end-of-life, recyclability rating, was also assessed for this case study. *Recyclability rating* – an estimate of the percentage of the vehicle's mass likely to be recycled at the end-of-life – is equivalent to the total mass of all vehicle components in recyclability categories 1 or 2 divided by the total mass of the vehicle:

$$r = \frac{\sum_i m_i f(R_i - 1,2)}{M}$$ <Equation 8>

where: r = recyclability rating

m_i = mass of component i (kg)

R_i = recyclability category for component i

$$f(R_i - 1,2) = \begin{Bmatrix} 1 & R_i = 1,2 \\ 0 & R_i = 3,4 \end{Bmatrix}$$ = unit function with nonzero value when R_i= 1or2

M = mass of vehicle (kg)

Based on Equation 8, the recyclability rating of the baseline vehicle was 80.15%.

As stated previously, for Phase 2, performance is measured in terms of: (1) *reductions* in direct materials and production cost, vehicle mass, vehicle fuel consumption (per Equation 4), drive cycle tailpipe emissions (per Equation 5), and resource use and emissions in material production (per Equation 1), operation (per Equation 3), and for the life cycle (per Equation 6) and (2) *increases* in the recyclability of the vehicle (per Equation 8). In Phase 3, three types of scenario analyses will use these performance equations to estimate the twelve inventory metrics in Equation 7 for potential system scenarios.

3. PHASE 3: Scenario Analysis and Interpretation

In this phase, material and energy use, recovery, and waste for alternative, product design scenarios are estimated. In addition, the contribution of material and energy use, recovery, and waste to select impacts to the environment, economy, or society may be analyzed.

Phase 3 of LCMD (Scenario Analysis and Interpretation) is the process of evaluating the range of product design scenarios being considered by the design team. For this phase, three types of scenario analyses are proposed (each may be performed individually or in conjunction with one another):

- *Optima Analysis* – the process for identifying optimal system scenarios
- *Preference Analysis* – the process of estimating the probable performance and cost of a design, given the design preferences of the design team and other stakeholders

- *Constraint Analysis* – an extension of preference analysis used to estimate the influence of specific design decisions on performance metrics and cost

Similar to LCA, LCMD also requires interpretation. Specifically, the design team and other stakeholders should review the results of each scenario analysis, and a sensitivity analysis may be used to determine the scenario attributes and other modeling variables that most significantly influence performance and cost. The following sections describe each analysis for Phase 3 in detail.

3.1. Optima Analysis

Optima Analysis is the process of identifying optimal system scenarios. Optimization methods are used to identify system scenarios that maximize the expected performance using a single metric, minimize expected cost while satisfying performance constraints, or maximize a utility function based on performance metrics and cost. Optima analysis is appropriate for identifying candidate design scenarios for further consideration (e.g., Optimum 1 and Optimum 2 shown in Figure B2), not for choosing a single, "ideal" solution.

In the sedan case study, performance was optimized relative to a single inventory item when one of the twelve inventory metrics within $(\bar{b}_{LC})_{baseline}$ (Equation 7) was minimized or when the recyclability rating (Equation 8) was maximized. For example, when no other constraints were imposed, the optimal design scenario in terms of carbon dioxide was the one that minimized the expected life cycle carbon dioxide emissions for the vehicle. For this case study, optima analysis was used to identify an optimal vehicle design scenario for each performance metric, given uncertainty in component attributes (component mass, the recyclability category, and cost). As a result, design uncertainty was limited to uncertainty in attributes for each component scenario and did not include uncertainty related to the selection of component scenarios.

Table B1 and Figure B2 present two optimized system scenarios. The first scenario, Optimum 1, represents best performance relative to six inventory metrics. The second scenario, Optimum 2, demonstrated the best performance relative to three other inventory metrics. As shown in Figure B2, besides reduced iron ore consumption, both scenarios provide only small improvements relative to several inventory metrics. Optimum 2 achieves these small improvements at the cost of coal consumption and sulfur oxide emissions. Similarly, Optimum 1 achieves improvements at the cost of bauxite consumption. Both system scenarios are expected to increase direct material costs by more than \$100 per vehicle and may require additional costs as well. This analysis may also be repeated using constraints to avoid unacceptable design scenarios (e.g., too costly, too massive, or too energy intensive scenarios).

Table B1. Example Profiles from Optima Analysis

		Optimum 1	**Optimum 2**
Best Performance Relative to:		1. Carbon Dioxide Emissions 2. Particulate Matter Emissions 3. Energy Consumption	1. Carbon Monoxide Emissions 2. Hydrocarbon Emissions 3. Gasoline Consumption
Materials (net values are relative to baseline)	Aluminum	+110 components (+143.4 ± 11.9 kg)	+101 components (+5.4 ± 0.04 kg)
	Iron	-14 components (-34.6 ± 1.5 kg)	-24 components (-29.9 ± 1.4 kg)
	Magnesium	+50 components (+8.7 ± 0.3 kg)	+59 components (+106.9 ± 8.6 kg)
	Steel	-146 components (-286.8 ± 18.2 kg)	-136 components (-287.6 ± 16.9 kg)
	Acrylonitrile Butadiene Styrene	-1 component (-0.7 ± 0.01 kg)	+7 components (+0.4 ± 0.03 kg)
	Polyamide	-6 component (+0.5 ± 0.01 kg)	-13 components (-0.4 ± 0.01 kg)
	Polycarbonate	+7 components (+0.0 ± 0.01 kg)	+6 components (+0.1 ± 0.02 kg)
	Polyethylene	+6 components (+2.8 ± 0.05 kg)	+2 component (+0.5 ± 0.05 kg)
	Polypropylene	-6 components (-2.8 ± 0.05 kg)	-2 component (-0.5 ± 0.05 kg)
Vehicle Mass		1015 ± 22 kg	980 ± 19 kg
Vehicle Fuel Consumption		32.5 ± 0.3 mpg	33.0 ± 0.2 mpg
Recyclability Rating for the Vehicle		76.9 ± 0.5 %	76.0 ± 0.4 %

Relative Performance of Optimized Scenarios

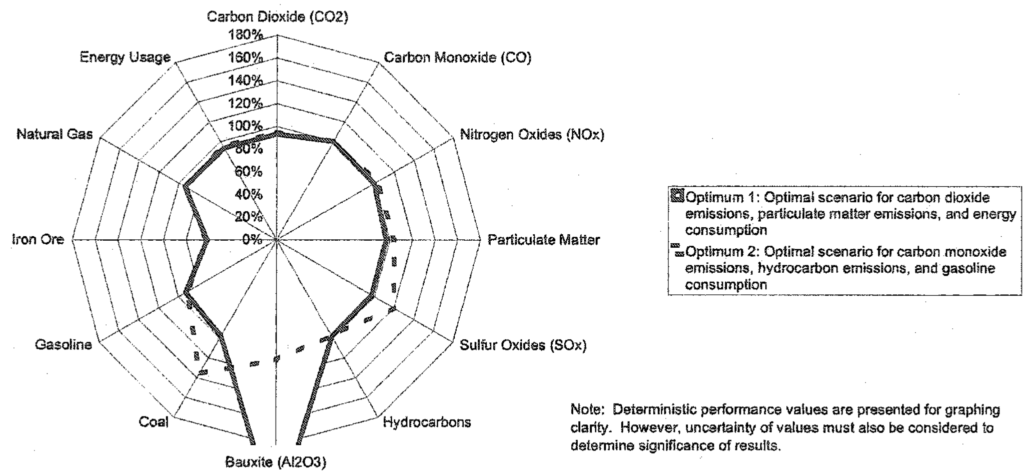

Figure B2. Example Results from Optima Analysis

3.2. Preference Analysis

Preference Analysis is the process of estimating the probable performance and cost of a design, given the design preferences of the design team and other stakeholders. Using stochastic modeling such as Monte Carlo simulation, preference analysis allows the design team to assess how the design is progressing relative to performance and cost objectives. Specifically, this analysis allows the design team to answer the following questions:

- Given the design scenarios under consideration, is it possible to meet the design program's performance and cost objectives?
- Is the most preferred system scenario likely to meet the design program's performance and cost objectives?
- Do the design scenarios under consideration offer realistic opportunities for cost reduction and environmental performance improvement?

The primary outputs of preference analysis are histograms or probability density plots for design metrics such as vehicle mass. The method proposed here is an adaptation of that proposed in SAWE (1996) for aircraft mass estimation. Whereas SAWE's method relies heavily on data from past aircraft development programs to predict the outcome of future configurations, the method proposed here uses design preferences of the current design team. When significant historical design data is available, such a method is appropriate and, in certain situations, may even be used for LCMD. However, preference analysis may be used in the absence of such data. In addition, preference analysis is used for a range of metrics beyond just mass.

For sedan case study, *design preference*, p_{ij}, was described using a 1/3/9 rating system. For each component, the design team rated the preferred material with a nine. Any other seriously considered material received a rating of three. The remaining materials received a rating of one. Note that any material ruled out by the design team was never considered in the example.

To simulate the affect p_{ij} has on the performance and cost of the final product design, Monte Carlo simulation was used to generate an array of design scenarios and estimate the twelve inventory metrics. To generate each system scenario, component scenarios were created by selecting a material for each component based on an approximation of the likelihood of use, l_{ij}:

$$l_{ij} \approx \frac{p_{ij}}{\sum_{j} p_{ij}}$$ <Equation 9>

where: l_{ij} = the likelihood material j will be used for component i

p_{ij} = the design preference (1, 3, or 9) of material j for component i

For each resulting system scenario, the twelve inventory performance metrics were estimated using Equations 1-6. The resulting array of system scenarios is shown in Figures B3-B5. Figure B3 illustrates the maximum, median, and minimum life cycle inventory metric estimates for the array of system scenarios generated. The values presented are normalized relative to the performance of baseline design scenario. Though several of the inventory metrics illustrated in Figure B3 show potential for substantial change (mostly in a worsening direction), the median values suggest that the likelihood for significant change relative to the baseline scenario is low. Only median values for bauxite and iron ore consumption are greater than 10% more or less than baseline performance. These potential changes in bauxite and iron ore consumption reflect the likely replacement of numerous steel components with aluminum components.

