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Probabilistic Graphical Modeling as a Use Stage Inventory Method for Environmentally Conscious Design

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Probabilistic Graphical Modeling as a Use Stage Inventory Method for Environmentally Conscious Design

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For my family and friends

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Probabilistic Graphical Modeling as a Use Stage Inventory Method for Environmentally Conscious Design

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Probabilistic graphical models (PGMs) provide the capability of evaluating uncertainty and variability of product use in addition to correlating the results with aspects of the usage context. Although energy consumption during use can cause a majority of a product's environmental impact, common practice is to neglect operational variability in life cycle inventories (LCIs). Therefore, the relationship between a product's usage context and its environmental performance is rarely considered in design evaluations. This dissertation demonstrates a method for describing the usage context as a set of factors and representing the usage context through a PGM. The application to LCIs is demonstrated through the use of a lightweight vehicle design example. Although replacing steel vehicle parts with aluminum parts reduces the weight and can increase fuel economy, the energy invested in production of aluminum parts is much larger than that of steel parts. The tradeoff between energy investment and fuel savings is highly dependent upon the vehicle fuel economy and lifetime mileage. The demonstration PGM is constructed from relating factors such as driver behavior, alternative driving schedules, and residential density with local conditional probability distributions derived from publicly available data sources. Unique scenarios are then assembled from sets of conditions on these factors to provide insight

for sources of variance. The vehicle example demonstrated that implementation of realistic usage scenarios via a PGM can provide a much higher fidelity investigation of energy savings during use and that distinct scenarios can have significantly different implications for the effectiveness of lightweight vehicle designs. Scenarios with large families, for example, yield high energy savings, especially if the vehicle is used for commuting or stop-and-go traffic conditions. Scenarios of small families and efficient driving schedules yield lower energy savings for lightweight vehicle designs.

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Chapter 1

Introduction

This research focuses on operational variability, and specifically the effect of variation in usage context on the energy consumption of consumer products. It is hypothesized that modeling variability in the usage context increases the precision with which the energy consumption of a product's use stage can be estimated and helps designers evaluate the effectiveness of specific product features for reducing energy consumption. The magnitude of a product's energy consumption is often subject to significant variability. For example, the type and efficiency of energy consumption for a plug-in electric vehicle is influenced by the technologies and mix of feedstocks (e.g.,coal, wind, natural gas, oil, nuclear, solar) powering the electric grid, and this mix is determined partially by the grid's dynamic loads and capacities (Samaras & Meisterling, 2008). Additionally, the energy consumption related to feedstock materials and component parts of a vehicle can depend significantly on the characteristics of the facility in which they are processed or manufactured (Ayres, 1995). Furthermore, the efficiency of a vehicle varies significantly with the context in which it is used, including not only situational factors (e.g., city versus highway driving, congestion levels) but also human factors (e.g., driving style) (Ridge, 1998; Greene et al., 2006).

Specifically, three types of usage context factors are considered: human factors (who uses the product and their skills or habits), situational factors (where, when, and for what task the product is being used), and product factors (design features and specifications that influence how a product is used.)

1.1 Environmental Design and Product Use

Environmentally conscious design focuses on reducing the environmental impact of a product throughout its life cycle. The life cycle of a product, depicted in Figure 1.1, includes all processes from raw material extraction through product disposal. Energy life cycle inventories (LCIs) are an accepted approach for measuring the total energy inputs of each process. For convenience, life cycle processes are commonly grouped into four stages: material production, part manufacture, use, and end-of-life. LCI procedures help designers avoid transferring environmental impacts from one stage to another by measuring all the inputs, such as energy and materials, and outputs, such as solid waste and emissions, of each stage. Although many environmental impacts exist at many levels, higher level impacts, such as greenhouse gases, are evaluated post-LCI. LCIs measure energy and material consumption and exhaust of individual substances, such as the carbon dioxide and methane emissions that combine to create greenhouse gases. This dissertation focuses in particular on the consumption of energy.

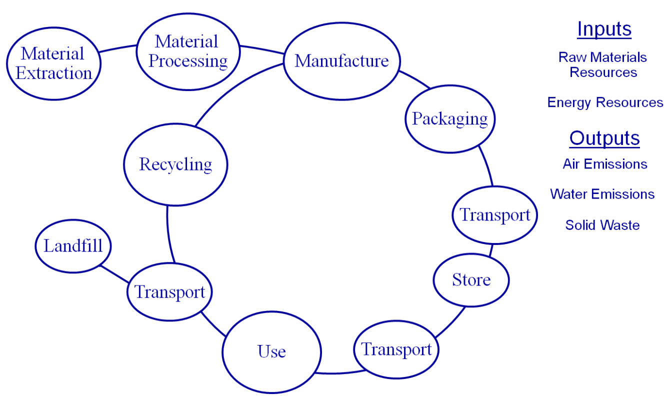


Figure 1.1: Flowchart of a Generic Product Life Cycle

Usage characteristics are important for consumer products because energy consumption during use can be more significant than energy consumption during manufacturing and end-of-life. Automobiles provide one example of a product with intensive manufacturing processes and a heavy mass of energy expensive components. Regardless, more than 60% of a vehicle's lifetime energy consumption occurs during its use stage (Sullivan & Cobas-Flores, 2001). For simpler household products, the significance of the use stage may be even higher (Throne-Holst et al., 2007; Peattie, 2010; Oberender et al., 2001; Telenko & Seepersad, 2010). Figure 1.2, from previous research by the author, depicts the environmental impacts of an electric kettle, a product that operates at high power but contains only a few lightweight components. The energy consumption of the use stage dominates the kettle's total life cycle impacts. Parameter used for estimating energy consumption, such as the useful life of the product and the operating temperatures, in the case of the kettle, are highly variable and thus make realistic energy values difficult to predict.

A variety of product classes are subject to use variability. Table 1.1 lists three different products for industrial and residential applications and several aspects of the usage context that contribute to variable energy use for each product. For example, the Selective Laser Sintering (SLS) machine is an additive manufacturing machine for rapid production of commercial parts by sintering successive cross-sections of a product in a bed of powder. Research has found that energy efficiency is highly dependent upon utilization of the full build volume of the machine. Partial builds incur substantially higher energy costs per part, because energy is consumed during a pre-heating stage that must be completed before each build, regardless of the size of the build (Telenko & Seepersad, 2012; Baumers et al., 2011; Mognol et al., 2006). In another example, electric kettles consume energy in proportion to the amount of water heated and the initial and final temperatures of the water. Thus, substantial variability in energy consumption can result from regularly heating too much water or from over-boiling the water.

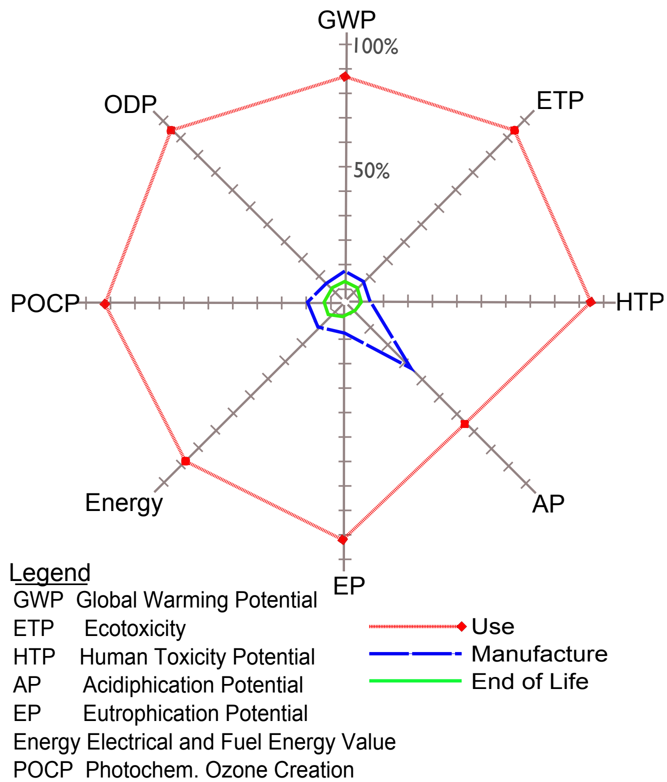


Figure 1.2: Environmental Impacts of an Example Kettle from Telenko et al. (Telenko 2010)

Some modern commercial designs are beginning to implement feedback systems at the product-user interface to reduce the energy consumption of products during operation. General Motors and OnStar offer an iPhone app, shown in Figure 1.3, that monitors tire pressure for safety and fuel economy purposes (Diehlman, 2010). Additionally, automotive manufacturers are introducing feedback systems to correct driving behavior in hybrid vehicles. Ford recently patented their Smartgauge EcoGuide, shown in Figure 1.4, to display the image of a tree progressively blooming or wilting in real-time response to driver fuel efficiency (Ford Motor Company, 2011). Both a tool and a game, the feedback provided by this gauge helps drivers keep their hybrid vehicles in electric mode longer and maximize fuel economy in both

Product	SLS Machine	Electric Kettle	Vehicle
User(s)	Technician	Household Member	Driver
Human	Build Planning	Focus on Task	Aggressiveness
Factors	Powder Waste	Culinary Preferences	Maintenance
Situational	Part Dimensions	Desired Temperature	Luggage
Factors	Part Density	Input Temperature	City/Hwy
Product	Max Dimensions	Water Measurement	Engine Efficiency
Factors	Powder Reusability	Notifications	Size

Table 1.1: Usage Context Factors that Contribute to Variable Energy Use for Three Types of Products

driving modes. Ford's EcoGuide and Toyota's similar Prius dashboard suggest that automakers recognize the influential role that consumers play in maximizing vehicle fuel economy. Nevertheless, examples like these are limited; it can be difficult for designers to consider the interaction of product features with a usage context and evaluate sustainability of those features.

Figure 1.3: GM OnStar App for monitoring vehicle maintenance (Diehlman, 2010)

Despite advances, energy saving design changes can be undermined in unex-

.

Figure 1.4: The Ford Smartguage EcoGuide increases the efficiency of hybrid powertrains (Ford Motor Company, 2011)

pected ways by product, human and situational factors. For example, Thollier & Jansen (2008) report that users often disable stand-by mode for computers and conclude that user behavior should be better addressed in energy saving designs. The rebound effect is a prominent economic example of how energy efficient design may increase overall energy consumption. As a result of being more fuel efficient than a competing compact car, a hybrid vehicle may be driven more often and incur the same fuel costs and consumptions, thereby negating the investment of battery and hybrid technology. Herring & Roy (2007) review studies of the rebound effect in energy efficiency and conclude that innovation aimed at reducing consumption during product use must take consumer lifestyles into account. Throne-Holst et al. (2007) reach a similar conclusion studying consumer contributions to household energy consumption and waste disposal. In each case, consumer habits and product use are deciding factors in the efficiency of design solutions. Therefore, assessment of variability in usage patterns and contexts is essential for evaluating the potential energy savings of a design change.

Although use variability is beginning to be addressed through commercial design, it is not well characterized in quantitative, energy LCIs. There is, therefore, a need to explore techniques for addressing the variability and uncertainty of consumer behavior and how it influences design changes intended to reduce the energy footprints of products. Specifically, this dissertation work leverages usage context based design and probabilistic graphical models to quantify and model variability in product operation.

1.2 Research Hypothesis

> Modeling the usage context of a product using a probabilistic graphical model (PGM) in conjunction with a life cycle inventory (LCI) can effectively: (1) facilitate estimation of a product's variable resource consumption during its use stage and (2) expose usage scenarios that most influence life cycle resource consumption.

This hypothesis includes two primary goals of this research. The first goal is to utilize a stochastic model of a product's usage context to rationally estimate a product's energy and resource consumption during use. These environmental metrics are difficult to predict, but can be rationally estimated through the use of underlying usage context factors. The second goal is to increase a designers understanding of a product's energy consumption by exploring and targeting usage scenarios, or sets of conditions for one or more factors. This capability allows designers to explore scenarios that might inspire new design ideas, define opportunities for creating product variants or more robust designs, or simpy enhance a designer's understanding of the usage scenarios for which their designs are most energy and resource efficient.

1.3 Related Research

Shipworth (2006, 2002) has previously proposed the use of Bayesian networks, a form of PGM, for predicting household and community energy consumption. PGMs use graph representation to decompose a complex system, such as the product usage context, into a set of composing random variables. These random variables might include stakeholders, environmental factors and design features. These variables are then related stochastically using Bayes theorem and sets of conditional and joint probability distributions. Shipworth's (2006) model relates a number of nodes describing functional attributes of homes including social and political factors at an aggregate level. The model, however, is a nave Bayes model and assumes that all factors are independent of each other (Olivier, 2008). Unlike Shipworth's (2006) model, the tool proposed here is aimed at understanding conditional dependencies in a more detailed usage context, and it is structured to aid the product designer.

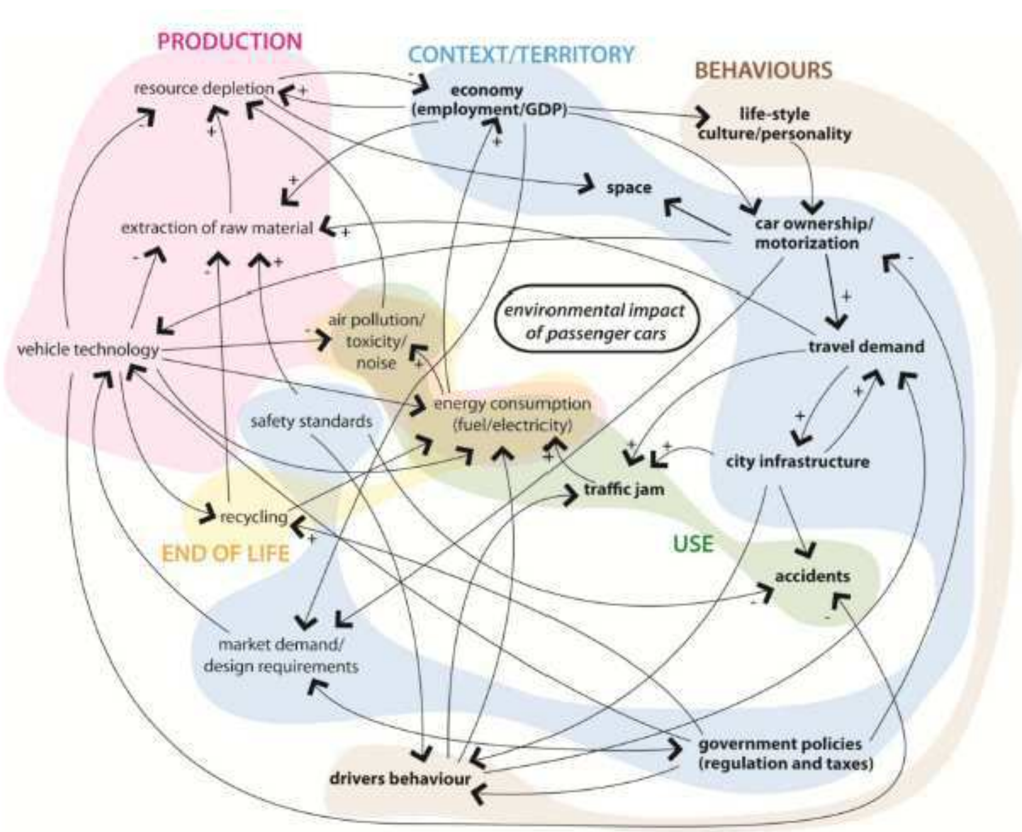


Figure 1.5: Causal Map of a Vehicle's Life Cycle from Laurenti et al. (2012)

Similar to PGMs, Bayesian networks in particular, Laurenti et al. (2012) have proposed the use of causal maps for modeling the entire life cycle. A causal map requires the identification of variables, and drawing arrows between these variables to signify causal relationships. These relations are then classified as one of two types, reinforcing (increase the value of the child variable) or balancing (reducing the value of the child variable.) Laurenti et al. (2012) showed the ability to include uncommon variables, similar to the factors in this research, through the use of causal maps. The variables that are novel for LCIs are shown in bold in Figure 1.5. Although causal maps are often used to create quantitative models, called system dynamics models, Laurenti et al. (2012) did not incorporates equations to their maps.

Such an addition would create a system dynamics model that measures the changes of each variable in a system on a time scale. Although predominantly physical relationships, these models can include stochastic relationships. In contrast with PGMs, causal maps are usually used for understanding system behavior over time, rather than for predicting outcomes and performing statistical analysis on those outcomes. Furthermore, causal maps imply causality and not independence relationships as in PGMs. Furthermore, the PGMs proposed in this research are simpler models, that account for variability, and are limited to the usage context. PGMs provide the added future capability of learning network structures from data, rather than expert knowledge, but this capability is outside of the scope of this dissertation.

1.4 Research Scope

LCIs are generally used towards the end of the product development process as a validation tool (Ulrich & Eppinger, 2011). The primary reason is that LCIs require detailed design information in order to be carried out. Screening methods and guidelines have been developed for earlier stages of design when less information may be available. These tools allow a designer to prioritize possible environmental design avenues. Although, screening methods and guidelines are very useful for generating new design concepts, LCIs can also be useful if made to be more flexible. Design researchers often cite that "all of design is redesign" with some quantifying the number at a more conservative "80% of designs are redesigns" (Jozwiak, 1997). Using information from previous designs, LCIs can be used to test possible redesigns and explore the impacts of different usage contexts during future generations of designs. Such activities are enabled by the methods presented in this dissertation work, and it is expected that the results can aid in environmentally conscious design for both validation and redesign purposes.

Although the motivating examples included designs inspired by aspects of a product's use, this research does not attempt to create new designs. This research is isolated to the addition and development of a new tool for the environmentally conscious design field. The scope encompasses three main research questions addressing the goals of the hypothesis:

1. How can the usage context be characterized for environmentally conscious design?
2. What new information is made available by considering conditional dependencies within the usage context?
3. How can this information be organized in a useful way?

It is assumed that the usage context is modeled as part of a redesign process and that data and knowledge about the usage context are available through previous design experience. Although it is assumed that exposing usage scenarios will help designers create better designs, this result is not explicitly part of the hypothesis and is outside the scope of the current research. Instead, the current research is limited to describing the possible range of information and exploring methods to organize that information in a useful way for designers. Insights include the types of tasks, loads, and climates that create the best and worst energy consumption.

1.4.1 Q1: How can the usage context be characterized for environmentally conscious design?

Research question 1 addresses the need for a formal recognition of usage context factors in environmentally conscious design and for a method of identifying these factors. Because LCIs are generally used for validation purposes, most implementations attempt to separate the usage context from studies of energy consumption by defining strict scenarios of use. Either products are evaluated in comparison to a single set of assumptions about its use and the user's requirements, or products are evaluated in comparison to a few limited sets of assumptions about their use. These assumptions, generally called functional units, are usually estimates of average or modal usage parameters, such as the average lifetime of a product, and reflect the practitioner's bias in their selection. These studies miss the opportunity to explore how usage parameters might vary, in a predictable way, from context to context and design to design.

The central contribution of this work is a framework for stochastically evaluate designs in a range of usage contexts. A fundamental requirement for this research is, therefore, a taxonomy for the usage context as it relates to environmentally conscious design and a transparent investigation of stochastic relationships between usage context factors. The latter half of this requirement is addressed under research question 2 in the following subsection. Developing a taxonomy is the primary task to answer research question 1. The subtasks are as follows:

Task 1: Develop a Taxonomy for the Usage Context with Respect to Environmentally Conscious Design

- *Subtask 1*: Review existing usage context taxonomies
- *Subtask 2*: Identify and define a usage context taxonomy for environmentally conscious design
- *Subtask 3*: Create a method and set of guiding questions to identify factors relevant to the taxonomy
- *Subtask 4*: Apply the taxonomy to the dissertation example

First, the area of Usage Context Based Design (UCBD) has defined the types of factors relevant to customer preference. These factors will be reviewed, modified, and categorized into three types of factors: human, situational, and product factors, as described previously. Within these categories, a set of guiding questions will also be developed to aid in creating a large set of candidate factors for the PGMs. Then this process will be applied to demonstration example problem and data will be collected.

The demonstration is a LCI-based material selection problem for lightweighting automobiles. In an effort to improve fuel economy, automobile designers sometimes employ lightweight materials at the expense of increased energy for material production. This tradeoff between product operation and material production is often measured using an LCI of energy use. Vehicle LCIs usually indicate that fuel savings during operation validate the decision to replace heavy steel with lightweight aluminum that consumes five times more energy during production. These energy LCIs, however, rarely consider the variability of vehicle operation, such as driving schedules and lifetime mileage. There is, therefore, a need for an appropriate method for evaluating variance in product operation, further understanding of the influence of product operation upon LCI results, and design solutions that minimize and are robust to consumer behavior.

1.4.2 Q2: What new information is made available by considering conditional dependencies within the usage context?

Research question 2 validates the application of PGMs by comparing it with traditional methods. It is a requirement that this method provide new information that is not typically obtained from an LCI. Three advantages are anticipated. Firstly, PGMs are a visual tool. They use graph structures that allow designers and researchers to quickly gauge the factors that are directly and indirectly influencing energy consumption and other environmental impacts. These graphs can also be easily saved and updated. PGMs also include information about the effects of individual factors and how those factors can be combined, to predict statistical distributions of performance values. This model differs from existing methods by not only providing statistical distributions of performance for difference functional units and usage scenarios, but also providing statistical distributions over a broad variety of scenarios.

The motivating examples showed how unplanned, but predictable behavior can undermine the intent of a design, as when disabling a computer's stand-by mode. A stochastic evaluation of how often these actions may occur, and what causes these actions could help design. Stochastic and dependent relationships are not often considered when assigning and testing functional units. Any consideration of uncertainty is usually limited to manufacturing or end of life processes. Furthermore, evidence supporting choices and statistics used for modeling in LCIs is usually missing (Ayres, 1995; Lloyd & Ries, 2007).

The primary task related to research question 2 is a comparison of results using existing methods and a PGM for the vehicle example. The subtasks are as follows:

Task 2: Implement PGM for Usage Context Modeling and Compare PGM Results with those from a Conventional LCI

Subtask 1: Establish a procedure for implementing PGM for usage context modeling, including evaluating conditional dependencies and creating graph structure

Subtask 2: Apply PGM to the vehicle example

Subtask 3: Evaluate the quality and quantity of new information obtained from the PGM relative to a conventional LCI

The relative value of the PGM will be established by comparing its predictions with LCI-based models available in the background literature for the same example problem.

1.4.3 Q3: How can this information be organized in a useful way?

Although graphical models provide a useful qualitative picture for designers, the shear quantity of information can be difficult to process and search manually. A useful property of a PGM is the ability to set conditions for one or more factors, perhaps in the form of usage scenarios, and conduct what-if queries of environmental impact based upon those assumptions. These scenarios can then be used to strategize about markets and product subsystems or features. IDEO describes scenario building as creating human stories about a user's product experiences in a physical, social and cultural environment. These scenarios are useful to help inspire concept generation, explore variable issues, and evaluate prototypes (Suri & Marsh, 2000) The overall aim is to create a variety of user stories and profiles and to understand the comparative environmental impact of a product as a function of those scenarios.

The primary task under research question 3 is to create motivating scenarios that provide novel insights about significant types of consumers, situations, or markets. The subtasks are as follows:

Task 3: Investigate the effects of different scenarios on PGM results
Subtask 1: Create scenarios from multiple factors
Subtask 2: Analyze what-if queries
Subtask 3: Compare results with previous analyses

The scenarios will be created manually by assigning conditions to combinations of background factors in the model. Background factors are generally considered root causes for effects on variables of interest. These background variables will become evident through construction of the graph, as background factors are not influenced by any other factors.

1.5 Organization

Design examples from this chapter motivate the hypothesis that PGMs can be used to consider variable usage contexts in energy LCIs. The literature review in Chapter 2 highlights the role of the functional unit and the current lack of a flexible functional unit for considering usage variability. Although the usage context is not well described in energy LCIs, customer preference studies reviewed in Chapter 2 have begun to model the effects of usage contexts. The use of PGMs to model energy performance has yet to be demonstrated and developed as a general approach.

Although descriptions of the usage context are easily understood, identifying a comprehensive set of relevant factors to model is not a trivial task. In Chapter 3, a checklist and usage context taxonomy are developed and discussed. Reducing the space of potential factors to a manageable and descriptive set is the primary focus and demonstrated through the use of an electric kettle example. The specific approach to creating PGMs is presented in Chapter 4. Continuing use of the electric kettle example, energy LCIs for multiple usage scenarios are estimated using a PGM.

In Chapter 5, the vehicle lightweighting example is introduced. First, an LCI for life cycle stages other than use is established and common assumptions and results from the literature are reviewed. Second, the taxonomy and procedure for identifying factors is applied to the vehicle and statistics are presented for characterizing the resulting graph.

In Chapter 6, the results of the lightweight vehicle PGM are compared with more traditional point estimates and Monte Carlo analysis. Four scenarios are developed to exhibit the unique benefits of using a PGM. Chapter 7 concludes the results with a summary of the contributions, recommendations, and possible future research avenues.

Chapter 2

The Usage Context in Environmentally Conscious Design

For many products, the majority of energy consumption occurs during use. Consequently, environmentally conscious designs often focus on reducing consumption during use at the expense of other stages in the life cycle. For example, hybrid vehicles reduce fuel consumption by including environmentally expensive battery technology. Although uncertainty of manufacturing impacts and variability of end of life impacts are common research topics, variable usage contexts are not well explored, and current life cycle inventories (LCIs) provide little usage information that designers can exploit. Therefore, the goal of this research is to provide a tool for designers to consider the effects of different usage contexts just as easily as they might consider different manufacturing methods or materials.

In this chapter, common practices and challenges with respect to LCI methods are introduced, including definitions of the functional unit. Because the functional unit generally describes how a product will be used, it constrains the ability of designers to model and consider different usage contexts. Next, the potential contributions of usage context based design (UCBD) are presented including tools and methods relevant to environmentally conscious design. Finally, the potential value of probabilistic graphical models (PGMs) will be summarized in the context of UCBD and environmental decision making.

2.1 Measures of Environmental Impact

The International Organization for Standardization (ISO) provides the accepted framework for LCIs (International Organization for Standardization, 2006). This framework provides guidelines for conducting and documenting each of two phases in an LCI. During the goal and scope phase, the purpose and system boundaries of the LCI are defined. The goal is articulated to guide decisions throughout the analysis. The boundary and scope is selected to include a manageable breadth of processes and underlying data addressing the goals of the study. Additionally, the functional unit is selected to serve as the unit of reference by which two or more alternatives are compared and to which inputs and outputs of processes are related. During the inventory phase, the inputs and outputs are calculated for each process within the study scope. These values are estimated from process models and experimental or reported data. Although data gaps and uncertainties are recognized issues in LCI, variable usage contexts are rarely considered.

Criticisms of LCIs are numerous, and the robustness of decisions and product comparisons based on LCIs is often questioned. Uncertain, missing, and erroneous data are major concerns that are increased by the potential bias of scopes and system boundaries. Ayres (1995) has published a thorough critique of data reporting in LCIs. Drawing from numerous examples from LCIs, he shows inconsistencies and errors in material balances. The lack of transparency and the frequency of such errors can discredit LCI results that are otherwise helpful. Finnveden (2000) argues that LCIs are indeed useful, despite errors in data and the subjectivity of the scope. He states that, "[LCI's] can increase the environmentally related knowledge of the studied systems, identify critical parts (or "key issues"), and separate important parts from less important parts,"(Finnveden, 2000). Despite inaccuracies, LCIs are necessary for understanding tradeoffs, and accounting for variability in usage contexts contributes to this central purpose.

Although reducing the energy consumption of product use is an important design strategy, LCI results generally scale linearly with some unit of performance, and that unit of performance contains inherent assumptions about operating conditions. The difficulty with this practice can be described through the example of additive manufacturing. Additive manufacturing machines build parts directly from CAD models by successively layering and joining material. In contrast, traditional manufacturing methods are subtractive; they remove material from a block to form a part. Manufacturing processes are usually compared, for energy LCIs, in units of specific energy per mass produced. The specific energy used by these processes is dependent upon usage factors: build arrangement, part geometries, and material recycling practices (Telenko & Seepersad, 2010; Mognol et al., 2006; Baumers et al., 2011). Mognol et al. (2006) found that the amount of energy consumed by a process similar to SLS is not a linear function of the mass of product produced. The size and orientation of parts is a significant factor because it influences the height of the build and the amount of time spent heating the powder bed and layering powder. Baumers et al. (2011) compared the specific energy consumption of a number of rapid manufacturing machines and found that capacity utilization, the density that can be achieved by a build, can change the specific energy consumption by as much as 90%. Finally, Telenko & Seepersad (2012) compared SLS with injection molding for two different products and found that the energy tradeoff between processes depends strongly on the size and shape of the fabricated products. For a small, 1g product, injection molding and SLS consume equivalent amounts of energy per product when 1.5 to 3.2 kg of products are fabricated, whereas a larger 36g product reaches an equivalence at about 54 to 108kg of fabricated product. The variability is attributed partially to the energy embedded in the injection mold itself. Enabling inclusion of these non-linear use effects is important for helping engineers explore and compare energy saving design opportunities and better understand how the usage context can impact the energy savings of a product.

2.2 Flexible Functional Units

Variability makes functional units problematic, and the the ISO's definition of a functional unit is necessarily open ended. Functional units are simply references that allow comparisons of products and establish a basis for calculating or scaling LCIs. In practice, the functional unit relates to some measure of how a product is used. For example, a vehicle might be driven in single-kilometer increments according to a specified drive cycle. The criticism is that LCI results do not scale linearly with many functional units, as in the previous example of additive manufacturing. The primary reason is that these units do not account for the variability in how a product is used. For example, energy does not scale by mass for all additive manufacturing systems and a vehicle's fuel consumption is not constant for every kilometer of travel.

In their evaluation of the challenges associated with LCIs, Reap et al. (2008a,b) conclude that the ambiguity of functional units is a fundamental and severe problem. They suggest that future research ascertain classes and archetypes for guiding the creation of functional units. In regards to the usage context, Reap et al. (2008a,b) suggest "identifying, decomposing, specifying, and/or prioritizing [sub-functions]"of products in order to represent the reality that products are used for multiple tasks. Alternatively, Finnveden (2000) proposes that functional units for non-linear comparisons should be as accurate as possible and that products with different functions should have broader functional units. In his example, the functional unit should be a need, such as “the cooling of food”, rather than specified aspects of use, such as a refrigerator that cools to 15C below room temperature. To accommodate a broader set of operating parameters, functional units must become more flexible.

A few researchers have proposed qualitative methods for developing functional units that consider multiple functions of a product or similar products. Lagerstedt et al. (2003) introduced the concept of functional profiles as preliminary to functional units. Arguing that functional units do not allow for innovations of a product’s function, they define a function profile as a list of all of the functional requirements of a product, such as product lifetime and technical flexibility that relate to the consumer. The functional profile is expected to aid designers in evaluating the relative importance of functions before an LCI is carried out. Although Lagerstedt et al. (2003) showed that functional profiles help put the designer in the context of the user, they did not explore the potential for quantifying environmental performance within the context of the user or create flexible functional units.

While functional profiles present qualitative functional requirements, Collado-Ruiz & Ostad-Ahmad-Ghorabi (2010) propose that practitioners reference lists of functional unit parameters for a family of products. Their concept is called a functional unit icon (fuon) and aids in the association of products by a general primary function. Each fuon includes a name and description of the primary function, for example a box isolates physical elements from the surrounding environment. The fuon also includes a list of engineering parameters, such as volume, that are common to all products within a family that fulfills the primary descriptor. Finally, the fuon lists engineering parameters or constraints that are common to sub-classes of products within a family. For example, refrigerators and coolers are primarily containers for thermal management. The fuon is a useful tool for dissecting the primary function into a set of potentially scalable functional units while acknowledging functional differences between products. Despite the emphasis on fundamentals of use and the acknowledgement of diffrences, this method still results in a rigid functional unit.

Following from the concepts of fuon, Esterman et al. (2012) extend the application of functional analysis to attempt decoupling of consumer behavior from functional units. They note, as discussed in this literature review, that the inclusion of consumer behavior in functional units limits comparability of LCIs. Esterman et al. (2012) propose functionally decomposing a product, such as a printer, into subfunctions that can be combined or scaled by use scenarios. They use scenarios to describe sets of conditions within a product's usage context. Both fuons and functional decomposition can aid in LCI modeling and creating a more realistic picture of how a product is used, but neither concept has been demonstrated to incorporate variable usage contexts in LCI.

Most LCI studies focus on unrealistic, one-to-one comparisons of products, instead of exploring methods for creating flexible functional units that explore realistic scenarios. More specifically, Cooper (2003) used the example of aircraft material selection to publish a comparison of common methods for defining the functional unit. In opposition to linear models, Cooper (2003) suggests the use of parametric models for modeling multiple product features. Nevertheless, in her work, the full extent of a parametric model is not realized. The significance and uncertainty of user behavior and product lifetimes are acknowledged, but not operationalized.

In contrast, some studies artificially devalue the importance of functional units and product use in favor of rigid comparisons. For example, Matheys et al. (2007) tested discrepancies between three different functional units for comparing identical electric vehicles using different battery types. They concluded that uncertain functional units are less important than other sources of uncertainty because the resulting changes to total driving impacts were relatively small (5-10%), and battery preference did not change (Van den Bossche et al., 2006; Matheys et al., 2007). The analysis, however, disregarded variability of a number of important factors. For example, lifetime driving range was not examined, reducing the environmental impacts of use intensity on product life (Cooper, 2003). Furthermore, only one driving cycle was considered despite being a fundamental and highly variably consideration for battery use. Other usage context effects that should be considered, like thermal cycling were left out. Matheys et al. (2007) did acknowledge that, when using functional units defined by other researchers, the results and preferences changed significantly. Instead of comparing a few functional units, a goal of this dissertation is to present a method for allowing inclusion of transparent stochastic parametric studies of a product's usage.

2.3 Temporal and Usage Scenarios in LCIs

The definition of a scenario varies among some LCI studies. For the purposes of this research, a scenario is a set of usage conditions that defines how a product will be used. In some studies, best and worst case scenarios are used to create conservative and optimistic LCI estimates. For example, a comparison of cell phones may estimate annual and biannual phone replacement. A second definition of scenario regards the future developments of technology and society. These temporal scenarios model the effects of policy decisions, and are less concerned with the design of products. Nevertheless, research in modeling temporal scenarios provides some useful insights.

The SETAC-Europe working group published definitions of scenarios for LCIs (Pesonen et al., 2000). They define scenarios as the frame of conditions or systems to be modeled that reflect some snapshot in time. This definition reflects questions of policy decision makers, for whom time scales and future developments are important considerations. Scenarios are classified into two groups: what-if scenarios that reflect a search for best and worst cases in a linear, short term perspective and cornerstone scenarios that provide information about the overall development space. The distinction is subtle, in that cornerstone scenarios are exploratory, by being farther removed from current situations. Spielmann et al. (2004) present a method for determining cornerstone scenarios by first evaluating the relative sensitivity of results to different variables. Although not expressly discussed, the temporally inspired scenarios of these papers are analogous to scenarios of different usage contexts within this dissertation.

Fukushima & Hirao (2002) define the creation of four types of cornerstone scenarios. These four types are technological, environmental, process, and valuational. Technology and process scenarios change the performance and flow rates of processes, respectively. Environmental scenarios describe changes in the environment, and valuational scenarios describes changes in values of stakeholders. They encode models of these aspects into their own life cycle modeling language(LCML) consisting of tables and graph representation to allow for sharing and visual adjustments of scenarios. The graph representation uses shapes and arrows to represent flows and sub-models. Their method is similar to that proposed in this dissertation work in that it uses graph representation and allows for the implementation of select scenarios. This dissertation work, however, extends the notion of LCML by including stochastic relationships and removing the temporal aspect to focus on the variability among usage contexts at a snapshot in time.

2.4 From Scenarios to Usage Context Based Design

Just as policy-oriented scenarios have been helpful for decision making in the environmental design of systems, inclusion of usage contexts can aid in the environmental design of products. IDEO defines scenarios as human stories that relate product experiences in a physical, social and cultural context. These scenarios are useful to help inspire concept generation, explore variable issues, and evaluate prototypes (Suri & Marsh, 2000). In particular, usage context based design (UCBD) is an emerging area of product design that has not been explicitly applied to environmentally conscious design and LCI. UCBD research includes the development of tools for describing unfamiliar usage contexts and informing product specifications.

In marketing research, descriptions of the usage context are used to discover a consumer's product preferences and decision variables. Belk (1974, 1975) uses a stimulus - organism - response paradigm to categorize both the situation and objects (stimuli) influencing a consumer (organism) and his or her purchasing behavior (response). He provides questionnaire results that suggest situational factors influence consumer choices. For example, the type of food a consumer chooses to buy for dinner can be influenced by the presence of guests or how tiring the work week was. Information about the types of users that are affected by situations and the types of situations that change choice behavior are useful for not only creating and segmenting product offerings, but also for shaping the suggestions of advertisements. la Fuente & Guillen (2005) further study the influence of product design on a product's suitability for different usage contexts. They compare the features of a number of cleaning products with a number of cleaning surfaces and ask consumers to select between combinations of product features and branding. The results indicate that choice is also influenced by functionality. Both Belk (1974, 1975) and la Fuente &

Guillen (2005) aim to help managers identify market gaps, identify opportunities for new product development and predict market share.

Research in engineering design has begun to integrate both the industrial and marketing design perspectives. The frontier design context method is one such area of UCBD described by Green (2005). He defines context as "the circumstances and settings in which an object occurs, and which influence its value." Frontier contexts are further defined cultures, countries, and consumers foreign to the designer's experiences. Green (2005) also outlines a contextual needs assessment method that considers the usage context (how and where), consumer context (who), and market contexts (alternative tools and products.) The first two categories are most closely related to environmentally conscious design. How encompasses questions about the specific task and frequency. Where encompasses questions about the local weather and infrastructure. Who describes aspects of the consumer, such as skills and education. A set of question prompts are proposed to help designers recognize context factors that influence customer needs, and define the design problem. These questions guide subsequent customer interviews and information gathering to create more appropriate design solutions. Although the definition of usage context put forth by Green (2005) is helpful, it is too general to predict energy consumption.