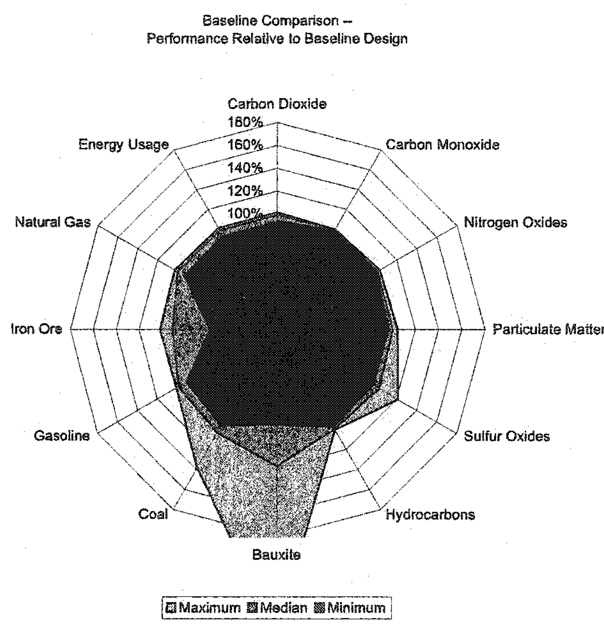

Figure B3. Summary Results of Preference Analysis

The histograms in Figures B4 and B5 illustrate the frequency of occurrence of different inventory metric estimates resulting from the preference analysis. For the metrics analyzed, the results take the form of a single, double, or triple mode. When a single mode is formed, no single design decision has dominant influence over the performance of the vehicle, relative to the given metric. In other words, no single design decision alone will ensure improved performance relative to the given metric. In these cases, the preferences of individual designers have only small influence on performance and a combination of multiple design decisions is necessary to ensure improved performance relative to the given metric. However, in the case of metrics with double and triple modes, a small number of design decisions (one or two) have dominant influence over the performance of the vehicle. In these cases, the dominating design decisions may be identified and made early in design to ensure preferred results.

As an example of multimodal results, the first histogram illustrates the probable range of life cycle carbon dioxide emissions for the array of design scenarios being considered by the design team. The multimodal distribution is primarily the result of multiple materials (steel, aluminum, and magnesium) being considered for the design of the vehicle frame. According to this histogram, the most likely amount of life cycle carbon dioxide emissions is approximately 44,100 kg; only about 0.2% lower than the life cycle emissions for the baseline vehicle. The histogram also suggests that there is a low likelihood (~35%) that carbon dioxide emissions will be cut by more than 1%.

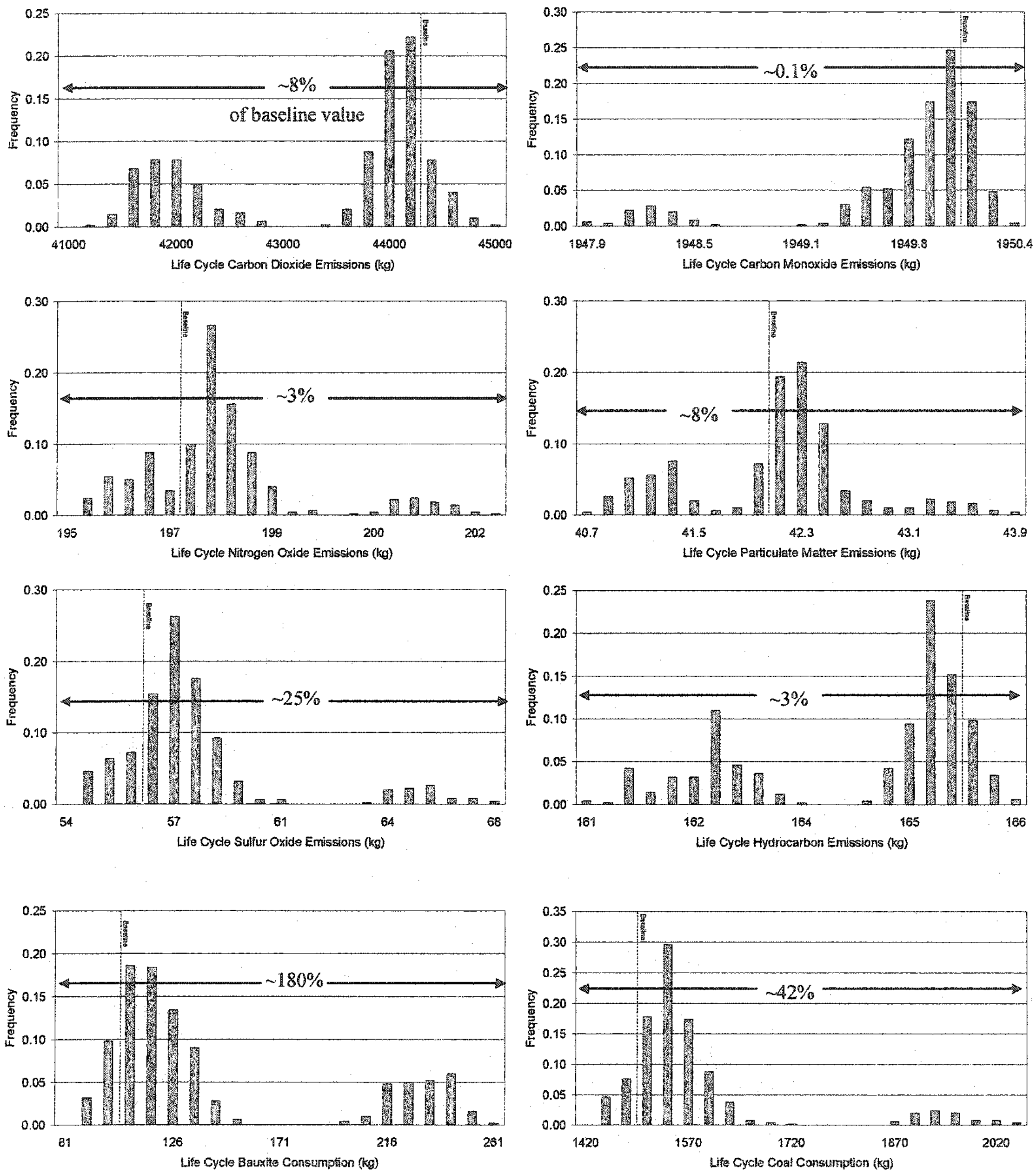

Figure B4. Monte Carlo Results from Preference Analysis

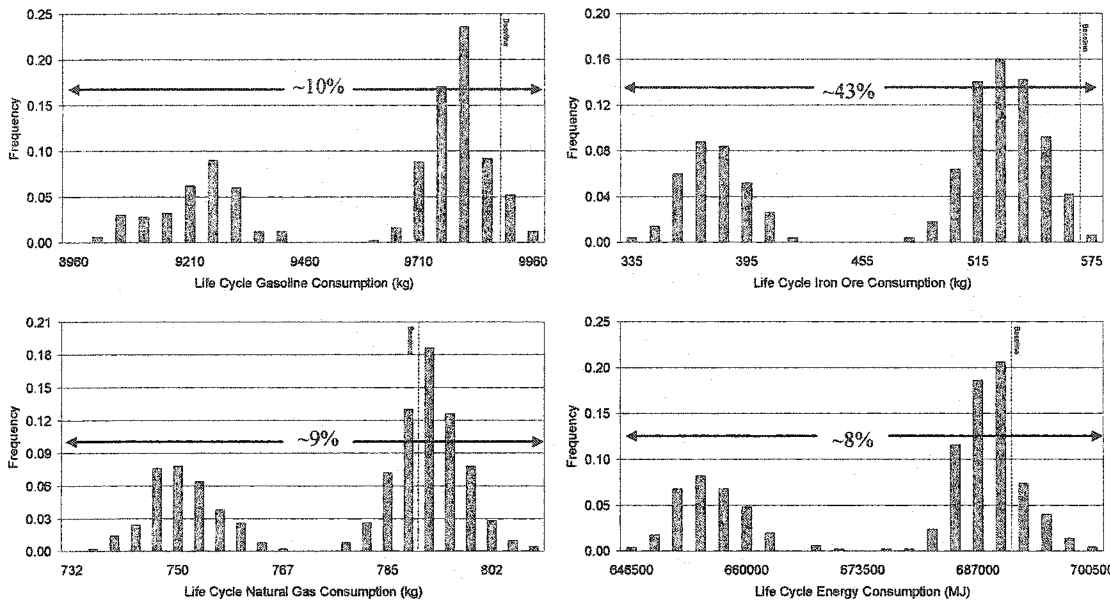

Figure B5. Additional Monte Carlo Results from Preference Analysis

3.3. Constraint Analysis

Constraint Analysis is an extension of preference analysis used to estimate the influence of a design decision on performance metrics and cost. This analysis involves performing two parallel, constrained preference analyses and comparing the results. For example, in the sedan case study, the design team considered switching from a steel frame design to an aluminum frame design. As a result, two preference analyses were performed and compared: one with all frame components constrained to steel scenarios, and one with all frame components constrained to aluminum scenarios. Figures B6 and B7 present the results of these two, constrained preference analyses. A cursory review of the histograms in Figures B6 and B7 suggests:

- An aluminum frame offers clear advantages in carbon dioxide emissions, hydrocarbon emissions, gasoline consumption, iron ore consumption, natural gas consumption, and energy consumption;

- A standard steel frame offers clear advantages in carbon monoxide emissions and bauxite consumption; and
- These two frame options are expected to perform similarly relative to nitrogen oxide emissions, particulate matter emissions, sulfur oxide emissions, and coal consumption.

A more thorough review is necessary to understand the significance of the advantages for each frame design. For example, aside from consuming about 30% less iron ore than a standard steel frame design, the aluminum frame design offers less than 3% advantage relative to other metrics. Conversely, aside from consuming about 60% less bauxite than an aluminum frame design, the standard steel frame design offers no significant advantages. The carbon monoxide advantage noted previously is only about 0.05%.

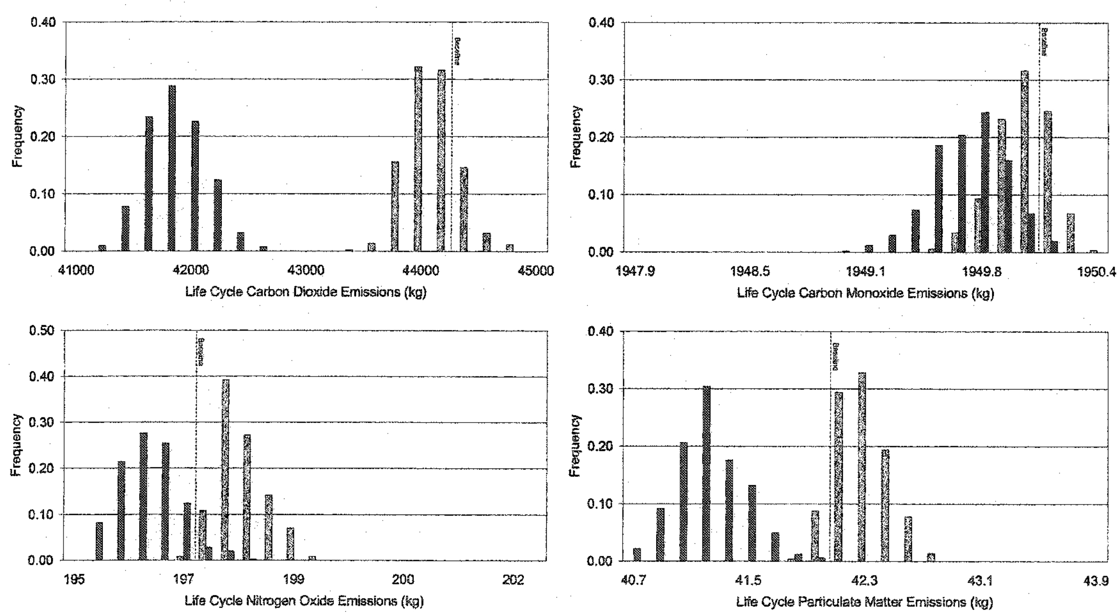

Figure B6. Monte Carlo Results from Constraint Analysis[3]

[3] Light bars represent Monte Carlo results for a steel frame vehicle. Dark bars represent results for an aluminum frame vehicle.

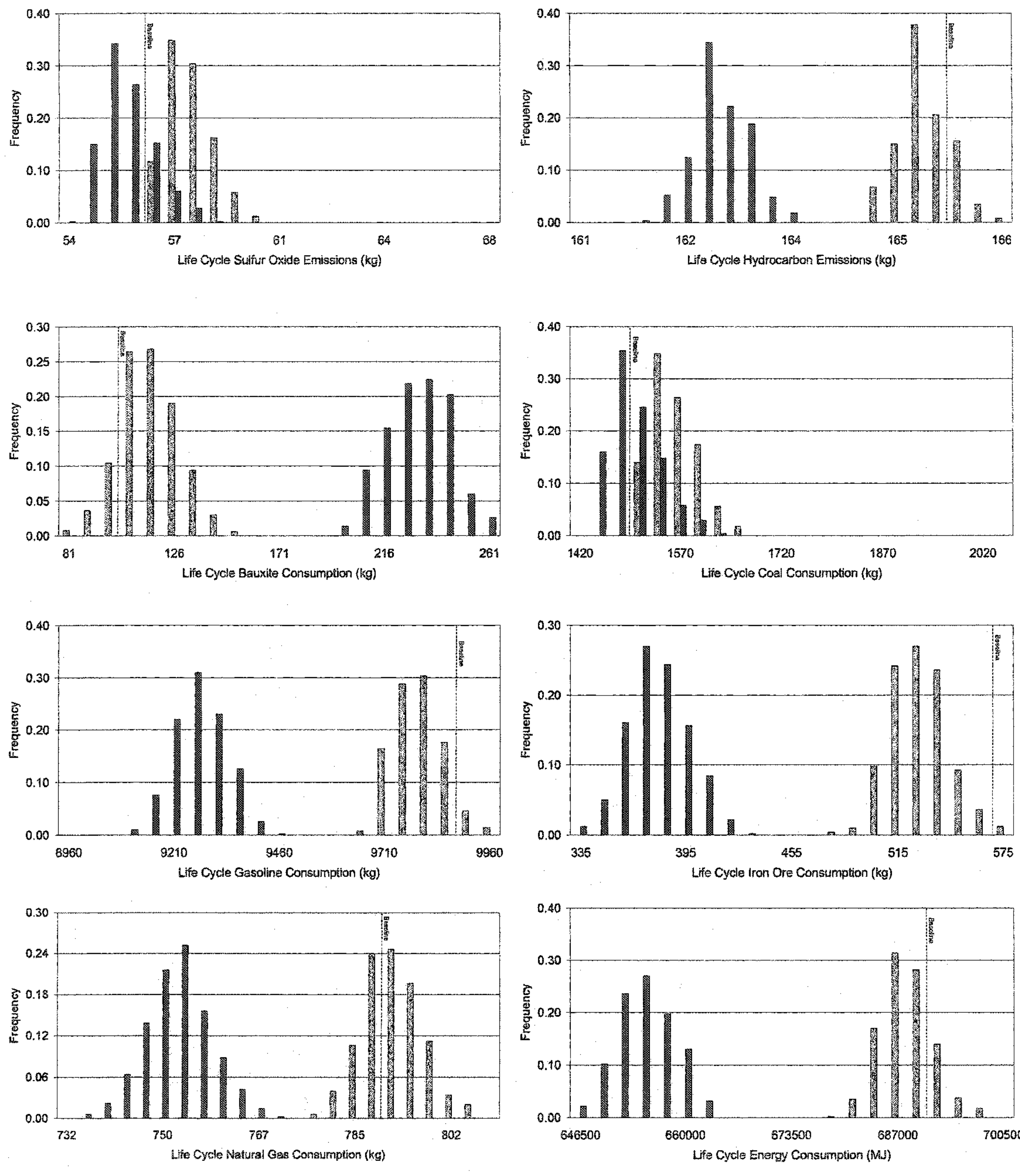

Figure B7. Additional Monte Carlo Results from Constraint Analysis[4]

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[4] Light bars represent Monte Carlo results for a steel frame vehicle. Dark bars represent results for an aluminum frame vehicle.

3.4. Interpretation of Results

All three scenario analyses suggest that a small number of design decisions have a dominating influence on critical resource use, waste, and emissions; the most notable being the choice of material for the frame of the vehicle. Under the original assumptions made in this example, an aluminum frame design offers advantages in carbon dioxide emissions, hydrocarbon emissions, gasoline consumption, iron ore consumption, natural gas consumption, and energy consumption over a standard steel frame design. Despite some clear disadvantages resulting from vehicle weight, a standard steel frame design still performs competitively and is currently the most likely to be used by automotive manufacturers.

As discussed in Part 1, the results presented in this article do not include high-strength steel frame options. As shown by Sullivan (2001), from an energy perspective, high-strength steel frame vehicles compete favorably with aluminum frame vehicles, especially when the lifetime of the vehicle is less than 135,000 miles. Also, the numbers used here may reflect the current levels of recycled material content used (70% or steel and 80% for aluminum); however, significant changes in automotive material use could potentially influence future levels of recycled material content. Any conclusions drawn from the results presented here should consider uncertainty in the assumptions. For example, reducing the assumed content of recycled aluminum to 50%, instead of 80%, significantly decreased the advantages of the aluminum frame design. Hydrocarbon emissions, iron ore consumption, and energy consumption for the aluminum frame design did not change significantly, however, performance relative to other metrics decreased noticeably when recycled content was reduced. Using this new assumption, the aluminum frame design performed poorly relative to most metrics when compared to the standard steel frame design.

A second issue is related to the use of lightweight vehicle materials and *weight compounding*. Weight compounding refers to the fact that the use of lighter components facilitates the use of other lighter components in the balance of the vehicle. For example, if the vehicle is lighter, a smaller (and therefore lighter) powertrain will move the vehicle. Because weight compounding was not considered in this example, any improvements that might be concluded would be conservative.

A third issue is related to the use of a single mass equivalence model (based on the specific strength performance index, $\square_y/\square$) for the entire analysis. Despite the assumption that choosing appropriate equivalent mass models for each component during design will be practical during embodiment and detailed design, doing so can be impractical for a very large number of components and during conceptual design. Though this simplification eliminated the need for information regarding the basic shape and loading conditions for 786 components, it decreased the expected accuracy of the mass equivalence modeling and increased the uncertainty of the final design attributes. However, as previously mentioned, because the results of the mass equivalents model compared favorably with anecdotal data for material substitution in automobiles, it has been assumed the method is adequate for use in LCMD during conceptual design.

Finally, the uncertainty of inventory results was understated here because the uncertainty and variation of the inventory data from Franklin Associates (1993) was not available. As a result, some design scenarios may appear to have clear advantages and disadvantages even in situations where no differentiation is truly possible. This lack of knowledge regarding uncertainty and variation in inventory data also made performing a meaningful sensitivity analysis impossible. In the future, a sensitivity analysis should be used to determine the aspects of the design scenarios that most significantly influence performance metrics and cost. Also, assessment of data quality and validation of all analyses should include a peer review of the design scenarios and analysis results by the design team and other stakeholders. Fortunately, efforts similar to the United States Life Cycle Inventory Database Project (Athena, 2002) are expected to simplify these problems for future analyses.

Despite these issues, several recommendations can be made based on the results of the example. First, the design team should investigate the feasibility and cost effectiveness of vehicle design scenarios resembling Optimum 1 presented in Table B1. According to the very basic cost analysis performed for this example, Optimum 1 is expected to be somewhat more expensive than the baseline vehicle. If this or a similar design scenario is found to be cost effective enough to develop further, program leadership should provide incentives or requirements for engineers to assure component level decisions are made consistent with the results of the optima analysis.

If none of the "optimal" solutions identified through optima analysis are found to be acceptable, the design team should make the most dominant design decisions (e.g., material selection for the vehicle frame) early in design and reassess the feasibility of finding an acceptable solution given the existing design scenarios being considered. If an acceptable solution is unlikely to be chosen, the design team must either reevaluate the targets for the design project or identify new, superior design scenarios to consider.

4. Evaluation of LCMD

To frame our evaluation, we discuss the features of LCMD on the basis of the design method evaluation criteria presented by Bras (1997) as compared to the basic framework presented by Nielsen & Wenzel (2002). As discussed in Table B2, LCMD's structured method for estimating unknown design attributes makes the methodology simpler for the design team and makes the analyses more definable and objective. In addition, LCMD's evaluation of numerous design scenarios and its estimation of design uncertainty enhances the design team's understanding of how it can influence environmental performance. However, the necessity of having appropriate equivalency models and/or anecdotal data for evaluating alternative design scenarios may make using LCMD in certain product domains difficult. Overall, the structured nature of LCMD provides mostly positive benefits within the basic framework developed by Nielsen & Wenzel.

Table B2. Comparison of LCMD to Nielsen & Wenzel (2002) Method

Bras Criteria for Design Method Comparison	Nielsen & Wenzel (2002)	Life Cycle Modeling for Design (LCMD)	Comments
Simple – the method should be easy to use	BASELINE	+	LCMD does not require the design team to derive any unknown information
Easily obtainable – the method should be available at a reasonable cost		S	LCMD may initially require additional time when new equivalency models are necessary, however, time is saved when additional data collection is avoided
Precisely definable – it is clear how the information can be evaluated		+	LCMD is more structured and, therefore, more precisely defined and objective
Objective – two or more qualified observers should arrive at the same result		+	
Valid – the method should measure, indicate, or predict correctly what it is intended to measure, indicate, or predict		S	Assessment for both methods is based on life cycle inventory and impact assessment models
Robust – the method should be relatively insensitive to changes in the domain of application		-	LCMD may require additional equivalency model development when changing domains
Enhancement of understanding and prediction – good metrics, models, and decision support tools should foster insight and assist in predicting process and product parameters		+	LCMD provides additional assistance in predicting product parameters and provides insight into more potential design scenarios

Key:

\+ Method performs better than the baseline

S Method performs the same as the baseline

\- Method performs worse than the baseline

The preceding evaluation is based on research experience using LCMD on snapshot automotive examples (i.e., development data and analysis results represent a single moment in time). However, LCMD has not been performed on a dynamic example (i.e., an example where data is updated throughout the design process) or for other product domains. In addition, the elements of LCA incorporated into LCMD and into the case study presented here could benefit greatly from additional validation methods. According to Hecht (2003), validation is an important research area because there are currently no widely suggested methods for validating LCA.