The work of He et al. (2010, 2011, 2012) and Yannou et al. (2009, 2010) establishes a taxonomy of usage context for choice modeling that includes performance predictions. In contrast with Belk (1975) and la Fuente & Guillen (2005), He et al. (2010) seek to predict consumer choice behavior by physical models of product performance. Rather than measuring suitability through surveys alone, they model engineering specifications that influence consumer needs. For example, the vibrational forces experienced by a user differ with cutting medium. Additionally, the authors utilize multinomial logit models to vary the importance of needs by situation, as suggested by marketing research. For example, the comfort of a jigsaw had reduced import in outdoor situations than in indoor situations.

As part of the series of papers summarized above, Yannou et al. (2009, 2010) incorporate a causal diagram to relate context variables and product variables. They measure performance by the degree of satisfaction of constraints. A physics based model is used estimate metrics, such as vibrational forces, that influence customer satisfaction. The researchers then introduce a constraint satisfaction problem which iteratively computes intervals for the constraint variables that are satisfied by the design. These intervals are then compared with each usage scenario or customer to evaluate fit. Although this method is useful for predicting customer preference, it does not include the stochastic predictions desired for evaluating tradeoffs in LCI.

A few researchers have focused on solutions for reducing energy consumption, but have not fully explored the usage context of a product at the level of an LCI. For example, van Nes & Cramer (2003, 2006) researched user-centered design techniques for increasing useful life at the level of the user-product interface. They cite four general motives that affect a consumer's decision to replace a product and focus on making upgradable, modular products. They suggest that designers be conscious of how products might be expected to change to encourage optimal replacement times. As another design solution, Srivastava & Shu (2011) propose the principle of discretization as a means of reducing resource use by consumers. This principle states that providing discrete increments of a resources will reduce consumption compared to continuous flows, regardless of the resources availability. Oberender et al. (2001) tested the use of feedback systems for reducing erroneous consumer behavior, and found limited success. These results provide evidence regarding the success of individual design avenues, but not the usage context as a whole.

2.5 The Potential of Bayesian Networks

This research combines the concepts of a more flexible functional unit and causal mapping of the usage context in order to predict energy consumption. The developed method uses a PGM, relying predominantly on a Bayesian network, or Bayes net. PGMs combine graph theory with probability theory, statistics and computer science. In Bayes nets, the graphs use directional dependencies between factors, or nodes, to describe the joint distribution of factors within a problem. The directionality of arcs connecting nodes indicates the direction of influence for predicting one node's state given some known set of states for the other nodes.

In design, Bayes nets have been applied to problems of predicting customer preference and needs without UCBD principles. Wang & Tseng (2008) use Bayes nets to customize products to a customer's specifications. They can then identify which query or specification node has the most influence (information gain) and ask the customer to specify that node. Given enough specifications, the program can generate a set of likely node values that will create a set of product specs (a whole product) for the user (Wang & Tseng, 2008). Takai et al. (2010) use Bayesian decision trees to forecast customer needs. In their example, they include forecasted and actual gasoline fuel prices to predict the importance of fuel economy to buyers. The conditional probabilities are influenced along this chain. This latter examples shows how general knowledge, or forecasts, can be used to predict future customer need distributions. Finally, Matthews (2010) implemented Bayesian networks as models for conceptual design. Similarly to the LCA model of Seo et al. (2005) the network connects design variables from a database of prior designs and calculates the probability of success for different variables and combinations of variables.

Bayes nets were first proposed for predicting energy consumption by Shipworth (2006). In his initial paper, Shipworth (2002) cites quantification of uncertainty and variability as essential for meeting targets of the Kyoto protocol. Current models, he argues, are deterministic and provide little decision information. He extends this argument in a later paper to assert that Bayes nets will extend ordinary technical and economic models to include social aspects (Shipworth, 2006). Thereby, the goal of using Bayes nets is to include correlations between technical variables and social factors for predicting household and community energy consumption as part of the UK Carbon Reduction in Building (CaRB) project. His research group published plans for collecting and modeling data (Lomas et al., 2006), and posted a partial manual on the web (Olivier, 2008), but they have yet to produce findings from their work. The manual describes a fully naive Bayes net model that uses a data set including data for occupancy, heating, cooling, bathing, and building features, but results are not available because buildings are very large systems and the researchers are still collecting data Shipworth et al. (2010). The contribution of Shipworth (2006) and Lomas et al. (2006) is, therefore, the idea of using Bayesian Networks to predict the energy use of buildings at household and regional levels, but not a demonstration of this capability or a general approach to a variety of problems.

A few researchers have applied PGMs to environmental decision making and life cycle analysis (LCA) (Varis, 1997; Seo et al., 2005; Zhu & Deshmukh, 2003). Seo et al. (2005) use an artificial neural network as a metamodel for LCA. The model was trained using information from LCA results of 40 products and embodiment specifications such as material types and masses. The model was able to predict impacts of additional product designs, but the similarities between the test and training designs were not thoroughly discussed. Although, such a meta model may be useful for LCA screening of products, it does not assess usage variability and was less accurate for heaters and other high energy use products.

Bayes nets have been applied to areas of environmental decision making, specifically environmental resource management (Aguilera et al., 2011; Varis, 1997). Varis (1997) and Varis & Kuikka (1999) reviewed models, including their own, that incorporate the influence of different stakeholders on fisheries and other natural resources for policy decisions relating to resource maintenance. Varis (1997) and Varis & Kuikka (1999) find Bayes nets to be a promising tool, but Aguilera et al. (2011) asserts that opportunities to model with missing data and combine continuous and discrete variables are not well explored in these studies. Furthermore, Aguilera et al. (2011) found that few of these models were validated, despite inclusion of expert knowledge. Later publications by Castelletti & Soncini-Sessa (2007) continue this work in modeling water resources and conclude that Bayes Nets are not as useful for modeling dynamic systems with wide range of structured variables. Instead, they propose integrating dynamic models with Bayesian networks in these cases. The model in this dissertation incorporates deterministic elements, but the scope of a single product-user relationship is much narrower than that of an entire natural resource or ecosystem.

2.6 Chapter Summary

The existing literature presents a variety of approaches and goals for addressing the usage context. In LCIs, the usage context is simply used for static comparison of products, assuming that environmental impacts, such as energy consumption, are scalable and that use variability has little effect on life cycle decision making. This latter assumption was shown to be incorrect in Chapter 1, and the prior assumption was discussed in depth here. In UCBD, the usage context has been used as a major factor in consumer purchasing behavior, and offers many analogies to understanding the influence of usage context on energy consumption. A major contribution of prior research to this dissertation is the established taxonomies. Both the LCI and UCBD research provide insight into alternative methods for classifying and defining usage context factors that can build a more flexible functional unit.

Additional work in choice prediction and environmental decision making has introduced probabilistic graphical modeling as an interesting technique for modeling human, situational, and product factors. The existing work, however, has not been applied to LCIs and product design . Most PGMs have been used to model either product design variables or large ecological systems. Additionally, little validation for PGMs exists in prior research. Shipworth (2006) proposed the use of PGMs for predicting the energy consumption of buildings but has yet to demonstrate this capability. Chapter 3 will describe the proposed method for incorporating techniques from the existing literature to identify factors that describe the usage context and influence energy consumption.

Chapter 3

A Taxonomy for Environmentally Conscious Design

The first task of this research is to develop a taxonomy and set of tools for defining the usage context with respect to an environmentally conscious design problem, specifically reducing energy consumption during use. Descriptions of the usage context and specific usage scenarios are easily understood and often provide useful information for designers. Nevertheless, characterizing the usage context as a concise but comprehensive set of factors is not a trivial task. This chapter presents a taxonomy and method for characterizing the usage context as sets of factors. Three sets of relevant factors are defined including: human factors, $\mathbf{H}$, related to *who* is using the product; product factors, $\mathbf{P}$, related to *how* the product is used; and situational factors, $\mathbf{S}$, describing *where* and *for what* the product is used. These factors will be elements in a set of vertices, $\mathbf{V} = [\mathbf{H}, \mathbf{P}, \mathbf{S}]$. A scenario is distinguished from a usage context in that a scenario specifies the values of some subset, $[v_{human}, v_{product}, v_{situation}]$, of the usage context. The general usage context is represented by the vertices in a graph, $\mathcal{G} = (\mathbf{V}, \mathbf{E})$, connected by a set of edges, $\mathbf{E}$, that define the relationships between the vertices. These relationships are directional and no factor can be traced back to itself. The resulting graph is, therefore, known as a directed acyclic graph (DAG). Checklists, activity diagrams, and interaction matrices are introduced as tools for specifying relevant factors and relationships among them. The resulting graph of the usage context can then be introduced into a PGM, described in Chapter 4.

3.1 Establishing a Usage Context Taxonomy for Environmentally Conscious Design

Three classifications of factors are utilized in this work. The first type is the human factor and encompasses user characteristics that change the consumption or wastefulness of the product. The second type is the situational factor and encompasses environmental and task characteristics that set operating parameters for the product and constrain user behavior. The third type is the product factor and encompasses parameters of the product that are influenced by the user or environment, and features of the product that influence user behavior or regulate environmental effects. Specific definitions were created by consulting the environmentally conscious design literature.

Table 3.1: Relevant considerations and guidelines from design literature

ENVIRONMENTALLY CONSCIOUS DESIGN CONSIDERATIONS	
consumables:	discrete/continuous, reusable, disposable
controls:	defaults, automatic, human, intuitive
durability:	structural, failure modes, upgrades, damage sources, hazardous substances
energy:	efficiency, sources, ideal conditions
human:	proper use, probable use, fail safes
materials:	inputs, outputs, recycling
maintenance:	aesthetic, functional, modularity, servicing, cleaning
conditions:	intended, probable, possible, ideal

Existing sources describe over 60 unique principles and guidelines for environmentally conscious design that span all life cycle stages Telenko et al. (2008). Telenko & Seepersad (2010) also include an environmental requirements lists for describing environmentally conscious design objectives. Table 3.1 summarizes a number of environmentally conscious design considerations informed by designers' experiences and research (Telenko et al., 2008; Ulrich & Eppinger, 2011; Srivastava & Shu, 2011). These considerations include the flow rates and permanence of materials being used by the product, and the sources of losses or inefficiencies in operation. Other considerations include ease and frequency of maintenance as well as aesthetic life and aids for the user. Detailed definitions for each category of factors are as follows:

Product factors describe variable operating parameters and any product features that influence the user or adjust the response of the product to changes in the environment. Important characteristics are parameters of the fundamental physical equations governing operation, and any control or feedback features that instruct the user. User or environmental controlled settings, failure modes, failure frequencies, rates of obsolescence, and aesthetic lifetimes are also important.

Situational factors describe aspects of the task and environment that change the behavior of the product or the user. Task characteristics include the states of inputs and outputs of the product and properties of the task including durations and distances of operation, mass or energy loads, and flow rates of consumables. Environmental characteristics describe the state of the environment in which a product is used or stored, such as the surrounding temperature or humidity or population density. Important environmental characteristics also constrain or influence user behavior through social rules, interactions with other humans, availability of materials, reduced physical comfort, and increased mental loads.

Human factors aspects of the user that influence task specification, environment selection, and operating procedures. Important human characteristics include the number of users, frequency of use, more or less efficient behavioral tendencies, unique procedures or user types, accuracy of the user, and task preferences.

3.1.1 Departure from Existing Research

The primary difference between these definitions and previous work is the focus on environmental performance instead of consumer preferences or customer needs. Table 3.2 summarizes the comparison of five approaches to describing the usage context of a product and includes this dissertation in the right most column. The definitions of this work focus on product operation, while alternative definitions focus on the user's perspective. The result is that taxonomies related to customer preference predominantly define human factors as preferences for products and features. Additional factors are only described in relation to the user and decision variables.

Table 3.2: Methods for Defining Usage Contexts

	Green	Belk	He *et al.*	Kurakawa	Galvao	Telenko
Define Factors	✓	✓	✓	✓	✓	✓
Consider Customer Preference		✓	✓			
Consider Customer Needs	✓			✓	✓	
Consider Energy Consumption						✓
Provide Specification Tools	✓				✓	✓
Quantify Performance	✓		✓			✓

More specifically, consumer preference studies predict choice behavior by modeling changes in selection criteria and priorities given different consumer types and different purchasing situations. For example, He et al. (2012) showed that comfort was less of a priority for consumers purchasing a jigsaw that would be used outdoors rather than indoors. Customer needs studies uncover new design avenues to increase customer satisfaction. For example, Galvao & Sato (2005) compare procedural steps and product features to explore options for making a blender more intuitive and physically easy to use. In contrast, energy consumption is estimated for a single product given a range of users and situations. As an example of the difference between customer preference and energy consumption, programmable thermostats control thermal comfort without constant user intervention, but increase overall energy consumption in hotter areas because users do not turn off their air conditioning systems while at work (Peffer et al., 2011). In this example, customer preference and energy savings are in conflict and should be resolved.

Belk (1975) identifies the person, product and object as the three factors determining desirability of a product. But, because his research is concerned with marketing a certain product to a certain user, he only focuses on providing a taxonomy for situational characteristics. He defines the following five categories: physical surroundings, temporal perspective, task definitions, social surroundings, and antecedent states. The latter two categories, social surroundings and antecedent states, relate to psychological aspects of a situation, including interpersonal relationships and moods. The prior categories include more physical and measurable factors. Physical surroundings include location, weather, and other environmental characteristics. Temporal perspectives includes dynamic considerations such as seasons or frequencies of actions. Task definitions include intents or requirements. These latter categories support the definitions introduced in this section, but are much broader to encompass a number of different choice criteria. They also exclude interactions between the product and situation, a central subject of this research.

Kurakawa (2004) and Kurakawa & Tanaka (2004) describe actors, actions, and situations as relevant parts of scenarios used for mentally evaluating design concepts during brainstorming. Actors/agents encompass the subject of an event as an object, abstract thing, or person. Actions/events are movements or behaviors of the actor/agent, and the situation is the surroundings and states of events. The definitions supplied are more akin to parts of a sentence, as they are use for formulating motivating scenarios as stories. For example, the scenario for a Walkman is a person (actor) listening to music (event) anywhere and at anytime (situation) (Kurakawa & Tanaka, 2004). This scenario is used to help designers generate concepts and propose product solutions. Because scenarios are being used for qualitative evaluation, one need not specify all parts of the usage context "if the general idea can be understood," (Kurakawa & Tanaka, 2004). This caveat does not apply to LCI models which require multiple assumptions or evaluations of multiple scenarios.

An additional difference between this and previous work is the focus on modeling a product's performance. Belk (1974, 1975) uses descriptions of scenarios to survey consumers about the desirability of a product given different situations, but are not concerned with more objective measures of product performance. Kurakawa & Tanaka (2004) uses descriptions of scenarios to brainstorm design ideas, and Galvao & Sato (2004) use task flows and functional diagrams to understand human-product interactions, but neither quantify performance at the product level. Green (2005) uses descriptions of different usage contexts to understand constraints on a product and quantify design targets, but don't do an extensive analysis of trade-offs and conflicts. He et al. (2012) use physical models of a product to quantify product performance for unique consumer types and estimate the percentage of users who will be satisfied (Yannou et al., 2010). Although He et al. (2012) and Green (2005) consider more objective design targets for products, these analyses are still focused on customer needs for comfort and task completion. Additionally, these studies do not attempt to estimate the likelihood of different usage senarios.

Green (2005) defines the usage context through qualitative studies of products. He defines three types of factors that can be used to understand a customer's perspective. These categories are customer characteristics, primary usage environment, and usage applications. Each of these categories are used to describe desirable product attributes. Customer characteristics include physical abilities and skills. Usage environments are similar to physical surroundings described by Belk (1975). Usage applications include task characteristics, functions, frequencies and durations. These contexts are used to understand constraints on the design and a user's basic requirements. Because frontier design does not presume a design goal, the definitions and tools that Green (2005) provides are very broad. The LCI focus of this work narrows these definitions to a more manageable set of characteristics.

The work of He et al. (2012) includes product performance as part of the larger set of customer preferences. They provide examples of a jigsaw and a hybrid electric vehicle. They define the usage context as "all aspects describing the context of product use that vary under different use conditions and affect product performance and/or consumer preferences for the product attributes," (He et al., 2010, 2012). Consequently, the researchers separate their usage context vectors for each subset into performance related attributes and preference related attributes. They define situational factors similarly to Belk (1975), and define product factors as design variables or characteristics of the product specified by the designers and characteristics of competing products that consumers compare while shopping.

He et al. (2012) also provide definitions for human factors in usage context modeling. They define customer profile attributes as those attributes of a consumer that are constant for the time frame being modeled, such as age, gender or income. They also define customer-desired product attributes as part of their set of human factors. This set includes performance, ergonomic or aesthetic criteria that are unique to a user. These definitions are useful for predicting resource consumption. For example, water consumption associated with dishwashers should include user tolerance for the cleanliness of dishes to estimate how often dishes get rewashed or pre-washed. Nevertheless, user preferences or tolerances are not a central theme of this work providing a narrower focus. As an example of this fundamental difference, customer feedback was used in lieu of performance modeling for the hybrid vehicle example (He et al., 2012).

Although all of these studies provide some form of taxonomy for describing usage contexts, only Green (2005) and Galvao & Sato (2004, 2005) provide tools for identifying and specifying these factors. Galvao & Sato (2005, 2004) introduce procedures as a major component of the usage context and focus on tools like function structures, that show flows of materials, energy and signal in products, and task flow or activity diagrams, that show the procedures that users undertake. They model the usage context using three types of information: structure-function information, procedural information, and context-of-use information. Structure-function information describes the product design and operation. Procedural information describes the activities that user engage in with the product, and context-of-use information describes all other relevant information to understand the causes and effects relevant to predicting product performance. Their focus is on affordance design, specifically how product functions, such as buttons, better support user activities, such as choosing settings. Their blender study identifies which blender functions are engaged in the most user-interactions. This information can be used to increase the ease of use. In contrast, this dissertation seeks to understand not the most frequent interactions, but the most and least efficient interactions and their causes. It is desired to understand the range of product performance beyond redesign of the product-user interface.

Green (2005) suggested the most complete approach to scoping and describing the usage context including a wide variety of design tools. The central tool in their research is a template for creating customer interview questions. These questions are very useful for describing broadly scoped contexts before the design space is narrowed to the most significant customer needs. After the design space has been narrowed, as in energy saving design, such a template is too general to provide direct insights for LCI. For example, a set of guiding questions was initially developed for this work, and tested using the examples of a cell phone, a printer, a vehicle, and an electric kettle. The application led to much broader results than needed, shown in Appendix A. The next section presents an alternative set of tools, more appropriate for modeling the energy consumption of products. These tools include a checklist, activity diagrams, and physical equations. The purpose is to focus on performance, and reduce additional complications of customer preferences. Additionally, the use of physical equations details aspects that pertain to energy consumption, specifically consumption of materials and energy. An electric kettle study is used to illustrate the method.

3.2 Tools for Specifying Factors and Edges

Checklists, physical equations, and diagrams of usage activities were found to be the most useful tools for identifying factors that are pertinent to energy consumption. These tools are presented as part of a series of steps shown in Figure 3.1. The first step narrows the problem by scoping three terms of the LCI. These terms are then expounded upon using a checklist that reminds the practitioner of the range of influences on LCI parameters. Next, fundamental process equations are produced and analyzed. The parameters of these equations are separated into design, noise, and output variables to guide further exploration of uncontrolled parameters. Activity diagrams are then used to create flowcharts of the procedures at the level of the entire usage stage and at the individual task level. The activities within these flowcharts are then used to prompt specification of additional relevant factors. Finally, the set of factors after this step are included in an initial description of $\mathbf{V}$, and entered into an interaction matrix that determines the directional set of edges, $\mathbf{E}$, that are used to create the final DAG.

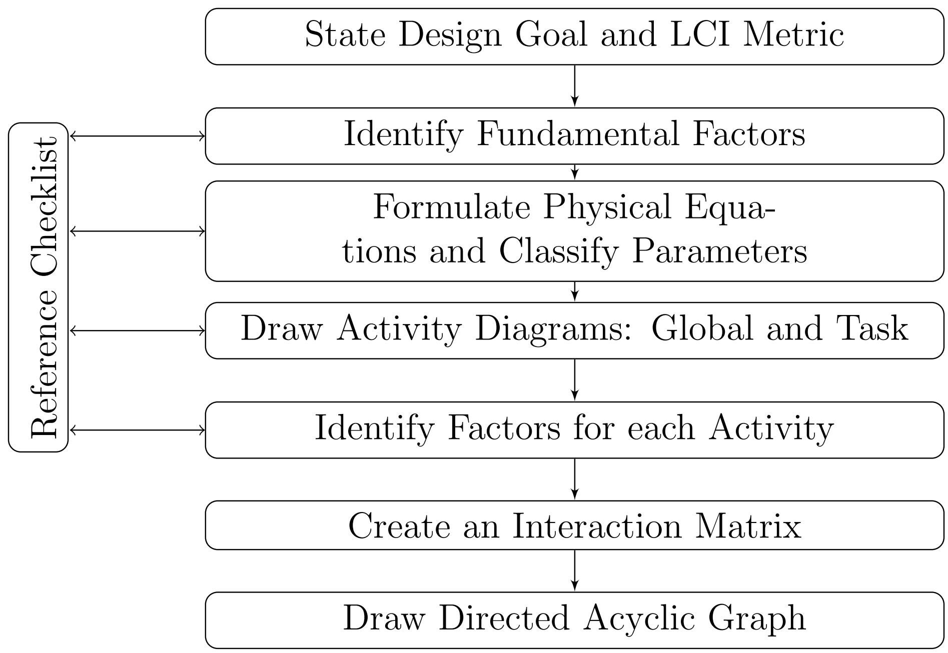


Figure 3.1: Steps for Identifying Usage Context Factors

In the rest of this section and in the next chapter, the electric kettle example from Telenko & Seepersad (2010) is revisited to test the use of PGMs for identifying factors, creating life cycle inventory data and recognizing design opportunities. This example was introduced briefly in Chapter 1 and Figure 1.2. Previous research by the authors indicated that minimizing the duration of kettle operation can significantly reduce energy use and overall environmental impact, and three alternative concepts were introduced (Telenko & Seepersad, 2010). Overall, the lifetime energy consumption, and the potential benefits of resource-saving features were found to be strongly related to the user's preferred final water temperature. Thus, the goal of the electric kettle example is to estimate the distribution of final water temperatures during use.

3.2.1 Stating the Design Goal and LCI Metric

The first step is to specify the environmental impact, such as energy consumption, to be improved and the high level parameters of the LCI used to estimate it. Stating the LCI problem involves three general terms shown in Equation 3.1. These terms are used to quantify the chosen environmental impact metric for the total use stage, $I_{useTotal}$. A normalizing unit of use, the functional unit U, is determined for which the performance metric is estimated individually as I. This unit of use occurs with some estimated frequency, f, during the useful life, t, of the product in question. As described in Chapters 1 and 2, each of these terms includes underlying assumptions that influence the values of I and $I_{useTotal}$.

$$I_{useTotal} = \left(\frac{I}{U}\right) ft \tag{3.1}$$

In the kettle examples, these terms quantify the energy used to heat water over the kettle's lifetime. Energy consumed per use,$\left(\frac{I}{U}\right)$, is measured by specifying the change in temperature of a certain amount of water. For example, two cups of water from 25°C to 100°C. The frequency may be 8 times a week, and the average expected lifetime may be four years. For simplicity, the frequency and lifetime terms are assumed to be constant in the model of Chapter 4, but are discussed in this chapter.

The importance of estimating these variables is evident from uncertainty in the previous study shown in Figure 3.2. Each design concept is assigned an intended average final water temperature, and consequently energy consumption, and a range of possible energy consumptions, indicated by bars and dictated by differing final water temperatures. These values include manufacturing and end-of-life energy consumption. Although the original concept is designed to cease heating at 100°C, the consumer has the option of interrupting the heating process and reducing energy consumption. The same possibility exists for the kettle concept that incorporates a lower default setting of 95°C with no additional manufacturing investment. While both designs have an intended energy consumption, actual energy consumption can be lower. The final two concepts are intended to encourage minimal energy consumption by heating the water to 76°C; however, it is possible that the user could ignore the variable temperature setting and continually heat the water to the maximum setting, 100°C. The selected temperature determines the viability of each new feature. If the user continually selects the maximum temperature, 100°C, for example, there are no energy savings during use to offset the energy consumption associated with the additional components in the concepts with variable temperature settings.

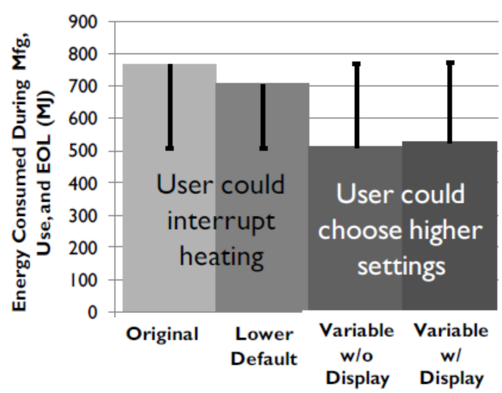


Figure 3.2: Possible Energy Impacts of Alternative Electric Kettle Designs

The outcomes of this step are a basic description of what the LCI should measure, and what variables are present in the functional unit. The ranges of values for these terms are the result of multiple usage context factors and differ between scenarios. Each additional step of Figure 3.1 will identify factors that provide background information useful in estimating values for Equation 3.1.

3.2.2 Identifying Fundamental Factors

The next step prompts practitioners to describe essential factors relevant to evaluating the LCI problem. A central reference for this step and the following three steps is the checklist developed from the literature and shown in Table 3.3. To begin brainstorming, practitioners should address each of the fundamental categories in the left column, with User, Task, and Functionality being the most universal. Location and Maintenance are also important considerations, but not as significant across commercial products. Aesthetics are easy to forget, but have significant contributions to prolonging the life of many products. The column on the right provides examples of considerations for the fundamental categories.

Table 3.3: Checklist for Factors

HUMAN FACTORS	
User:	number of users, task preferences, efficient habits, inefficient habits, use frequency, high/low demand, level of wear, replacement schedules, maintenance schedules
SITUATION FACTORS	
Task:	types, reusable materials, consumable, durations, energy and mass loads, material inputs, masses, dimensions, quantities, physical properties
Location:	altitude, population density, public/private/commercial setting, physical or social restrictions, storage protection, environmental erosion, temperatures, humidity, precipitation, wind, solar insolation
PRODUCT FACTORS	
Maintenance :	cleanliness, repair frequency, upgradeability, expected life, failure modes, expected declines in performance, normal and abnormal wear
Aesthetic:	vulnerability to changes style, expected aesthetic life, cosmetic wear, upgradeability
Functionality:	physical equations and scientific principles, efficiency metrics, ideal operating conditions, design variables, obsolescence, default and user settings, user guiding features, automatic functions, capacity for energy and material loads

A list of fundamental factors for the electric kettle is shown in Table 3.4. The primary insights from this list are descriptions of different user habits and different tasks. For example, some users heat water and collect the water immediately. Others are delayed in collecting the heated water and may have to reheat the water. Many users overfill their kettle and heat two or more times the required amount of water. Different tasks present different requirements for water mass and temperature. For example, pre-heating water for boiling pasta requires more water and boiling temperatures, but gives the user less room to overfill the kettle. Additionally, green teas are best brewed in water near 80°C while black teas are best brewed in water near 100°C. Further considerations revealed in this list include the influence of climate on task selection and the governing physical equations.

Table 3.4: Fundamental Factors for an Electric Kettle

HUMAN FACTORS	
User:	number of residents, preferred serving size, tendency to overfill, tendency reheat, frequency of use, preferred uses, task selection criteria (e.g. weather, disposition)
SITUATION FACTORS	
Task:	hot teas, cooler teas, iced teas, coffees, other food, hot water for cleaning, required final temperatures, average serving size,
Location:	climate, seasons
PRODUCT FACTORS	
Maintenance :	none
Aesthetic:	none
Functionality:	energy balance, electricity to heat conversion, temperature measurement, indicates completion (e.g. click or boiling sound), measuring gradients

Using the checklist in Table 3.3 to create the set of fundamental factors scopes the problem by targeting users and differentiating between tasks. The causes for different tasks, and the repercussions of different task requirements can follow from this foundation. The checklist also prompts brainstorming of fundamental process equations that govern the product's operation. At the end of this step, the practitioner should have identified the most influential aspects, instead of becoming overwhelmed by a review of all possible aspects of the usage context.

3.2.3 Formulating Physical Equations and Classifying Parameters

The third step is to address the fundamental process equations and classify these variables using a P-diagram. The P-diagram is used to sort the equation parameters into design variables, noise factors, and output variables, as shown in Figure 3.3. The design variables are controlled by the manufacturer and are nearly constant throughout a product's life. The noise factors are parameters controlled by or classified as human and situational factors. These factors are outside of the designer's control, but typically within the user's influence. The output variables describe the state of outputs with regard to task requirements and are affected by both noise and design inputs. This third step is useful for predicting which factors are of direct physical importance, but outside of the designer's control and require additional consideration or modeling.

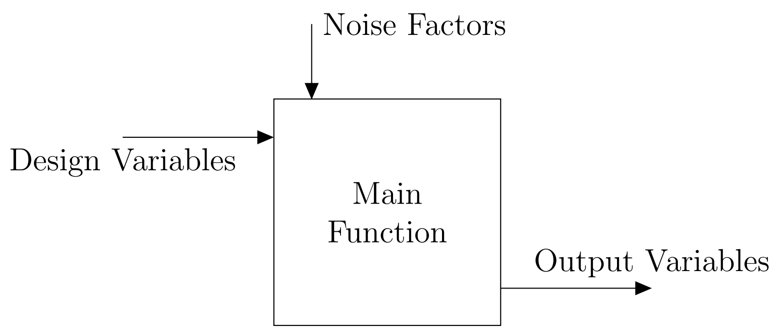


Figure 3.3: P-Diagram Template

Recall from the fundamental factors, that the kettle is governed by an energy balance, shown in Equation 3.2 and the schematic of Figure 3.4. In this equation, the kettle's efficiency, ε is calculated as the ratio of power in, $P_{electric}$, to the sum of power lost during conversion, which is the first term in the denominator, $P_{electric}\varepsilon_r$, and the heat flux to the surroundings, which is the second term in the denominator. $P_{electric}$ is the power drawn from the outlet. ε_r is the efficiency of the resistive heating element. k is the thermal resistance of the kettle walls, with $\frac{A}{L}$ representing the heat transfer area of the wall, A, and wall thickness, L. This heat transfer is assumed to be primarily conductive heat transfer, driven by the difference in water temperature and room air temperature, $(T_{air} - T_{water})$.

$$\varepsilon = \frac{P_{electric}}{P_{electric}\varepsilon_r + k\frac{A}{L}\left(T_{air} - T_{water}\right)} \tag{3.2}$$

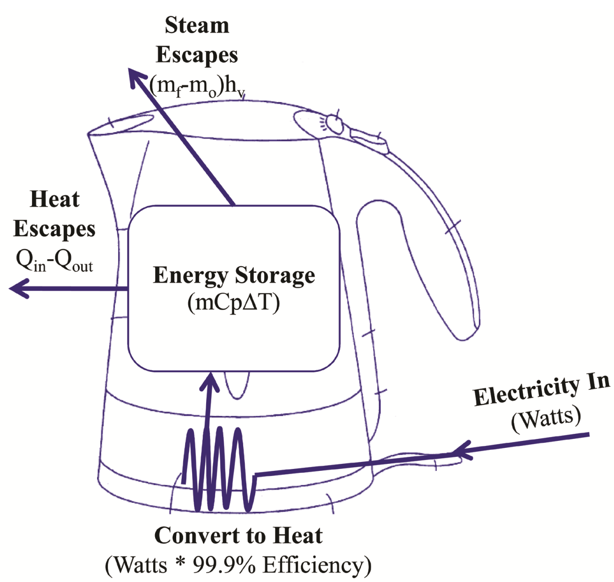


Figure 3.4: Schematic of an Electric Kettle

The kettle efficiency during use is then included in the updated LCI term shown in Equation 3.3. The metric of lifetime energy use, E, is calculated as the product of the frequency of use, f, the lifetime of the product, L, the efficiency of the kettle, ε, and the energy storage term in which m is the mass of the water, C_p is the thermal capacity of water, T_f is the final water temperature, and T_i is the initial water temperature.

$$E = Lf\varepsilon mC_p(T_f - T_i) \tag{3.3}$$

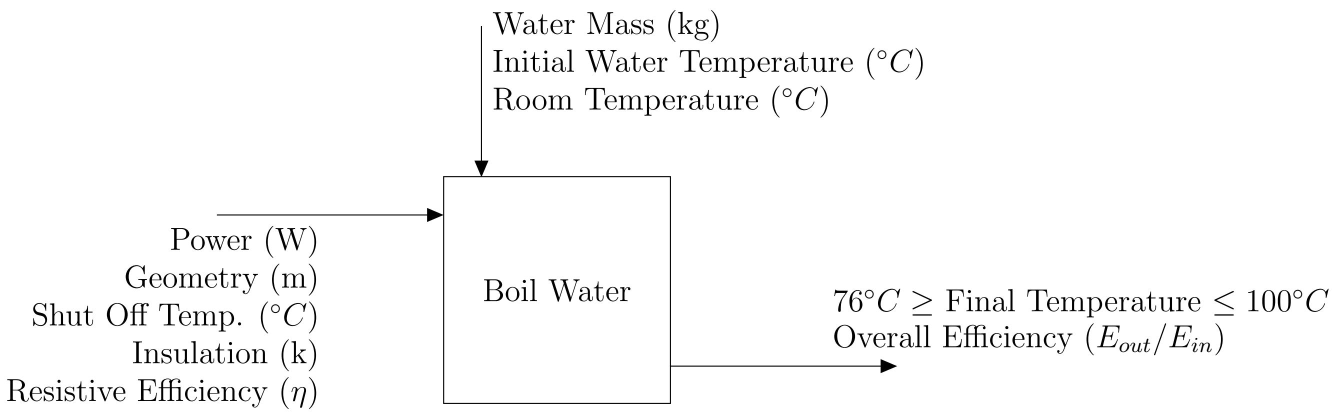


Figure 3.5: P-Diagram for a Kettle

Figure 3.5 depicts the p-diagram used to identify usage context variables related to Equations 3.3 and 3.2. The p-diagram categorizes each parameter as a design, noise, or output variable. Control variables are usually independent of the usage context, but the user can sometimes circumvent intended operation in a context-dependent way. For example, shut-off temperature for an electric kettle is not necessarily pre-defined. Although the kettle comes equipped with a default shut-off sensor, the user may end the heating process prematurely depending on their desired output. In this and other ways, control variables may become noise variables and require further exploration.

The outcome of this step is an objective set of parameters that need to be quantified for a performance model. Some of these parameters are controlled by the design, as illustrated by the P-Diagram, while others are vulnerable to the usage context. These noise factors can then be used as the focus for subsequent studies of usage procedures.

3.2.4 Drawing Activity Diagrams and Identifying Factors for Each Activity

The final brainstorming steps employ activity diagrams to understand typical procedures for product use. Activity diagrams are flow charts describing each activity in which a user engages while operating or interacting with a product. Two levels of diagrams are suggested for LCI studies, as shown in Figures 3.6 and 3.7.

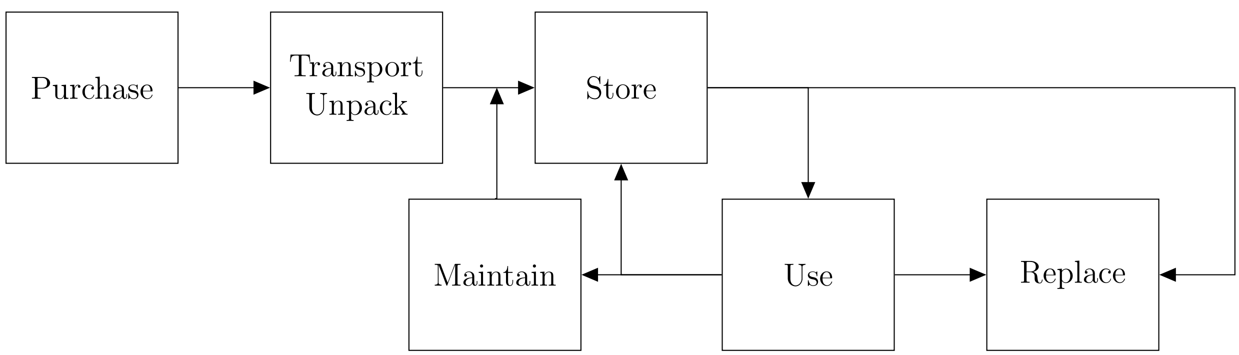


Figure 3.6: Global Level Activity Diagram Template

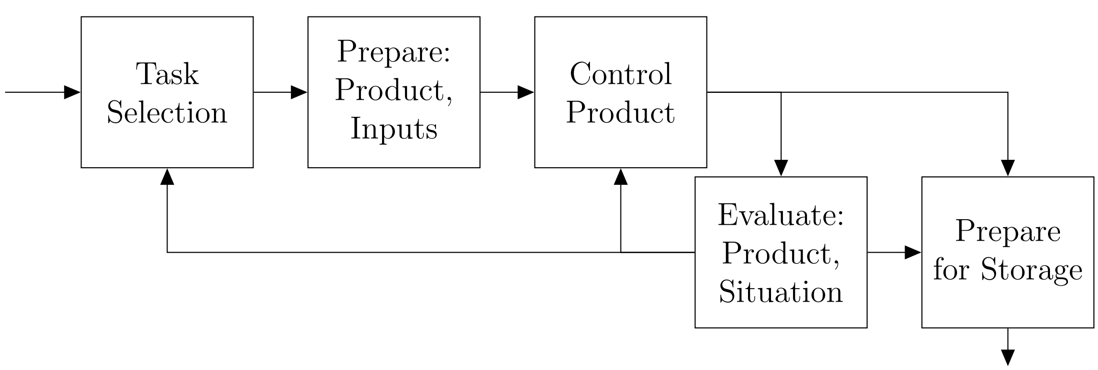


Figure 3.7: Task Level Activity Diagram Template

First, there is the global diagram, shown in Figure 3.6. This diagram is generally independent of a given task. It involves the higher level aspects of a product's useful life including storage, maintenance, and replacement activities. These aspects relate to the last two terms of Equation 3.1. The second level of diagramming is the task level activity diagram, shown in Figure 3.7 which describes aspects of the functional unit of use. Each task can have identical or different activity diagrams, depending upon the task and its complexity, but tasks usually share similar procedures for a given design. The templates in Figures 3.6 and 3.7 show the general, but not necessarily universal types of activities and ordering that should be considered.

After drawing the activity diagrams, the factors that are important to each activity are listed with the help of the checklist. For maintenance, this requires listing the product factors that are maintained and the situational factors or product factors prompting maintenance. Similar considerations are made for each activity. Again, building from the activity diagram focuses the factor identification task to directly relevant factors.

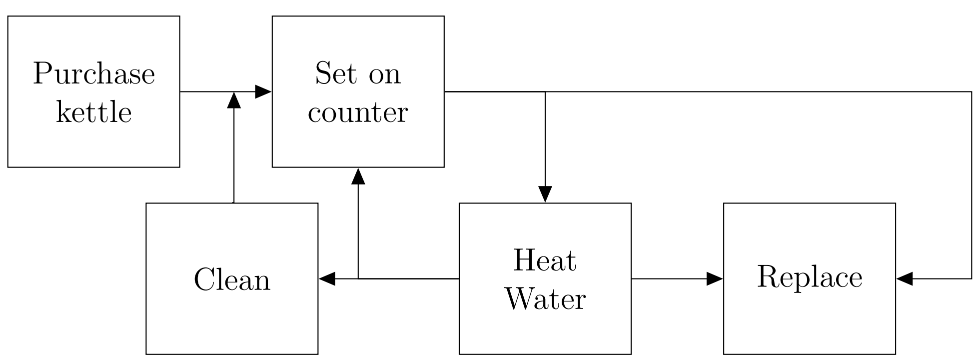


Figure 3.8: Global Level Electric Kettle Activities

Figure 3.8 depicts the global activity diagram for the electric kettle. Electric kettles require very little to no maintenance. The rate at which minerals from the water are deposited is barely noticeable to a consumer, but the kettle may be cleaned. It is assumed that additional energy from cleaning is negligible. Replacement of the electric kettle is likely to be a function of how often the product is used. The wires could be damaged from stress during everyday handling, and the electronics could fail from age and frequency of loading. Storage is usually indoors and does not affect the useful life. It is most likely that the product will be replaced for aesthetic reasons or to obtain kettles with additional features. These factors are described as: (1) expected functional life, and (2) expected aesthetic life.

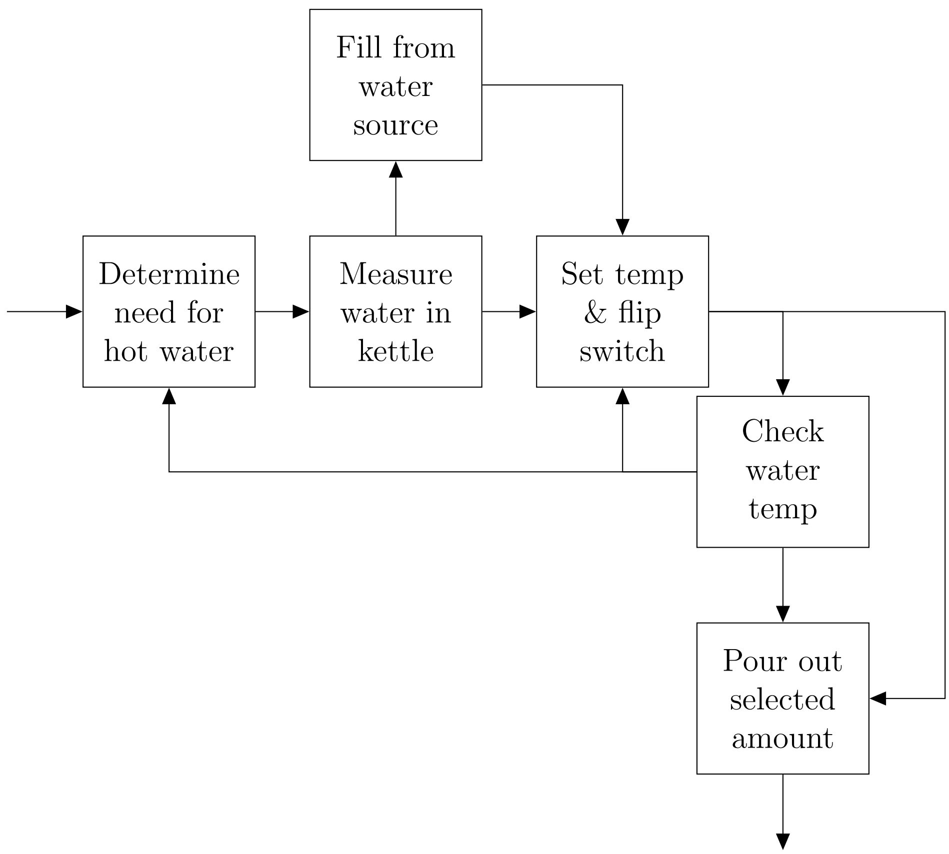


Figure 3.9: Heat Water Sub-Activity Diagram for an Electric Kettle

Figure 3.9 depicts the activity diagram for the process of heating water. The first activity is to determine the need for hot water. This includes factors influencing choice, such as time of day or outdoor temperature. Time of day is strongly related to the tasks of brewing coffee or pre-heating water for boiling pasta. Outdoor temperature influences the selection of warmer drinks like hot chocolate or cooler drinks like iced teas. Where the water comes from can also be important. If the water comes from the tap, the initial water temperature may be a cold winter temperature or a hot summer temperature. If the water has been left sitting in the kettle, it is room temperature. Each task has different water volume and temperature requirements that might be controlled by the user. The user's habits and knowledge are important in understanding tendencies to overfill the kettle or use unnecessarily high water temperatures. Relevant factors also include the user's measuring method and accuracy. The user is then able to set the desired water temperature, which has a level of accuracy, and turn the kettle on. The user can then check the water temperature to stop the kettle early if they are impatient, or let the water cool if that is preferable. A binary factor to describe these two user types might be classified as an active or passive user. The water is then poured out, and some water may be left in the kettle.

After listing factors engaged in each task level and global level activity, the practitioner will have a broad and relevant set of factors to use as vertices in their PGM. These factors can then be used to iteratively construct a set of edges and DAG structure in the final step.

3.2.5 Creating an Interaction Matrix and Directed Graph

At the end of brainstorming, a considerable number of factors are available and should be organized into a Directed Acyclic Graph (DAG). Table 3.5 depicts an abridged interaction matrix for the electric kettle. Each factor is entered into a column and row. The columns represent parent vertices or factors that influence other factors directly. The rows represent child vertices or factors that are influenced by other factors. The cells are filled to match parent factors directly with child factors. Factors without any parents are background variables that might be considered root causes and provide primary distinctions between different usage scenarios. The matrix is useful for coding and relating variables without the additional cognitive load of drawing a full DAG. Additionally, the matrix may require iterative revisions before informing the sketch of a DAG.

Table 3.5: Factor Relationship Matrix for Electric Kettle

Child \ Parent	Region	Month	Climate	Residents	Mass of water	Type of Drink	Required Temp	Final Temp	Frequency of use	Intial water temp
Region										
Month										
Climate	■	■								
Residents										
Mass of water				■		■				
Type of drink										
Required temp						■				
Type of drink			■							
Final temp							■			
Frequency of use			■	■						
Intial water temp			■							
Energy					■			■	■	■

In Table 3.5, it is easy to identify climate and the number of residents as important usage context factors. Initial water temperature is influenced by the climate, as the faucet temperature is a function of outdoor temperature. The final temperature that the user selects is some approximation of the required temperature dictated by the type of drink. The type of drink is selected based upon the climate which is determined by the region and time of year. The mass of water is influenced by the number of residents and the type of drink. The frequency of use is influenced by the number of residents and the climate. Total energy consumption during the useful life is added to the bottom row to represent the metric of interest. It is a deterministic function, from Equations 3.3 and 3.2, that will be included in the model to evaluate the LCI. Energy is not listed as a column and cannot be a parent node, because it would introduce a directed cycle into the DAG, and the model does not allow for dynamic feedback loops. Finally, the interaction matrix can be illustrated in graph form shown in Figure 3.10 where it may be more easily checked for accuracy.

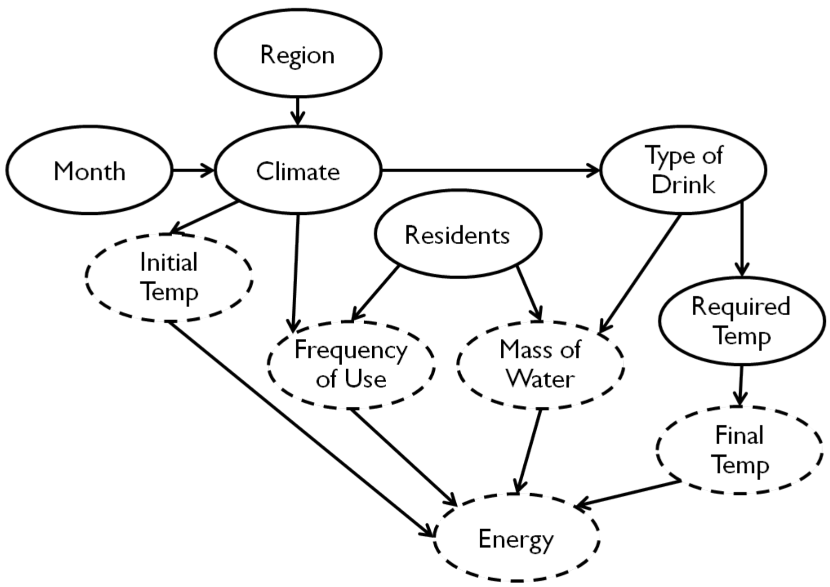


Figure 3.10: PGM of an Electric Kettle

The outcome of this final step is the initial graph structure. This structure can then be evaluated qualitatively or quantitatively, and the PGM model can be specified. The next chapter introduces some methods for checking the accuracy of reasoning in the graph structure, assigning probability distributions and creating LCI estimates. The kettle example is continued in Chapter 4 to illustrate the phases of data collection, statistical inference, and model analysis.

3.2.6 Chapter Summary

This chapter described the contributions of the first task of this dissertation. A taxonomy and set of tools were introduced for creating a graph, $\mathcal{G}$, of the usage context. Existing taxonomies and definitions from the literature were consulted and reviewed in defining the taxonomy for this dissertation. A unique taxonomy of human, $\mathbf{H}$, product, $\mathbf{P}$, and situation, $\mathbf{S}$, factors were defined. The new set of definitions reflects the departure of this work from previous work, in that most existing taxonomies focus on the user or the consumer and are not focused on energy consumption or efficiency. Consequently, a new approach to identifying factors was developed.

Brainstorming of factors to specify the set of vertices, V, and edges, E, of $\mathcal{G}$ was found to be a difficult and broadly scoped problem when following examples in the existing literature. The steps outlined in Figure 3.1 provide a framework for developing a comprehensive set of factors that are specialized for environmentally conscious designs and LCIs. An advantage of the framework is the re-purposing of common design tools. The resulting approach combines analysis of physical equations with analysis of user activities. A specialized checklist was also developed using the usage context based design literature and the environmentally conscious design literature.

The result of using these tasks and tools is an initial DAG that can be used for probabilistic graphical modeling. The process and expected results are illustrated through the use of an electric kettle example. This example is continued while demonstrating the next task of this dissertation. Chapter 4 describes the PGM procedure for estimating usage context effects and analyzing unique scenarios. The contributions of this chapter and Chapter 4 will then be applied to a lightweight vehicle example problem in Chapters 5 and 6.

Chapter 4

The Probabilistic Graphical Modeling Method

Without a quantitative understanding of the usage context, LCIs are not very useful for evaluating the effect of design changes on energy consumed during product use. In estimating the amount of energy consumed during the use stage of a product, it is necessary to make assumptions about the operating conditions and frequencies as well as the product's service life. The previous chapter demonstrated that these operating conditions can be related to more predictable aspects of the usage context. For example, the designer of an air conditioning system can predict its energy consumption more reliably given knowledge of the local climate. The central task of this chapter is to demonstrate that probabilistic graphical models can operationalize such knowledge in order to stochastically estimate LCIs and quantify the uncertainties associated with an LCI.

In the previous chapter, the usage context is represented as a directed acyclic graph. Each factor of the usage context is a node in the graph, and each edge of the graph indicates a directional dependency between nodes. This representation is developed using causal reasoning, and belongs to the family of PGMs called Bayesian Networks (Pearl, 1988). Each set of parent and child nodes is characterized using a locally specified probability distribution. The result is a factorized joint distribution for the entire set of usage context factors. More complex distributions can then be estimated for the whole usage context or some subset of factors that constitutes a unique scenario. The term PGMs is maintained in this work because not all of the relationships are modeled using conditional probability distributions. Therefore, the models are not strictly Bayesian but the terms may be used interchangeably throughout this chapter.

The PGM method is introduced in this chapter, beginning with the probability and graph theory behind PGMs in Section 4.1 and the ability to predict distributions for an LCI in Section 4.3. The review of probability theory includes the chain rule for conditional probability and Bayes' Rule. Together, these theorems enable the factorization of high-dimensional distributions and estimation or exact calculation of distributions of interest. Additionally, frequentist and Bayesian inference methods are discussed for specifying the parameters of local probability distributions. Gibbs sampling for approximating the total distribution is also explained (Casella & George, 1992). Finally, the complete process is introduced for specifying a graph structure and analyzing it. The process is then demonstrated by continuing the example of the electric kettle from Chapter 3.

4.1 Probabilistic Graphical Modeling Theory

The goal of constructing a PGM is to represent a joint distribution, $P(\mathbf{X})$, over some set of random variables, $\mathbf{X} = \{X_1, X_2, X_3, ..., X_n\}$. These random variables are structured in a graph, $\mathcal{G} = (\mathbf{V}, \mathbf{E})$, with vertices, $\mathbf{V} = \mathbf{X}$, and a set of edges, $\mathbf{E}$. For the graph shown in Figure 4.1, the joint distribution, $P(\mathbf{A,B,C,D})$, is represented using vertices, $\mathbf{V} = \{A, B, C, D\}$, and the set of edges, $\mathbf{E} = [(A, B), (B, C), (B, D)]$

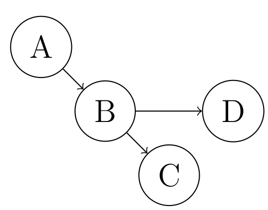


Figure 4.1: Graph of Random Variables A, B, C, D

The chosen graph is a directed acyclic graph (DAG) with the edges representing directional dependencies. For example, the structure in Figure 4.1 shows that C is dependent upon B and conditionally independent of D and A. Therefore, observing a value for C always increases our knowledge of the value for B, but only increases our knowledge of A and D if B is unknown. The fact that edges within this graph are directed, as indicated by the arrows, allows one to describe the dependencies as conditional probability distributions and build the structure using causal reasoning.

4.1.1 Relevant Graph Theory

Causal reasoning can be applied to graph building in one of three ways: the graph can be learned directly from data through automation; the graph can be constructed from expert knowledge; or the graph can be constructed semi-automatically. For LCIs, automated and semi-automated learning is not currently viable, as data for all factors cannot be measured concurrently to represent sampling from a joint distribution. Instead the graphs must be constructed from expert knowledge. This process was discussed in Chapter 3, but additional techniques for building and assessing these graphs warrant further discussion.

Table 4.1: Typical Variables and Relationships from Kjaerulff & Madsen (2007)

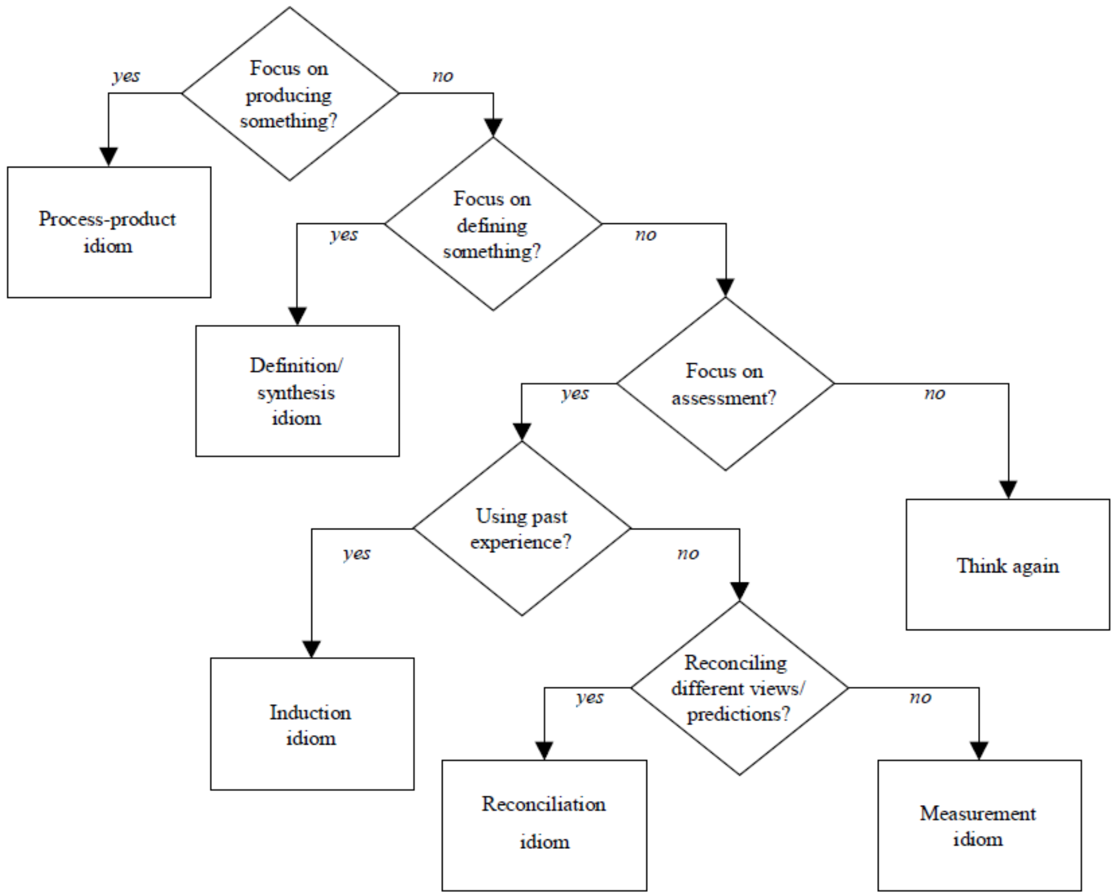
Type	Causally influenced by
Background variables	None
Problem variables	Background variables
Mediating variables	Background and problem variables
Symptom variables	Background, problem, and mediating variables

As shown in Table 7, Kjaerulff & Madsen (2007) define four types of variables 4.1 that compose PGMs. Problem variables are the unobserved variables a practitioner wishes to predict or understand. For example, one might wish to know the probability of a disease. Background variables are variables that can be directly observed, and are causes for other variables related to the problem. For example, family medical history is useful for estimating the probability of developing some diseases. Symptom variables are observable and affected by the problem variables. For example, observable symptoms of a disease, such as sneezing, would be symptom variables. Mediating variables are not usually of interest or easily observable, but they are necessary to obtain the correct independence relationships between other variables. For example, the disease may cause a change in internal chemistry that, in turn, may cause a symptom.

Building from this understanding of the types of variables, one can qualitatively and quantitatively assess the structure of a graph. Neil et al. (2000) identified four common problems in constructing graphs. First, the direction of edges must be chosen. Second, nodes must be representable by a Bayesian network. Third, the number of nodes should be minimized, but remain adequate for describing the conditional dependencies. Fourth, competing models and fragments of models might be reconciled. Neil et al. (2000) propose five unique idioms that can be applied to qualitatively evaluate fragments, or small clusters of nodes, in a Bayesian network. A flowchart for applying the idioms is shown in Figure 4.2.

The first idiom is the *Definitional/Synthesis idiom* describing the synthesis of multiple nodes into a single node. This idiom is of particular interest because it describes deterministic relationships which are often necessary in product performance models. For example, the number of pages being printed has a deterministic effect on printing time which influences the operator's decision to use duplex settings. This idiom can also be used to reduce the number of parents on a node and, consequently,

Figure 4.2: Idiom Selection Flowchart from Neil et al. (2000)



the complexity of the local probability distribution. By introducing an intermediate synthesis node, a subset of parents can be divorced from the child node.

The second idiom is the *Product-process idiom* or *Cause consequence idiom* and describes the direct causal relationship between two nodes. These nodes can also be considered as having inputs as parents and outputs as children.

The third idiom is the *Measurement idiom.* Some nodes represent measured values. These measured values have at least two parents: the accuracy of measurement, and the true value.

The fourth idiom is the *Induction idiom.* This idiom describes the process of statistical inference. Specifically, it describes the network fragment connecting a population parameter, such as a mean, and some set of observed instances. Each new observation increases knowledge of the parent population parameter that cannot be directly observes. The population parameter must be the parent node in this situation.

The fifth idiom is the *Reconciliation idiom.* This idiom introduces a node that compares and reconciles two competing model fragments. For example, the quality of a manufacturing system might be predicted through a model, or the quality may be inferred from observed physical outputs. These two model fragments might not agree, and require a reconciliation node to reconcile the two or indicate if the resulting hypotheses for quality are in conflict.

These idioms can be applied qualitatively as thought experiments and quantitatively once data has been collected. Qualitative assessment of the DAG structure is fundamental to data sampling because the structure prescribes the required local distributions. These probability distributions and quantitative aspects of PGMs are introduced in the next section.

4.1.2 Conditional Probability Theory

As mentioned, the goal of a constructing a PGM is to represent a joint distribution of random variables, $P(\mathbf{Y}, X)$. Generally, $\mathbf{Y}$ constitutes observable variables and X represents some unique variable of interest . To represent this joint distribution directly, one would need to specify the probability of X for every combination of possible values $\mathbf{Y}$. This section introduces the three fundamentals of probability theory that enable PGMs to factor the joint distribution into smaller, more manageable and measurable distributions.

Conditional probability is defined as the probability of one or more random variables, given values for one or more different random variables. Shown in Equation 4.1, the joint probability $P(\mathbf{Y}, X)$ can be factored into the conditional probability, $P(\mathbf{Y}|X)$ or $P(X|\mathbf{Y})$, and marginal probability, $P(X)$ or $P(\mathbf{Y})$, using the chain rule. These factors are the local conditional probabilities, and the factorization is dictated by the graph's edges.

$$P(\mathbf{Y}, X) = P(\mathbf{Y}|X)P(X) = P(X|\mathbf{Y})P(\mathbf{Y}) \tag{4.1}$$

Bayes' Rule in Equation 4.2 is the foundation for performing inference in a Bayesian network because it allows one to solve for inverse conditional probabilities. For example, it facilitates estimating the probability of a cause given observance of the effect. In Bayesian inference, the $P(X)$ term is called the prior probability of the cause X. It describes our belief in different values of X without observance of the effect Y. The $P(\mathbf{Y}|X)$ term is called the likelihood. It describes the probability that the effect $\mathbf{Y}$ will occur given the cause X occurs. $P(X|\mathbf{Y})$ is called the posterior probability. It reflects the updated belief that the cause X has occurred given that $\mathbf{Y}$ is observed.

$$P(X|\mathbf{Y}) = \frac{P(\mathbf{Y}|X)P(X)}{P(\mathbf{Y})} = \frac{P(\mathbf{Y}|X)P(X)}{\int P(\mathbf{Y}|X)P(X)dX} \tag{4.2}$$

Instead of specifying $P(\mathbf{y}$ directly in Bayesian network representation, it is often calcualted by integrating the product of the conditional probability, $P(\mathbf{Y}|X)$, and the prior probability, $P(X)$, over values of X as shown in the denominator of Equation 4.2.

Applying the chain rule and Bayes' rule to a network, such as the network of Figure 4.1 allows researchers to perform a number of interesting queries. Before those queries can be performed, each local distribution must be defined, as described in the following section.

4.1.3 Parameter Estimation

There are a number of approaches to parameter estimation in PGMs. An extensive treatment of these approaches can be found in Koller & Friedman (2009). Method selection is dictated by both practitioner preference and the availability of data. If substantial data are available, the parameters of the conditional distributions can be estimated using traditional frequentist methods. If very few data are available, Bayesian methods of inference can be applied to estimate the parameters. Bayesian methods can also be used to reconcile two distinct data sets that are not identically sampled. Both frequentist and Bayesian methods are utilized in this dissertation.

Most PGMs use frequentist statistical inference and rely solely on available data for characterizing distributions. Maximum likelihood estimation is the predominant method for approximating the true parameter of a distribution, such as the mean, from a sample of data. These parameters, called maximum likelihood estimates, maximize the likelihood of the observed data They are calculated by solving for zero gradients of the log-likelihood. For discrete data, this operation yields that the probability of a value is proportional to its frequency in the data set. The maximum likelihood estimate for a conditional probability,$P(x|y)$, is shown in Equation 4.3 for variable X with parent variable Y. The probability, $\theta_{x|y}$, for a value x given a value y is the count of paired instances of those values, $M[x, y]$, over the all instances of x, $M[y]$.

$$\theta_{x|y} = \frac{M[x, y]}{M[y]} \tag{4.3}$$

Just as the graph factors the joint probability distribution, the global decomposition property of likelihoods allows the maximum likelihood estimate to be calculated for each local conditional probability independently of the other conditional probability functions. Each local conditional probability may be discrete or continuous. PGMs often use discrete probability tables, but linear Gaussian distributions, shown in Equation 4.4 for a variable X with values for its n parents $\mathbf{y} = [y_1, y_2, ...y_n]$ are also common. These parameters, $(\beta_0, .., \beta_n, \sigma^2)$ are solved for individually to provide the highest likelihood of the observed data for X .

$$P(X|\mathbf{y}) = \mathcal{N}\left(\beta_0 + \beta_1 y_1 + \beta_2 y_2 + ... + \beta_n y_n, \sigma^2\right) \tag{4.4}$$

The usefulness of the maximum likelihood estimator is dependent on the size and quality of the data available. For this reason, Bayesian statistical inference combines estimates of the likelihood of observed data, $\mathcal{D}$, with prior beliefs about the parameter of interest, θ. These prior beliefs take the form of a prior probability distribution, $P(\theta)$, over the range of possible θ. Bayesian statistical inferences uses a modified form of Bayes' Rule, shown in Equation 4.5, that calculates a new posterior probability distribution,$P(\theta|\mathcal{D})$, for θ using the prior probability for θ, the likelihood of the data given θ, $P(\mathcal{D}|\theta)$, and the marginal likelihood of the data for all possible θ.

$$P(\theta|\mathcal{D}) = \frac{P(\mathcal{D}, \theta)}{P(\mathcal{D})} = \frac{P(\mathcal{D}|\theta)P(\theta)}{\int P(\mathcal{D}|\theta)P(\theta)d\theta} \tag{4.5}$$

The selection of a prior distribution for the parameters is constrained by the form of the likelihood distribution. In order to obtain a posterior probability density function of the same form as the prior probability density function, the prior must be a conjugate of the likelihood. More information on choosing priors and managing their influence on the resulting posteriors (i.e. weight relative to the data) can be found in Gelman (2003).

4.1.4 Inference via Sampling

Once the local probability distributions are estimated, the network can be used for inference. This task requires integration over multiple high-dimensional conditional probability distributions, and can become intractable. Sampling methods, most notably Markov Chain Monte Carlo (MCMC) methods, have enabled the use of PGMs for Bayesian inference by approximating the desired conditional and marginal distributions. This section introduces the Gibbs sampling algorithm, which is used frequently in Bayesian inference.

Gibbs sampling seeks to approximate a distribution, $P(X)$, by sampling from each unobserved variable in the network. Starting from an initial sample, either specified or generated randomly, the Gibbs sampler uses its current state to sample a new value for each variable given the current state of all of the other variables. For example, in Figure 4.3 sampling may be intiated at state $\mathbf{S} = a_1, b_1, c_1$, then B will be resampled and updated using $A = a_1$ and $C = c_1$ and so forth. The random walk that guides successive sampling is defined as a Markov process. In an MCMC sampling algorithm, such as Gibbs sampling, the probability of a future state, $\mathbf{S}$, is only dependent upon the current state.

Equation 4.2 satisfies this property and is the basis for forming Gibb's sampling chains. The resulting posterior probabilities used for each sample are shown generally

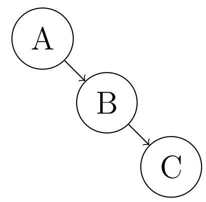


Figure 4.3: Graph of Random Variables A, B, C

in Equation 4.6 where **ch** are the child variables, and **pa** are the parent variables. This posterior probability is simply a normalization of the product of the local probability distributions for the variable being sampled, X. Although this posterior is not the true posterior, as it relies on samples generated from the prior, it is much closer than some alternative sampling methods (Koller & Friedman, 2009). The posteriors will eventually converge to approximate the true distribution as the number of samples increases.

$$P(X|\mathbf{S}) = \frac{P(X|\mathbf{pa})P(\mathbf{ch}|X))}{\sum P(X|\mathbf{pa})P(\mathbf{ch}|X)} \tag{4.6}$$

It is important to note that the time to convergence using the Gibbs algorithm cannot be predicted. Because the initial state guides subsequent sampling, the samples should be monitored to assess convergence and the required number of "burn in" samples (Gelman, 2003; Koller & Friedman, 2009). Time traces of samples usually exhibit asymptotic behavior as the distributions being sampled become mixed and near convergence. Monte carlo errors that report the variance between sample means should be less than 5% of the sample variance for convergence (Thomas et al., 2012). Nevertheless, the procedure may never converge or may converge to different results if the distribution has separate modes with strong probability. Consequently, multiple chains are usually sampled at once with different starting samples to ensure that all of the chains converge similarly.

4.2 Method Overview

Using the fundamentals reviewed in Section 4.1, this section presents the process for creating a PGM and for estimating use stage consumption for an LCI. The initial step is to create the graph structure by identifying and relating factors describing the relevant usage context. Next, data are collected for the local probability distributions, and statistical inferences are made using either frequentist or Bayesian methods that include prior qualitative information and collected quantitative data. Finally, inferences can be made about outcome variables given different scenarios. These values are incorporated into LCIs of the competing design concepts and sensitivity studies.

Recall that researchers begin by specifying the metrics and deterministic, engineering equations relevant to the life cycle analysis. Usually, the use stage of an LCI is defined by prescribing the product's operating performance and duration as related to some benchmark scenario. For example, a kettle's use is defined as a product of the amount of energy used for a specific operation at some frequency throughout its useful life. These LCI parameters should then be described by theoretical engineering equations, if possible. For example, the kettle's energy consumption is related to water mass and ambient temperatures using energy balances. These equations revealed further important use variables through the application of a P-diagram and checklist. Activity diagrams are also helpful for understanding the procedures and order of influence during product operation. Finally, interaction matrices help create the initial set of edges for a PGM.

The graph structure is revised and data collection begins with dedicated interviews, experiments, and literature studies. Previous studies in engineering, policy, marketing, and psychology may describe consumer activity and reasoning in the con-

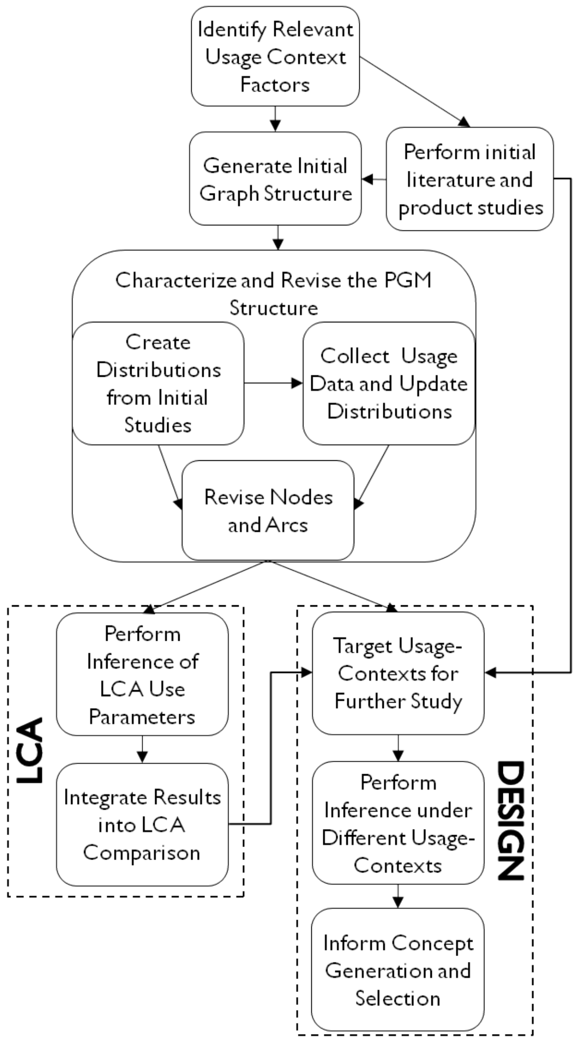


Figure 4.4: Flowchart of PGM Method

text of interest and should be consulted to improve understanding of the relevant factors and support selection of the graph structure. At the conclusion of these studies, the researcher will have a list of the influential usage factors and a corresponding set of edges, supported by qualitative and quantitative data.

Once the initial structure is created, probability distributions can be assigned to each node. Likelihood and prior distributions can be created by consulting literature values and expert judgment. If necessary, additional experiments can be designed to update the prior beliefs about parameters using Bayesian statistics as described in the previous section. During data collection, the structure may need to be revised given new insights. After the nodes are populated by data, the PGM can be integrated into the LCI and design process. The analysis is unique to every LCI. The next section demonstrates this process for the electric kettle.

4.3 Kettle Example

A previous study of electric kettles suggested four possible redesigns to take advantage of lower water temperature requirements (Telenko & Seepersad, 2010). The first new design concept required no additional manufacturing requirements. This concept simply employed an alternative bimetallic switch to turn off the heater at 95°C instead of 100°C. The second new design concept employed a variable temperature setting with two alternative embodiments with increasing energy consumption during manufacturing. The first embodiment specifies a dial for selecting the setting. The second embodiment adds an LCD screen with the dial. This section revisits the LCI study from this previous work by revising values for the energy use according to results of a PGM.

A summary of the environmental impacts of a Proctor Silex kettle was shown in Figure 1.1 to illustrate the use, manufacturing, and end-of-life contributions. As part of the LCA, the usage parameters of the electric kettle had to be estimated as part of the functional unit. In the initial study, the kettle was assumed to boil, raising the temperature from 25°C to 100°C, two and a half mugs of water, eight times a week for a lifetime of four years. Each of these parameters were assumed to be fixed, and relationships between them were not considered. The PGM facilitates concurrent variation of all variables that define the functional unit, along with additional variables that influence the variables in the functional unit. In most LCIs, only a range of possible values can be identified and correlations between these values are often ignored.

Creating distributions for a PGM involves two steps: (1) specifying the likelihood and prior distribution, and then (2) updating the prior using data. Figure 4.5 depicts the kettle network reduced to a simple chain with additional nodes to help illustrate the implementation of Bayesian statistical inference. Each node for which data is collected (climate, required temperature and final temperature) has an additional parent node to represent the associated conditional parameter.

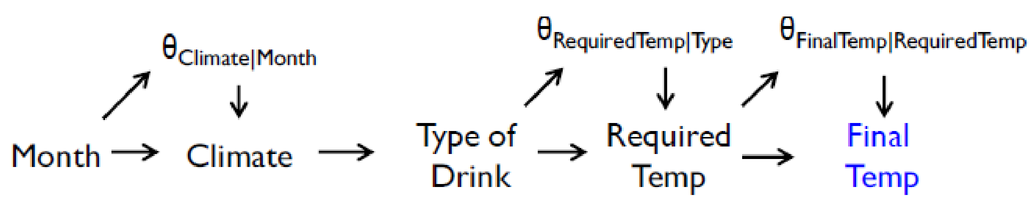


Figure 4.5: Reduced PGM of an Electric Kettle

Table 4.2 details each node, the assigned likelihood distribution and its associated mean and variance. The month node is a uniform distribution across values representing each month of the year. The climate is a continuous variable in degrees Celcius. The type of drink is a classifier which classifies the type as a hot drink if the

Table 4.2: Likelihood Distributions for the Kettle Graph

Variable Node	Likelihood Distribution	Assumed Variance (δ)
Month	Uniform(1,12)	N/A
Climate	Normal($\theta_{Climate\|Month}$, δ)	30
Type of Drink	Hot if Climate<70°C; else Cool	N/A
Required Temp	Normal ($\theta_{ReqT\|Type}$, δ)	20
Final Temp	Normal($\theta_{FinalT\|ReqT}$, δ)	5

Table 4.3: Prior Distributions for the Kettle Graph

Parameter Node	Prior Distribution	Conditional Mean of Prior (μ)	Initial Variance (τ)
$\theta_{Climate\|Month}$	N($\mu_{Climate\|Month}$, $\tau_{Climate\|Month}$)	Jan-March -4; April-June 18; July-Sept 27; Oct-Dec 15	6
$\theta_{ReqT\|Type}$	N($\mu_{ReqT\|Type}$, $\tau_{ReqT\|Type}$)	Cooler Drink 80; Hot Drink 95	5
$\theta_{FinalT\|ReqT}$	N($\mu_{FinalT\|ReqT}$, $\tau_{FinalT\|ReqT}$)	Cooler Temperature 95; Hotter Temperature 100	5

outdoor air temperature is below 21°C and as a cooler drink otherwise. The required temperature corresponds to the specifications of a type of drink. Finally, if the required temperature is above 92°C, a distribution of higher final temperatures is used. Otherwise, the need is classified as cool, and a distribution of lower temperatures is used.

Table 4.3 describes the prior distributions for the means. The most probable parameter is chosen according to Equation 4.7. Climate values are estimated from online weather sites to provide a mean and range in accordance with historic high and low temperatures. The other values are best guess estimates informed by the prior research (Telenko & Seepersad, 2010). Data from online weather sites and a survey of 34 respondents from 4 regions of the United States were used to condition prior beliefs about the mean for each likelihood distribution.

$$\mu_{i|j} = argmax_\theta \left(P(\theta_{i|j}|\mathcal{D}_{i|j})\right) \tag{4.7}$$

The survey included a number of multiple choice questions aimed at refining the structure. Each respondent reported their regional location described as the South, West, Midwest, Northeast or Southeast United States. Each respondent also submitted information regarding his or her types of water needs according to season. Table 4.4 shows a sample question and the aggregate number of responses for each selection. All of the qualitative data is quantified using a single point estimate for temperature needs. For example, a respondent who indicated a preference for coffee in the winter would be assigned a required temperature of 95°C. A respondent who indicated a preference for iced tea in the summer would be assigned a required temperature of 80°C.