5. Conclusion

The research described in this article is significant because it: 1) defines a previously informal or even nonexistent process within design decision-making and 2) provides a sound framework for future, scholarly research. LCMD combines Life Cycle Assessment with probabilistic design methods in a systematic, yet flexible, manner that allows rigorous review, improvement, and customization of individual, underlying models. By proving methods for modeling design uncertainty, LCMD facilitates the incorporation of life cycle modeling and, hence, environmental assessment into product design.

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Appendix C

Life Cycle Energy Analysis as a Method for Material Selection [1]

List of Figures

List of Tables

[1] This article has been accepted for publication in the Journal of Mechanical Design.

Life Cycle Energy Analysis as a Method for Material Selection[2]

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ABSTRACT

This paper presents a method of performing Life Cycle Energy Analysis (LCEA) for the purpose of material selection. The method applies product analysis methods to the evaluation of material options for automotive components. Specifically, LCEA is used to compare material options for a bumper-reinforcing beam on a 1030 kg vehicle. From an energy perspective, glass fiber composites and high-strength steel beams performed best. This paper also presents a set of life cycle energy terms designed to clearly distinguish between energy consumption occurring during different phases of a product's life cycle. In addition, this paper compares the results of the LCEA method to those of other energy analyses and demonstrates how different methods of varying thoroughness can result in different material selections. Finally, opportunities are identified for extending this type of analysis beyond both automotive components and energy consumption.

Keywords: Material Selection, Energy Analysis, Design for Environment, Life Cycle Assessment, Automotive Components

1. INTRODUCTION

1.1 Material Selection

Several general texts and articles provide overviews of material selection for mechanical design [1-3]. Dieter [4], a single chapter from ASM [3], describes both material selection for new designs and for material substitution. Since material selection is closely tied to manufacturing process selection, Dieter describes both the material-first and the process-first approaches identified by Dixon & Poli [5]. In the material-first approach, the designer begins by selecting a material class, narrowing the choices within the class, and then considering manufacturing processes consistent with the selected material. Conversely, in the process-first approach, the designer begins by selecting the manufacturing process and then the material. Dieter also states that most design and materials engineers instinctively use the material-first approach, while manufacturing engineers typically gravitate toward the process-first approach.

The work of Ashby supports material selection for a new design and within a material-first substitution assessment [2,6]. Ashby also illustrates that for most mechanical systems, performance is limited not by a single property, but by a combination of them. For example, the materials with the best thermal shock resistance are those with the greatest values of $\sigma_f/E\alpha$; where σ_f is the failure stress, E is Young's modulus, and α is the thermal coefficient of expansion. Ashby illustrates the use of material parameters (i.e., material properties and other material parameters related to manufacturing processes, cost, and environment) to derive performance indices. These performance indices isolate the combination of material, shape, and other information that maximize performance within the constraints of appropriate property limits. These property limits are bounding values, within which certain properties must lie if a material is to be considered further.

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Ashby extends the use of his performance indices through the development of selection charts for use in conceptual design [2] and a relational database-software system called the Cambridge Engineering Selector (CES) [7]. CES enables engineers to select from linked material, process, and shape databases a small subset of records that optimally satisfy given design objectives and constraints. CES also provides additional material, process, and supplier information to support final selection from this subset of options.

1.2 Considering Environment in Material Selection

Numerous methodologies exist for considering environmental concerns during material selection. Some methods, such as Ishii [8], emphasize selecting materials based on a single portion of a product's life cycle (e.g., end-of-life material recovery). Others methods attempt to consider the entire life cycle, either qualitatively or quantitatively.

Material selection guidelines [9] are an example of qualitative selection methodologies. Material selection guidelines are simply rules-of-thumb such as "Choose abundant, non-toxic, non-regulated materials, if possible." Although using qualitative methods such as guidelines can help to classify materials as desirable or not desirable, prioritization of certain materials is very difficult.

Alternatively, existing quantitative approaches to environmental material selection rate materials based on:

- a single, aggregated environmental indicator (e.g., the Eco-Indicator used by Wegst and Ashby [10] or energy content as used by Ashby [2]), or
- an economic indicator (e.g., environmental cost as used by Clark, et al. [11] and calculated using the Swedish Environmental Priority Strategies (EPS) [12]),
- a set of environmental indicators (e.g., CO_2, SO_x, NO_x, a measure of grade of recyclability, and resource scarcity as suggested by Halada, et al. [13]).

As suggested by Baitz, et al. [14], the problems with using a single, aggregated environmental indicator are that it implies the existence of a universal eco-profile and that stressors always affect the environment the same way. Baitz, et al. also states that a DFE tool needs to reflect different sectors with their specific situation (energy supply, material efficiency, market region, etc.) to get information of a sufficient precision for setting up reliable assessments. The same problem exists when using a single economic indicator to quantify environmental performance. The EPS cost assessment technique [12] as applied by Clark, et al. [11], describes impacts on the environment in terms of impacts on one or several safeguard subjects (human health, biodiversity, production, resources and aesthetic values) and value changes in them according to the willingness to pay to restore them to their normal status. Although the EPS valuation method is activity-based and far more parameterized and transparent in its approach, it not universally transferable.

In contrast to the example presented by Wegst & Ashby [10] that uses an aggregated environmental indicator, Ashby's earlier work [2] demonstrates that the performance index methodology described in Section 1.1 may also be used to evaluate materials based on individual environmental parameters (e.g., energy consumption) in conjunction with other material parameters. Kampe [15] extends Ashby's methodology by recognizing that material selection affects more than just the amount of energy consumed during production of the material. In his example, Kampe defines a Lifetime Energy Consumption Index (LEC′) that incorporates the energy consumption of a generic automobile into an evaluation of potential materials.

An opportunity exists to further extend Ashby's and Kampe's methods [2,15] for considering the environment in material selection. These works, based on Ashby's performance indicator methods, require material-specific parameters that are indicative of environmental impact. Therefore, the set of environmental indicators suggested by Halada, et al. [13], for example, that result from impact assessment in Life Cycle Assessment (LCA), could be used as components of Ashby's performance indices. Also, this could be taken a step further by developing material- and application-specific parameters. For example, environmental indicators that are specific to the use of aluminum in automobiles or to the use of ABS in personal computers would be developed. Such a method is demonstrated as follows using life cycle energy analysis for material selection in automobiles as an example.

1.3 Energy Analysis

According to Boustead & Hancock [16], energy analysis is a technique for examining the way in which energy sources are harnessed to perform useful functions. For example, Boustead & Hancock use energy analysis to calculate the energy required to:

- Produce fuels (e.g., coal, diesel, and natural gas),
- Transport freight (e.g., by truck, by train, and by ship),
- Produce and recycle metals (e.g., copper and aluminum)

Similarly, Brown, et al. [17] present detailed energy analyses for 108 industrial processes ranging from meatpacking and bread baking to aluminum production and iron and steel forging. Chapman & Roberts [18] also use energy analysis to calculate the energy required to produce and recycle metals.

Energy analysis is also used in DFE and LCA [19] literature as a methodology to assess the energy efficiency of products and processes [9,20]. For example, Graedel & Allenby [9] demonstrate how to calculate, based on process parameters, the energy consumed in manufacturing a material, and present a general approach for minimizing energy use in an industrial facility. Alternatively, from a product perspective, Sullivan & Hu [20] use Life Cycle Energy Analysis (LCEA) to calculate the life cycle energy consumption of both internal combustion engine vehicles and electric vehicles. Sullivan & Hu demonstrate how life cycle energy is most often considered during the development of automobiles; at the system level, rather than the component level.

One problem with this broad array of existing energy analyses, is the myriad of terms that have been developed to capture different types of energy use (use of fuel or electricity) for different processes throughout the life cycle (for material processing, product manufacture, use, and end-of-life). For example, the following terms have all been used to describe the energy required to extract a raw material from the earth (e.g., mine ore or pump oil) and to process (e.g., wash, concentrate, or refine) it into a material product (e.g., ingot or rolled sheet):

- Energy Content [2, 7]
- Energy Input [9]
- Fuel Requirements [18]
- Production Energy [20]
- Total Energy [16]

In addition to the use of multiple terms for the same idea, there is also conflicting usage of the term "energy content" by different authors. Boustead & Hancock [16] define energy content as the energy present in fuel that is actually available to the ultimate user (i.e., the energy that may be harnessed by combustion or other means from a fuel/material). However, as noted previously, Ashby's [2] and Granta Design's [7] use of energy content is broader and includes the energy necessary to mine, refine or synthesize, and form a material into usable sizes and shapes for manufacturing a product. To manage these terminology problems and provide consistency, the nomenclature described in the following section is used throughout this document.

2. NOMENCLATURE

2.1 Generic Energy Nomenclature

Disposal Energy – Energy consumed to shred and landfill the non-recycled portion of a product or component to a landfill (adapted from Sullivan & Hu [20]).

Energy Credit – Energy consumption averted by recycling or energy recovery.

Feedstock Energy – Combustion heat of raw material inputs, which are not used as an energy source, to a product system, expressed in terms of higher heating value or lower heating value [21].

Precombustion Energy – Energy required to extract, process, and deliver a fuel in a commercially useful form [22].

Process Energy – Energy consumed to fuel a process [22].

Total Energy – Sum total of feedstock, precombustion, process, transportation, and disposal energies, and energy credits.

Transportation Energy – Energy consumed to transport a product or material from one location to another [22].

2.2 Life Cycle Energy Nomenclature

E_{MP} – *Material Production Energy* – The total energy required to extract a raw material from the earth (e.g., mine ore or pump oil) and to process (e.g., wash, concentrate, or refine) it into a material product (e.g., ingot or rolled sheet) (adapted from Sullivan & Hu [20]).

E_{PMP} – *Primary Material Production Energy* – The material production energy for a primary (virgin) material.

E_{SMP} – *Secondary Material Production Energy* – The material production energy for a secondary (recycled) material.

E_{MD} – *Material Delivery Energy* – The transportation energy required to deliver a material product to a component fabrication facility.

E_{CF} – *Component Fabrication Energy* – The total energy required to fabricate a component from a useable material form (e.g., ingot or rolled sheet).

E_{CD} – *Component Delivery Energy* – The transportation energy required to deliver a component to a product assembly or maintenance facility.

E_{PA} – *Product Assembly Energy* – The total energy required to assemble a product from its individual components.

E_{PD} – *Product Delivery Energy* – The transportation energy required to deliver a product to its end user.

E_{USE} – *Use Phase Energy* – The total energy consumed by the normal use of a product throughout its life.

E_{MAINT} – *Maintenance Energy* – The total energy required to maintain the intended function of a component or product throughout the use phase of the product; not including the energy consumed by the normal use of the product.

E_{EOL} – *End-of-Life Energy* – The total energy necessarily consumed and actually avoided by the existence of a product after its intended life (e.g., all necessary transportation and disposal energies, and energy credits for the product's value as an energy and material resource).