During which seasons do you heat water for the following?

	Winter	Spring	Summer	Fall
Coffee	16	14	14	14
Food	32	33	31	33
Hot Tea	24	17	10	22
Iced Tea	2	3	7	2
Other	9	7	7	8

Table 4.4: Sample Kettle Survey Question

Because each response was structured to clarify the state of parent and child nodes in the chain, the quantified estimates for these responses were used to condition the successive child nodes. For instance, Equation 4.8 details Bayes Theorem for updating the prior belief about the mean outdoor temperature during winter,$P(\theta_{Climate|Month})$, given an observed data point for that variable, y. To simplify the calculation, only the kernels of the distributions were used. Equation 4.7 can still be applied without normalizing the joint distribution, as in Bayes rule (Equation 4.5).

$$P\left(\theta_{Climate|Month}|y\right) \propto P(y|\theta_{Climate|Month})P(\theta_{Climate|Month}) \tag{4.8}$$

Figure 4.6 shows a sample of the resulting prior and posterior distributions for the parameters of each node in the chain. Generally, these describe the distributions from which samples might be drawn for winter months. Although the data is estimated, a few observations can be made. Most of the respondents were from Texas, and the climate mean shifts towards a warmer temperature. The means of other temperatures did not vary as much, because the range of viable temperatures is much smaller. For example, most hot beverages should be heated to between 90°C and 100°C.

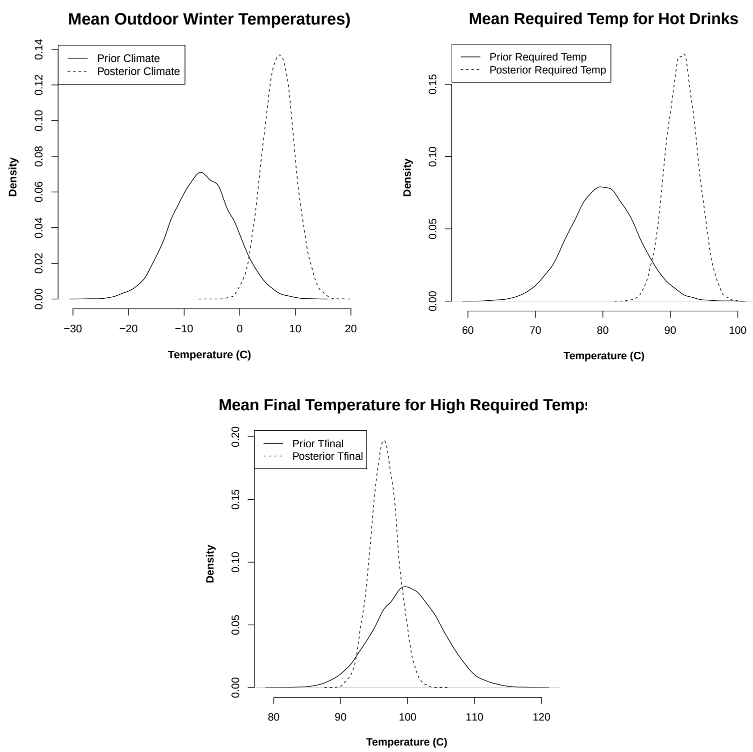


Figure 4.6: Prior and Posterior Distribution for Electric Kettle Factors

After defining the conditional distributions, inferences were made about the marginal distribution for the final temperature. For this example, a simple forward sampling sequence generates histograms for each usage context variable. Starting with a random month sampled from a uniform distribution, each subsequent distribution is prescribed and further samples are drawn, as shown in Figure 4.7. Ten thousand simulations generated ten thousand values for each node along the chain.

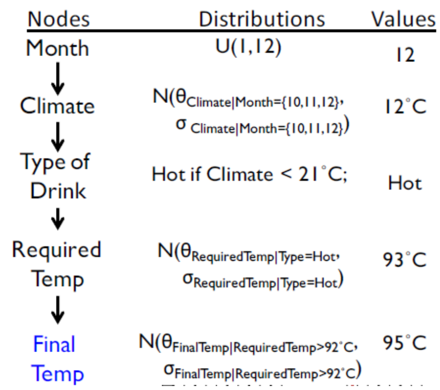


Figure 4.7: Example of Sampling for Kettle Network

Histograms of these results are shown in Figure 4.8. Although the required temperature is distributed approximately normally with a mean of approximately 95°C, the final temperature is determined by the user and can be very different than the required temperature. Recall that if the required temperature is above 92°C, the user is less likely to stop the heating process prematurely. Otherwise, the user is more conscientious of lower temperatures. Thus a bifurcation is present in final temperatures caused by the hot and cool temperature needs. Although a wide range of probable temperature values exist, the mean temperature value is still towards the upper end of the range, approximately 95°C.

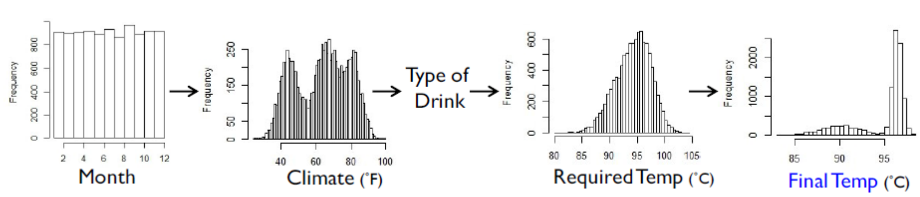


Figure 4.8: Histograms of Samples for the Electric Kettle PGM

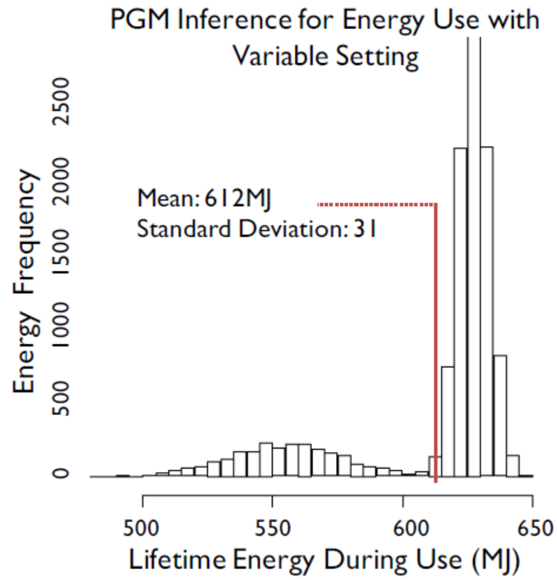


Figure 4.9: Histogram of Marginal Energy Use

Using the PGM tool, it is possible to quantitatively investigate the impact of usage variability on the lifetime energy consumption of the concepts with variable temperature settings. Recall that the first two concepts employ default temperature settings of 100°C and 95°C, and the final concept employs a variable temperature setting to take advantage of the range of temperature needs. Shown in Figure 4.9, the resulting histogram indicates that a wide range of energy consumption is possible, but that higher values are more probable. The lower temperature needs that inspired the variable setting design are improbable. This result is likely due to the frequency of water being used for high-temperature needs, such as coffee and cooking, by survey respondents.

Table 4.3 shows the results for lifetime energy consumption during use and the total energy LCI of each product concept. The PGM only models the final temperatures for the variable setting concept. Therefore, a final temperature of 95°C or 100°C is used for the respective bimetallic concepts without variable temperature

Table 4.5: Energy Comparison of Design Alternatives

Temp. Setting Design	Mean Lifetime Energy Use	Mfg Energy		Total LCI Energy
Variable Setting	612 MJ	Display	99 MJ	711MJ
		No Display	85 MJ	697MJ
Lower Default (95°C)	610 MJ	81 MJ		691MJ
Original (100°C)	670 MJ	81 MJ		751MJ

settings. Comparing the mean expected lifetime energy use for the variable setting concept shows a net increase in energy consumption relative to other embodiments. From this information, it seems that a lower default setting is preferable to a variable setting for the general population of users, but a different conclusion is reached if the product is designed for specific usage contexts, such as specific climates.

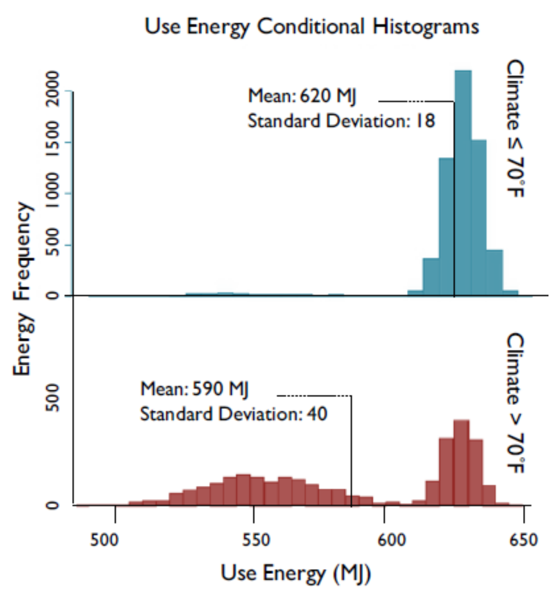


Figure 4.10: Histograms of Conditional Energy Use for Cool and Warm Climates

By testing two climate conditions, two additional histograms, shown in Figure 4.10, were created. The warmer and cooler climate conditional distributions represent two alternative usage-contexts for which a product could be designed. In colder climates, shown as the upper histogram, users are more likely to boil water for cooking and hot teas and coffees. In the warmer climates, shown as the lower histogram, users are more likely to boil water for iced teas. The mean energy use for warmer climates is 5% lower than that for the cooler climates and 3% lower than the general estimate for all possible climates in Figure 4.9. The predicted energy consumption for a variable setting device in warmer climates is also 3% lower than the estimate for the kettle with a lower default setting. Consequently, a variable temperature setting may be more suited for warmer regions with a larger variety of temperature needs, while a product with a lower default setting might be employed for cooler regions.

4.4 Chapter Summary

PGMs are promising tools for representing and quantitatively modeling the usage-context of a product and allowing for a more flexible functional unit. In this chapter, a PGM was used to compare the lifetime energy consumption of three competing kettle concepts. With the results, the designer could select the option with the least environmental impact, measured in terms of expected lifetime energy consumption. The kettle example presented in this paper shows the utility of a PGM for both LCI and environmentally conscious design. For LCI, the PGM aids in estimating values for use parameters. By creating a context for these variables, researchers can more easily and transparently perform uncertainty studies. This results in an improvement on current practice in which variability is not considered in a rigorous way. Current practice lacks similar depth or transparency that may aid in design.

In addition to making inferences about the stochastic nature of environmental performance variables, PGMs can help designers gain further insight into reducing variability. In the example, a variable temperature setting did not reduce net energy consumption over the product's life cycle for the general population of users. Nevertheless, isolating the effect of the variable temperature setting in different climates revealed that net energy consumptions can be reduced if designed for markets in warmer climates.

The current example study focused on a simplistic network centered on one variable of the functional unit. It did not include a comprehensive study of the usage context. The next chapter will introduce the central example of this dissertation, a lightweight vehicle design problem.

Chapter 5

The Lightweight Vehicle Example

The central example for this work, a lightweight vehicle LCI, represents a body of research with which the results of the PGM method can be compared. Two automobiles that achieved weight savings through the use of aluminum trunks–the 2006 Oldsmobile Aurora and the 2004 Chevy Malibu Maxx–are used to create engineering specifications for the study. The designers of both vehicles employed lightweight materials to reduce weight at the expense of increased energy for material production. Although these designs were not intended to improve fuel economy, designs that use lightweight aluminum to save energy are often validated in LCIs because operation accounts for 66-91% of a vehicle's lifetime energy use, while material production and part manufacture constitute less than 30% (Sullivan & Cobas-Flores, 2001).

Contrary to typical assumptions and representations, operational variability could prove critical to determining tradeoffs for vehicle design in different usage contexts. Greene et al. (2006) determined confidence intervals on the order of 20-30% for consumer reported vehicle fuel efficiencies. Ridge (1998) sought to report relations between weight reduction and fuel reduction for vehicle classes by coalescing data from industry and research partners, but the data were imprecise due to variations in drive cycles and testing methods. Instead of assessing the implications of such variability, researchers, such as Ridge, assume a constant lifetime fuel economy and driving scenario.

In this chapter, the method for identifying factors from Chapter 3 is applied to generate a PGM for an LCI of lightweight vehicle. The primary usage context factors, underlying data, and local probability distributions are introduced and explained. Section 5.1 reviews the existing body of LCI research and documents the energy LCI values for the manufacturing and end-of-life stages of the aluminum and steel vehicle designs. Eleven alternative approaches for estimating fuel consumption and uncertainty are compared. Section 5.2 details the selection of factors for modeling the usage context, and Section 5.3 details the data and parameter analysis required for specifying local probability distributions within the model.

5.1 Existing Life Cycle Inventories

Table 5.1 summarizes 11 research publications comparing LCIs of steel vehicle parts with lightweight aluminum alternatives. All of these studies estimate a net energy savings during vehicle use from lightweighting. The results, however, differ from study to study for a few reasons. First, as will be discussed in Section 5.2.1, not all of the studies agree on the specific energy consumption of material production and manufacturing. Second, the improvement in fuel economy is proportional to the weight savings and the base fuel economy, both of which differ from study to study. Third, each study assumes a different lifetime mileage. These disparities highlight the importance of specifying similar lightweight designs for comparison and the importance of functional units.

As the mass savings due to lightweighting increase, the payback time, in kilometers, decreases. Although fuel efficiency increases exponentially with weight reduction (Hakamada et al., 2007; Song et al., 2009), the energy investment in aluminum during material production and manufacture is assumed to increase linearly with increased mass of aluminum. The fuel efficiency gains are usually estimated at 6% per 10% weight reduction, achieved by additional downsizing of other sub-assemblies and

Table 5.1: Literature Lightweight Vehicle LCI Results

Authors	Overall Savings (kg)	Base FE (km/L)	Change in FE (km/L)	Mfg Cost (GJ)	Break Even Mileage (1000 km)	Assumed Mileage (1000 km)	Use Savings (GJ)
Allen et al. (2007)	60	10	0.3	17.6	173	193	19
Das (2000)	203	11.7	0.8	20	99	291	56
Das (2005)	5	8.62	0.02	1.9	280	281	2
Field et al. (2002)	-	-	-	-	116	18/year	-
Song et al. (2009)	482	-	-	-	-	190	204
Hakamada et al. (2007)	82	12.7	1.2	12	51	100	23
Kim et al. (2008)	132	14	1.7	-	88	193/291	52/78
Kim et al. (2008)	210	14	2.9	-	142	193/291	82/124
Kim et al. (2008)	249	14	3.6	-	169	193/291	98/147
Mayyas et al. (2012)	563	10	8	18	99	291	486
Kim et al. (2011)	69	14	0.5	-	54	291	25
Kim et al. (2011)	266	14	1.9	-	106	291	86
Davies (2003)	98	-	-	34	-	-	8
Davies (2003)	112	-	-	30	-	-	26
Stodolsky et al. (1995b)	271	10.7	1.3	0	-	-	108

optimization of the powertrain (Montalbo et al., 2008; Ridge, 1998). In contrast, the energy investment of aluminum maintains a rate of about 170 $\frac{MJ}{kg}$.

The functional unit introduces two sources of disparity by assuming lifetime mileage and average fuel economy. As the base fuel economy of a steel vehicle increases, the potential for energy savings is reduced. For example, a vehicle with a 6% fuel economy improvement over 10 $\frac{km}{L}$ will save 567 L over 100,000 km. A vehicle with a 6% fuel economy improvement over 12 $\frac{km}{L}$ will save 472 L. For more efficient steel vehicles, the aluminum vehicle will require a longer lifetime mileage to payback the energy investment. Therefore, justification for lightweighting requires reliable estimates of both fuel economy and lifetime mileage.

Sensitivity of payback time in years is sometimes estimated for published LCIs, but not well explored. For example, Allen et al. (2007) investigate the effects of increased annual mileage and fuel economy on vehicle payback time in years. They show that the benefits of lightweight designs increase as vehicles last longer, but do not discuss realistic values. In addition to negating any relationships between fuel economy and lifetime mileage, the results are rather simplistic and do not increase understanding of realistic usage scenarios.

Kim et al. (2008, 2011) considers two types of independent uncertainties in their analysis: vehicle mileage and recycling. As in Allen et al. (2007), crediting aluminum with off-setting future energy consumption of material processing improves payback time in kilometers. Although Kim et al. (2008, 2011) considers high and low lifetime mileage estimates, these estimates only provide ranges of possible energy savings; neither lifetime mileage is considered more or less likely.

Das (2000) compares single vehicle LCIs with fleet level LCIs developed in Field et al. (2002). Field et al. (2002) argue that policy level decisions should consider temporal energy savings as the steel fleet is replaced by a lighter aluminum fleet and scrap metal stockpiles. A steady state single product comparison cannot be used to estimate payback time in years for an entire fleet. Das (2000) shows that payback time increases at the fleet level, and checks the sensitivity of a fleet level analysis to manufacturing, material production, and fuel economy estimates. He shows that a 1% fuel economy change and 25% material production energy change have similar effects on pay back time. Because energy during use is so large, small uncertainties in fuel savings can be just as influential as larger uncertainties in investment cost. In a later paper, Das (2005) studies a smaller weight reduction, an aluminum vehicle liftgate, and finds that material production uncertainty becomes more important as fuel savings decreases. Again, neither Das (2000) nor Field et al. (2002) consider joint uncertainty effects within vehicle mileage and fuel economy. These results motivate the decision to consider smaller weight reductions in this dissertation.

Mayyas et al. (2012) consider the largest weight savings, just above the value reported by Song et al. (2009). Song et al. (2009) estimate weight savings from using aluminum in a small moving truck, but Mayyas et al. (2012) consider weight savings from the body in white of a sedan in addition to secondary weight savings. The body in white savings of about 135 kg allow for an over 400 kg additional weight savings in downsizing and very significant fuel economy improvement. Such secondary weight savings are not unique to Mayyas et al. (2012), but usually range on the order of 50% additional weight savings. Mayyas et al. (2012) draw mass reduction values from existing vehicle concepts without regard for the types of secondary design changes and their manufacturing effects.

Mayyas et al. (2012) consider uncertainty for each life cycle stage independently as ranges of $\pm 10\%$. They report that fuel economy has nearly double the effect of lifetime mileage and five times the effect of material production or recycling. They do not consider the joint effects of variable factors or the possible usage contexts that may incur such effects.

The existing publications of lightweight vehicle LCIs do not extensively consider the role of realistic functional units in their analysis. These studies do not ask or answer the questions of which types of vehicle or driving situations are most suited to mass reductions. It can be deduced from the findings that vehicles that achieve low service mileage and high fuel efficiency might be less suitable for lightweight designs. This dissertation seeks to identify scenarios that result in low mileage and high fuel efficiency or vice versa. The PGM will model the interactions between fuel economy and service mileage, as well as the underlying factors that lead to these performance values. Additionally, this research does not consider secondary weight savings, making it more conservative than some of the existing studies.

5.2 Overview of Vehicle LCI

The example problem of this dissertation considers three vehicles designed by General Motors. These vehicles are the 2001 Oldsmobile Aurora V8, the 2001 Oldsmobile Aurora V6, and the 2004 Chevrolet Malibu Maxx. The Auroras are both heavier than competing luxury sedans from other manufacturers, but manage to weigh 165 lbs and 285 lbs less than the previous model year (U.S. Department of Energy, 2012). The aluminum parts on the Aurora vehicles were stamped, but the development of quick plastic forming (QPF) allowed production of the aluminum deck lid on the 2004 Malibu Maxx (Peter, 2004). These weight savings are shown, in addition to other vehicle specifications in Table 5.2.

Table 5.2: Lightweight Vehicle Design Specs

	Aurora V8	Aurora V6)	Malibu Maxx
First Gear Ratio	2.96	2.92	2.96
Second Gear Ratio	1.63	1.57	1.62
Third Gear Ratio	1	1	1
Fourth Gear Ratio	0.68	0.71	0.68
Final Drive Ratio	3.71	3.29	3.29
Tire Radius	50 cm	48 cm	48 cm
Curb Weight	1725 kg	1645 kg	1569 kg
Steel Lid Weight	18 kg	-	18 kg
Al Lid Weight	11 kg	-	9 kg
Deck lid Weight Savings	7 kg	-	9 kg
Steel Hood Weight	15 kg	15 kg	15 kg
Al Hood Weight	9 kg	9 kg	9 kg
Hood Weight Savings	6 kg	6 kg	6 kg
Total Weight Savings	13 kg	6 kg	15 kg

The total weight savings and aluminum weight savings in the Aurora examples are not proportional, and are both examples of designs without predictable secondary weight savings. Other design features can be added to increase the weight. Consequently, this study is limited to the aluminum hoods and trunks without including secondary weight savings. The trunk lid savings values were published in press articles (Vasilash, 2001; Peter, 2004). The hood weights and savings were best guess estimates assuming weight reductions proportional to the trunk. All other vehicle characteristics are taken from the General Motors (2001, 2004) website. The additional characteristics in the table are necessary for creating drive cycle simulations in Section 5.4.2.

The LCI is scoped as a gate to gate analysis shown in Figures 5.2 and 5.1 for aluminum and steel, respectively. The LCI considers energy consumption of material production, part manufacturing, use, and melting the parts at end-of-life. No credits are given for offsetting future material production via recycling because these credits should be applied to future products using the materials. Storage costs for scrap stock and transportation of raw stock are outside of the scope. Additionally, the production of fuel is not considered. In almost all studies, aluminum is five or more times as energy intensive to produce as steel. Part manufacturing comparisons are inconsistent, with either material costing more. Finally, end-of-life energy consumption is estimated without assuming the part is recycled or crediting the aluminum gate to gate LCI. The uncertainty of these estimates is discussed briefly in the next section. Values from Davies (2003) that are taken from steel industry reports were used to create a more critical perspective of aluminums. Additionally, Davies (2003) cited specific processes for his analysis. For example, the manufacturing energy assumes the process of stamping. Energy consumption of QPF, used for the Malibu Maxx, could be much higher, but the process is proprietary and data are not obtainable. Compared with aggregate literature values, values from Davies (2003) are conservative and favor steel as the eleven sources cited in Table 5.1 report higher specific energy consumption for steel, but similar energy consumption values for aluminum.

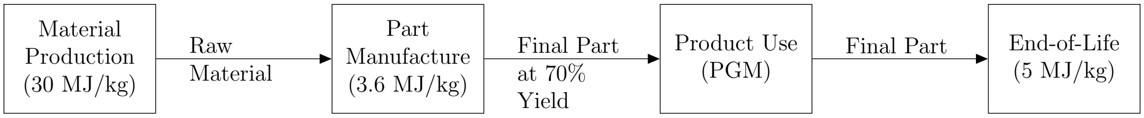


Figure 5.1: Flows Considered in the Gate to Gate LCI of a Steel Vehicle Part

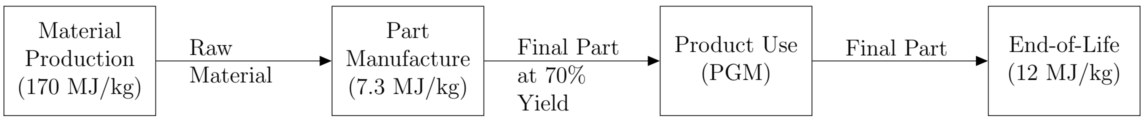


Figure 5.2: Flows Considered in the Gate to Gate LCI of an Aluminum Vehicle Part

Table 5.3 shows the energy LCI for all stages of Figures 5.2 and 5.1 for each vehicle. It lists the total energy consumption for each steel and aluminum design in MJ. The difference between these values is considered the total additional energy investment for aluminum. This energy investment is 3.4 GJ for the Aurora V8 which saves 13 kg, 1.5 GJ for the Aurora V6 which saves 6kg, and 2.9 GJ for the Malibu Maxx which saves 15kg. These weight reductions are 0.8%, 0.4%, and 1%, respectively.

Table 5.3: Estimating Energy Investment in Aluminum Parts

	Aurora V8		Aurora V6		Malibu Maxx	
	Steel	Aluminum	Steel	Aluminum	Steel	Aluminum
Material Production (MJ)	1414	4857	643	2186	1414	4371
Manufacturing (MJ)	396	360	180	162	396	324
End of Life (MJ)	119	146	54	66	119	131
Total (MJ)	1929	5363	877	2413	1929	4827
Al. Investment (GJ)	3.4		1.5		2.9	

5.2.1 Uncertainty of LCI Stages

Although this study is focused on representing variability and uncertainty associated with product use, it is helpful to understand variability and uncertainty within other stages of the life cycle, as well. Table 5.4 lists average inventory values reported from seven sources, as well as the standard deviation of these values (Davies, 2003; Das, 2000, 2005; Song et al., 2009; Stodolsky et al., 1995a; Tan & Khoo, 2005; Hakamada et al., 2007). There are large disparities in the reported data, and this disagreement in literature values was also observed by Sullivan & Cobas-Flores (2001) in a previous review of full vehicle life cycle assessments. Two explanations exist supporting the possibilities of poor data reporting and high inherent variability of material production processes.

Table 5.4: Material Production and Manufacturing Energy LCIs

	Aluminum			*Steel*		
	Virgin Material Production	Manufacture	Recycled Material Production	Virgin Material Production	Manufacture	Recycled Material Production
Average ($\frac{MJ}{kg}$)	172.9	13.7	15.6	37.5	18.4	12.5
Std Dev (%)	38	80	77	40	89	57

Song et al. (2009) note specifically that, although such variance is unacceptable in many engineering applications, it is an inherent reality of material processing. Examples are given by Song et al. (2009) of three glass fiber production plants. Each plant – PPG, OwensCorning, and Vetrotex – produce the same product, but with very different energy consumptions, 12.58, 25.3 and 32.0 MJ/kg respectively. The discrepancy in reported energy consumption is due to differences in plant sizes, efficiencies, and operations.

Nevertheless, poor reporting techniques are also possible causes of uncertainty. Ayres (1995) discusses the widespread lack of diligence in maintaining mass and energy balances in LCI reporting and modeling. Farla & Blok (2001) studied the quality of energy data for the iron and steel industry to find that quality in reporting is consistent within countries but not internationally. The data reported come from European, U.S., Australian and Japanese sources, but the global manufacturing infrastructure includes other countries such as China. Because of inherent variance and lack of disclosure, it is impossible to determine the causes of variance without extensive personal correspondence with the authors of each individual study and their data sources.

Another difficulty in determining the comparability and cause for variance in the reported values arose when determining process scrap rates. It seems necessary that the values reported for raw material extraction are per kilogram of raw material yield and the values reported for part production are per kilogram of the final part. Only one source reported yield values for the conversion of ores to raw materials (95% yield) and raw materials to parts (60-65% yield for sheet metal) (Hakamada et al., 2007). When accounting for yield, it is important to note that yield differs by plant, manufacturing process and geometry. For example, cast parts will have less material waste than sheet parts. Davies reports scrap rates of 15-40% for manufacturing processes (Davies, 2003). Most papers do not clearly specify these assumptions and characteristics of their data.

5.3 Refining the Problem and Identifying Factors

In the previous sections, the vehicle example was described along with the LCI for all stages except use. The review of existing LCI literature showed the importance of estimating realistic functional units and ranges for use stage energy consumption. The general calculation for inventorying energy during use is shown in Equation 5.1, where E_U is the total energy consumed during use. FE_T is the fuel economy and d_{life} is the total distance traveled over the vehicle's lifetime.

$$E_U = \frac{d_{life}}{FE_T} 34.8 \frac{MJ}{L} \tag{5.1}$$

In this equation, fuel efficiency is usually assumed, which ignores variability in vehicle speeds, accelerations, and loads. Additionally, lifetime mileage is assumed, but this value differs between vehicles and owners.

The efficiency of a vehicle can be described using physical equations. Most simply it is the ratio of power out, the power required to transport the vehicle and load, and power in, measured as the energy content of fuel consumed per second. The overall efficiency is a product of the engine, transmission, drive train, and other efficiencies. Beginning at the engine, Equation 5.2 shows the calculation of brake specific fuel consumption (BSFC) or rate of fuel intake, $\dot{m}_f$, normalized by power output, calculated as the product of the indicated power, P_i, at that engine speed and the engine mechanical efficiency, η_m. Most of the variables in Equation 5.2 are characteristics of the product design, but the fuel rate is influenced by atmospheric pressure and inlet temperatures. Both of these factors are situational.

$$BSFC = \frac{\dot{m}_f}{\eta_m P_i} \tag{5.2}$$

The rest of the mechanical efficiencies can be assumed as 70-95% from the engine to the drive shaft (Crolla & Mashhadi, 2012). The rest of the losses are from the rolling resistance, drag, and other increased loads. The net power required for motion and overcoming external forces can be calculated as the sum of inertial power, $P_{inertia}$, power to overcome drag, P_{drag}, power to overcome rolling resistance, $P_{rolling}$, and power to overcome road gradients, P_{grade}. These quantities are estimated in the following equations where m is the mass of the vehicle, g is the acceleration due to gravity, v is the velocity of the vehicle, and θ is the angle of the road gradient in Equation 5.3.

$$P_{grade} = mgv\sin(\theta) \tag{5.3}$$

ρ is the density of air, C_D is the coefficient of drag and A is the frontal area of the vehicle in Equation 5.4.

$$P_{drag} = 0.5\rho C_D A v^3 \tag{5.4}$$

t is time and $1.03m$ is the effective inertial mass accounting for inertia of the wheels in Equation 5.5.

$$P_{inertia} = 0.5(1.03)m\frac{\delta v^2}{\delta t} \tag{5.5}$$

C_R is the rolling coefficient in Equation 5.6.

$$P_{rolling} = C_R mgv \tag{5.6}$$

From Equations 5.3 through 5.6, it can be deduced that ambient pressure, wind conditions, road gradients, road roughness, vehicle cargo, passenger weight, and driving schedules for velocities and accelerations are all important factors to consider. The driver is a deciding factor for the most influential variables, velocity and acceleration. Figure 5.3 shows a diagram from Crolla & Mashhadi (2012) illustrating the vehicle driver relationship. Figure 5.4 shows the P-Diagram of factors gathered using the previous equations for driving power losses. Engine specifications, such as BSFC, are combined for space reasons. All loads are combined, but can be separated. Velocity and acceleration dynamics are included in the drive cycle specification. Rolling coefficient is a noise factor because the tires may be changed, and temperature and road conditions further affect this coefficient.

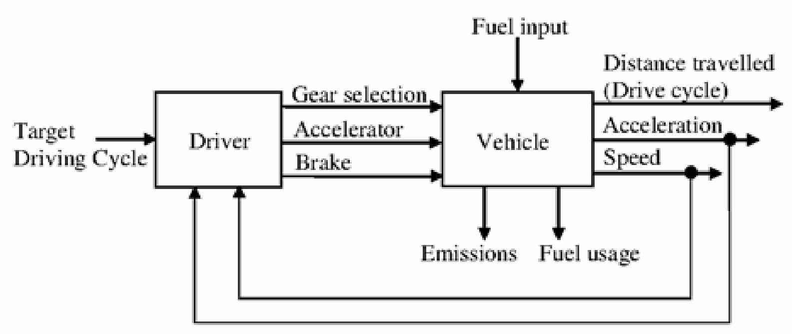


Figure 5.3: The Driver and Vehicle Interactions from Crolla & Mashhadi (2012)

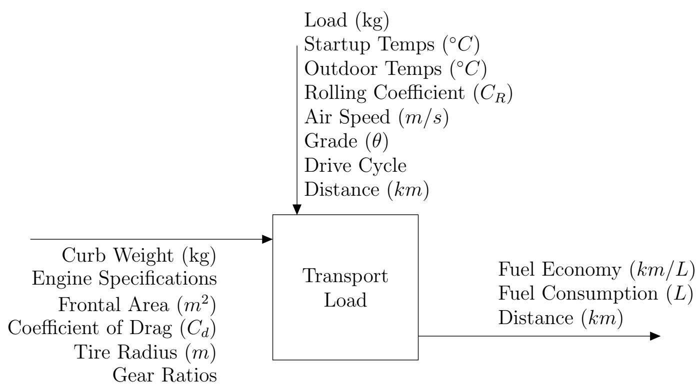


Figure 5.4: P-Diagram for a Vehicle

Activity diagrams introduce additional factors affecting a vehicle's useful life. Figure 5.5 shows the global level activity diagram. First, the vehicle is purchased and then parked. If the vehicle is parked in a garage, it experiences fewer environmental effects. For example, the parts may not rust as quickly in wetter climates and the finish, paints, and metal body are better protected. Mechanical inspection and maintenance also keep the vehicle running longer and more efficiently. Checking tire pressure reduces rolling losses and changing oil and filters maintains engine efficiency. Some sources also cite dirt on vehicles as a source of increased drag (Discovery Channel, 2009). The global activity diagram summarizes the activities that influence vehicle lifetime and fuel efficiency.

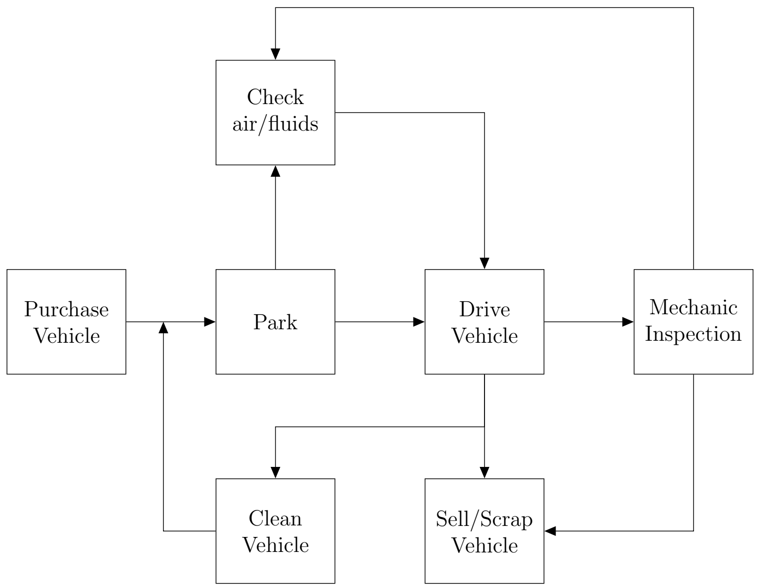


Figure 5.5: Global Level Automobile Activities

Figure 5.6 shows the task level activity diagram for driving a vehicle. Loading and unloading the vehicle are important, as some drivers store belongings in their trunks and backseats, and other vehicles often have multiple passengers weighing over 100lbs each. Also, the timing of starting the engine can be important. In colder climates, the engine may be started early to warm the interior. Additionally, accessories for heating and cooling, music, and electronics are increasingly prevalent in vehicles with satellite and other services. The diagram also shows the cycling between acceleration, cruising and braking phases. These are influenced by both the driver and surroundings. Traffic and street designs are major constraints, and can be related to residential areas or trip types.

The equations and diagrams expose many situational, human, and product variables. Situational factors include air temperature and pressure, residential density, traffic, drive cycles, trip lengths, and vehicle loads. Human factors include speeding

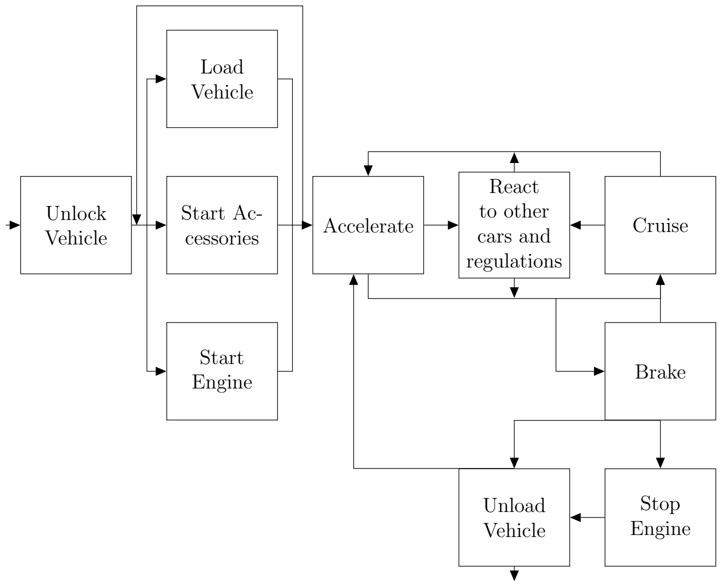


Figure 5.6: Task Level Activity Diagram for an Automobile

or acceleration tendencies, passenger weights, and vehicle maintenance frequencies. Product variables include engine efficiency, tire pressure, rolling and drag coefficients.

A select subset of factors for which data are readily available are shown in Table 5.5. Background variables are apparent as the fuel reduction ratio, defined in Section 5.4, and the population density, part age, cargo load, passenger weight, speeding and acceleration tendencies, family size, and commuting. Because this LCI is for a single part, part age was selected to allow for the possibility of replacement of the aluminum parts. These factors are used to create the graph and local probability distributions discussed in the next section.

Table 5.5: Factor Relationship Matrix for the Lightweight Vehicle Example

Child \ Parent	Fuel Reduction Ratio	Population Density	Part Age	Cargo Load	Passenger Weight	Speeding	Acceleration	Family Size	Passengers	Commuter	Hwy Fraction	Hwy Drive Cycle	City Drive Cycle	Hwy Economy	City Economy	Lifetime Mileage	Avg Fuel Economy
Fuel Reduction Ratio																	
Population Density																	
Part Age																	
Cargo Load																	
Passenger Weight																	
Speeding																	
Acceleration																	
Family Size																	
Passengers								■									
Commuter																	
Hwy Fraction		■															
Hwy Drive Cycle										■							
City Drive Cycle										■							
Hwy Economy				■	■	■	■					■					
City Economy				■	■	■	■						■				
Lifetime Mileage		■	■					■									
Avg Fuel Economy	■										■			■	■		

5.4 Building the Model: Factors and Data Collection

The graph used for modeling the vehicle usage context and predicting the difference in energy consumption between the steel and aluminum vehicles is shown in Figure 5.7. The central components of the graph are the energy consumption, the fuel economy, and the lifetime mileage. This energy is calculated according to Equation 5.7, where E_{saved} is the energy saved during the use stage, d_{life} is the lifetime mileage in km, and $FE_T(base)$ and $FE_T(lightweight)$ are the fuel economies of the steel and aluminum vehicles respectively.