3. LCEA FOR MATERIAL SELECTION

LCEA for Material Selection is a method for estimating the life cycle energy of a component as a part of the material selection process. The method is adapted from Sullivan & Hu's [20] method for estimating the life cycle energy of internal combustion and electric vehicles.

In LCEA, life cycle energy (LCE) is estimated at the component level as the sum of energy use at and between each stage of the life cycle for that component:

$$\begin{aligned} LCE_i \approx & \left(E_{MP}\right)_i + \left(E_{MD}\right)_i + \left(E_{CF}\right)_i + \left(E_{CD}\right)_i \cdots \\ & + \left(E_{PA}\right)_i + \left(E_{PD}\right)_i + \left(E_{USE}\right)_i \cdots \\ & + \left(E_{MAINT}\right)_i + \left(E_{EOL}\right)_i \end{aligned} \tag{1}$$

where:

LCE_i = life cycle energy for a component made from material i (MJ)

Energy consumed during each life cycle stage and for transport between each stage may be estimated as shown in Eqs. (2-11). First, material production energy, E_{MP}, is estimated for each component as:

$$(E_{MP})_i \approx m_i\left[(1-\psi_i)(e_{PMP})_i + \psi_i(e_{SMP})_i\right] \tag{2}$$

where:

$(E_{MP})_i$ = material production energy for a component made from material *i* (MJ)
m_i = mass of a component made from material *i* (kg)
ψ_i = recycled content fraction of material *i*
$(e_{PMP})_i$ = primary material production energy per unit mass for material *i* (MJ/kg)
$(e_{SMP})_i$ = secondary material production energy per unit mass for material *i* (MJ/kg)

Next, material delivery energy, E_{MD}, component fabrication energy, E_{CF}, and component delivery energy, E_{CD}, are omitted based on: 1) lack of data and 2) similar omission from Sullivan & Hu [20]. The material and component delivery energies are assumed to be small relative to other types of energy, and component fabrication energy is omitted because uniformly quantified fabrication data are scarce. Though considering component fabrication energy is desirable and more thorough, its omission is not expected to affect the results of the energy analysis significantly [20].

$$(E_{MD})_i \approx (E_{CD})_i \approx 0 \tag{3}$$

where:

$(E_{MD})_i$ = material delivery energy for a component made from material *i* (MJ)
$(E_{CD})_i$ = component delivery energy for a component made from material *i* (MJ)

$$(E_{CF})_i \approx m_i(e_{CF})_i \approx 0 \tag{4}$$

where:

$(E_{CF})_i$ = component fabrication energy for a component made from material *i* (MJ)
m_i = mass of a component made from material *i* (kg)
$(e_{CF})_i$ = component fabrication energy per unit mass for material *i* (MJ/kg)

Next, product assembly energy, E_{PA}, is estimated for each component as:

$$(E_{PA})_i \approx m_i(e_{PA}) \tag{5}$$

where:

$(E_{PA})_i$ = product assembly energy for a component made from material *i* (MJ)
m_i = mass of a component made from material *i* (kg)
e_{PA} = primary material production energy per unit mass for material *i* (MJ/kg)

Next, product delivery (or vehicle delivery) energy, E_{PD}, is estimated for each component as:

$$(E_{PD})_i \approx m_i(e_{PD}) \tag{6}$$

where:

$(E_{PD})_i$ = product delivery energy for a component made from material *i* (MJ)
m_i = mass of a component made from material *i* (kg)
e_{PD} = primary material production energy per unit mass for material *i* (MJ/kg)

Next, use phase energy, E_{USE}, is estimated for each component as:

$$(E_{USE})_i \approx \rho_f (e_{MP})_f (L_V)\left(\frac{1}{(MHFE')_i} - \frac{1}{MHFE}\right) \tag{7}$$

where:

$(E_{USE})_i$ = use phase energy for a component made from material *i* (MJ)
ρ_f = density of fuel (kg/gal)
$(e_{MP})_f$ = material production energy of fuel per unit mass (MJ/kg)
L_V = vehicle life (miles)
MHFE = metro-highway fuel economy of vehicle without component (mpg)
$(MHFE')_i$ = metro-highway fuel economy of vehicle with component made from material *i* (mpg)

Based on the fuel efficiency algorithm used by Sullivan & Hu [20], metro-highway fuel efficiency is estimated both for the vehicle without a component and for the vehicle with a component for each material using Eqs. (8,9). Fuel efficiency percentage increase (FEPI), the exponent in Eqs. (8,9), accounts for the nonlinear, lessening improvement in fuel efficiency realized by additional vehicle weight reduction.

$$MHFE \approx F(M_b - m_b)^{-FEPI} \tag{8}$$

$$(MHFE')_i \approx F(M_b - m_b + m_i)^{-FEPI} \tag{9}$$

where:

MHFE = metro-highway fuel economy of vehicle without component (mpg)
$(MHFE')_i$ = metro-highway fuel economy of vehicle with component made from material *i* (mpg)
F = constant used to balance equation = 1052.57 for 2270 lb (1030 kg) vehicle presented by Sullivan & Hu [20]
M_b = baseline vehicle mass (kg)
m_b = baseline component mass (kg)
m_i = mass of a component made from material *i* (kg)
FEPI = fuel efficiency percentage increase for a 10% weight savings = 0.50 for 2270 lb (1030 kg) vehicle presented by Sullivan & Hu [20]

Finally, maintenance and end-of-life energies are estimated using Eqs. (10,11). These equations assign energy credits for recycling based on the difference between primary material production energy and secondary material production energy multiplied by the recycle fraction. This allocation for open-loop recycling is identical to Sullivan & Hu (1992). Vigon, et al. [23] discuss additional allocation methods for both open and closed loop recycling. Also, despite its mention by Sullivan & Hu, credit for energy recovery is omitted from this analysis because Sullivan & Hu do not present relevant energy recovery data.

$$\left(E_{MAINT}\right)_i \approx m_i\left(\frac{L_V}{L_C}-1\right)\left[(1-\psi_i)\left(e_{PMP}\right)_i \cdots \right.$$
$$+\psi_i\left(e_{SMP}\right)_i+\left(e_{CF}\right)_i+(1-\phi_i)e_{DE}\cdots$$
$$\left.-\phi_i\left[\left(e_{PMP}\right)_i-\left(e_{SMP}\right)_i\right]\right] \tag{10}$$

$$\left(E_{EOL}\right)_i \approx m_i\left[(1-\phi_i)e_{DE}\right]-\phi_i\left[\left(e_{PMP}\right)_i-\left(e_{SMP}\right)_i\right] \tag{11}$$

where:

$(E_{MAINT})_i$ = maintenance energy for a component made from material *i* (MJ)
$(E_{EOL})_i$ = end-of-life energy for a component made from material *i* (MJ)
m_i = mass of a component made from material *i* (kg)
L_V = vehicle life (miles)
L_C = component life (miles)
ψ_i = recycled content fraction of material *i*
$(e_{PMP})_i$ = primary material production energy per unit mass for material *i* (MJ/kg)
$(e_{SMP})_i$ = secondary material production energy per unit mass for material *i* (MJ/kg)
$(e_{CF})_i$ = component fabrication energy per unit mass for material *i* (MJ/kg)
ϕ_i = recycle fraction of material *i*
e_{DE} = disposal energy per unit mass of material *i*

4. COMPARISON AND RESULTS OF ENERGY ANALYSIS METHODS

As discussed in the Introduction, Ashby [2] and Kampe [15] present methodologies for integrating energy consumption with material, shape, and other parameters for material selection. Specifically, Ashby uses a metric called Energy Content (EC) and Kampe uses his Lifetime Energy Consumption Index (LEC′). When component masses for each material are known, Eqs. (12, 13) may be used to calculate EC and LEC′ for a component made from a given material.

$$EC_i \approx m_i\left[(1-\psi_i)\left(e_{PMP}\right)_i+\psi_i\left(e_{SMP}\right)_i\right] \tag{12}$$
$$LEC_i' \approx m_i\left[(1-\psi_i)\left(e_{PMP}\right)_i+\psi_i\left(e_{SMP}\right)_i+C_E\right] \tag{13}$$

where:

EC_i = energy content for a component made from material *i* (MJ)
LEC_i' = Lifetime Energy Consumption Index for a component made from material *i* (MJ)
m_i = mass of a component made from material *i* (kg)
ψ_i = recycled content fraction of material *i*
$(e_{PMP})_i$ = primary material production energy per unit mass for material *i* (MJ/kg)
$(e_{SMP})_i$ = secondary material production energy per unit mass for material *i* (MJ/kg)
C_E = Exchange Constant ~ 236.8 MJ/kg for a 120,000 mile vehicle life [15] (MJ/kg)

The following section compares Ashby's Energy Content and Kampe's Lifetime Energy Consumption Index with Life Cycle Energy using an automotive example; and discusses the relevance of these results to non-automotive components.

4.1 Automotive Bumper-Reinforcing Beam Example

In this example, Ashby's Energy Content (EC), Kampe's Lifetime Energy Consumption (LEC′), and Life Cycle Energy (LCE) are used to evaluate material alternatives for a bumper-reinforcing beam used on cars and light trucks. A bumper-reinforcing beam is a structural component, hidden behind a bumper's fascia, that helps preserve the frame of an automobile by absorbing kinetic energy during a collision. Table

C1 presents the beam masses for different materials used in this example from the American Iron & Steel Institute (AISI) [24].

Table C1. Mass Comparison for Equivalent Reinforcing Beams [24]

Reinforcing Beam Material	Mass (kg)
PP/GF (unidirectional)	2.09
M220HT Steel	2.50
M190HT Steel	2.82
Al 7129-T6	2.84
PUR S-RIM 54% Glass (chopped or mat)	2.90
PC/PBT (injection molded)	3.40
M160HT Steel	3.44
140X or T Steel	3.76
PUR S-RIM 41% Glass (chopped or mat)	3.90
Al 6061-T6	3.90
PP/GF (direct melt / random)	4.50
PC/PBT (blow molded)	4.54
SMC	4.81
PP	6.80
180 Plannja Steel	7.71

The mass of each reinforcing beam represents the mass required for equivalent performance on the same size vehicle; though the AISI report does not state the approximate size vehicle for which these reinforcing beams are most appropriate. Though the AISI report does not state how this particular set of materials was selected, at least a subset of these materials may have been identified from a survey of 1990s passenger cars and light trucks.

In addition to the beam masses, the three analyses presented here require material-specific, vehicle-specific, and life cycle energy data. Table C2 presents the material-specific data including primary and secondary material production energy data from Sullivan & Hu [20] and recycle fraction data from CES [7]. CES also provides primary material production energy data, but calls it "energy content" and does not provide secondary production energy data. Table C3 documents the vehicle-specific and life cycle energy data used in the following analyses.