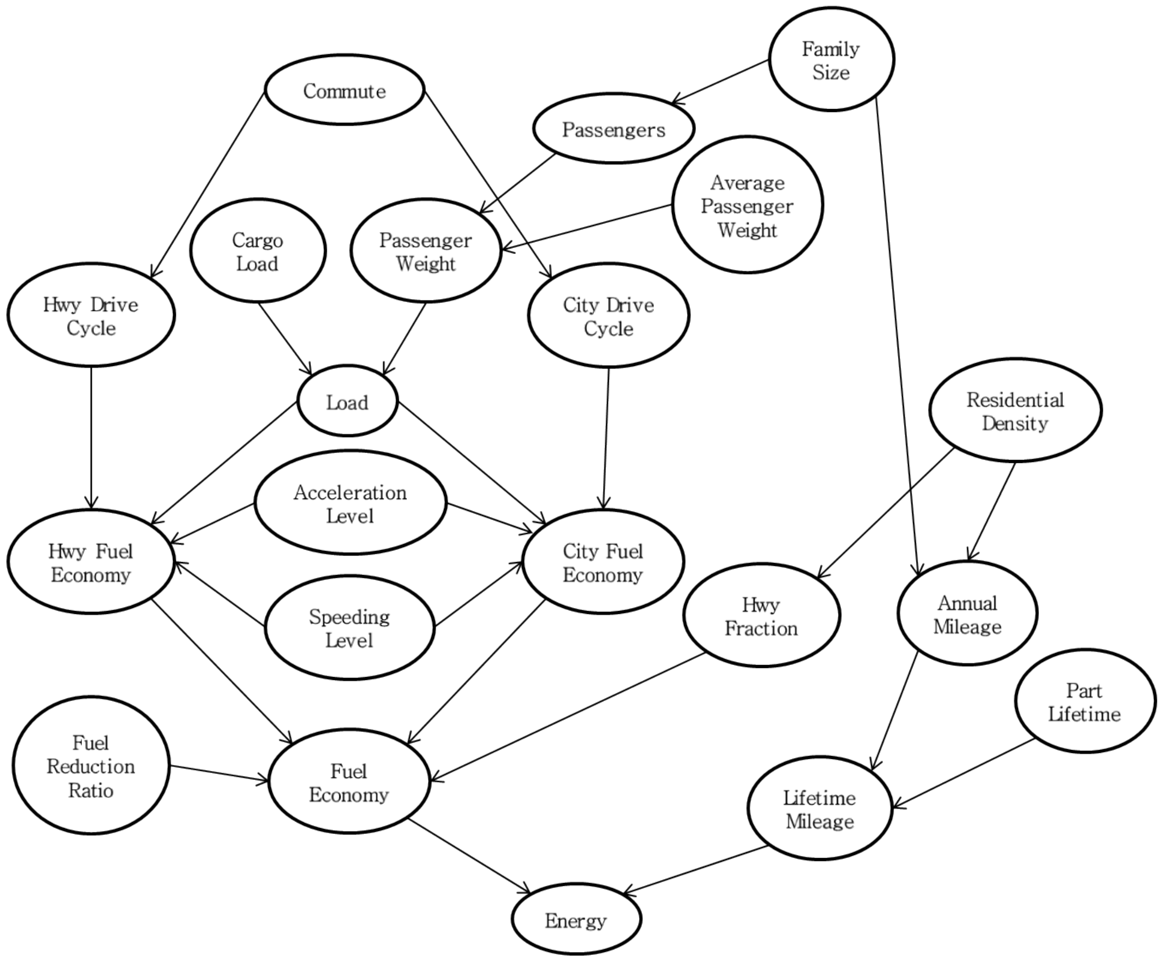


Figure 5.7: Graph of the Vehicle Usage Context

$$E_{saved} = (\frac{d_{life}}{FE_T(base)} - \frac{d_{life}}{FE_T(lightweight)})34.7\frac{MJ}{L} \quad (5.7)$$

The values for FE_T are calculated from Equation 5.8. It consists of the parent variables, R_{hwy} representing the fraction of highway driving which is influence by the residential density, and R_{FRR} representing the fuel reduction ratio for estimating the effect of reduced design weight on fuel economy. The mass values for weight savings, $m_{reduced}$, and curb weight, m_{curb}, are taken from Table 5.2 with $m_{reduced} = 0$ for the base vehicle.

$$FE_T = (R_{hwy} FE_{hwy} + (1 - R_{hwy}) FE_{city})(1 + R_{FRR} \frac{m_{reduced}}{m_{curb}}) \quad (5.8)$$

The rest of this section will discuss the data, probability distributions, and simulations used to estimate the rest of the variables in the graph. The sections are organized to follow a counter clockwise path around the graph in Figure 5.7 Section 5.4.1 will explain the selection of the fuel reduction ratio, R_{FRR}, and its marginal probability distribution. Section 5.4.2 will introduce the simulation used for estimating highway, FE_{hwy}, and city, FE_{city}, fuel economies and the effects of mass, velocity and speeding on fuel economy. Section 5.4.3 will discuss aggressive driving as a combination of acceleration, L_a, and speeding, L_v, tendencies. Section 5.4.4 will discuss the background factors describing household characteristics. Section 5.4.5 will discuss the lifetime mileage characteristics.

5.4.1 Fuel Reduction Ratio

The fuel reduction ratio (FRR) determines the proportionality between fuel savings and mass savings. A common, but rarely cited, rule of thumb is to assume power train efficiency gains of 6% for every 10% of weight reduction (Montalbo et al., 2008; Ridge, 1998). Alternatively, some sources suggest using a linear fuel reduction value (FRV). This value would be in the units of liters per 100km reduced per 100kg weight saved (L/(100km100kg)).

Ridge (1998), Koffler & Rohde-Brandenburger (2009) and Montalbo et al. (2008) have evaluated the fuel reduction values most commonly used and reported. Ridge (1998), on behalf of the European Council of Automotive Research and Development, collected measurements and tests from a number of private sources aiming to determine an FRV for small, medium, and heavy vehicles. Although the median values reported by Ridge (1998) are 0.14 $\frac{L}{100km100kg}$ for vehicles without adjustments to the power train and 0.38 $\frac{L}{100km100kg}$ for vehicles with power train adjustments, the committee suggested the use of 0.6 $\frac{L}{100km100kg}$ citing agreement with the 6% fuel reduction ratio for a vehicle of 1000kg and $10\frac{L}{100km}$. Nevertheless, this argument obfuscates the distinction between an FRV and an FRR. The FRV values suggested by Ridge (1998) would apply equally to 1000kg and 1300kg (a more common value) regardless of their initial fuel economy and weight. In contrast, the 6% rule determines very different FRVs. Assuming $10\frac{L}{100km}$ initial fuel economy, the FRV for the 1000kg vehicle remains $0.6\frac{L}{100km100kg}$, but the FRV for the 1300kg vehicle becomes $0.46\frac{L}{100km100kg}$.

Koffler & Rohde-Brandenburger (2009) argue that a constant FRV reflects the proportional relationship between power and weight. The power required for inertia and rolling resistance is the same for identical weights under the same driving cycle. Therefore, one can numerically derive a fuel reduction value by calculating the work required to move 100kg of mass through an established drive cycle if the engine efficiency is known. Koffler & Rohde-Brandenburger (2009) provide further evidence that "the differential efficiency of engines with the same working process is, in contrast to their overall efficiency, very similar." They calculate that the efficiency of a gasoline engine is approximately 0.073 L/MJ or 42% and the gasoline consumed for 100kg of mass is 0.15 $\frac{L}{100km100kg}$. This estimate is similar to the median value of data reported by Ridge (1998), 0.14 $\frac{L}{100km100kg}$, for vehicles with unadjusted power trains. Therefore, a constant FRV may be more suitable for vehicles without power train redesign.

Montalbo et al. (2008) simulated tuned and un-tuned SUV power trains to test a range of FRRs. Shown in Figure 5.8, the tuned scenario reflects power train redesign to maximize fuel economy "without sacrificing performance". The un-tuned

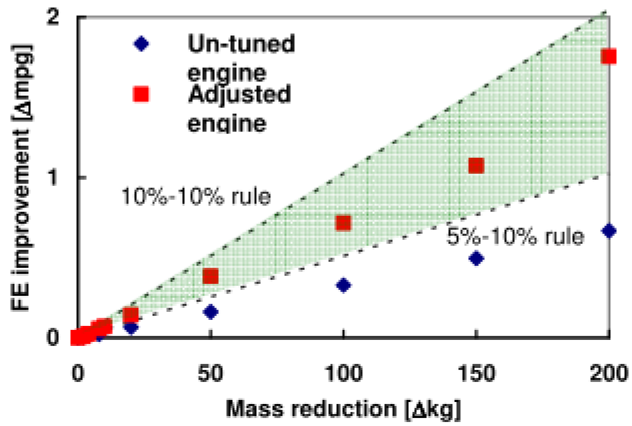


Figure 5.8: Montalbo et al. (2008) compared fuel reduction ratios and simulations for modified and un-modified different power trains

data points reflect a vehicle of reduced weight, but with no additional improvements. The results of Montalbo et al. (2008) suggest that weight reduction for an un-tuned engine, follows an FRR or FRV that is much less than 5%. In contrast, the tuned engine is between 5% and 10%.

This comparison of literature suggests than an FRV of 0.15 L/100kg is appropriate for weight changes without power train adjustments. The 6% rule seems to be more appropriate for power train improvements to maximize fuel economy. All methods were compared with a Future Automotive Systems Technology Simulator (FASTSim) from the National Renewable Energy Laboratory. The simulation was run for a 1388 kg Toyota Camry over a range of weights, shown in Table 5.6. The results are compared with the median and suggested values of FRV reported by Ridge (1998). An FRV of 0.14 corresponds to an un-tuned engine and agrees with Koffler & Rohde-Brandenburger (2009), 0.38 corresponds to tuned engines, and 0.6 is the suggested value. The results indicate that all methods are fairly similar for small weight changes. As weight savings become larger, simulations become more important. Overall, it seems that the 6 % rule is the closest approximation of the FASTSim values.

Table 5.6: Comparison of FRVs and 6% FRR with FASTSim Simulation in $\frac{km}{L}$*

Weight (% Base)	Weight (kg)	FASTSim	6% Rule	0.14 FRV	0.38 FRV	0.6 FRV	AVG	StdDev	StdDev (%)
108%	1499	9.30	9.29	9.59	9.33	9.09	9.32	0.18	2%
100%	1388	9.76	9.76	9.76	9.76	9.76	9.76	-	-
92%	1277	10.26	10.22	9.92	10.18	10.42	10.20	0.18	2%
84%	1166	10.81	10.69	10.09	10.60	11.09	10.66	0.37	3%
76%	1055	11.43	11.16	10.25	11.02	11.75	11.12	0.56	5%
68%	944	11.93	11.63	10.42	11.44	12.42	11.57	0.74	6%
60%	833	12.68	12.10	10.59	11.86	13.09	12.06	0.96	8%

*9.76 km/L = 10.27 L/100km = 22.91 MPG

In accordance with the above findings, an FRR was used for the PGM. The FRR was treated as a uniformly distributed random variable because the actual FRR is a result of design effort and not determined by the mass reduction. The upper and lower bounds are calculated as 4%/10% = 0.4 and 7%/10% = 0.7 to encompass the variations in FRR found in the literature. Most commonly used values are 5%, 6%, and 6.5%. The FRR is incorporated into Equation 5.8.

$$R_{FRR} = \mathcal{U}(0.4, 0.7) \tag{5.9}$$

5.4.2 Drive Cycles

A vehicle driving simulation was written in MatLab to explore the effects of different drive cycles on fuel economy. Standard driving schedules are specified by the EPA and used by automobile manufacturers to estimate advertised fuel economy. The two central driving schedules are the Highway Fuel Economy Test (HWFET) Driving Schedule, shown in Figure 5.9, and the Federal Test Procedure (FTP), shown in Figure 5.10.

The FTP represents urban driving and is derived from measurements during

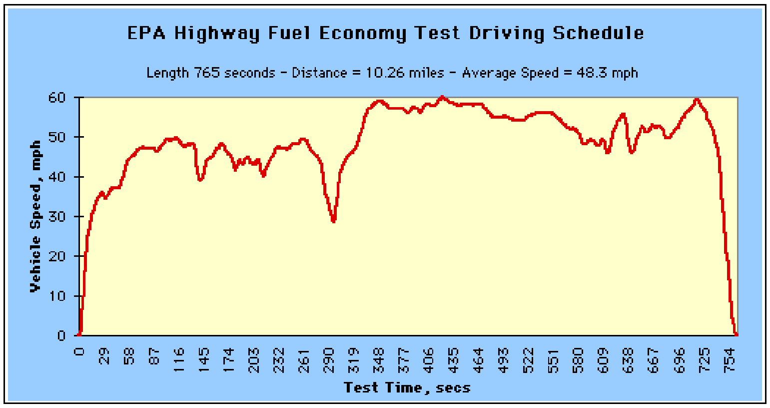


Figure 5.9: The HFET Driving Schedule from the United States Environmental Protection Agency (2012)

Table 5.7: Speed and Acceleration Comparisons for EPA Driving Schedules (United States Environmental Protection Agency, 2006)

Test	Average Speed	Max Speed	Max Acceleration
FTP	9 $\frac{m}{s}$ (21mph)	33 $\frac{m}{s}$ (58mph)	1.47 $\frac{m}{s^2}$
HFET	21.5 $\frac{m}{s}$ (48mph)	27 $\frac{m}{s}$ (60mph)	1.47 $\frac{m}{s^2}$
US06	21.5 $\frac{m}{s}$ (48mph)	36 $\frac{m}{s}$ (80mph)	3.8 $\frac{m}{s^2}$

a commute in Los Angeles in the 1970s (United States Environmental Protection Agency, 2006). The HFET is designed to represent rural driving. Both drive cycles were found to overestimate vehicle mileage, and the EPA revised their standards in 2006 to include five different driving cycles. These include the US06 for high speed, aggressive driving, the SC03 for air conditioning, and the Cold FTP for cold temperature driving. The latter two do not represent factors in this study, and are not considered further. The average speed, max speed, and max acceleration for the HFET, FTP, and US06 cycles are show in Table 5.7.

Instead of requiring that all five tests be completed, the EPA specifies two equations for a composite calculation using only the HFET and FTP test results. The following Equations 5.10 and 5.11 show the composite calculation for the city

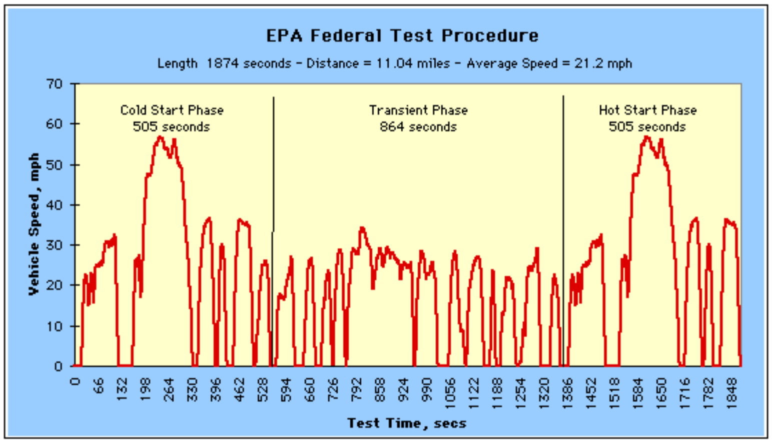


Figure 5.10: The FTP Driving Schedule from the United States Environmental Protection Agency (2012)

and highway fuel economy estimates given measured values for the FTP fuel economy, FE_{FTP}, and the HFET fuel economy, FE_{HFET}.

$$\text{City MPG} = \frac{1}{0.003259 + \frac{1.1805}{FE_{FTP}}} \tag{5.10}$$

$$\text{Highway MPG} = \frac{1}{0.001376 + \frac{1.3466}{FE_{HFET}}} \tag{5.11}$$

These calculations are good estimates for average driving, but every car owner will achieve slightly different mileage given their own driving habits, the local traffic, and local highway speeds. The EPA (2006) estimates a combined fuel economy by assuming that 57% of driving is highway driving. This estimate may vary depending on the residential density of the vehicle, and is discussed in Section 5.4.5. Drivers habits are described and explored in Section 5.4.3 as tendencies to speed or accelerate. The remaining influence on driving cycles is traffic. A vehicle used for commuting during peak hours of traffic is likely to achieve lower fuel economy than a vehicle which is not used for commuting.

A factor is included in the PGM for expressing the indicating whether a vehicle is used for commuting to work frequently. This factor is a boolean variable where Commute = T or Commute = F. The discrete probability for each value is 70% and 30% respectively. These values are estimated from a Bureau of Transportation Statistics (2010) report. According to the U.S. Census (2010), 76% of 136 million workers drive alone to work.

It is assumed that a commuter engages in more stop-and-go driving. The U.S. Environmental Protection Agency (EPA) (2012) website has multiple driving schedules posted, including the Urban Dynanometer Driving Schedule (UDDS) from which the FTP is composed, the LA92 driving schedule which simulates higher speed, more aggressive city driving, and the New York City Cycle which simulates low speed, stop-and-go traffic conditions. Fuel economy is not usually measured or published for these driving cycles, so a simulation was written in MatLab to estimate alternative commuting and non-commuting fuel economies. This simulation is also used later to estimate the effects of additional loads (Section 5.4.6) and aggressive driving (Section 5.4.3) on fuel economy.

The simulation uses vehicle information about gearing, curb weights, drag, and frontal area from Table 5.2 and EPA velocity time series to calculate the required power and engine efficiency during a drive cycle. Given the driving schedule's unique time series, the simulation iterates each time interval, calculating average velocity, v, and acceleration, a. These estimates are then used to estimate power requirements from Equations 5.4, 5.5, and 5.6 from Section 5.3. These power requirements are summed in Equation 5.12 accounting for the mechanical efficiency of the drive train, $\eta_m = 0.85$ (Crolla & Mashhadi, 2012).

$$P_{out} = \frac{P_{inertia} + P_{drag} + P_{rolling}}{\eta_m} \tag{5.12}$$

The engine efficiency over each time interval is then estimated according to Equation 5.13. This equation is borrowed from Ross (1997). It calculates the fuel requirements, P_{fuel}, as the embodied energy of fuel and its flow rate. This is calculated by estimating mechanical losses in the engine as a function of the friction mean effective pressure in the pistons, $\text{fmep}_0 = 160\text{kPa}$ for the Aurora V8 and $\text{fmep}_0 = 140\text{kPa}$ for the Aurora V6 and Malibu Maxx, as well as the displacement in Liters, V, which is 3.5L for the Aurora V6 and Malibu Maxx and 4L for the Aurora V8, and the engine speed, N.

$$P_{fuel} = \frac{\frac{\text{fmep}_0 + NV}{2000} + 0.94 P_{out}}{\eta_t} \tag{5.13}$$

The engine speed is calculated from the vehicle velocity and current gear ratio, R_{gear}, according to Equation 5.14. The wheel slip is estimated at $R_{slip} = 1.1$ times the revolutions, and the wheel radius,r_w, is given in Table 5.2.

$$N = \frac{v}{r_w 2\pi} R_{slip} R_{gear} \tag{5.14}$$

The results from using this simulation are shown in Table 5.8. The results are compared with the EPA estimates using Equations 5.10 and 5.11, and are shown in bold. The simulated fuel economies are similar to the EPA estimates within 10%. An NYCC Mix cycle was created to approximate a level of city commuting. A full NYCC estimate was undesirable, as it cannot represent average driving. Instead, the NYCC Mix is a compromise, combining 50% NYCC and 50% UDDS.

Table 5.8: Simulated Fuel Economy Values

	Simulated MPG		
	Aurora V6	Aurora V8	Malibu Maxx
UDDS	21.8	20.5	23.6
LA92	23.4	22.1	25.3
FTP	22.8	21.5	24.8
HFET	33.6	31.9	36.0
NYCC	13.5	12.6	14.8
NYCC Mix	17.7	16.6	19.2
US6	25.9	24.8	26.9
City MPG	18.2	17.2	19.6
Hwy MPG	24.1	23.0	25.8

	EPA MPG		
	Aurora V6	Aurora V8	Malibu Maxx
City MPG	17	15	19
Hwy MPG	25	23	28

Table 5.9: Conditional Probability Table for Highway Drive Cycle Given Commute

	Commute = T	Commute = F
LA92	0.4	0.1
EPA HWY	0.5	0.5
HFET	0.1	0.4

Three different drive cycles were selected the City Drive Cycle and three for the Highway Drive Cycle, both of which are factors in the PGM. These cycles are LA92, EPA Hwy, and HFET for the Highway Drive Cycle, represented as μ_{hwy}, and NYCC Mix, EPA City, and FTP for the City Drive Cycle, represented as μ_{city}. Drive cycles are selected using the conditional probability tables in Tables 5.9 and 5.10. The parameters are best guess estimates, designed to provide higher fuel economies for non-commuters, and lower fuel economies for commuters.

These categories are used to generate City Fuel Economy, FE_{city}, and Highway

Table 5.10: Conditional Probability Table for City Drive Cycle Given Commute

	Commute = T	Commute = F
NYCC Mix	0.4	0.1
EPA City	0.5	0.5
FTP	0.1	0.4

Fuel Economy, FE_{hwy}, from the normal probability distributions of Equations 5.15 and 5.16. The linear approximation for the mean includes a coefficient,β_{city} or β_{hwy}, to represent the effect of aggressive driving behavior and a correction for additional loads, such as passengers or cargo, w_{city} or w_{hwy}. Specification of these terms are discussed in Sections 5.4.3 and 5.4.6. The standard deviation is taken from Greene et al. (2006) who reported standard deviations of about 1.2 $\frac{km}{L}$, $\sigma_{hwy} = \sigma_{city} = 1.2\frac{km}{L}$.

$$FE_{city} = \mathcal{N}(\beta_{city}\mu_{city} - w_{city}, \sigma_{city}) \tag{5.15}$$

$$FE_{hwy} = \mathcal{N}(\beta_{hwy}\mu_{hwy} - w_{hwy}, \sigma_{hwy}) \tag{5.16}$$

5.4.3 Driver Aggressiveness

The previous section introduced a method for estimating fuel economy of a vehicle given driving schedules. Cycles with very high or very low speeds and high acceleration, such as the NYCC or US06, exhibited lower fuel economy than their city or highway counterparts. Nevertheless, these results do not distinguish between the effects of speed and acceleration. Some drivers are more prone to higher or lower speeds, and others prefer to accelerate more quickly to the speed limits. This section will discuss the decision to separate aggressive driving into speed and acceleration variables and how these variables were combined into the coefficients, β_{city} and β_{hwy}

introduced in Equations 5.15 and 5.16 of the previous subsection.

To assess the affects of aggressive driving on fuel economy, each time step of a drive cycle was augmented by adjusting the velocity or the time step. Adjusting the time step increase or decreases the acceleration values but maintaining the velocity. Increasing the velocity would also increase the magnitude of acceleration or the duration of acceleration. In order to isolate velocity effects from acceleration effects, only the velocity was increased at each time step. For the PGM, it was desired to estimate factors β_{city} and β_{hwy} that are functions of the level of acceleration, L_a or speeding, L_v. The calculations are shown in Equations 5.17 and 5.18, where the ratios k_{vel} and k_{acc} represent a fractional change in fuel economy per 10% in speed or acceleration, respectively.

$$\beta_{hwy} = (1 + (L_v - 2)k_{vel} + (L_a - 2)k_{acc}) \tag{5.17}$$

$$\beta_{city} = (1 + (L_v - 2)k_{vel} + (L_a - 2)k_{acc}) \tag{5.18}$$

In order to separate the effects of velocity and acceleration, the simulation described in Section 5.4.2 was adjusted and run for all three vehicles. Given a velocity level,L_v, of 1, 2, or 3, the simulation adjusted the velocity of each one second time step by -10%, 0%, or 10%. Given an acceleration level,L_a, of 1, 2, or 3, the simulation adjusted the acceleration of each time step by -10%, 0%, or 10%. The effects of acceleration and speeding levels were found to be approximately linear, but different for each driving cycle. The results of these simulations are shown in Table 5.11. The resulting value for US06 was used with the EPA HWY drive cycle category, and the resulting value for FTP was used for both the FTP and EPA City. The remaining values for k_{vel} and k_{acc} were used with their respective cycles.

Table 5.11: Aggressiveness Coefficients by Drive Cycle (% km/L per 10%)

	US06	HFET	LA92	FTP	NYCC Mix
k_{vel}	-.032	-.04	.045	.051	.06
k_{acc}	-.017	-.007	-.011	-.009	-.002

Table 5.12: Conditional Probability for Aggressiveness Characteristics

	90%	100%	110%
$P(Vel)$	0.2	0.4	0.4
$P(Acc)$	0.2	0.4	0.4

The results in Table 5.11 follow the general findings of an extensive study of models and real driving data done by Berry (2010). From Berry (2010), it was expected that acceleration would have some positive effects for low speed drive cycles below 35 kph, but negative impacts for all other drive cycles. It was expected that velocity would have positive effect for low speed cycles, and increasingly negative effects at mid- and high speed drive cycles from 35-75kph and above 75kph. Berry (2010) also estimated the effects of reduced acceleration and reduced speed on highway driving, and found both to be on the order of 2-3%, similar to the results reported here.

For the model, the Acceleration and Speeding level factors were assigned parameters shown in Table 5.12. These represent a lack of data for driver aggressiveness. Berry (2010) analyzed the results of 100 real world driving samples from the city of Boston, and found that most drivers experienced acceleration and speeding levels similar to the LA92 cycle, which is a highly aggressive cycle. For this reason, it was assumed that more drivers exhibit level 2 and 3 (100%,110%) accelerations and speeds than level 1 (90%).

5.4.4 Household Characteristics

Two household characteristics, family size and residential density, were chosen as factors for the graph. It was assumed that family size directly correlates to the average number of passengers and therefore load on a vehicle. Residential density was expected to influence the fraction of highway driving in addition to the annual mileage of the vehicle. It was assumed that vehicles in high density areas do not drive as far or last as long, reducing the annual mileage over the vehicle's lifetime. This section will introduce the parameters used to represent the proportion of vehicles in urban, suburban and rural areas, and the parameters used to determine the vehicle owner's family size.

In order to determine the number of vehicles in urban, suburban and rural areas, it was necessary to consult statistics from the U.S. Census Bureau (2010) and the U.S. Department of Transportation (Office of Highway Policy Information, 2010b). According to the United States Census Bureau (2010), about 70% of the population lived in urban areas with over 50,000 residents in 2010. Urban areas with 2,500 to 50,000 residents constituted about 10% of the population, and rural areas with less than 2,500 people accounted for the remaining 20% of the population.

It was decided to estimate the number of vehicles registered per capita is estimated by weighting the population and estimates of per capita vehicle registrations for urban, suburban, and rural regions. The number of vehicles per capita is not consistent across urban and suburban areas. The US Department of Transportation Office of Highway Policy Information (2010a) reports that is an average of 0.42 registered vehicles per capita in the US. From the U.S. Census (2010) data, the state with the highest urban population is Washington D.C. with 100% of the population living in an urban area. According to the Department of Transportation, D.C. has a per capita vehicle registration of 0.36 (Office of Highway Policy Information, 2010a). Vermont and West Virginia have the lowest urban populations at 38% and 40% of the population, respectively. Per capita vehicle registrations for these states are 0.47 and 0.38, respectively. Because the third lowest urban population of 46% in Maine had a per capita registration rate of 0.39, a value of 0.40 was assumed for rural areas. In the middle, 70% of the population of Minnesota lives in urban areas, and Minnesota has a 0.46 per capita vehicle registration rate. The population weighted sums of these per capita registration rates yields a U.S. per capita vehicle registration rate of 0.38, very close to the official estimate of 0.42. The results suggest that 66% of vehicles are urban vehicles, 13% are suburban, and 21% are rural. These values are used for the discrete probability of each residential category in Table 5.13.

Table 5.13: Probability of Residential Density

	Rural	Suburban	Urban
$P(D)$	0.21	0.13	0.66

According to the U.S. Census (2012), the average number of residents in a US household is 2.59. Because the number of household residents determines the probability of vehicle passengers, family size is constrained to a maximum of four members. The parameters determining the probability of each family size are shown in Table 5.14. The expected value of this distribution is 2.3.

Table 5.14: Probability of Family Size

	1	2	3	4
$P(n_{HH})$	0.3	0.3	0.2	0.2

The next sections discuss the conditional probability distributions for highway fraction, passenger loads, and lifetime mileage. Highway fraction is influenced by the residential density while passenger loads are influenced by the family size. Lifetime mileage is influenced by both household characteristics, as urban drivers may drive fewer miles and households with more members drive more frequently.

5.4.5 Highway Fraction

The EPA estimates a combined fuel economy by assuming that 57% of driving is highway driving (United States Environmental Protection Agency, 2006). Previously, this estimate was 55%. For this model, it was assumed that the percentage of highway driving is influenced by the residential density. Areas with a lower proportion of highways would have a lower proportion of highway driving. Due to lack of per vehicle data, the Highway Fraction, R_{hwy}, is characterized by a uniform distribution given in Equation 5.19. The parameters a and b are determined by the residential density variable.

$$R_{hwy} = \mathcal{U}(a, b) \tag{5.19}$$

The parameters for determining the highway fraction given the residential density are shown in Table 5.16. These parameters are calculated from the U.S. Department of Energy published data on vehicle miles traveled on roadways by functional system. Separated into urban and rural roadways, the functional systems distinguish between travel on interstates, freeways, arterials, collectors, and local roads. This data sheet estimates that 60% of vehicle miles traveled are on roads with highway speeds, such as interstates, freeways, and arterials. 40% are on collectors and local roads. Table 5.15 shows the summary statistics for fraction of highway travel on rural and urban roads for all 50 states. The maximum and mean values are shown to be good estimates of parameters for a uniform distribution. The average of highway

Table 5.15: Fraction of Highway Miles Traveled on Urban and Rural Road Systems

	Rural	Urban
Max	0.8	0.7
Min	0.45	0.42
Mean	0.64	0.56
$E[R_{hwy}]$	0.63	0.56

Table 5.16: Uniform Distribution Parameters for Highway Fraction

	Rural	Suburban	Urban
a	0.45	0.42	0.42
b	0.8	0.8	0.7

fractions calculated from the data is very close to the expected value of Equation 5.19 given the minimum and maximum values.

The parameters for R_{hwy} are shown in Table 5.16. The parameters for suburban areas were not supported directly by data, and so they encompass both urban and rural ranges.

5.4.6 Passenger and Cargo Loads

Both the number of passengers and mass of cargo vary from vehicle to vehicle. For example, a set of golf clubs in a trunk can add almost 10kg to a vehicle's load. Bjelkengren (2008) states that vehicles are designed for their maximum load, which is the sum of the vehicle's curb weight, m_{curb}, the maximum mass of cargo, $m_{cargomax}$, and the product of the maximum rated number of passengers, n_{pmax}, and the average passenger mass, $m_p = 68kg$.

$$\text{Max Load} = m_{curb} + m_p n_{pmax} + m_{cargo} \tag{5.20}$$

The cargo mass estimation given by Bjelkengren (2008) is in Equation 5.21. The cargo mass is calculated by multiplying the available cargo volume in liters, V_{cargo}, by an average density of 0.155 $\frac{kg}{L}$. This equation suggests a nominal cargo mass of 4.2 kg.

$$m_{cargomax} = 0.155V_{cargo} + 4.2 \tag{5.21}$$

Data for actual vehicle loads are not available. The range of possible loads was estimated from the nominal cargo load of 4.2 kg to the maximum cargo load from Equation 5.21. For the Malibu Maxx, $m_{cargomax} = 104kg$. Both Aurora models share a max cargo load of 70kg. It did not seem reasonable to estimate a uniform distribution over this range. Therefore, a shorter range was used from 4.2kg to 20kg. 20kg was chosen to represent a range of sports equipment, baggage, and groceries. Therefore, m_{cargo} is assigned the uniform distribution shown in Equation 5.22.

$$m_{cargo} = \mathcal{U}(4.2, 20) \tag{5.22}$$

The mass of the passengers is estimated by independently determining the number of passengers and their average mass. The factors are independent to avoid increasing complexity by estimating the ratio of children to adults and the sexes of the passengers. The number of passengers are estimated from the family size, , n_{HH}, according to the uniform distribution in Equation 5.23. The lower bound is chosen as less than one for the case of $n_{HH} = 1$.

$$n_p = \mathcal{U}(0.95, n_{HH}) \tag{5.23}$$

The average passenger weight is derived from the U.S. Department of Health and Human Resources (McDowell et al., 2008). The average weight of an adult US citizen over 20 years old is 74.7 kg with a standard error of 0.5 kg. The average weight of a 10 year old girl is 42 kg, heavier than the average boy weight of 40 kg, with a standard deviation of 1.06 kg. A normal distribution is used to approximate the range of adult and child weights, with the mean passenger weight estimated as 60 kg with a standard deviation of 10 kg. The mass of passengers, m_p, is given as the product of the number of passengers, n_p, and their normally distributed average weight,$\mathcal{N}(60kg, 10kg)$, in Equation 5.24.

$$m_p = n_p\mathcal{N}(60kg, 10kg) \tag{5.24}$$

The sum of the cargo mass, m_{cargo} and passenger mass, m_p, are then multiplied by an FRV, k_w, in the units of $\frac{km/L}{kg}$, as shown in Equation 5.25. The FRV, k_w, is a function of the drive cycle, and is responsible for calculating unique fuel economy adjustment values for w_{city} or w_{hwy}.

$$w_{city}\mathrm{OR}w_{hwy} = k_w(m_{cargo} + m_p) \tag{5.25}$$

Values for k_w are averaged for all vehicles using the drive cycle simulations introduced in Section 5.4.2. The results for individual vehicles can be found in Appendix B, Figure B.1. The resulting averages are shown in Table 5.17 and used for calculations in the model.

5.4.7 Lifetime Mileage

A number of data sources were used to estimate lifetime mileage. The calculation for lifetime mileage is shown in Equation 5.26 where d_{life} is the lifetime mileage,

Table 5.17: Weight Coefficients by Drive Cycle (km/L per 10% mass)

	US06	HFET	LA92	FTP	NYCC Mix
k_w	0.0016	0.002	0.0015	0.001	0.001

d_a is the annual mileage, and t_life is the aluminum parts' or vehicle's age. The annual mileage and part lifetime are estimated separately. d_a is conditioned on the residential density and family size, and t_{life} has no parent factors.

$$d_{life} = d_a t_{life} \tag{5.26}$$

The lifetime of a vehicle is estimated using data from the Transportation and Energy Data Book. They estimate vehicle survival rates over vehicle ages from 4 to 30 years using a model developed by Oak Ridge National Laboratory. The estimated median lifetime of vehicles from 1990 is 16.9 years. About 55% of model year 1990 vehicles survive 16 years or longer, while only 30% of 1980 vehicles are estimated to have survived 16 years. This predicted age is much longer than the years cited in LCIs reviewed in Section 5.1. Most LCIs assume a lifetime of 10-14 years. The simulation results show 80% survival rates at 11 years and 30% survival rates for 21 years. The general trend is that vehicles are living longer, so these higher estimates were chosen for the PGM. The vehicle lifetime is estimated from a normal distribution with mean of 16 years and standard deviation of 5 years, shown in Equation 5.27.

$$t_{life} = \mathcal{N}(16\text{years}, 5\text{years}) \tag{5.27}$$

The annual mileage is estimated from a conditional probability distribution given the residential density and family size. The Transportation Energy Data book

Table 5.18: Mean Annual Mileage by Residential Density (km)

	Rural	Suburban	Urban
μ_a	$18000 + 1200n_{HH}$	$16000 + 800n_{HH}$	$15000 + 800n_{HH}$

(Davis et al., 2010) reports shares of annual vehicle mileage by age. The average annual kilometers traveled ranges from 8,000 km to 24,000 km. The mean value is 18,000 km, and the standard deviation is about 3,000 km. Additional values are collected from the National Household Transportation Survey (Oak Ridge National Laboratory, 2009b) that indicate the annual mileage for different residential densities and household sizes, n_{HH}. A linear approximation of each average value is shown in Table 5.18. These results were used to approximate each conditional mean, μ_a, for the annual mileage, d_a, estimated from the normal probability distribution shown in Equation 5.28.

$$d_a = \mathcal{N}(\mu_a, 3000\text{km}) \tag{5.28}$$

5.5 Chapter Summary

In this chapter, the lightweight vehicle LCI was introduced as a demonstration problem for the PGM method. Existing LCI studies of lightweighting were reviewed, and none of the existing studies include considerations of different usage context or consider joint effects of uncertainty on LCI parameters. The LCI values for aluminum lightweighting of hoods and trunk lids were calculated for the 2001 Oldsmobile Aurora V6 and V8, and the 2004 Chevrolet Malibu Maxx.

Applying the method from Chapter 3, a number of usage context factors were identified and used to create a graph for the vehicle's use stage model. The central component is calculating the difference in energy consumption of the steel and aluminum vehicles. Each factor in the graph was addressed, and probability distributions or physical equations were derived for each local probability distribution. A MatLab simulation was created to study the effects of acceleration, speeding, and weight on different driving cycles. Resulting values for parameters were in agreement with national data or the existing literature.

Chapter 6 will describe the results of inference using the graph and data developed in this chapter. It will consider different scenarios described as conditions on background variables of the graph, such as residential density, family size, and aggressiveness. Each scenario presents greater understanding of how human and situation factors affect LCIs. Uncertainty of parameters will also be addressed, and the model results will be compared with values obtained using more common methods.