Table C2. Material Data Used for LCEA

Reinforcing Beam Material	Primary Material Production Energy Data	Secondary Material Production Energy Data	Recycle Fraction
	$(e_{PMP})_i$	$(e_{SMP})_i$	ϕ
	(MJ/kg)	(MJ/kg)	
PP/GF (unidirectional)	56.7	30.6	0.04
M220HT Steel	40.1	18.2	0.75
M190HT Steel	40.1	18.2	0.75
Al 7129-T6	196	26.8	0.85
PUR S-RIM 54% Glass (chopped or mat)	49.4	31.7	0.00
PC/PBT (injection molded)	159	48.2	0.25
M160HT Steel	40.1	18.2	0.75
140X or T Steel	40.1	18.2	0.75
PUR S-RIM 41% Glass (chopped or mat)	54.9	31.7	0.00
Al 6061-T6	196	26.8	0.85
PP/GF (direct melt / random)	56.7	30.6	0.04
PC/PBT (blow molded)	159	48.2	0.25
SMC	53.7	50.5	0.04
PP	74.4	42.3	0.30
180 Plannja Steel	40.1	18.2	0.85

Table C3. Vehicle and Energy Data for LCEA

Vehicle & Energy Data		Source Value		Converted Value	
Vehicle Life [20]	L_v	120000	miles		
Component Life [20]	L_c	60000	miles		
Fuel Density	ρ_f	2.8	$\frac{kg}{gal}$		
Baseline Component Mass [24]	m_b	7.71	kg		
Baseline Vehicle Mass [20]	M_b	2270	lbs	1030	kg
Material Production Energy of Fuel [16]	$(e_{MP})_f$	194.7	$\frac{MJ}{gal}$	58.0	$\frac{MJ}{kg}$

Table C3. Vehicle and Energy Data for LCEA (cont.)

Vehicle & Energy Data		Source Value		Converted Value	
Product Assembly Energy per Unit Mass [20]	e_{PA}	7,500	$\frac{BTU}{lb}$	17.4	$\frac{MJ}{kg}$
Product Delivery Energy per Unit Mass [20]	e_{PD}	394	$\frac{BTU}{lb}$	0.916	$\frac{MJ}{kg}$
Disposal Energy per Unit Mass [20]	e_{DE}	260	BTU/lb	0.605	MJ/kg

The results of the Life Cycle Energy Analysis are presented in Table C4 and Fig. C1. Table C4 contains the itemized results of the analysis for each material and Fig. C1 illustrates the relative magnitudes of material-specific (i.e., material production energy + end-of-life energy) and product-specific (i.e., product assembly energy + product delivery energy + use phase energy + maintenance energy) types of energy consumption. Use phase energy is shown separately from other product-specific types of energy in the figure to emphasize its large size relative to other types of life cycle energy.

Table C4. Life Cycle Energy Analysis Results for a Bumper-Reinforcing Beam on a 1030 Kg Vehicle

Reinforcing Beam Material	Material Production Energy	Product Assembly Energy	Product Delivery Energy	Use Phase Energy	Maintenance Energy	End-of-Life Energy
	MJ	MJ	MJ	MJ	MJ	MJ
PP/GF (unidirectional)	118	36	2	604	117	-1
M220HT Steel	100	44	2	722	60	-41
M190HT Steel	113	49	3	815	67	-46
Al 7129-T6	558	50	3	820	148	-409
PUR S-RIM 54% Glass	143	51	3	838	145	2
M160HT Steel	138	60	3	994	82	-56
140X or T Steel	151	66	3	1086	90	-61
Al 6061-T6	766	68	4	1126	204	-562
PUR S-RIM 41% Glass	214	68	4	1126	216	2
PP/GF (random)	255	79	4	1299	253	-2
PC/PBT (inj. molded)	539	59	3	982	447	-92
SMC	258	84	4	1389	261	2
PC/PBT (blow molded)	720	79	4	1311	597	-123
180 Plannja Steel	309	135	7	2224	166	-143
PP	506	119	6	1962	443	-63

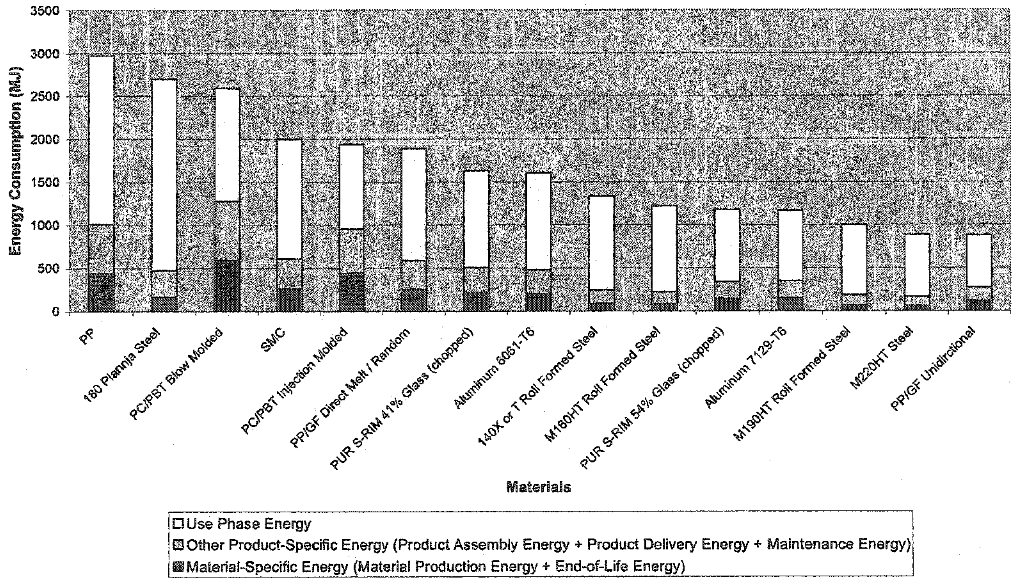

Figure C1. Aggregated Material and Product Specific Energy Analysis Results for a Bumper-Reinforcing Beam on a 1030 Kg Vehicle

Table C5 presents the quantitative results of each of the three analyses performed for the bumper-reinforcing beam example. From the table, it is clear that LEC′ and LCE produce similar results, despite the obvious magnitude differences between the two sets of results. For example, five of the top six performing materials are the same for both LEC′ and LCE. The only obvious difference between the two sets of results is the performance of aluminum grades relative to other materials. This discrepancy is primarily due to aluminum's large energy credits for recycling. LCE includes those credits; LEC′ does not.

Table C5. Comparison of Energy Analysis Results

Reinforcing Beam Material	LCE	LEC′	EC
		(MJ)	
PP/GF (unidirectional)	875	613	*118
M220HT Steel	885	692	100
M190HT Steel	998	781	113
Al 7129-T6	1167	*1230	*558
PUR S-RIM 54% Glass	1178	830	143
M160HT Steel	1218	953	138
140X or T Steel	1331	1041	151
Al 6061-T6	1602	*1689	*766
PUR S-RIM 41% Glass	1627	1138	214
PP/GF (random)	1884	1321	255
PC/PBT (inj. molded)	1935	1344	*539
SMC	1994	1397	258
PC/PBT (blow molded)	2584	1795	*720
180 Plannja Steel	2692	2135	309
PP	2968	2116	506

* Denotes material ranked more than two positions lower by LEC′ or EC methods than by LCE method.

Relative to the other two sets of results, the EC results differ more significantly. Specifically, these results for LCE and LEC′ correlate with an R^2 value of 0.875; whereas the highest correlation EC has with either of the other metrics is 0.483. Intuitively, this makes sense for this example because the use phase is a significant energy consumer and EC is the only metric that does not account for product use.

The influence of vehicle life on the results presented in Table C5 requires further investigation. In this paper, vehicle life is assumed to be 120,000 miles. However, Kampe [15] uses two other vehicle lives (50,000 and 200,000 miles) for his example. Kampe's chosen vehicle lives produce minimal or no change in the rankings generated using LCE and EC. However, the rankings produced using LEC′ change noticeably with vehicle life. Using 50,000 miles, LEC′ results correlate more favorably with EC (R^2 = 0.780) than LCE (R^2 = 0.717). However, as vehicle life increases to 200,000 miles, LEC′ results become increasingly similar to LCE results (R^2 = 0.894) and less similar to EC results (R^2 = 0.331).

The results appear to suggest that even though calculating LCE is most thorough, relative to the other two metrics, LEC′ is sufficient for use as a rough criterion for material selection. Conversely, EC appears less desirable in material selection for automotive components. However, these conclusions are dependent on the assumption that, in this instance, thoroughness corresponds to accuracy (i.e., that LCE is most accurate because it accounts for energy consumption during more life cycle stages than LEC′ and EC). However, this assumption is not verified by this work.

4.2 Beyond Automotive Components

The automotive results presented in the previous section provide some basic insight into using energy analyses for non-automotive components. The large factor that distinguishes Energy Content from the other two analyses in the automotive example is use phase energy. For computer components such as computer housings and printer trays, the use phase energy is presumably much smaller than that for an automotive component. As a result, EC and LCE analyses performed on computer components would likely provide very similar results; making the added calculations necessary for LCEA less justifiable.

5. EXTENDING METHODS BEYOND ENERGY

Energy consumption is only one way in which the selection of materials affects the environment. For example, some materials can be toxic, pose potential disposal problems, or cause the destruction of habitat [9]. The selection of certain materials can also lead to increased global warming and changes in land use [25]. Through its influence on vehicle emissions, material selection can also affect air quality (e.g., low level ozone and particulate matter).

Since energy consumption, like any other single metric, is unable to serve as a universal indicator of environmental impact, being able to estimate other metrics as quickly and easily as energy would be advantageous for material selection. However, most other metrics are still harder to quantify than energy [2]. A cause for this disparity stems from the fact that there is a financial incentive to measure energy and extensive data sets exist.

However, increasing concern about the environment and increasing use of quantitative analyses such as Life Cycle Assessment (LCA) appear to be having a positive impact on the availability of environmental data beyond energy consumption. For example, extensive databases such as IDEMAT [26] and the Franklin US LCI database [27] are needed to support LCA software such as SimaPro [28] and GaBi [29]. With the growing availability of these databases, opportunities exist to begin developing simple assessment methodologies for environmental metrics, such as: CO_2 equivalent emissions, particulate matter emissions, and precious metal consumption. In addition to material-specific data, process and product specific data will also need to be collected to develop appropriate models.

6. CONCLUSION

This paper presented a method of performing Life Cycle Energy Analysis for the purpose of material selection. The method applied product analysis methods to the evaluation of material options for automotive components. By comparing material options for a bumper-reinforcing beam on a 1030 kg vehicle, oriented glass fiber composites and high-strength steels were found to be preferable from a life cycle energy perspective. This paper also presented a set of life cycle energy terms designed to clearly distinguish between energy consumption occurring during different phases of a product's life cycle. In addition, this paper compared the results of the LCEA method to those of other energy analyses and demonstrated how different methods of varying thoroughness resulted in different material selections. Finally, opportunities were identified for extending this type of analysis beyond both automotive components and energy consumption.

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Appendix D

Evaluation Matrices for DFFA Case Study

This appendix contains the eight evaluation matrices used to develop the DFFA case study presented in Chapter 4. There is one evaluation matrix for every major component in the washer and wiper systems of a standard Ford C-class sedan:

Table Number Page

Table D1. Evaluation of New Reservoir Design

		Baseline Design	New Design	Sources of Design Uncertainty (Design Scenarios)				
				Shape	Material	Fit	Manufacturing	Other
Attributes (i.e., Input Variables)	Variable Class	Shape A HDPE 2 x screw & nut Injection molding	Unknown	Shape A Shape B Shape C ...	HDPE PP	2 x screw & nut 3 x screw & nut ...	Injection molding Blow molding	
Mass	Number	0.554	Unknown	X	X			
Kg				The mass of the new design depends on its shape and material.				
Fragility / durability problems	Yes/No	No	No					
Is the component prone to break, scratch, bend, dent, or crinkle?								
Nesting / tangling problems	Options	No nesting/ tangling	No nesting/ tangling					
No nesting/ tangling, nesting/ tangling, severe nesting/ tangling								
Tool requirements	Options	No tool	No tool					
No tool, tweezers, other tool								
Part size	Levels	>12 mm	>12 mm					
<2 mm, 2-6 mm, 6-12 mm, >12 mm								
Part thickness	Levels	>2 mm	>2 mm					
<0.5 mm, 0.5-2 mm, >2 mm								
Orientation about insertion axis	Options	1 obvious	1 obvious					
1 subtle, 1 obvious, 2 or more								
End-to-end alignment	Options	1 obvious	1 obvious 2 or more	X				
1 subtle, 1 obvious, 2 or more				The shape may be changed to allow for 2 acceptable alignments.				
Insertion direction	Options	Down	Down Side					X
Down, side, diagonal, twist/turn/tilt, up				The design does not fully constrain the insertion direction.				
Constrained motion	Yes/No	No	Yes No					X
Is operator access limited by fixturing or other components?				Changes to other components outside this system may limit operator access.				
Temporary hold down required	Yes/No	No	No					
Will component stay in place only if supported until another subsequent component is added?								
Two hands required	Yes/No	No	Yes No					X
Are two hands required to insert component?				Changes to components outside this system may make two hands necessary.				
Rotation required	Yes/No	No	No					
Is reorientation required before inserting component?								
Fixturing required	Yes/No	No	No					
Is fixturing required before inserting component?								
Flexible part	Yes/No	No	No					
Does the component require extra manipulation during insertion? or does it not stay in place when released?								
Insertion clearance	Levels	1-10%	1-10% 10-50%			X		
<1%, 1-10%, 10-50%, >50%				The fit may be changed to allow for more insertion clearance.				
Fastening process	Options	Separate fasteners	Separate fasteners					
Snap fit, press fit, bending, crimping, screwing, polymer weld or stake, solder, metal weld, braze, adhesive, separate fasteners								
Separate fasteners	Options	2 x screws & nuts	2 x screws & nuts 3 x screws & nuts ...			X		
Washer, snap fit, pin, retaining ring, screw, nut, rivet				The choice of separate fasteners corresponds directly to a selection of fit.				

Table D2. Evaluation of New Spout Design

		Baseline Design	New Design	Sources of Design Uncertainty (Design Scenarios)				
				Shape	Material	Fit	Manufacturing	Other
Attributes (i.e., Input Variables)	Variable Class	Shape A PP Snap fit w/washer Blow molding	Unknown	Shape A Shape B Shape C ...	PP HDPE	Snap fit w/washer	Blow molding Injection molding	
Mass	Number	0.037	Unknown	X	X			
Kg				The mass of the new design depends on its shape and material.				
Fragility / durability problems	Yes/No	No	No					
Is the component prone to break, scratch, bend, dent, or crinkle?								
Nesting / tangling problems	Options	No nesting/ tangling	No nesting/ tangling					
No nesting/ tangling, nesting/ tangling, severe nesting/ tangling								
Tool requirements	Options	No tool	No tool					
No tool, tweezers, other tool								
Part size	Levels	>12 mm	>12 mm					
<2 mm, 2-6 mm, 6-12 mm, >12 mm								
Part thickness	Levels	>2 mm	>2 mm					
<0.5 mm, 0.5-2 mm, >2 mm								
Orientation about insertion axis	Options	1 obvious	1 obvious					
1 subtle, 1 obvious, 2 or more								
End-to-end alignment	Options	1 obvious	1 obvious					
1 subtle, 1 obvious, 2 or more								
Insertion direction	Options	Side	Down Side					X
Down, side, diagonal, twist/turn/tilt, up				The architecture of the system may be changed to allow for downward insertion.				
Constrained motion	Yes/No	No	Yes No					X
Is operator access limited by fixturing or other components?				Changes to other components outside this system may limit operator access.				
Temporary hold down required	Yes/No	No	No					
Will component stay in place only if supported until another subsequent component is added?								
Two hands required	Yes/No	No	Yes No					X
Are two hands required to insert component?				Changes to components outside this system may make two hands necessary.				
Rotation required	Yes/No	No	Yes No					X
Is reorientation required before inserting component?				The design does not fully constrain assembly.				
Fixturing required	Yes/No	No	No					
Is fixturing required before inserting component?								
Flexible part	Yes/No	No	No					
Does the component require extra manipulation during insertion? or does it not stay in place when released?								
Insertion clearance	Levels	1-10%	1-10% 10-50%			X		
<1%, 1-10%, 10-50%, >50%				The fit may be changed to allow for more insertion clearance.				
Fastening process	Options	Snap fit	Snap fit					
Snap fit, press fit, bending, crimping, screwing, polymer weld or stake, solder, metal weld, braze, adhesive, separate fasteners								
Separate fasteners	Options	Washer	Washer					
Washer, snap fit, pin, retaining ring, screw, nut, rivet								

Table D3. Evaluation of New Pump Design

		Baseline Design	New Design	Sources of Design Uncertainty (Design Scenarios)				
				Shape	Material	Fit	Manufacturing	Other
Attributes (i.e., Input Variables)	Variable Class	Pump A	Pump A Pump B Pump C …					
Mass	Number	0.072	Unknown					X
Kg				The mass of the new design equals the mass of the pump selected.				
Fragility / durability problems	Yes/No	No	No					
Is the component prone to break, scratch, bend, dent, or crinkle?								
Nesting / tangling problems	Options	No nesting/ tangling	No nesting/ tangling					
No nesting/ tangling, nesting/ tangling, severe nesting/ tangling								
Tool requirements	Options	No tool	No tool					
No tool, tweezers, other tool								
Part size	Levels	>12 mm	>12 mm					
<2 mm, 2-6 mm, 6-12 mm, >12 mm								
Part thickness	Levels	>2 mm	>2 mm					
<0.5 mm, 0.5-2 mm, >2 mm								
Orientation about insertion axis	Options	1 obvious	1 obvious					
1 subtle, 1 obvious, 2 or more								
End-to-end alignment	Options	1 obvious	1 obvious					
1 subtle, 1 obvious, 2 or more								
Insertion direction	Options	Side	Down Side					X
Down, side, diagonal, twist/turn/tilt, up				The design does not fully constrain assembly.				
Constrained motion	Yes/No	No	Yes No					X
Is operator access limited by fixturing or other components?				Changes to other components outside this system may limit operator access.				
Temporary hold down required	Yes/No	No	No					
Will component stay in place only if supported until another subsequent component is added?								
Two hands required	Yes/No	No	Yes No					X
Are two hands required to insert component?				Changes to components outside this system may make two hands necessary.				
Rotation required	Yes/No	No	Yes No					X
Is reorientation required before inserting component?				The design does not fully constrain assembly.				
Fixturing required	Yes/No	No	No					
Is fixturing required before inserting component?								
Flexible part	Yes/No	No	No					
Does the component require extra manipulation during insertion? or does it not stay in place when released?								
Insertion clearance	Levels	1-10%	1-10%					
<1%, 1-10%, 10-50%, >50%								
Fastening process	Options	Snap fit	Snap fit					
Snap fit, press fit, bending, crimping, screwing, polymer weld or stake, solder, metal weld, braze, adhesive, separate fasteners								
Separate fasteners	Options	Washer	Washer					
Washer, snap fit, pin, retaining ring, screw, nut, rivet								

Table D4. Evaluation of New Hose Design

		Baseline Design	New Design	Sources of Design Uncertainty (Design Scenarios)				
				Shape	Material	Fit	Manufacturing	Other
Attributes (i.e., Input Variables)	Variable Class	Length A EPDM	Unknown	Length A Length B Length C …	EPDM PA PVC	Press fit w/snap fits	Molding & Extrusion	
Mass	Number	0.054	Unknown	X	X			
Kg				The mass of the new design depends on its shape and material.				
Fragility / durability problems	Yes/No	Yes	Yes No		X			
Is the component prone to break, scratch, bend, dent, or crinkle?				EPDM and PA may be kinked during assembly.				
Nesting / tangling problems	Options	Nesting/ tangling	Nesting/ tangling					
No nesting/ tangling, nesting/ tangling, severe nesting/ tangling								
Tool requirements	Options	No tool	No tool					
No tool, tweezers, other tool								
Part size	Levels	>12 mm	>12 mm					
<2 mm, 2-6 mm, 6-12 mm, >12 mm								
Part thickness	Levels	>2 mm	>2 mm					
<0.5 mm, 0.5-2 mm, >2 mm								
Orientation about insertion axis	Options	1 subtle	1 subtle 1 obvious					X
1 subtle, 1 obvious, 2 or more				The hose may be changed to make one end obvious (e.g., color).				
End-to-end alignment	Options	1 obvious	1 obvious					
1 subtle, 1 obvious, 2 or more								
Insertion direction	Options	Down	Down Diagonal					X
Down, side, diagonal, twist/turn/tilt, up				The design does not fully constrain assembly.				
Constrained motion	Yes/No	No	Yes No					X
Is operator access limited by fixturing or other components?				The design does not fully constrain assembly.				
Temporary hold down required	Yes/No	No	No					
Will component stay in place only if supported until another subsequent component is added?								
Two hands required	Yes/No	Yes	Yes					
Are two hands required to insert component?								
Rotation required	Yes/No	No	Yes No					X
Is reorientation required before inserting component?				The design does not fully constrain assembly.				
Fixturing required	Yes/No	No	No					
Is fixturing required before inserting component?								
Flexible part	Yes/No	Yes	Yes					
Does the component require extra manipulation during insertion? or does it not stay in place when released?								
Insertion clearance	Levels	1-10%	1-10% 10-50%			X		
<1%, 1-10%, 10-50%, >50%				The fit may be changed to allow for more insertion clearance.				
Fastening process	Options	Press fit	Press fit					
Snap fit, press fit, bending, crimping, screwing, polymer weld or stake, solder, metal weld, braze, adhesive, separate fasteners								
Separate fasteners	Options	4 snap fits	3 snap fits 4 snap fits 5 snap fits	X				
Washer, snap fit, pin, retaining ring, screw, nut, rivet				The number of snap fits depends on length.				