Chapter 6

Model and Results

This Chapter provides a comparison of use stage energy estimates for a lightweight vehicle LCI using existing methods and a PGM. Point estimates and Monte Carlo analysis are analyzed for insights in Section 6.1. These methods are found to estimate the range of possible energy savings, but not provide any additional understanding of the usage context. The results of the PGM are introduced in Section 6.2. Analysis of individual background variables provides additional insight about the types of scenarios that increase the benefits of lightweighting, and the types of scenarios that decrease the benefits of lightweighting. Fictional scenarios, postulated without the use of PGMs, are introduced and analyzed as well. These fictional scenarios emulate realistic types of consumers, and show that although some situations display very good normalized energy consumption values, the same scenarios may yield very poor estimates of total use stage energy savings.

6.1 Advantages of Considering Joint Variability

When estimating energy during a product's use, most LCI studies limit the number of variables considered. For LCIs of light weight vehicle designs, E_{saved}, the total energy savings during use, is calculated using Equation 6.1. The fuel economy increase is estimated from the original vehicle's fuel economy in $\frac{km}{L}$, FE_{base}, and a proportional improvement in fuel economy,R_{FRR}, given the fraction of mass saved, $\frac{m_{reduced}}{m_{curb}}$. This fuel economy is then assumed to occur over some lifetime mileage, d_{life}, in kilometers. Sensitivity is then considered on each assumption, independently. Most studies do not test assumptions on the FRR, R_{FRR}, but a few test assumptions on the fuel economy and the lifetime mileage.

$$E_{saved} = \left(\frac{d_{life}}{FE_{base}} - \frac{d_{life}}{FE_{base}(1 + R_{FRR} \frac{m_{reduced}}{m_{curb}})} \right) 34.7 \frac{MJ}{L} \tag{6.1}$$

The following subsections will present the results of sensitivity analyses on Equation 6.1. Each example references the 2004 Malibu Maxx which has a fuel economy of 9.35 $\frac{km}{L}$ (22 MPG) and a curb weight of 1569 kg after a 15 kg weight savings. The expected energy saved during its lifetime must exceed the 2.9 GJ investment in lightweighting in order to validate the use of lightweighting. Each sensitivity analysis reflects current practice in the literature and motivates questions that the PGM will be used to answer in Section 6.2. These questions include: How confident can a designer be in the results of a single point use stage LCI? How would confidence increase with sensitivity analysis? How would confidence increase when using a PGM?

6.1.1 Independent Sensitivity Analyses

Table 6.1 summarizes the assumptions and results of more than ten sensitivity calculations. Intervals for fuel savings are estimated by testing ranges on each term of Equation 6.1. The first row summarizes the founding set of assumptions, and each row below summarizes results for a new set of assumptions, with either one or more variables changed. The intervals of ±10% and ±1% are replicates of sensitivity analysis in the literature (Das, 2000; Mayyas et al., 2012). It is important to note that all variables are changed independently, any connection between driving distance and fuel economy, for example, is not tested. Although the final two rows of Table 6.1 show combinations of variables, these variables are still considered independently. There is no physical or statistical relationship between the values being tested. The results suggest that actual fuel savings can vary by as much as 45% of the initial estimate. Furthermore, it is difficult to make decisive arguments favoring any single set of assumptions.

Table 6.1: Sensitivity Analysis on LCI Terms

	Fuel Savings (GJ)	Payback Mileage (1000 km)	Assumed FRR ($\frac{\%\text{fuel economy}}{\%\text{weight savings}}$)	Assumed Fuel Economy (km/L)	Assumed Mileage (1000 km)
Average Values	4.7	136	6	9.35	193
-10% Fuel Economy	5.2	123	-	8.4	-
+10% Fuel Economy	4.2	150	-	10.3	-
+1% Fuel Economy	4.7	135	-	9.3	-
-1% Fuel Economy	4.6	138	-	9.4	-
Lowest FRR	3.1	205	4	-	-
Highest FRR	6.2	102	8	-	-
-10% Lifetime Mileage	4.2	137	-	-	173
+10% Lifetime Mileage	5.1	137	-	-	212
Worst Joint Case	2.5	225	4	10.3	173
Best Joint Case	7.6	92	8	8.4	212

- indicates average value used

The final two rows of Table 6.1 detail the best and worst case estimates when individual variables are changed together. The results show a 5 GJ interval of possible energy savings. When any single variable is adjusted, the energy savings during use justify the energy investment of 2.9 GJ for aluminum lightweighting, but in the worst joint case, the energy savings are less than the investment. This lack of justification can be even worse when considering uncertainty in the magnitude of the lightweighting investment, as highlighted in Table 6.2. The top row summarizes best and worst case estimates for the energy investment in material production, part manufacture and part recycling for aluminum lightweighting. Each value reflects a ±25% sensitivity analysis from the literature (Das, 2000; Mayyas et al., 2012). The next two rows summarize the best and worst values from Table 6.1, and the final row show the range of net energy consumption for all life cycle stages.

Although most of the estimated range for net energy savings is positive, there

Table 6.2: Comparison of LCI Sensitivities

	Average	Best	Worst
Redesign Investment	2.9 GJ	2.2 GJ[a]	3.6 GJ[b]
Single Variable Uncertainty	4.7 GJ	6.2 GJ	3.1 GJ
Multiple Variable Uncertainty	4.7 GJ	7.6 GJ	2.5 GJ
Net Savings	1.2 GJ	5.4 GJ	-1.1 GJ

[a] 25% decrease
[b] 25% increase

is the possibility of a negative net energy savings. Without further information, it is not possible to quantify the probability of realizing negative net energy savings, because the results are derived from simple interval calculations. While variations in lifetime mileage and fuel economy have similarly large effects on net energy savings, the probabilities of these variables are not known. Probability distributions should be present in life cycle analyses and LCIs, but are not usually considered or directly supported (Lloyd & Ries, 2007).

To emulate studies that employ probability estimates, a Monte Carlo analysis was used to create a final estimate of net energy savings during the Malibu Maxx's use stage. In this analysis, lifetime mileage was assumed to follow a normal distribution, $\mathcal{N}(\mu = 220, \sigma = 100)$, with a mean of 220,000 km and standard deviation of 100,000 km. Fuel Economy for the base vehicle, pre-aluminum, was assumed to follow a normal distribution, $\mathcal{N}(\mu = 9.3, \sigma = 1)$, with a mean of 9.3 $\frac{km}{L}$ and standard deviation of 1 $\frac{km}{L}$. The FRR was assigned a uniform distribution, $\mathcal{U}(0.4, 0.8)$, between 4% per 10% weight savings and 8% per 10% weight savings.

These probability distributions were input into the OpenBUGS software (Thomas et al., 2012), and a Monte Carlo analysis with 10,000 samples was used to estimate the use stage energy consumption of the base and light weight vehicles and the energy savings of the lightweight vehicle during use. The code is shown in Appendix C, along with a discretized version created in a spreadsheet. The results indicated that the average lightweight vehicle consumes 830 GJ during use with a standard deviation of 392 GJ and MC Error of 3.5 GJ. Recall that the MC error is an estimate of the error associated with predicting a mean using a Monte Carlo sampling method. The heavier, base vehicle has a mean energy consumption of 835 GJ with a standard deviation of 392 GJ and MC Error of 4.2. Estimates of energy savings yielded a mean of 4.97 GJ and standard deviation of 2.6 GJ and MC Error of 0.5. Because the energy investment is between 2.2 and 3.6 GJ, it lies within a standard deviation of expected energy savings. While most vehicles will yield a net energy savings over their lifetime, many vehicles will not.

From these results, it is difficult to determine which vehicles, markets, or consumers are more likely to pay back or fail to pay back the initial energy savings. Furthermore, these analyses assume complete independence between variables and ignore underlying causal relationships. Factors such as residential density and family size, for example, influence both fuel economy and lifetime mileage; rural driving may include more high efficiency, highway driving, and rural driving may require more miles of travel over a vehicle's life. Additionally, a larger family will usually require more travel and heavier payloads on the vehicle. The next section describes how the PGM can be used to estimate the effects of individual background variables and combinations of variables to create more informative estimates of energy savings.

6.2 Results of the Full Model

Table 6.3 summarizes the resulting energy distributions for the Malibu Maxx under different usage scenarios. The underlying PGM is constructed using OpenBUGs software (Thomas et al., 2012), the code for which is shown in Appendix C.

The marginal scenario represents the entire usage context, as modeled, and is equivalent to existing techniques; it tests the range of values for all factors in the model, and yields similar results. The Monte Carlo analysis of the previous section yielded a mean energy consumption of 4.97 GJ and standard deviation of 2.6 GJ, and the marginal energy distribution of the PGM yielded a similar mean value of 4.94 GJ and standard deviation of 2.13 GJ. The PGM yields lower results because it includes slightly higher fuel economies for the base vehicle than the EPA estimates, about 10.53 $\frac{km}{L}$ instead of 9.3 $\frac{km}{L}$. Recall from Chapter 5 that higher base fuel economies reduce the effects of weight reductions. Consumer reported fuel economies support the PGM results, and range from 8 $\frac{km}{L}$ to 14.9 $\frac{km}{L}$ with an average of 11.6 $\frac{km}{L}$ (U.S. Department of Energy, 2012).

Although fuel economy is the primary factor reducing the energy savings estimate, it is balanced by an increase in lifetime mileage. The energy saved per km traveled is much lower in the PGM, but the average lifetime mileage of a vehicle is much longer. While the Monte Carlo analysis assumed an average lifetime mileage of 220,000 km, the PGM yields an average lifetime mileage of about 270,000 km, influenced by the factors presented in Chapter 5.

Because lifetime mileage is one of the least controllable factors and one of the most influential factors, distance normalized energy values are also evaluated and reported in Table 6.3. From these values, one can calculate the minimum lifetime mileage required to payback the energy investment of aluminum parts. These values range from 160,000-180,000 km, well below the expected value.

In Table 6.3, background factors, defined as factors without parents, are used to define scenarios. Scenarios can be represented by specific values of individual

Table 6.3: Effects of Different Vehicle Use Scenarios Estimated Using the PGM

Malibu Maxx Scenarios	Energy Saved During Use Mean (GJ)	Energy Saved During Use Std Dev(GJ)	Energy Saved per km Mean (kJ)	Energy Saved per km Std Dev(kJ)	Payback (1000km)
Marginal	4.94	2.13	17.4091	3.5615	167
Velocity Scenarios					
110%	4.90	2.11	17.2486	3.3846	168
100%	4.95	2.15	17.4460	3.5685	166
90%	5.02	2.22	17.6765	3.8343	164
Acceleration Scenarios					
110%	4.99	2.16	17.5691	3.5886	165
100%	4.93	2.13	17.3761	3.5393	167
90%	4.88	2.11	17.1876	3.4923	169
Commute Scenarios					
TRUE	5.09	2.19	17.8921	3.5350	162
FALSE	4.64	2.01	16.2980	3.3827	178
Family Size Scenarios					
1	4.60	1.98	17.3201	3.5200	167
2	4.86	2.08	17.3863	3.5386	167
3	5.13	2.18	17.4533	3.5579	166
4	5.40	2.29	17.5210	3.5781	166
Residential Scenarios					
Rural	5.70	2.37	17.1956	3.5331	169
Suburban	4.92	2.09	17.2783	3.5551	168
Urban	4.72	2.02	17.5358	3.5598	165
Cargo Scenarios					
0 kg	4.95	2.14	17.4068	3.5478	167
10 kg	4.95	2.15	17.4290	3.5541	166
20 kg	4.96	2.15	17.4512	3.5603	166
Multi-Factor Scenarios					
1	4.24	1.83	15.7930	3.4365	184
2	4.74	1.98	17.8743	3.3863	162
3	4.89	2.06	15.9600	3.4872	182
4	5.98	2.41	16.4076	3.3375	177

background factors or multiple background factors. When the PGM is exercised for different scenarios, the results indicate that while a single factor has minimal effects on energy savings, scenarios can have significant effects when they define multiple factors to describe a specific type of consumer.

6.2.1 Effects of Individual Background Factors

As shown in Figure 5.7, the background factors present in the model are velocity, acceleration, commute, cargo load, family size, and residential density. Velocity and acceleration are categorical factors evaluated at three levels, the lowest level indicates that the driver has a tendency to use speeds or accelerations 10% below the specified drive cycle, which defines the middle level, and the high level indicates an increase of 10%. Commute indicates that the driver uses the vehicle to commute to work, and may encounter more traffic situations. Cargo load is a measure of the average mass of cargo in a vehicle. Family size indicates the number of members in a vehicle's household. Residential density indicates higher or lower population densities and the proximity of driving destinations through the categories of rural, suburban or urban areas.

Figures 6.1 and 6.2 show the energy distributions yielded by each category of velocity, acceleration, and cargo load. The marginal distribution is shown in black. None of the scenarios exhibit significant changes from the unspecified, marginal case. These results suggest that velocity and acceleration effects are dominated by the variety of drive cycles, and that a driver can store heavy cargo in a vehicle before seeing substantial reductions in fuel economy.

The variance in drive cycles could be one cause for the lack of significant effects. The effects of velocity and acceleration have been shown to be highly dependent upon the drive cycle Berry (2010). Increasing velocity, for example, increases fuel efficiency for speeds lower than 72 kph, but reduces fuel efficiency at speeds above 88 kph. Reducing acceleration increases efficiency at all speeds, but is most helpful for slow and moderate speeds below 72 kph.

Additionally, in the case of velocity, it is important to note that the normalized energy savings do not indicate that a factor has no effect on fuel efficiency of a vehicle, but that the effects do not change relative to the heavier and lighter vehicle design. Velocity predominantly increases the forces of drag that a vehicle must overcome, and any other effects are relatively insignificant. At lower speeds, higher velocities

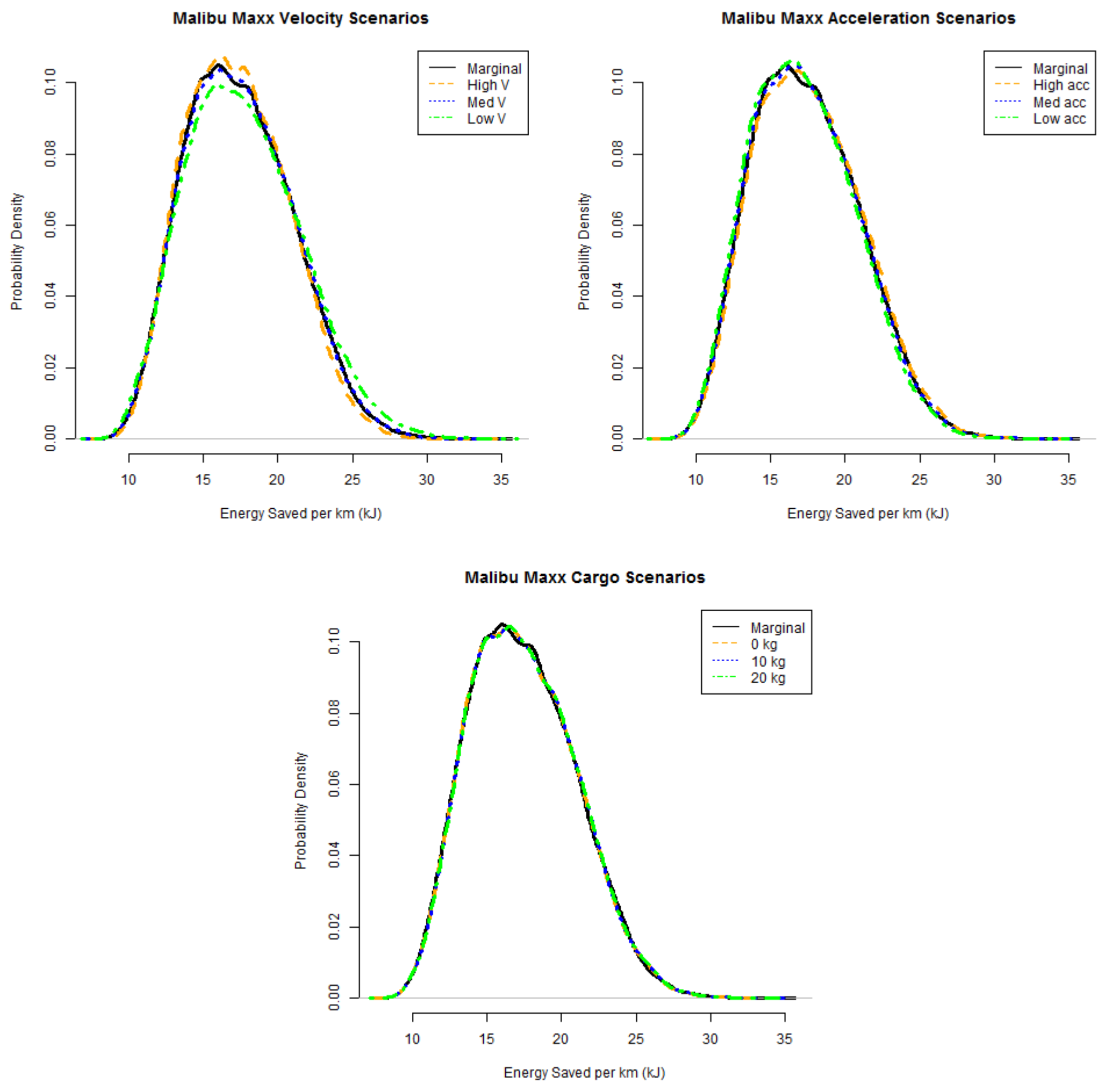


Figure 6.1: Velocity, Acceleration, and Cargo Scenarios Exhibit Insignificant Effects on Distance Normalized Energy Savings for the 2004 Malibu Maxx

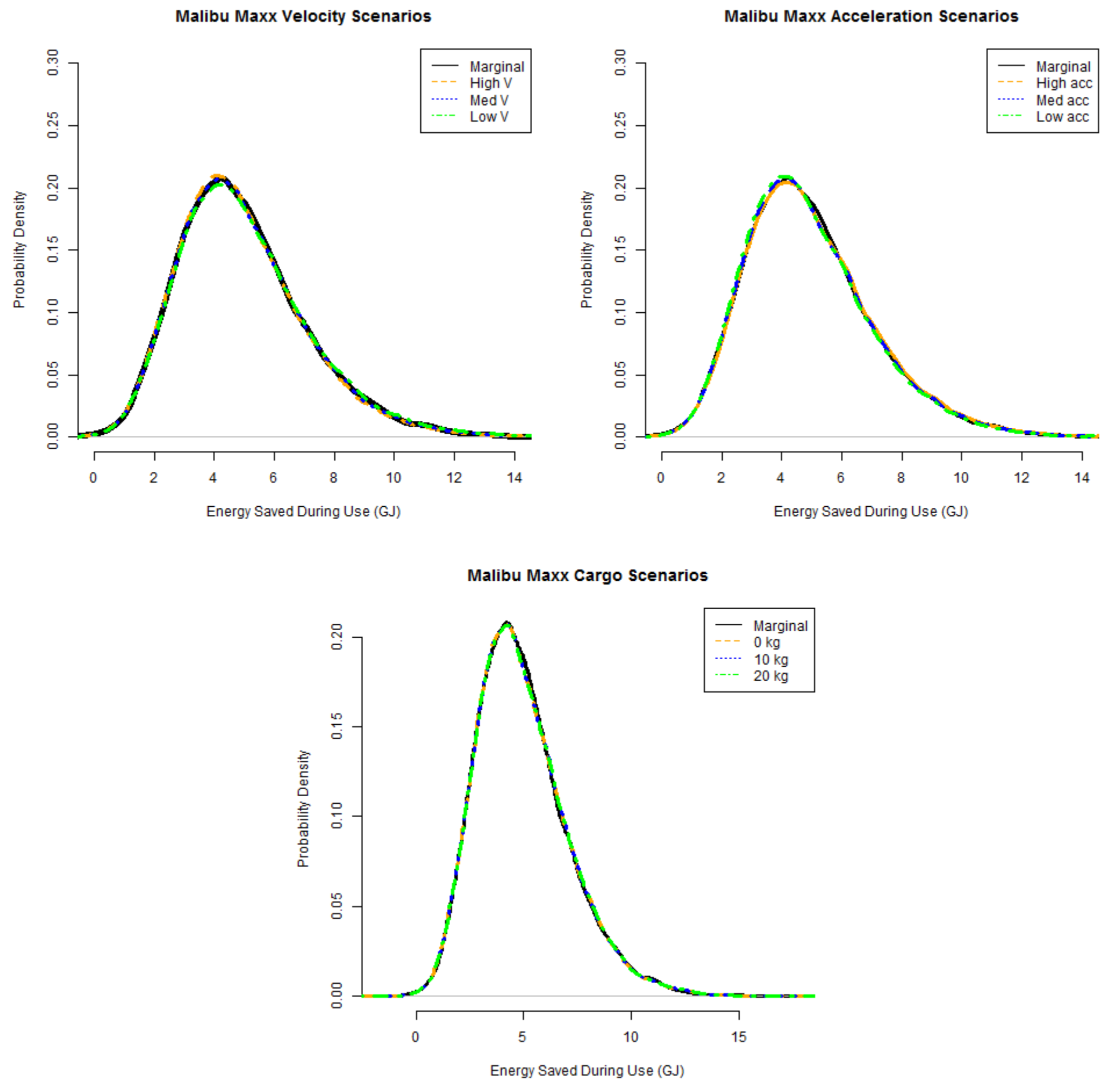


Figure 6.2: Velocity, Acceleration, and Cargo Scenarios Exhibit Insignificant Effects on Lifetime Energy Savings for the 2004 Malibu Maxx

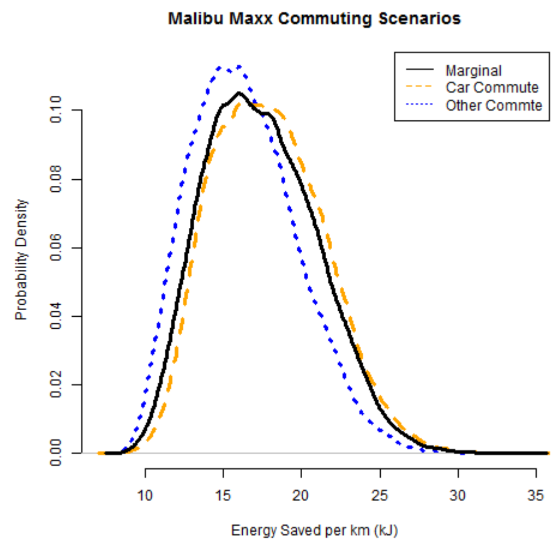


Figure 6.3: Commute Scenarios Exhibit Significant Effects on Distance Normalized Energy Savings for the 2004 Malibu Maxx

increases vehicle efficiency, but only by about 5%. This effect is much less than that caused by different drive cycles.

It likely that the effects of acceleration are too small. Acceleration in particular has been tested by Larsson & Ericsson (2009) through the design of an acceleration adviser. This technology was used to increase the resistance of an acceleration pedal on a mail delivery truck. This resistance causes the driver to use reduced accelerations; a result that should increase fuel economy. Despite the neighborhood driving schedules and observed reductions in acceleration, the overall fuel economy was not significantly decreased.

In contrast to the effects of velocity and acceleration, the commute factor has a more significant effect on the drive cycle and energy savings. A vehicle that is used for commuting, and is more likely to experience stop-and-go traffic, can have an increased energy savings of about 10% from lightweighting over a non-commuter

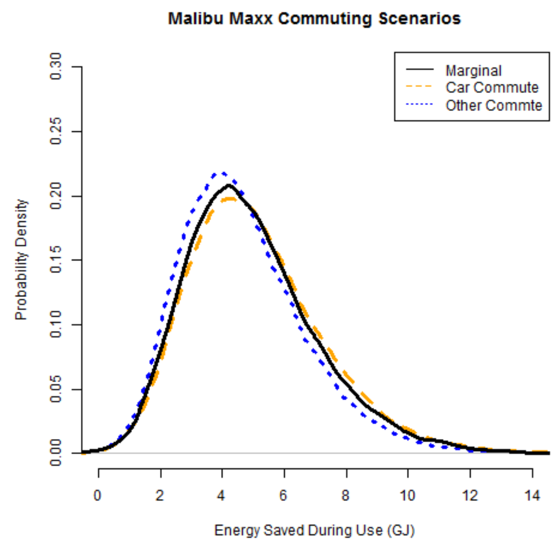


Figure 6.4: Commute Scenarios Exhibit Significant Effects on Total Energy Saved During Use for the 2004 Malibu Maxx

vehicle. Shown in Figures 6.3 and 6.4, this result applies equally to energy per km and total use energy because it is directly related to fuel economy. Both results for non-commuters have a P-value less than 0.05, while the commuter scenario has a P-value of 0.06 for the use stage energy savings and 0.03 for energy saved per km. It is the only variable with a significant effect on energy saved per km.

Residential density has a significant effect on total use energy savings, but little effect on energy saved per km of travel. The urban and rural scenarios yield P-values less than 0.05 for the use stage energy savings. The significant effect on total use energy shown in Figure 6.6 is due to the increased distance between destinations and, consequently, increased annual mileage of rural vehicles compared to urban vehicles. The only effect that residential density has on fuel economy is the fraction of highway travel. This fraction was only slightly higher for rural and suburban areas, so little effect can be seen in Figure 6.5.

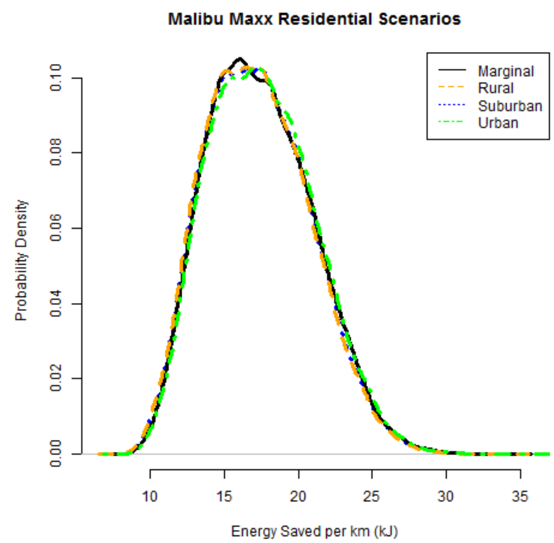


Figure 6.5: Residential Density Scenarios Exhibit Insignificant Effects on Distance Normalized Energy Savings for the 2004 Malibu Maxx

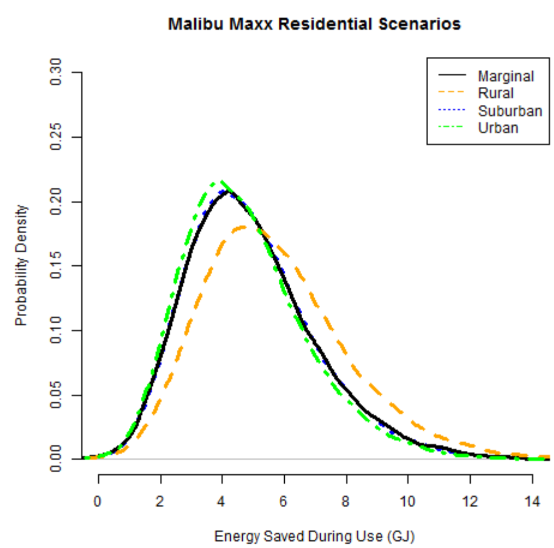


Figure 6.6: Residential Density Scenarios Exhibit Significant Effects on Total Energy Saved During Use for the 2004 Malibu Maxx

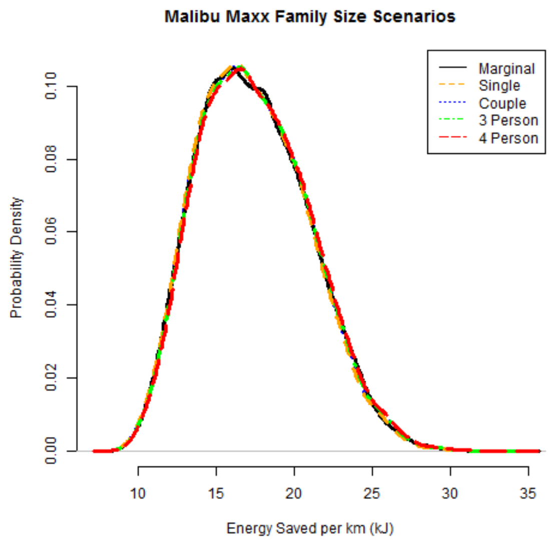


Figure 6.7: Family Size Scenarios Exhibit Insignificant Effects on Distance Normalized Energy Savings for the 2004 Malibu Maxx

Family size had similar effects as residential density. Despite the potential to increase loads by hundreds of kilograms, increased passenger loads had little effect on energy savings per km, shown in Figure 6.7. In contrast, family size had a substantial effect on total energy savings, shown in Figure 6.8. The single and four person households yield P-values less than 0.05 for the use stage energy savings. Because larger families average higher annual mileages, their vehicles tend to have higher lifetime mileages and, therefore, longer distances for accumulating savings.

Only one of the background factors, commute, had significant effects on distance normalized energy savings. Accordingly, any designs aimed at reducing accelerations, optimizing speeds, or reducing loads may lead to distance normalized energy savings for either the base vehicle or the lightweight vehicle, but those distance normalized energy savings are not likely to be higher for the lightweight designs.

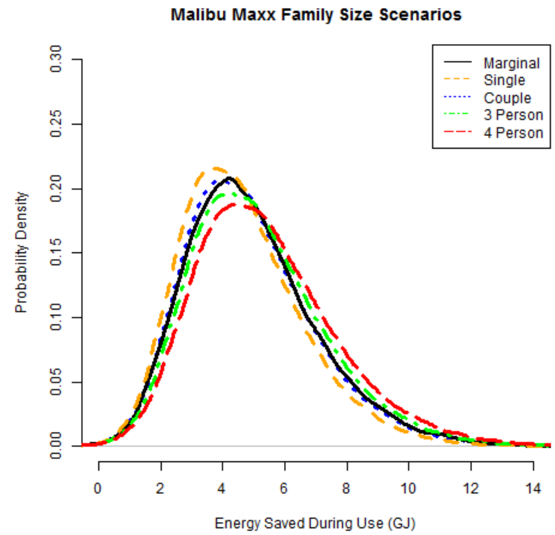


Figure 6.8: Family Size Scenarios Exhibit Significant Effects on Total Energy Saved During Use for the 2004 Malibu Maxx

6.2.2 Effects of Individual Scenarios

Multiple factors can be combined into scenarios, and those scenarios can have significant effects on energy savings. This section presents four fictional scenarios inspired by four types of vehicle-consumer combinations:

1. Older Driver - single person household, suburban area, low speeds, low accelerations, no commute
2. Urban Couple - two person household, urban, high speeds, high accelerations, commute
3. Suburban Family - four person household, suburban, low speed, low acceleration, no commute
4. Rural Family - four person household, rural, high speed, high acceleration, no commute

Energy estimates for these scenarios can be seen in Table 6.4 and Figures 6.9 and 6.10. Compared with varying individual factors, varying combinations of multiple factors yielded more interesting and meaningful results. Of all of the scenarios, the suburban and rural families yield the highest use stage energy savings while th urban couple yields the highest energy savings per km. These results suggest that vehicles with large families tend to perform better, as they have higher annual mileages and lower base fuel economies from heavier loads.

Table 6.4: Effects of Vehicle Use Scenarios, Estimated Using the PGM

Malibu Maxx	Energy Saved During Use		Energy Saved per km		
Scenarios	Mean (GJ)	Std Dev(GJ)	Mean (MJ)	Std Dev(MJ)	Payback (1000km)
Marginal	4.39	2.07	0.0174	0.0036	167
Multi-Factor Scenarios					
1	4.24	1.83	15.7930	3.4365	184
2	4.74	1.98	17.8743	3.3863	162
3	4.89	2.06	15.9600	3.4872	182
4	5.98	2.41	16.4076	3.3375	177

With regards to energy saved per km, commuting vehicles perform the best, followed by high occupancy vehicles. The urban couple and rural family scenarios share no traits other than high speeds, and high accelerations, but both scenarios share low base fuel economies for additional reasons. The urban couple inspired scenario has a reduced fuel economy due to high traffic situations from commuting, while the rural family inspired scenario has low fuel economies due to the large family size. These normalized energy results suggest that commuting vehicles and vehicles with large numbers of passengers in addition to slightly more aggressive driving are promising candidates for lightweight vehicle design.

With regards to total use energy savings, high mileage scenarios continue to perform the best. The urban couple scenario yields the third lowest total energy savings despite having the highest energy savings per km. Because the urban couple

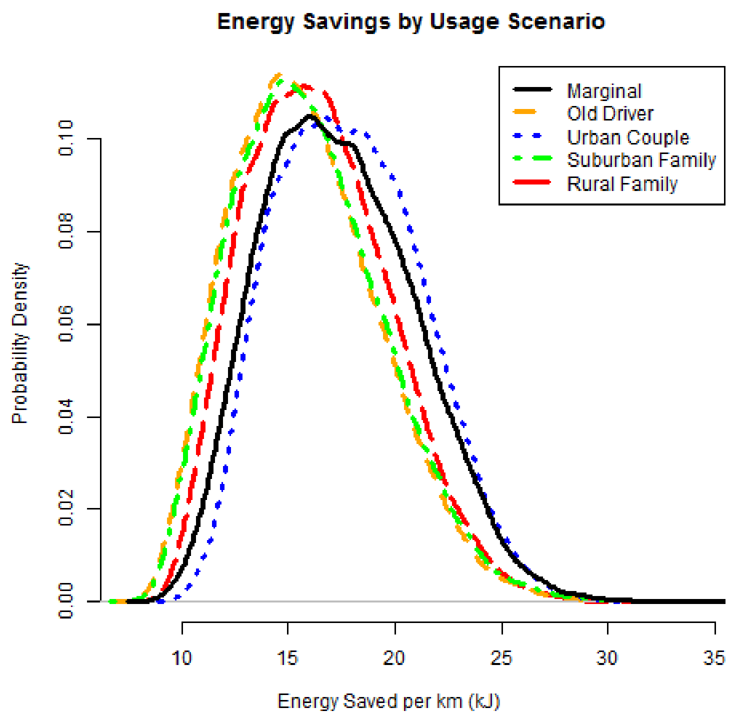


Figure 6.9: Four Usage Scenarios Exhibit Unique Effects on Distance Normalized Energy Savings for the 2004 Malibu Maxx

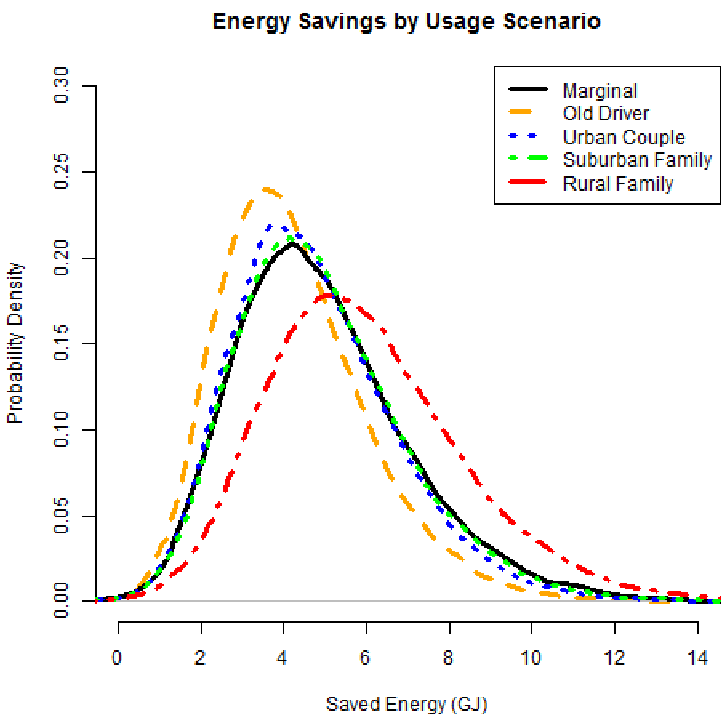


Figure 6.10: Four Usage Scenarios Exhibit Unique Effects on Total Energy Saved During Use for the 2004 Malibu Maxx

is assumed to travel fewer miles every year, this scenario accumulates lower energy savings. In contrast, the rural and suburban family scearios share the important aspect of having high annual mileages due to large families and travel outside of urban areas. Although the suburban family scenario has a lower energy savings per km, possibly from a lack of commuting traffic, the high lifetime mileage makes it a good choice for light weight design. These total energy results suggest that high mileage vehicles do not have to achieve high fuel economy improvements, and are good candidates for lightweight redesign.

With regards to total LCI energy savings, all scenarios have expected energy savings greater than the 2.9 GJ investment. The rural family is the only scenario with a standard deviation that does not overlap with the 2.9 GJ investment. The payback mileage is highest for the old driver scenario and lowest for the urban couple scenario. The prior involves the least active driver. The driver lives alone, travels below the speed limit and does not use the vehicle for commuting.

Table 6.5: Effects of Aggressive Driving and Commuting Estimated Using the PGM

Malibu Maxx	Energy Saved During Use		Energy Saved per km		
Scenarios	Mean (GJ)	Std Dev(GJ)	Mean (MJ)	Std Dev(MJ)	Payback (1000km)
Marginal	4.39	2.07	0.0174	0.0036	167
Multi-Factor Scenarios					
Non-Aggressive, Non-Commute	4.56	2.01	16.04	0.34	181
Non-Aggressive, Commute	5.13	2.24	18.06	0.38	161
Aggressive, Non-Commute	4.69	2.03	16.49	0.33	176
Aggressive, Commute	5.06	2.16	17.77	0.34	163

The combined effects of aggressive driving and commuting were sampled to help understand different scenarios. The results, shown in Table 6.5, suggest that lightweighting provides more energy savings for non-aggressive commuting, with commuting having the dominant affect. The net energy savings from commuting vehicles are higher than average unless combined with a low expected lifetime mileage.

The effect of commuting on lifetime mileage was not considered in this PGM. Oak Ridge National Laboratory (2009a) reports that 30-40% of miles traveled are commuting, and that the average commute is 19km. Traveling 38km 250 days a years creates about 9,500km of travel, suggesting that commuting may be a significant factor increasing annual vehicle mileage. Nevertheless, data were not found for comparing the annual mileage for commuter and non-commuter vehicles, and the relationship is excluded from this model.

6.3 Chapter Summary

This chapter compared the use of PGMs for uncertainty analysis with common types of sensitivity analysis used in published LCIs. While the expected values are similar for all methods, a PGM allows for greater understanding. Existing techniques for assessing uncertainty of use stage assumptions include point estimates and Monte Carlo analysis. Point estimates provide intervals without knowledge of the relative likelihood of values within this interval, making decisions difficult when intervals overlap. Monte Carlo estimates provide distributions for energy use, but do not provide any understanding of background information that may improve the results. Both techniques assume that variables are independent, and both techniques fail to consider the inherent variability of product use in an intuitive way.

Although the marginal PGM results are similar to the Monte Carlo results, the vehicle example demonstrated that implementation of realistic usage scenarios via a PGM can provide a much higher fidelity investigation of energy savings during use and that distinct scenarios can have significantly different implications for the effectiveness of lightweight vehicle designs. Scenarios with large families, for example, yield high energy savings, especially if the vehicle is used for commuting or stop-and-go traffic conditions. Scenarios of small families and efficient driving yield lower energy savings for lightweight vehicle designs.

All scenarios had expected values greater than the worst case energy investment value of 3.6 GJ. Most expected use stage energy savings include a standard deviation that overlaps with the estimated 2.9 GJ of energy investment. Regardless, P-values for every distribution are less than 0.02, rejecting the null hypothesis that the net energy savings are random. The widest confidence interval was 0.062 GJ, and existed for the rural scenarios. All other confidence intervals are between 0.04 GJ and 0.06 GJ. These insights would not have been obtained without creating a PGM. Although it was possible to foresee the general trends from background research, creating the graph structure and evaluating different scenarios facilitated quantification of those trends and confirmation or refutation of preconceived assumptions. For example, the effect of aggressiveness is lower than one might expect, while location and traffic conditions are the most influential factors in energy savings.

Future work could involve investigating lifetime mileage more closely, and specifically the factors that contribute to increased lifetime mileage. Most LCIs simply estimate a payback time in km and avoid assumptions of lifetime mileage. Here, gross assumptions about lifetime mileage are found to provide useful insights to guide future design efforts and to motivate a more complex PGM.

Chapter 7

Closure

The benefits of environmentally conscious designs vary with usage context, and PGMs enable practitioners to consider this variability when conducting LCIs. Because of the large number of complex scenarios, some researchers attempt to isolate environmental metrics from variable usage factors. Through the lightweight vehicle example, this research revealed that using a PGM to consider usage variability can help identify high and low impact scenarios. For the vehicle example, it was shown that metrics which try to isolate usage variability, such as energy saved per km of travel, are not dominant indicators of total energy savings during a vehicle's use. Instead, scenarios that increase the lifetime mileage of a vehicle, such as more rural contexts, can be more beneficial, without high changes in fuel economy. Designers should focus their lightweight design efforts on vehicles with long expected lifetimes, in addition to vehicles operating at low fuel efficiencies. In contrast with PGMs, most vehicle LCIs do not consider the cause or likelihoods of high or low mileage during a vehicle's use stage. The PGM, therefore, provides a unique framework and set of data for decision making that is rarely discussed in the LCI literature (Lloyd & Ries, 2007).

7.1 Contributions

This dissertation presents one of the first works to create a detailed model of energy consumption during use specifically for the purposes of an LCI. Although designers often create detailed physical models of their designs, stochastic models representing different usage scenarios are not common in design and are generally avoided in LCIs. The primary departure from existing research is the decomposition of a usage context into a set of human, product, and situational factors that can be used to create large numbers of unique scenarios. For example, the five discrete background variables considered in the vehicle lightweighting example can be used to specify over 216 unique scenarios.

The first contribution of this dissertation, presented in Chapter 3, is a checklist and method for employing existing design tools for a new purpose: identifying factors that are relevant to LCI metrics and describe a product's usage context. The checklist includes six fundamental factors: Users, Tasks, Locations, Maintenance, Aesthetics, and Functionality. Possible individual factors are also suggested for each category, and include items such as expected aesthetic lifetime and inefficient habits. Physical equations describing the product's operation and activity diagrams are essential tools for understanding both the product's operation and the user's procedural tendencies. Activity diagrams can also provide evidence for the directional influence of factors. For example, situational effects, such as temperature or time of day, may influence a user's decision to make tea or coffee. The result of using these tools is a comprehensive, but still LCI-focused set of factors, organized in an interaction matrix.

This initial contribution applies to both the LCI and design research fields. Some existing works in the LCI literature describe system level characteristics of a product's functions in order to identify trade-offs between energy saving design goals, such as improved fuel economy, and customer needs, such as fast vehicle acceleration. Additionally, other studies present methods for identifying essential functional characteristics at the subsystem level, such as volume of storage or temperature requirements in a refrigerator, for identifying scalable units for finding products with comparable functionality. Although usage context based design is not new, these publications are focused on modeling the user's perceptions and needs, instead of thoroughly considering the product's variable energy performance across different usage contexts.

The second contribution is the application of PGMs to model use stage energy consumption in an LCI. Graphical modeling theory, discussed in Chapter 4, allows practitioners to represent understandings of how one factor influences and is influenced by one or more other factors in a visual and analyzable format. For example, one might usually rely on marginal probability information: that the average user does not turn off his programmable thermostat while away. But, one may be more confident in conditional probability information: that the average user in very hot climates is more conscientious of energy savings and is more likely to turn off his home thermostat while away. Each node of the graphical model can then be characterized using data from isolated conditions for a variety of factors. In the vehicle model, the graph structure enabled the use of conditional statistics to populate a network of over 20 factors. Additionally, different data sources were used for each local cluster of factors within the graph. Then Gibbs sampling, a Markov Chain Monte Carlo sampling method, was used to estimate the total use stage energy saved by a lightweight vehicle across all values of all factors in the model. The results, in Chapter 6, were similar to prior estimates from single variable data sets, indicating that PGMs can be used to reasonably infer estimates when single variable data sets are not available, as in the electric kettle example of Chapter 4.

The third contribution of this dissertation is evidence that different usage scenarios, defined using multiple background factors of a usage context, can greatly increase or greatly reduce the net life cycle energy savings of a product. Chapter 4 defined a background factor as any factor that has no parents in the graph, and can be considered a root cause of the effects of interest. Chapter 6 compared sampling results for values of six background factors: commute, residential density, family size, speeding, acceleration, and cargo load. Residential scenarios, family size, and commute were found to have the greatest effects on total energy savings during use. Four usage scenarios were created to determine the effects of different background variables in combination. Large family, rural usage scenarios yielded the greatest total energy savings during use, due to the high lifetime mileage associated with the scenario, while scenarios specifying commuting yielded the greatest distance normalized energy savings during use.

The final contribution of this dissertation is the lightweight vehicle example problem. The contents are based on an extensive review of publicly available data and existing research. Though many aspects of a vehicles use have been studied, such as speed and acceleration profiles or user demographics, the combination of these factors is unique to this model. The model is also novel with regards to the LCI. To the Author's knowledge, no existing product LCI goes beyond physical equations to include both situational and human factors at the depth provided by this dissertation.

7.2 Recommendations

PGMs can operationalize knowledge of a product's usage context and provide reasonable estimates for LCIs. The primary advantage is that practitioners need not average out assumptions that are outside of the designer's control. For example, some lightweight vehicle LCI studies only consider lifetime mileage until payback when evaluating their redesigns. The likelihood of achieving that payback is not quantified. In contrast, the PGM provides the capability of estimating the likelihood of each outcome and investigating multiple scenarios to understand which customers or markets benefit the most from a design change.

It is recommended that LCI practitioners and environmentally conscious designers begin characterizing the usage context as a set of factors for study. The checklist and method for identifying factors presented in Chapter 3 of this dissertation should be consulted when forming LCI assumptions. This process reveals interesting sources of variability that should be leveraged in decision making and strategizing. If one use for LCI is to prioritize between use stage improvements and manufacturing stage improvements, then it would also be useful to prioritize different users or markets within that usage context.

PGMs were found to be a useful tool for analyzing usage context variability across all scenarios and for well-defined individual scenarios. It is the intent of the author to inspire further research in this area. Probabilistic models and graphical models are not the only method that might be applied to this problem, and it was not feasible to concurrently develop and compare potential alternative methods. The graphical structure of the PGM, however, helped visualize the usage context space and segment local clusters of factors into parent and child factors so that conditional probability information could be employed. PGMs, therefore, are a promising avenue for further advancement of LCI studies.

7.3 Future Work

A number of areas for future work exist, particularly in formalizing methods for incorporating data into the PGM. Chapter 4 discussed alternative methods for specifying local probability parameters, including Bayesian inference and traditional Frequentist techniques. Bayesian inference was used to estimate the conditional probability parameters for annual mileage given family size and residential density. The prior was the marginal average, and the National Household Transportation survey results and standard deviations were used to calculate the likelihood term. The resulting posterior distributions were nearly identical to Frequentist inference, mainly because of the large sample size and small differences in means ($\approx 10\%$) between marginal and conditional distributions for annual mileage. It would be of interest to model usage context for which few data and conflicting data sets exists. These data situations would better reflect the difficulties in a majority of LCIs.

An additional opportunity for the future is incorporation of unsorted data collected from smart grid applications and mobile networking. PGMs can be learned from fully observed data sets, that is, sets where all of the interesting factors are measured concurrently. Learning algorithms analyze correlations within the data to create clusters of nodes and edges between nodes, and have been used successfully in image processing and medical analysis (Koller & Friedman, 2009). While automated construction of a PGM of the usage context is an attractive prospect, the collection of the required data sets is a challenge.

Development of an algorithm for automating discovery of significant usage scenarios should be a goal for the more immediate research time frame, and may be even more useful be applied to learned networks in the future. The fictional scenarios analyzed in this research were designer driven. It would be interesting to automatically identify scenarios or clusters of background variable values that yield specific levels of energy savings. This information could provide unexpected design insights.

Finally, this dissertation focused on the use stage of LCIs because a significant amount of energy is consumed during this stage for most products. Nevertheless, it is hypothesized that the PGM method can be very useful for estimating the effects of other stages. The amount of materials reclaimed for recycling, for example, is difficult to predict in addition to the storage time between uses . Energy and material consumption also varies across manufacturing process as the supplier, country of origin, and plant design vary.

Appendices

Appendix A

Taxonomy Examples

Table A.1: Application of Guiding Questions

Factor Type	Guiding Questions	Product Answers: Cell Phone	Kettle	Printer
Human Variables	*Who is using the product?*	Owner	Individual or Shared Use	Individual or Shared Use (owners or customers)
	What are the users habits?	Takes the cell phone everywhere, charges frequently, texts, makes call, surfs the web, accessorizes, take photos	Overfill, Reheat, Frequent use, Task preferences, Attentiveness, Temperature testing	read on/off screen, paper/digital storage, patience
	What physical constraints affect the user?	Battery life, Speed to accomplish tasks, light for photos, tower location	Effort to fill the kettle, relating water gauge to task, Minimum water level, Maximum water level	storage space, vision, laziness,
	What knowledge constraints affect the user?	Familiarity with features, Proper charging, Maintaing hardware and software and OS	Relating water gauge to task, Water temperature, Task specs, distractions	knowledge of features, fatigue
	What are personal task preferences and criteria?	Using GPS, downloading apps, making calls, texting, background information, app updating, checking and writing emails, surfing the web, watching videos, taking photos	Water temperature, Number of servings, Refill frequency, Task types, Task frequency	amount of paper, font size, weight of paper, purchasing paper, purchasing ink,
Product Variables	*What are the product specifications?*	Durability of materials, OS speed, storage, memory, hardware specs, battery life, charging schedule	Maxmum water level, minimum water level, temperature accuracy, temperature settings, water gauge precision	rate of ink use, printing options, printing speed, clogging, amount of paper in tray
	What are the product features?	data, download apps, calls, texts, software, charger, touch screen, sliding screen	Fill mechanism, water gauge, settings, feedback mechanisms	duplex printing, ink replacement, color printing, 3rd party ink, paper tray
	What are the fundamental process equations?	fatigue of connectors, software clogging, material degradation, material failure	Thermal energy balance of around open water system	ink use, fluid clogging, ink deterioration, deposits on runners, jamming
	What are the process inputs?	touch screen, buttons, forces, water, heat, cold, connectors, light	Water, Electricity, Temperature Settings	paper, data, ink
	What are the process outputs?	visual display, vibration, noises	Hot water	inked paper
Situational Variables	*What tasks might the user select?*	Texting, Calling, Apps, Browsing, Streaming, Photographing, Navigation, Timing	Iced Tea, Hot tea, Hot Chocolate, Pre-boil water, Coffee	duplex, single, multiple per sheet, colors, paper size, personal printing (air tickets, recipes, directions), work printing (reports, memos)
	What physical environments might the user select?	Work, Out, Home, Daytime, Nighttime, Rural, Urban, Suburban, Wet, Dry, Hot, Cold (anywhere or anytime)	Kitchen, Breakfast bar	Home, office, store, school, library
	What social environments might the user select?	All	Home, Office, Hotel	Roommates, Family, Coworkers, Other Customers, Employees, Owners
-Product Signal, Energy and Material Flows	*What are the sources of flows from the product to the user?*	LCD Display, Vibration Mechanism, LEDs, Speakers	noise, water dynamics, steam, water gauges, water level, water weight	LCD, software, cost
	What are the sources of flows from the user to the product?	Fingers, Hands, Other Body Parts	filling orifice, buttons, handle	Hands, Computer, Paper, Ink
	How do flows from the product influence user behavior?	Guide the user, Transfer signals, Suggest maintenance, Indicate status	Steam/boiling/clicking signal completion, weight/gauge/visual signals fill	Low paper creates constraint, Low ink creates constraing, Incurs maintenance, Errors create repeats, Cost reduces waste
	How do flows from the user influence product performance?	Increase load, Cause damage	amount of water, temperature selection, switches	User selects wrong setting, User puts in paper in wrong orientation, User puts in bad ink, User creates mess
	What mental or physical hinderances exist between the user and product?	Visibility, Knowledge, Tech Savviness	Kettle weight, kettle height, gauge comprehension, gauge visibility, water visibility	knowledge of features, lack of paper, lack of ink, maintenance preferences

Human	*What mental or physical aids exist between the user and product?*	Tech savviness, Instructions	Gauge, kettle height, handle, lid lever, noise, clear screen	Default settings
Situation-Product Signal, Energy and Material Flows	*What are the sources of flows between different situations and the product?*	temperature, surfaces, sun light, artificial lighting, user noise, cell tower, surrounding noise, gravity	cold/hotwater from faucet, ambient temperature	Users, Maintenance schedule, Frequency of use, task types
	How do flows between the situation and product increase product performance?			
	How do flows between the situation and product decrease product performance?	heat changes material life, heat changes efficiency, heat affects the battery, surfaces create impact, gravity creates impact, sun light and artifical light create or reduce loads on digital camera, proximity to towers changes processing time, noise changes processing, remote use reduces available functionality	ambient temperature can increase or reduce temperature difference, ambient temperature can increase or reduce heat loss from the kettle, low ambient or faucet temperature can increase temperature difference, low ambient temperature can increase heat loss, high ambient or faucet temperature can reduce temperature difference, high ambient temperature can reduce heat loss from the kettle	Stores may have less errors, Homes have more errors, Frequency of changing materials in higher in homes and reducing ink waste, stores have better maintenance, Stores have experts, Work has maintenance person, Public places have more users, Copy store has more color printers, Public places print more, User doesn't pay for paper at work, Physical environment sets cost to user
	How do situation factors change product factors and performance?			
Human-Situational Signal, Energy and Material Flows	*What are the sources of flows from the physical environment to the user?*	People, Cars, Upgrades, Social Pressure, Trends, Work needs, Availability of technology, Cell towers, Availability of power sources, Sales, Wealth, Cost, Airplane	Weather, Water sources	Cost
	What are the sources of flows from the social environment to the user?	Games with friends, Friends, Photo opportunities, Fashion, Comparison, Etiquette, regulations	Guests, Cohabitants	Colleagues expectations, Rules on usage,
	How do flows from the physical environment influence task selection?	Light affects LCD brightness, noise affects speaker use, proximity to cell phone towers affects use frequency, international affects use frequency, airplane induces airplane mode, laws and regulations for driving	Task temperature counteracts outside temperature, Beverage and cooking follows a temporal pattern	
	How do flows from the social environment influence each task identified?	games cause more frequent use and updating, trends change expectations, photo opportunities create use of camera, etiquette restrics phone use, regulations affect phone use	Additional servings may be made at a single time, social interactions may distract	In a rush use defaults, Rules limit task selection
	How do task requirements influence physical environmen t selection?	find quiet for phone call	Purchaser selects home/office/hotel	personal printing at home or work or store, low important work at work, high importance work at store
	How do task requirements influence social environment selection?	find friends to play games with	Purchaser selects home/office/hotel	high quality require professional help
	What mental or physical hinderances exist between the user and situation?		Other users may be cause distraction or stress and increase erroneous behavior, poor lighting makes measuring difficult, noisy environment reduces ability to respond to auditory signals	
	What mental or physical aids exist between the user and situation?		Other users may hasten process and reduce erroneous behavior, good lighting, quiet environment	

Figure A.1: Rejected Guiding Questions

Human Variables

- Who is using the product?
- What habits does the user have?
- What physical constraints does the user have?
- What knowledge constraints does the user have?
- What are personal task preferences and criteria?

Product Variables

- What are the product specifications?
- What are the product features?
- What are the fundamental process equations?
- What are the process inputs?
- What are the process outputs?

Situational Variables

- What tasks might the user select?
- What physical environments might the user select?
- What social environments might the user select?
- What tasks might be imposed upon the user?
- What physical environments might be imposed upon the user?
- What social environments might be imposed upon the user?

Human-Product Signal, Energy and Material Flows

- What are the sources of flows from the product to the user?
- What are the sources of flows from the user to the product?
- How do flows from the product influence user behavior?
- How do flows from the user influence product performance?
- What mental or physical hinderances exist between the user and product?
- What mental or physical aids exist between the user and product?

Situation-Product Signal, Energy and Material Flows

- What are the sources of flows from the physical environment to the product?
- How do flows from the physical environment influence product performance?
- What mental or physical hinderances exist between the product and situation?
- What mental or physical aids exist between the product and situation?

Human-Situational Signal, Energy and Material Flows

- What are the sources of flows from the physical environment to the user?
- What are the sources of flows from the social environment to the user?
- How do flows from the physical environment influence task selection?
- How do flows from the social environment influence task selection?
- How do task requirements influence physical environment selection?
- How do task requirements influence social environment selection?
- What mental or physical hinderances exist between the user and situation?
- What mental or physical aids exist between the user and situation?

Appendix B

Vehicle Data

B.1 Nomenclature of Vehicle Factors

Fuel Use ($\mathcal{V}$) lifetime fuel use in liters (Section 5.4)

Fuel Economy (FE) average fuel economy over the aluminum part's lifetime in km/L (Section 5.4.1)

Lifetime Mileage (d_{life}) km traveled during the aluminum part's life (Section 5.4.7)

Design Stage Mass Reduction ($m_{reduced}$) mass saved by aluminum part (Section 5.2)

Fuel Reduction Ratio (FRR) (R_{FRR}) the ratio of %fuel economy Improvement per 10% weight savings (Section 5.4.1)

Part Lifetime (t_{life}) lifetime of the aluminum part (less than or equal to the vehicle lifetime) in years (Section 5.4.7)

Speeding (L_v) level of driver adjustment for drive cycle speeds (Section 5.4.3)

Acceleration (L_a) level of driver adjustment for drive cycle accelerations (Section 5.4.)

Commute tendency of the driver to be in high traffic situations (Section 5.4.3)

Cargo Load (m_{cargo}) the mass of non-passenger cargo in a vehicle in kg (Section 5.4.2)

Passengers(n_p) the average number of passengers (including the driver) (Section 5.4.6)

Passenger Weight(m_p) the average weight of passengers in the vehicle in kg (Section 5.4.6)

Family Size(n_{HH}) the number of household members (Section 5.4.4)

Residential Density Indicator (D) indicator of urban, suburban, or rural residence (Section 5.4.4)

Highway Fraction (R_{hwu}) the fraction of highway driving (Section 5.4.5)

City Drive Cycle (μ_{city}) the expected fuel economy (km/L) for a driver adhering to an EPA city drive cycle (Section 5.4.2)

Highway Drive Cycle (μ_{hwy}) the expected fuel economy (km/L) for a driver adhering to an EPA highway drive cycle (Section 5.4.2)

City Fuel Economy (FE_{city}) city drive cycle fuel economy adjusted to driver habits and vehicle loads (Section 5.4.2)

Highway Fuel Economy (FE_{hwy}) highway drive cycle fuel economy adjusted to driver habits and vehicle loads (Section 5.4.2)

B.2 Simulation Results

B.2.1 Matlab Code for Vehicle Drive Cycle Simulation

```
function FuelEconomy = CalcFuelEconomy(accelchange,velocitychange,car, curbweight,↙
massreduction, load, frontalarea, dragK, rollK, litersengine, frr, drivecycle,↙
wheelradius, gearing)
%%%%%%%%%%%%%%%%%%%%%%5
% This function accepts vehicle design parameters and a vector of drive
% cycle velocities in second intervals. It returns the average engine
% efficiency and fuel economy of that drive cycle.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

INTERVAL = accelchange;
%lowercase variables are inputs to the function
%uppercase variables are intermediate variables
%initialize outputs
TOTAL.DISTANCE = 0;
TOTAL.FUEL = 0;
TOTAL.ACCEL = 0;
TOTAL.POWER = [];
TOTAL.ENGINE = [];
%assumptions
MECHEFF = 0.85;
AIRDENS = 0.5*1.2;
WEIGHT = curbweight - massreduction + load;
GRAVITY = 9.8;
if car==1
  FMBEP = 140 ;%*(1-massreduction/curbweight*frr); %140 - Malibu, 160 - Aurora
else
   FMBEP = 160 ;%*(1-massreduction/curbweight*frr); %140 - Malibu, 160 - Aurora
end

INERTIALFACTOR = 1.03;
SLIPRATIO = 1.1;
NUNPWR = 15-litersengine; %unpowered engine speed in rps

%Determine number of second intervals
STEPS = length(drivecycle)-1;
EFFSTEPS = 0;

for I=1:STEPS

    % Calculate drive cycle characteristics for the interval
    % 1 mph is 0.447 m/s
    AVGVELOCITY = velocitychange*0.447* [drivecycle(I+1)+drivecycle(I)]/2; % (in M/s)↙
Average of initial and final velocities during the interval
    AVGACCEL = 0.447* [drivecycle(I+1)-drivecycle(I)]/INTERVAL; % (in M/s^2) Change in↙
velocity divided by time
    DISTANCE = AVGVELOCITY*INTERVAL; %(in M)

    ACCESS = 1;

    if (AVGVELOCITY > 1)
```

```
        % Calculate the power required by the drive cycle
       if AVGACCEL < 0
            DRAG = AIRDENS * dragK * frontalarea * AVGVELOCITY^3/(1000*MECHEFF); % in kW
            ROLLING = rollK * WEIGHT * GRAVITY * AVGVELOCITY / (1000*MECHEFF);  % in kW
            INERTIA = 0; % in kW
       else
            DRAG = AIRDENS * dragK * frontalarea * AVGVELOCITY^3/(1000*MECHEFF); % in kW
            ROLLING = rollK * WEIGHT * GRAVITY * AVGVELOCITY / (1000*MECHEFF);  % in kW
            INERTIA = (0.5 * INERTIALFACTOR * WEIGHT * AVGACCEL * AVGVELOCITY) /↙
(1000*MECHEFF); % in kW
            TIMEACCEL = TIMEACCEL+1;
            TOTAL.ACCEL = TOTAL.ACCEL + AVGACCEL;
        end;
        POWER.OUT = DRAG + ROLLING + INERTIA + ACCESS; %in kW

        %Calculate engine operating characteristics
        %gear is mph/10 but no greater than 4
        GEAR = floor(AVGVELOCITY/4.447);
        if GEAR > 4
            GEAR = 4;
        elseif GEAR < 1
            GEAR = 1;
        end
        ENGINE.SPEED = AVGVELOCITY * 60 / (wheelradius * 2 * pi) * SLIPRATIO * gearing↙
(GEAR); %in RPM


        %Calculate fuel consumption
        POWER.IN = [FMBEP*ENGINE.SPEED/60*litersengine/2000 + 0.94 * POWER.OUT]↙
/ENGINEEFF; %in kW
        %POWER.IN = POWER.OUT/ENGINEEFF; %in kW
        TOTAL.ENGINE = [TOTAL.ENGINE, ENGINEEFF];
        GALDRIVE = GALDRIVE + POWER.IN / (34800) * 1;
    else
        POWER.IN = (FMBEP*NUNPWR*litersengine/2000) + ACCESS; %
        GALIDLE = GALIDLE + POWER.IN / (34800) * 1;
        TIMEIDLE = TIMEIDLE+1;
    end
    TOTAL.POWER = [TOTAL.POWER, POWER.IN];
    TOTAL.DISTANCE = TOTAL.DISTANCE  + DISTANCE/1000; %in km
    FUEL = POWER.IN / (34800) * INTERVAL; % 34800 kJ/L
    TOTAL.FUEL = TOTAL.FUEL + FUEL; % in L
end

    FuelEconomy = TOTAL.FUEL / TOTAL.DISTANCE * 100; %in L/100km
```

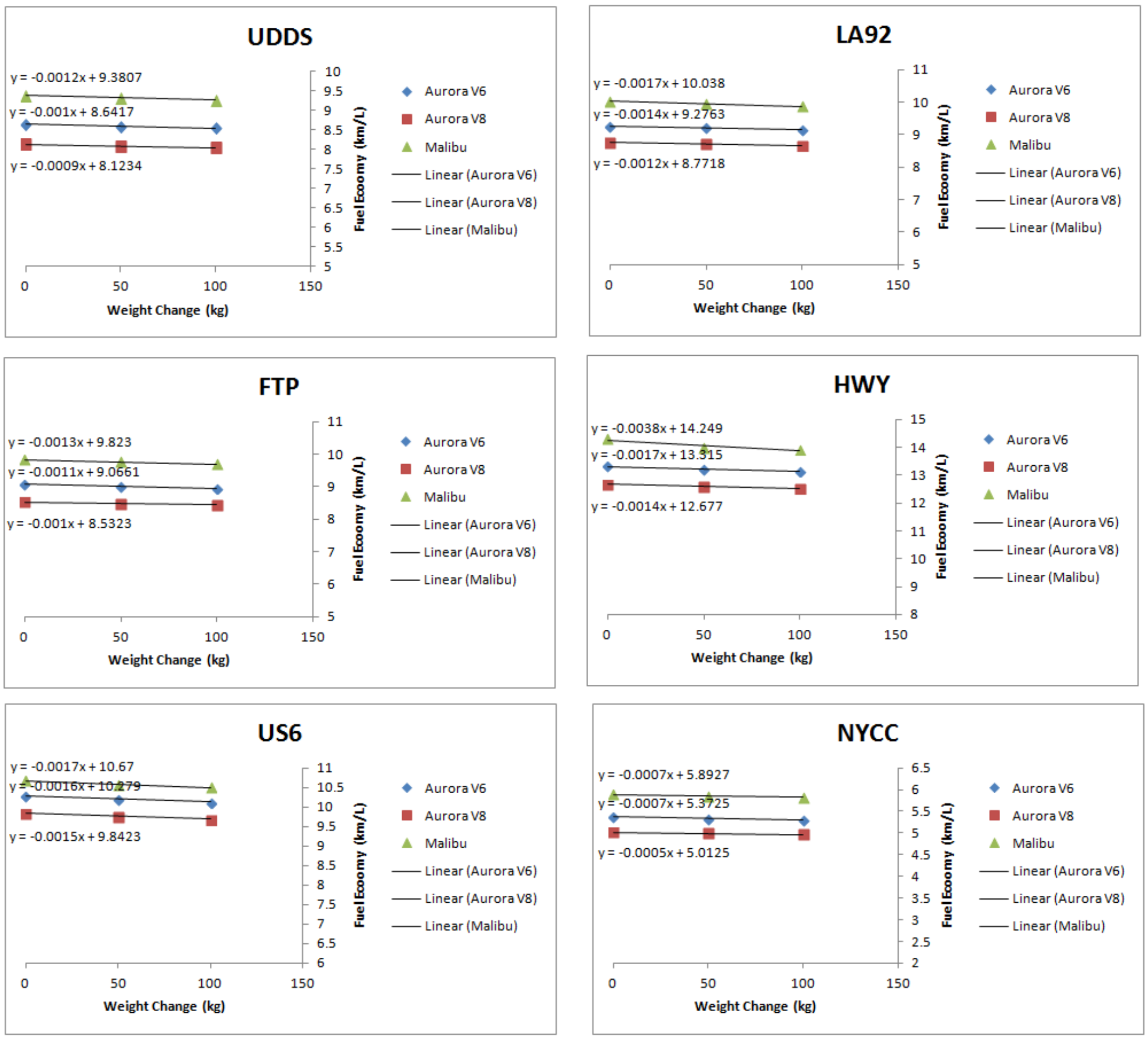


Figure B.1: Simulation Results for Weight

Table B.1: Acceleration and Velocity Effects on Malibu Maxx for 6 EPA Drive Cycles

Malibu Maxx Adjusted Fuel Economies (km/L)

EPA LA92 "Unified" Driving Schedule

	90% Vel	*100% Vel*	*110% Vel*
110% Acc	**7.69**	**8.09**	**8.44**
100% Acc	**7.77**	**8.18**	**8.55**
90% Acc	**7.86**	**8.28**	**8.65**

EPA Federal Test Procedure (FTP)

	90% Vel	*100% Vel*	*110% Vel*
110% Acc	**7.39**	**7.91**	**8.32**
100% Acc	**7.46**	**7.99**	**8.40**
90% Acc	**7.52**	**8.06**	**8.48**

EPA US06 Supplemental FTP

	90% Vel	*100% Vel*	*110% Vel*
110% Acc	**10.02**	**9.84**	**9.52**
100% Acc	**10.20**	**10.06**	**9.73**
90% Acc	**10.36**	**10.24**	**9.92**

EPA Urban Dynanometer Schedule

	90% Vel	*100% Vel*	*110% Vel*
110% Acc	**6.97**	**7.50**	**7.93**
100% Acc	**7.03**	**7.56**	**8.00**
90% Acc	**7.08**	**7.63**	**8.08**

EPA Highway Fuel Economy Test

	90% Vel	*100% Vel*	*110% Vel*
110% Acc	**12.03**	**12.14**	**12.09**
100% Acc	**12.09**	**12.20**	**12.15**
90% Acc	**12.13**	**12.25**	**12.19**

EPA New York City Cycle

	90% Vel	*100% Vel*	*110% Vel*
110% Acc	**3.36**	**3.69**	**4.00**
100% Acc	**3.39**	**3.73**	**4.04**
90% Acc	**3.41**	**3.75**	**4.06**

Table B.2: Acceleration and Velocity Effects on Aurora V6 and V8 for 6 EPA Drive Cycles

Aurora V6 Adjusted Fuel Economies (km/L)

EPA LA92 "Unified" Driving Schedule

	90% Vel	100% Vel	110% Vel
110% Acc	5.98	6.34	6.60
100% Acc	6.04	6.42	6.70
90% Acc	6.09	6.48	6.77

EPA Federal Test Procedure (FTP)

	90% Vel	100% Vel	110% Vel
110% Acc	5.70	6.13	6.49
100% Acc	5.73	6.18	6.54
90% Acc	5.77	6.22	6.59

EPA US06 Supplemental FTP

	90% Vel	100% Vel	110% Vel
110% Acc	8.01	7.96	7.78
100% Acc	8.16	8.13	7.95
90% Acc	8.27	8.25	8.10

EPA Urban Dynanometer Schedule

	90% Vel	100% Vel	110% Vel
110% Acc	5.36	5.79	6.16
100% Acc	5.39	5.83	6.21
90% Acc	5.42	5.86	6.25

EPA Highway Fuel Economy Test

	90% Vel	100% Vel	110% Vel
110% Acc	9.53	9.75	9.75
100% Acc	9.58	9.80	9.80
90% Acc	9.62	9.84	9.83

EPA New York City Cycle

	90% Vel	100% Vel	110% Vel
110% Acc	2.56	2.81	3.05
100% Acc	2.57	2.83	3.07
90% Acc	2.58	2.85	3.09

Aurora V8 Adjusted Fuel Economies (km/L)

EPA LA92 "Unified" Driving Schedule

	90% Vel	100% Vel	110% Vel
110% Acc	5.49	5.81	6.04
100% Acc	5.55	5.88	6.12
90% Acc	5.61	5.96	6.20

EPA Federal Test Procedure (FTP)

	90% Vel	100% Vel	110% Vel
110% Acc	5.24	5.65	5.96
100% Acc	5.29	5.71	6.03
90% Acc	5.34	5.76	6.09

EPA US06 Supplemental FTP

	90% Vel	100% Vel	110% Vel
110% Acc	7.34	7.22	7.00
100% Acc	7.49	7.35	7.14
90% Acc	7.61	7.48	7.27

EPA Urban Dynanometer Schedule

	90% Vel	100% Vel	110% Vel
110% Acc	4.92	5.33	5.66
100% Acc	4.97	5.38	5.72
90% Acc	5.01	5.43	5.77

EPA Highway Fuel Economy Test

	90% Vel	100% Vel	110% Vel
110% Acc	8.95	9.16	9.15
100% Acc	9.02	9.22	9.21
90% Acc	9.07	9.27	9.27

EPA New York City Cycle

	90% Vel	100% Vel	110% Vel
110% Acc	2.33	2.56	2.78
100% Acc	2.35	2.59	2.80
90% Acc	2.36	2.60	2.82

Appendix C

PGM Models

C.1 Discrete Test PGM in Excel with Three Factors of Monte Carlo Analysis

Figure C.1 shows the joint probabilities of use stage energy consumption estimated using chain rule for the three factors, FRR, Lifetime Mileage, and Fuel Economy, shown in Table C.1. Because of the FRR, the lightweight vehicle has more scenarios to calculate, 104 unique points, and 34 unique points for the base vehicle. The graph depicts the probability density for each scenario. Discrete models could work well for LCIs as well, but it would still require the use of specialized software, as calculations across the large number of factors are beyond the capabilities of a spreadsheet.