Table D5. Evaluation of New Nozzle Design

		Baseline Design	New Design	Sources of Design Uncertainty (Design Scenarios)				
				Shape	Material	Fit	Manufacturing	Other
Attributes (i.e., Input Variables)	Variable Class	Shape A PP Snap fit	Unknown	Shape A Shape B Shape C …	PP PA PET	Snap fit	Injection molding	
Mass	Number	0.005	Unknown	X	X			
Kg				The mass of the new design depends on its shape and material.				
Fragility / durability problems	Yes/No	No	No					
Is the component prone to break, scratch, bend, dent, or crinkle?								
Nesting / tangling problems	Options	No nesting/ tangling	No nesting/ tangling					
No nesting/ tangling, nesting/ tangling, severe nesting/ tangling								
Tool requirements	Options	No tool	No tool					
No tool, tweezers, other tool								
Part size	Levels	>12 mm	>12 mm					
<2 mm, 2-6 mm, 6-12 mm, >12 mm								
Part thickness	Levels	>2 mm	>2 mm					
<0.5 mm, 0.5-2 mm, >2 mm								
Orientation about insertion axis	Options	1 obvious	1 obvious					
1 subtle, 1 obvious, 2 or more								
End-to-end alignment	Options	1 obvious	1 obvious					
1 subtle, 1 obvious, 2 or more								
Insertion direction	Options	Down	Down Diagonal					X
Down, side, diagonal, twist/turn/tilt, up				The design does not fully constrain assembly.				
Constrained motion	Yes/No	No	Yes No					X
Is operator access limited by fixturing or other components?				The design does not fully constrain assembly.				
Temporary hold down required	Yes/No	No	No					
Will component stay in place only if supported until another subsequent component is added?								
Two hands required	Yes/No	No	Yes No					X
Are two hands required to insert component?				The design does not fully constrain assembly.				
Rotation required	Yes/No	No	Yes No					X
Is reorientation required before inserting component?				The design does not fully constrain assembly.				
Fixturing required	Yes/No	No	No					
Is fixturing required before inserting component?								
Flexible part	Yes/No	No	No					
Does the component require extra manipulation during insertion? or does it not stay in place when released?								
Insertion clearance	Levels	1-10%	1-10% 10-50%			X		
<1%, 1-10%, 10-50%, >50%				The fit may be changed to allow for more insertion clearance.				
Fastening process	Options	Snap fit	Snap fit					
Snap fit, press fit, bending, crimping, screwing, polymer weld or stake, solder, metal weld, braze, adhesive, separate fasteners								
Separate fasteners	Options	None	None					
Washer, snap fit, pin, retaining ring, screw, nut, rivet								

Table D6. Evaluation of New Motor & Linkage Design

		Baseline Design	New Design	Sources of Design Uncertainty (Design Scenarios)				
				Architecture	Material	Fit	Manufacturing	Other
Attributes (i.e., Input Variables)	Variable Class	Arch. A Steel linkage AL mount 3 screws	Unknown	Arch. A Arch. B Arch. C …	Linkage Steel Mount AL MG	3 screws 3 screws w/nuts 4 screws …	Supplier A	
Mass	Number	3.104	Unknown	X	X			
Kg				The mass of the new design depends on its shape and material.				
Fragility / durability problems	Yes/No	No	No					
Is the component prone to break, scratch, bend, dent, or crinkle?								
Nesting / tangling problems	Options	Nesting/ tangling	Nesting/ tangling No nesting/ tangling	X				
No nesting/ tangling, nesting/ tangling, severe nesting/ tangling				The architecture may be changed to reduce likelihood of tangling.				
Tool requirements	Options	No tool	No tool					
No tool, tweezers, other tool								
Part size	Levels	>12 mm	>12 mm					
<2 mm, 2-6 mm, 6-12 mm, >12 mm								
Part thickness	Levels	>2 mm	>2 mm					
<0.5 mm, 0.5-2 mm, >2 mm								
Orientation about insertion axis	Options	1 obvious	1 obvious					
1 subtle, 1 obvious, 2 or more								
End-to-end alignment	Options	1 obvious	1 obvious					
1 subtle, 1 obvious, 2 or more								
Insertion direction	Options	Down	Down Side					X
Down, side, diagonal, twist/turn/tilt, up				The design does not fully constrain assembly.				
Constrained motion	Yes/No	No	Yes No					X
Is operator access limited by fixturing or other components?				The design does not fully constrain assembly.				
Temporary hold down required	Yes/No	No	No					
Will component stay in place only if supported until another subsequent component is added?								
Two hands required	Yes/No	Yes	Yes No	X				
Are two hands required to insert component?				The architecture may be changed to require only one hand for insertion.				
Rotation required	Yes/No	No	No					
Is reorientation required before inserting component?								
Fixturing required	Yes/No	No	No					
Is fixturing required before inserting component?								
Flexible part	Yes/No	No	No					
Does the component require extra manipulation during insertion? or does it not stay in place when released?								
Insertion clearance	Levels	1-10%	1-10% 10-50%			X		
<1%, 1-10%, 10-50%, >50%				The fit may be changed to allow for more insertion clearance.				
Fastening process	Options	Separate fasteners	Separate fasteners					
Snap fit, press fit, bending, crimping, screwing, polymer weld or stake, solder, metal weld, braze, adhesive, separate fasteners								
Separate fasteners	Options	3 screws	3 x screws 3 x screws & nuts 4 screws …			X		
Washer, snap fit, pin, retaining ring, screw, nut, rivet				The choice of separate fasteners corresponds directly to a selection of fit.				

Table D7. Evaluation of New Arm Design

		Baseline Design	New Design	Sources of Design Uncertainty (Design Scenarios)				
				Shape	Material	Fit	Manufacturing	Other
Attributes (i.e., Input Variables)	Variable Class	Shape A Zinc head Steel arm Nut	Unknown	Shape A	Head Zinc AL Arm Steel	Nut	Supplier A	
Mass	Number	0.319/0.336	Unknown	X	X			
Kg				The mass of the new design depends on its shape and material.				
Fragility / durability problems	Yes/No	No	No					
Is the component prone to break, scratch, bend, dent, or crinkle?								
Nesting / tangling problems	Options	No nesting/ tangling	No nesting/ tangling					
No nesting/ tangling, nesting/ tangling, severe nesting/ tangling								
Tool requirements	Options	No tool	No tool					
No tool, tweezers, other tool								
Part size	Levels	>12 mm	>12 mm					
<2 mm, 2-6 mm, 6-12 mm, >12 mm								
Part thickness	Levels	>2 mm	>2 mm					
<0.5 mm, 0.5-2 mm, >2 mm								
Orientation about insertion axis	Options	1 obvious	1 obvious					
1 subtle, 1 obvious, 2 or more								
End-to-end alignment	Options	1 obvious	1 obvious					
1 subtle, 1 obvious, 2 or more								
Insertion direction	Options	Down	Down					
Down, side, diagonal, twist/turn/tilt, up								
Constrained motion	Yes/No	No	No					
Is operator access limited by fixturing or other components?								
Temporary hold down required	Yes/No	No	No					
Will component stay in place only if supported until another subsequent component is added?								
Two hands required	Yes/No	No	Yes No					X
Are two hands required to insert component?				The design does not fully constrain assembly.				
Rotation required	Yes/No	No	No					
Is reorientation required before inserting component?								
Fixturing required	Yes/No	No	No					
Is fixturing required before inserting component?								
Flexible part	Yes/No	No	No					
Does the component require extra manipulation during insertion? or does it not stay in place when released?								
Insertion clearance	Levels	10-50%	10-50%					
<1%, 1-10%, 10-50%, >50%								
Fastening process	Options	Separate fasteners	Separate fasteners					
Snap fit, press fit, bending, crimping, screwing, polymer weld or stake, solder, metal weld, braze, adhesive, separate fasteners								
Separate fasteners	Options	Nut	Nut					
Washer, snap fit, pin, retaining ring, screw, nut, rivet								

Table D8. Evaluation of New Blade Design

		Baseline Design	New Design	Sources of Design Uncertainty (Design Scenarios)				
				Shape	Material	Fit	Manufacturing	Other
Attributes (i.e., Input Variables)	Variable Class	Blade A	Blade A	Shape A	Steel	Snap fit	Supplier A	
Mass	Number	0.175/0.091	0.175/0.091					
Kg								
Fragility / durability problems	Yes/No	No	No					
Is the component prone to break, scratch, bend, dent, or crinkle?								
Nesting / tangling problems	Options	No nesting/ tangling	No nesting/ tangling					
No nesting/ tangling, nesting/ tangling, severe nesting/ tangling								
Tool requirements	Options	No tool	No tool					
No tool, tweezers, other tool								
Part size	Levels	>12 mm	>12 mm					
<2 mm, 2-6 mm, 6-12 mm, >12 mm								
Part thickness	Levels	>2 mm	>2 mm					
<0.5 mm, 0.5-2 mm, >2 mm								
Orientation about insertion axis	Options	1 subtle	1 subtle					
1 subtle, 1 obvious, 2 or more								
End-to-end alignment	Options	1 obvious	1 obvious					
1 subtle, 1 obvious, 2 or more								
Insertion direction	Options	Side	Down Side					X
Down, side, diagonal, twist/turn/tilt, up				The design does not fully constrain assembly.				
Constrained motion	Yes/No	No	No					
Is operator access limited by fixturing or other components?								
Temporary hold down required	Yes/No	No	No					
Will component stay in place only if supported until another subsequent component is added?								
Two hands required	Yes/No	Yes	Yes					
Are two hands required to insert component?								
Rotation required	Yes/No	No	Yes No					X
Is reorientation required before inserting component?				The design does not fully constrain assembly.				
Fixturing required	Yes/No	No	No					
Is fixturing required before inserting component?								
Flexible part	Yes/No	No	No					
Does the component require extra manipulation during insertion? or does it not stay in place when released?								
Insertion clearance	Levels	1-10%	1-10%					
<1%, 1-10%, 10-50%, >50%								
Fastening process	Options	Snap fit	Snap fit					
Snap fit, press fit, bending, crimping, screwing, polymer weld or stake, solder, metal weld, braze, adhesive, separate fasteners								
Separate fasteners	Options	None	None					
Washer, snap fit, pin, retaining ring, screw, nut, rivet								

Vita

Peder Fitch was born in Seattle, Washington, but moved to Portland, Oregon at a young age. After starting elementary school in Portland, he moved back to Seattle. Then, after high school, he left the Northwest to attend the University of Michigan. At the University of Michigan, he earned a Bachelor of Science degree in Mechanical Engineering. He later moved to California and earned a Master of Science degree in Mechanical Engineering from Stanford University. After leaving Stanford, he moved back to the Northwest and eventually worked his way back to Seattle. In 2004, he earned a Doctor of Philosophy in Mechanical Engineering at the University of Washington.