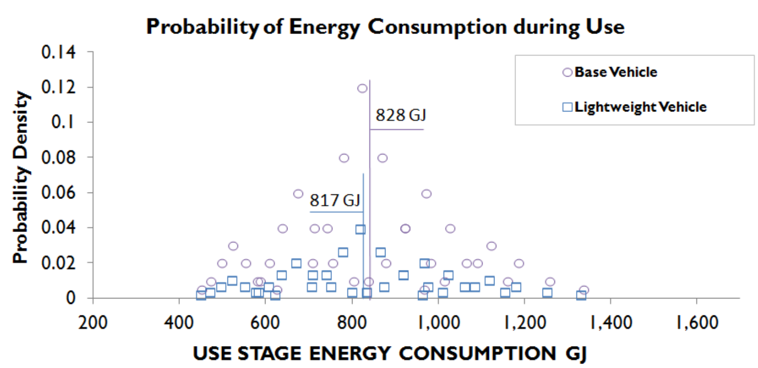


Figure C.1: Joint Probabilities of Discrete Usage Scenarios and Corresponding Energy Values

Table C.1: Discrete Lifetime Mileage, Probabilities

LIFETIME MILEAGE (km)	140,000	180,000	220,000	260,000	300,000		
Probability	10%	20%	40%	20%	10%		
FRR ($\frac{\%\text{fuel economy}}{\%\text{weight savings}}$)	0.4	0.6 km	0.8 km				
Probability	33%	33%	33%				
Fuel Economy[a] ($\frac{km}{L}$)	≈7.8	≈8.3	≈8.8	≈9.3	≈9.8	≈10.3	≈10.8
Probability	5%	10%	20%	30%	20%	10%	5%

C.2 OPENBugs Models

C.2.1 Monte Carlo Analysis

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```
model{
FRR ~ dunif(0.4,0.8)
Mileage ~ dnorm(220,mile.tau)

Fuel ~ dnorm(fuel.mu,fuel.tau)

Energy <- (Mileage / Fuel - Mileage / (Fuel   * (1 + FRR*0.01))) * 34.8
mile.tau <- 1/(100*100)
fuel.tau <- 1/(1*1)
fuel.mu <- 9.3
}
```

C.2.2 Vehicle PGM

```
model{
##############################
# Constants - Fixed values and explanatory variables
##############################


##############################
# Stochastic or random - model parameters (nodes) and response variables
##############################
FuelReductionRatio ~ dunif(0.4,0.7)

PopDensity ~ dcat(p.PopDensity[1:3])

#Drive Cycles call CPTs P(1:3|CommuteType)
HwyDriveCycle ~ dcat(p.HwyDriveCycle[CommuteType,1:3])
CityDriveCycle ~ dcat(p.CityDriveCycle[CommuteType,1:3])
HwyEconomy ~ dnorm(AdjHwyEconomy.mu,HwyEconomy.tau[HwyDriveCycle])
CityEconomy ~ dnorm(AdjCityEconomy.mu,CityEconomy.tau[CityDriveCycle])

# 1. low 2. med 3.  high
Speeding ~ dcat(p.Speeding[1:3])
Acc ~ dcat(p.Acc[1:3])
CommuteType ~ dcat(p.CommuteType[1:2])
HwyFraction ~ dunif(HwyFraction.a[PopDensity],HwyFraction.b[PopDensity])
PartAge ~ dnorm(PartAge.mu,PartAge.tau)
AnnualMiles ~dnorm(AnnualMiles.theta,AnnualMiles.tau)
CargoLoad ~ dunif(4.2,20)
AvgPassengerWeight ~ dnorm(60,AvgPassengerWeight.tau)
FamilySize ~ dcat(p.FamilySize[1:4]) #additional family members
Passengers ~ dunif(0.95 , Members[FamilySize])

##############################
# Logical - variables specified mathematically
##############################
FuelEconomy.light <- (HwyFraction * HwyEconomy + (1 - HwyFraction) * CityEconomy)* (1
 + FuelReductionRatio * MassReduction/Curbweight)
FuelEconomy.base <- (HwyFraction * HwyEconomy + (1 - HwyFraction) * CityEconomy)
FuelSave <- LifetimeMileage / FuelEconomy.base - LifetimeMileage / FuelEconomy.light
Energy <- FuelSave * 0.0348
EnergyperKM <-  (1 / FuelEconomy.base - 1 / FuelEconomy.light)*34.8
# inGJ
PassengerWeight <- AvgPassengerWeight * Passengers
TotalLoad <- CargoLoad + PassengerWeight

PartAge.mu <- 16
PartAge.sd<- 5
PartAge.tau <- 1 /( PartAge.sd*PartAge.sd)
```

```
AvgPassengerWeight.var <-10 * 10
AvgPassengerWeight.tau <- 1/(AvgPassengerWeight.var)

LifetimeMileage <- AnnualMiles * PartAge
AnnualMiles.theta <- (AnnualMiles.mu[PopDensity]  + AnnualMiles.K[PopDensity] *
FamilySize)
AnnualMiles.var <- 3000 * 3000
AnnualMiles.tau <- 1/AnnualMiles.var

AdjHwyEconomy.mu <- HwyEconomy.mu[HwyDriveCycle] *(1+(Speeding-2)*VelK.hwy[
HwyDriveCycle]+(Acc-2)*AccK.hwy[HwyDriveCycle])  - WeightK.hwy[HwyDriveCycle] *
TotalLoad
AdjCityEconomy.mu <- CityEconomy.mu[CityDriveCycle] *(1+(Speeding-2)*VelK.city[
CityDriveCycle]+(Acc-2)*AccK.city[CityDriveCycle]) -  WeightK.city[CityDriveCycle] *
TotalLoad
}

##############################
#Data
##############################
list(

Members = c(1,2,3,4),
#Rural Suburban Urban
p.PopDensity = c(.21,.13,.66),
HwyFraction.a = c(.45,.42,.42),
HwyFraction.b = c(.8,.8,.7),

#Mean Annual Mileage
AnnualMiles.mu = c(18000, 16000, 15000),
AnnualMiles.K = c(1200, 800, 800),

#Data from Matlab Simulations in km/L
#      LA92        (EPA HWY)        HFET
HwyEconomy.mu = c(10.75, 11.9, 15.3),
HwyEconomy.tau = c(0.7, 0.7, 0.7),

#      NYCC Mix  EPACity     FTP
CityEconomy.mu = c(8.2, 8.1, 10.5),
CityEconomy.tau = c(0.7, 0.7, 0.7),

# Speeding
p.Speeding = c(0.2,0.4,0.4),

# Acc
p.Acc = c(0.2,0.4,0.4),

# CommuteType
p.CommuteType = c(0.70,0.30),
```

```
# HwyDriveCycle  LA92            (EPA HWY)        HFET
# (TrafficType)
# (1)        .4     .5     0.1
# (2)        0.1    0.5    0.4
p.HwyDriveCycle = structure(.Data =c(.4,.5,.1,
.1,.5,.4), .Dim=c(2,3)), #RowsXColsXTables

# CityDriveCycle  NYCC Mix       EPACity     FTP
# (TrafficType)
# (1)        .4     .5     0.1
# (2)        0.1    0.5    0
p.CityDriveCycle = structure(.Data =c(.4,.5,.1,
.1,.5,.4), .Dim=c(2,3)), #RowsXColsXTables

p.FamilySize = c(0.3,0.3,0.2,0.2),

#   NYCC Mix     EPACity     FTP
WeightK.city = c(0.001,0.001, 0.0001),
#  LA92          (EPA HWY)       HFET
WeightK.hwy = c(0.0015, 0.0016,0.002),

#   NYCC Mix     EPACity     FTP
VelK.city = c(.06,.051,.051),
#  LA92          (EPA HWY)       HFET
VelK.hwy = c(0.045,-.032,-.05),

#  NYCC Mix      EPACity     FTP
AccK.city = c(-.002,-.009,-.009),
#  LA92          (EPA HWY)       HFET
AccK.hwy = c(-.009,-.017,-.007),

MassReduction = 15,
Curbweight = 1584
)
```

C.3 Results for the Aurora Models

C.3.1 Aurora V8

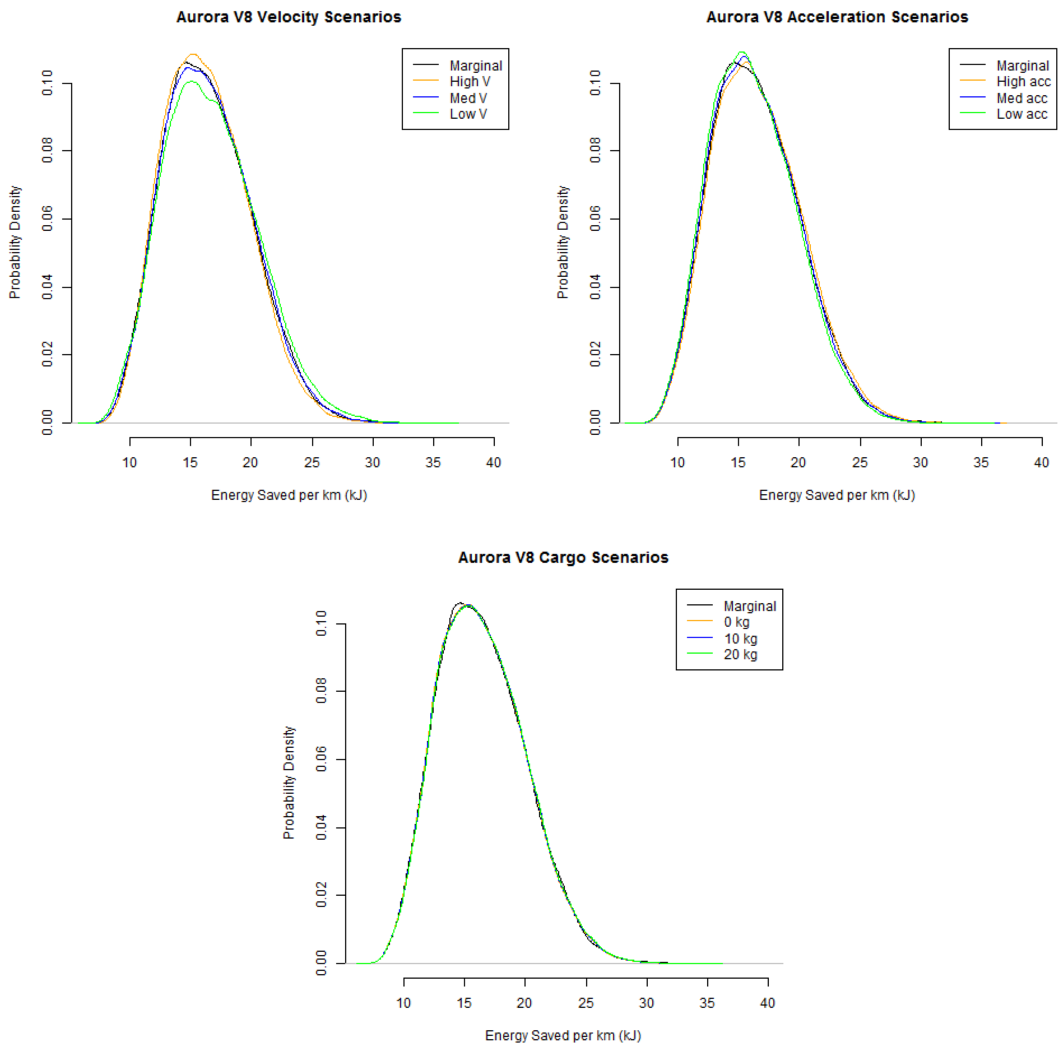

Figure C.2: Velocity, Acceleration, and Cargo Scenarios Exhibit Insignificant Effects on Distance Normalized Energy Savings for the Aurora V8

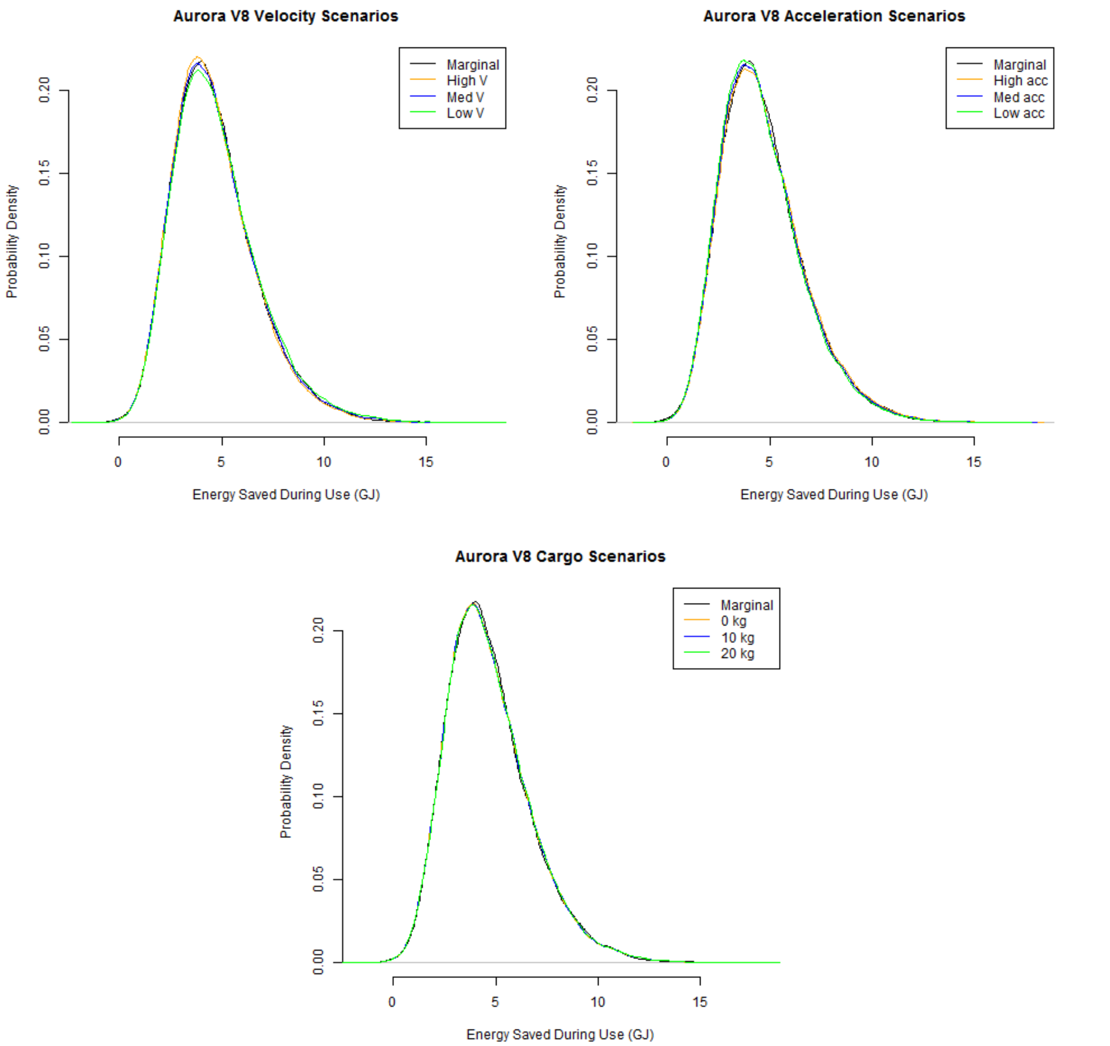

Figure C.3: Velocity, Acceleration, and Cargo Scenarios Exhibit Insignificant Effects on Lifetime Energy Savings for the Aurora V8

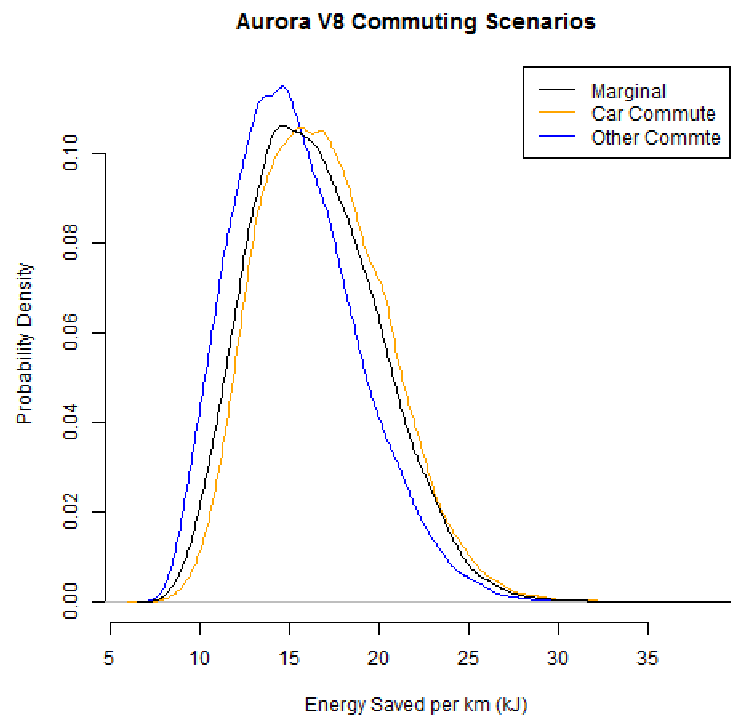

Figure C.4: Commute Scenarios Exhibit Significant Effects on Distance Normalized Energy Savings for the Aurora V8

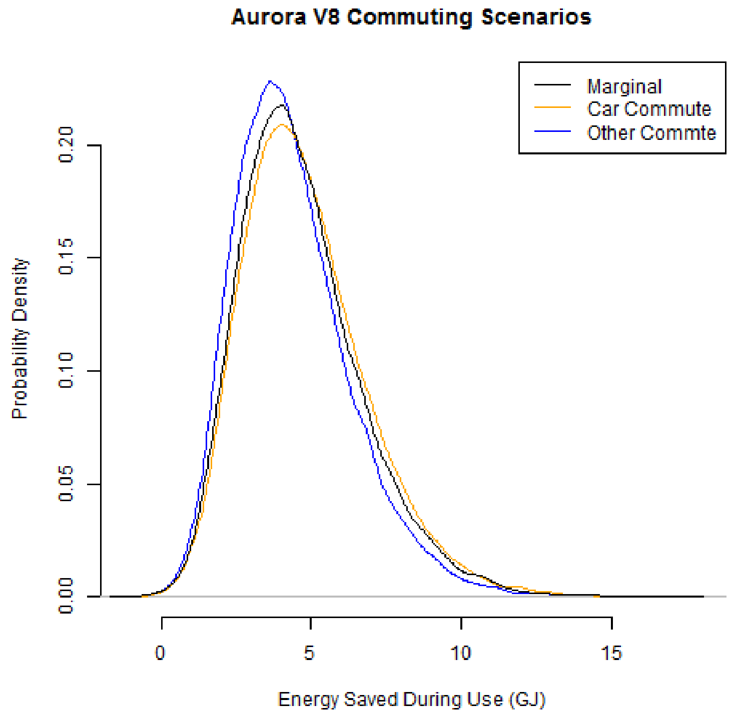

Figure C.5: Commute Scenarios Exhibit Significant Effects on Energy Savings for the Aurora V8

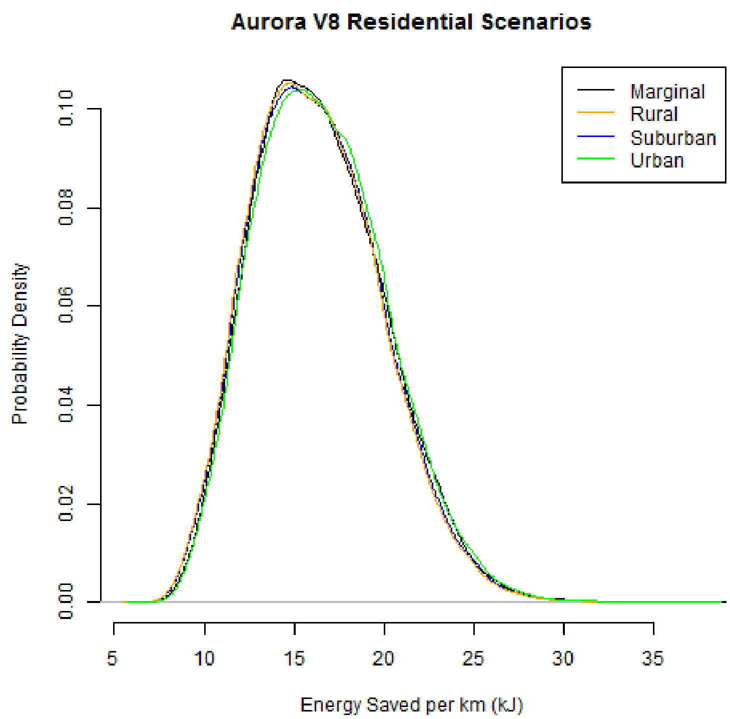

Figure C.6: Residential Density Scenarios Exhibit Significant Effects on Distance Normalized Energy Savings for the Aurora V8

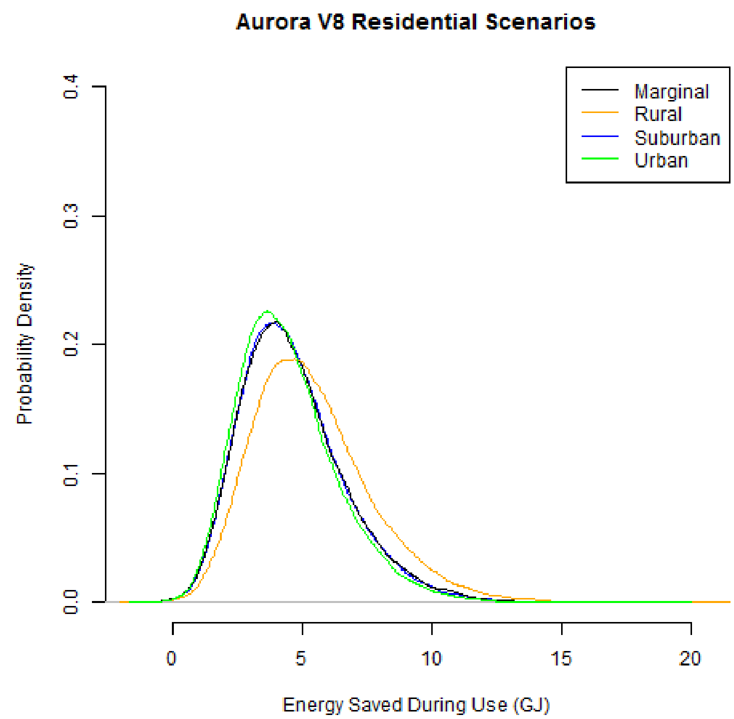

Figure C.7: Residential Density Scenarios Exhibit Significant Effects on Energy Savings for the Aurora V8

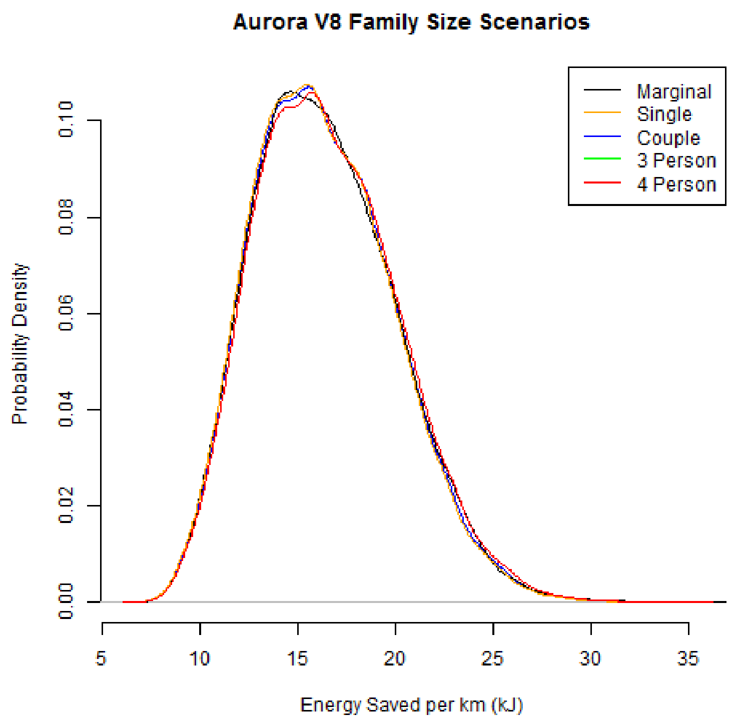

Figure C.8: Family Size Scenarios Exhibit Significant Effects on Distance Normalized Energy Savings for the Aurora V8

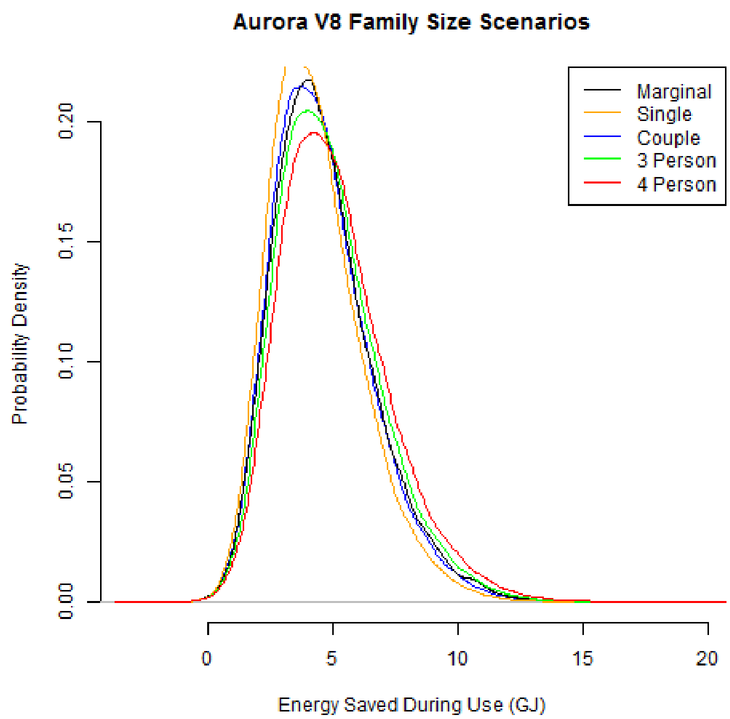

Figure C.9: Family Size Scenarios Exhibit Significant Effects on Energy Savings for the Aurora V8

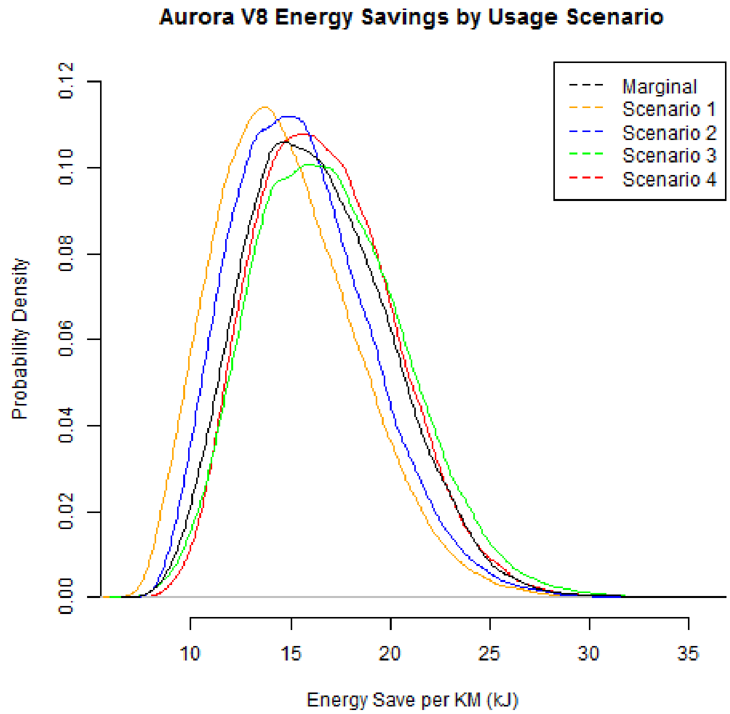

Figure C.10: Four Usage Scenarios Exhibit Unique Effects on Distance Normalized Energy Savings for the Aurora V8

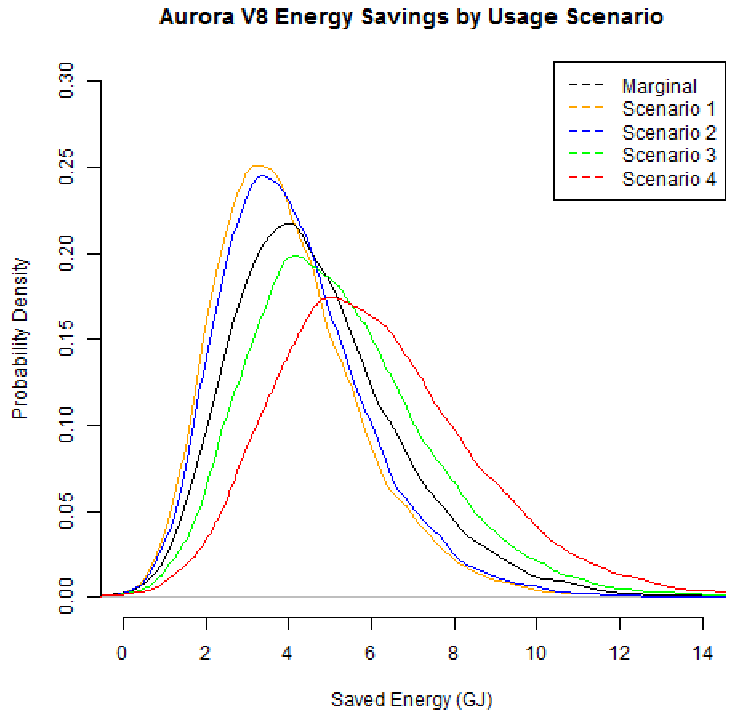

Figure C.11: Four Usage Scenarios Exhibit Unique Effects on Energy Savings for the Aurora V8

C.3.2 Aurora V6

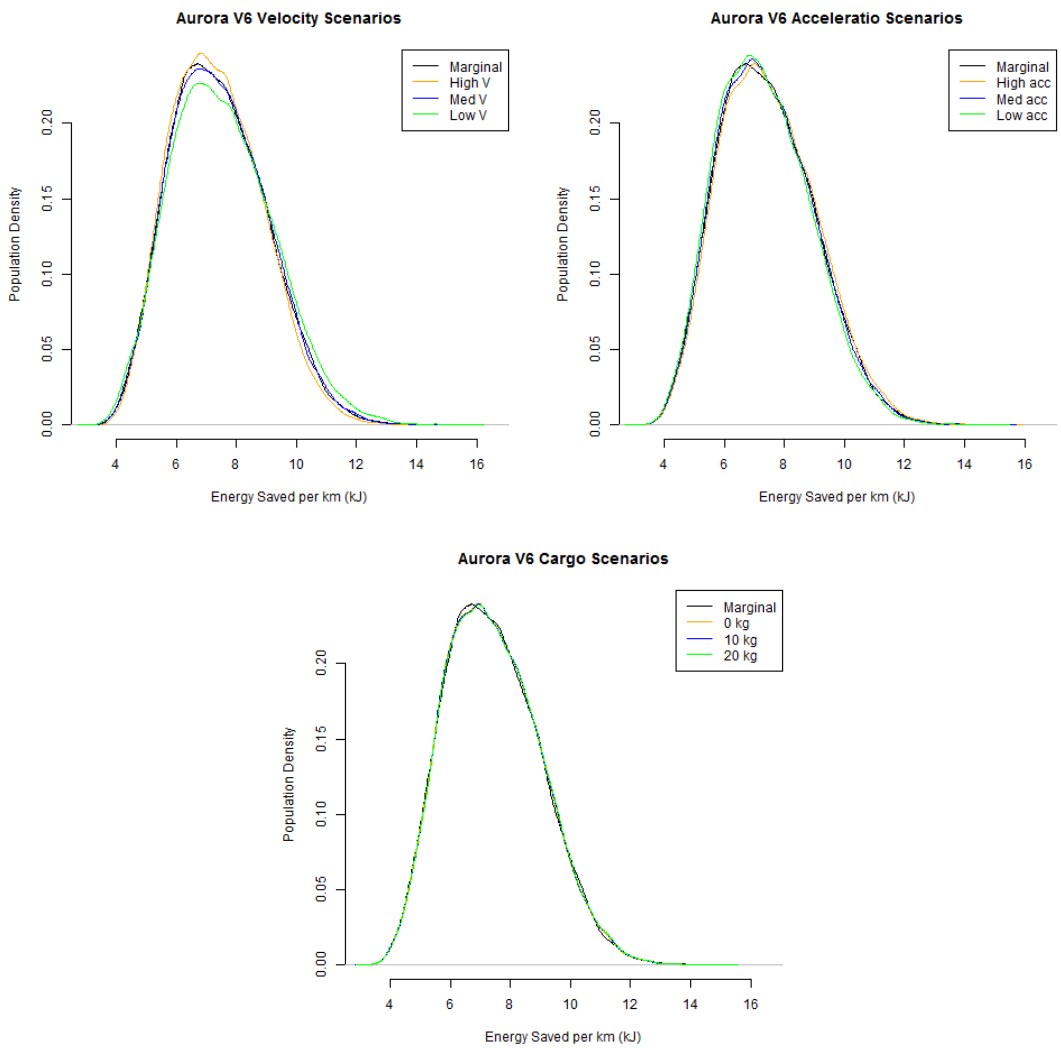

Figure C.12: Velocity, Acceleration, and Cargo Scenarios Exhibit Insignificant Effects on Distance Normalized Energy Savings for the Aurora V6

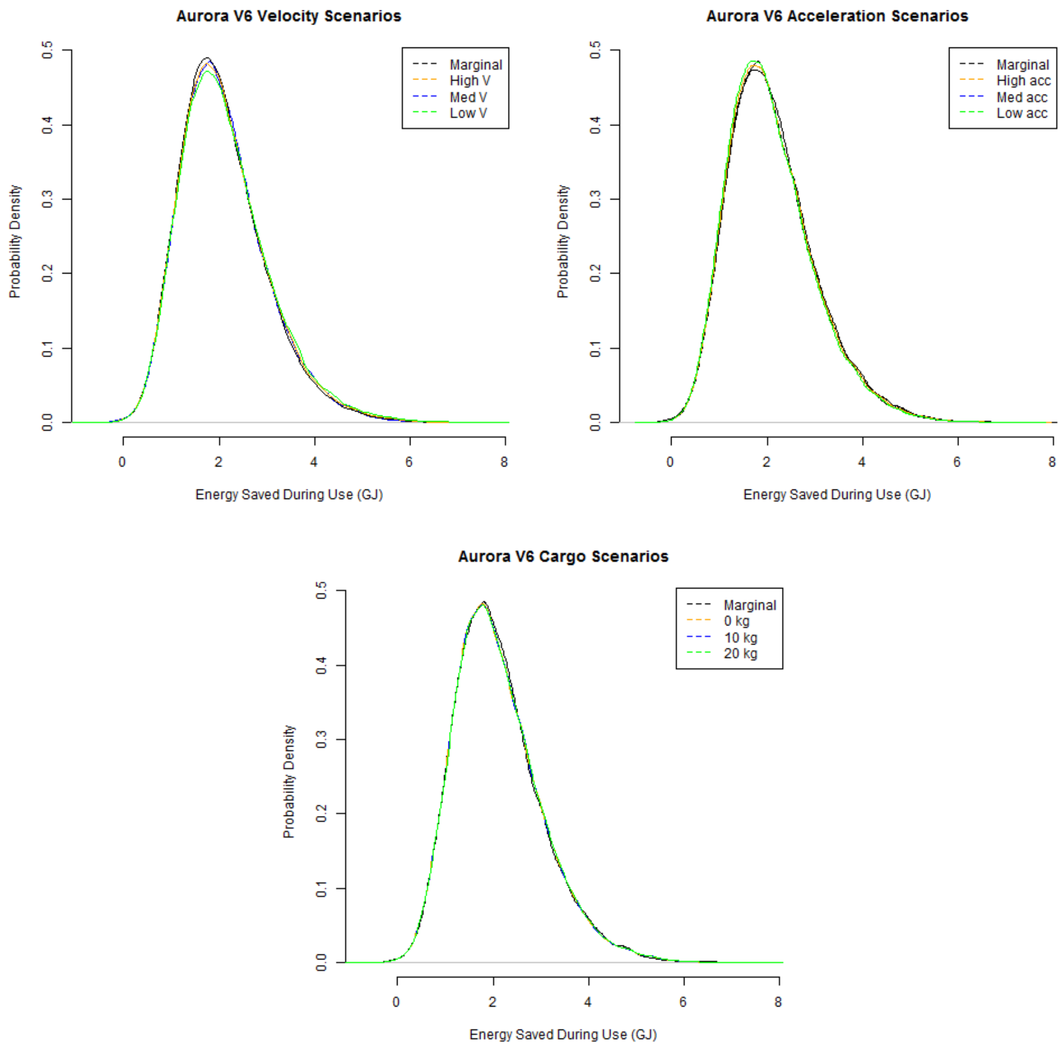

Figure C.13: Velocity, Acceleration, and Cargo Scenarios Exhibit Insignificant Effects on Lifetime Energy Savings for the Aurora V6

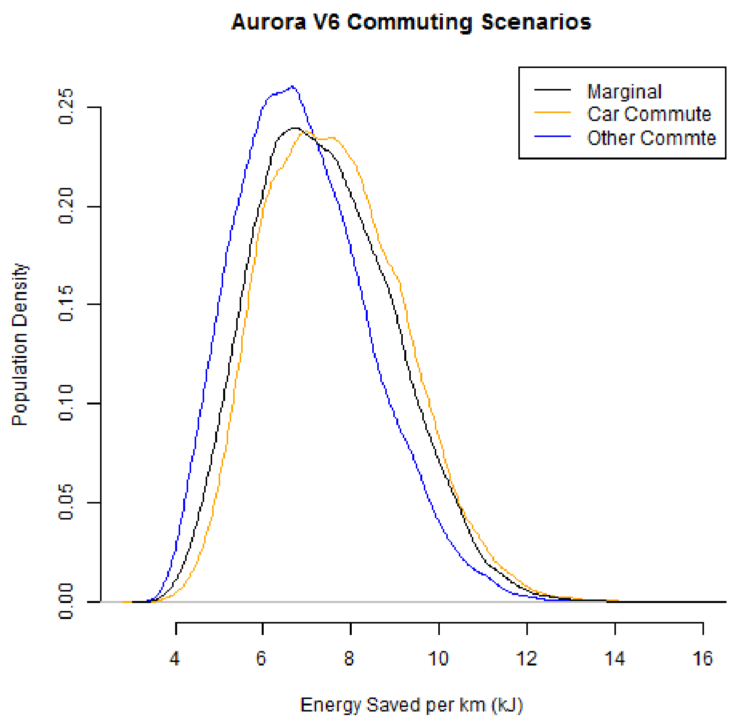

Figure C.14: Commute Scenarios Exhibit the Significant Effects on Distance Normalized Energy Savings for the Aurora V6

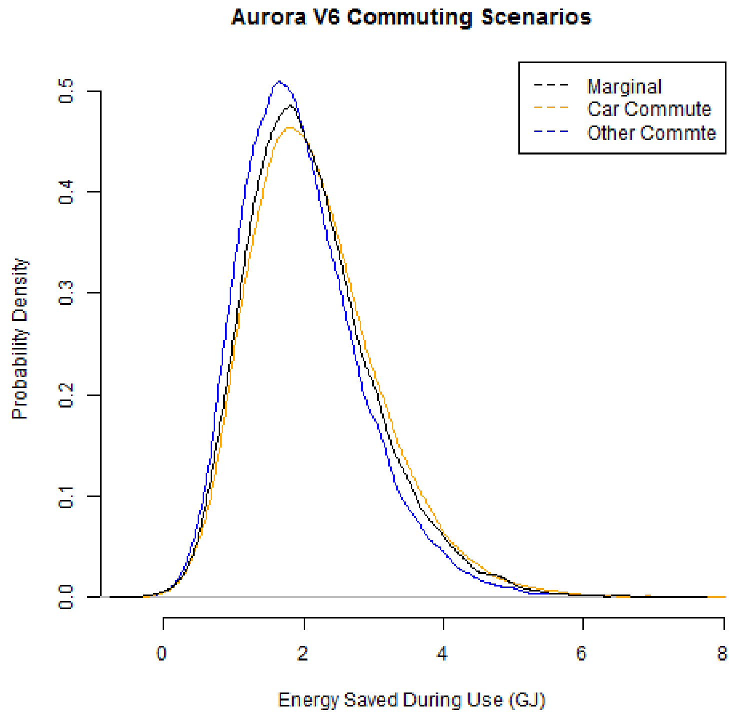

Figure C.15: Commute Scenarios Exhibit the Significant Effects on Energy Savings for the Aurora V6

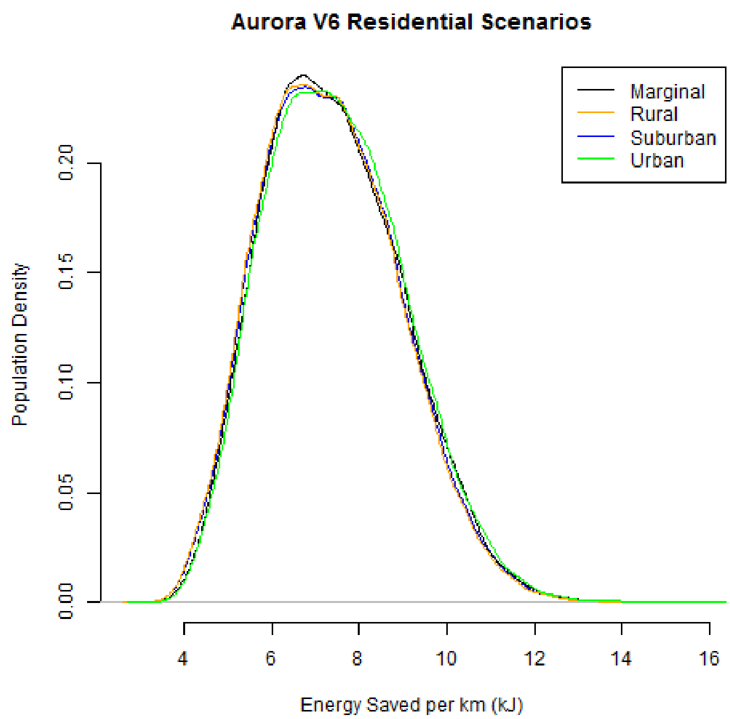

Figure C.16: Residential Density Scenarios Exhibit Significant Effects on Distance Normalized Energy Savings for the Aurora V6

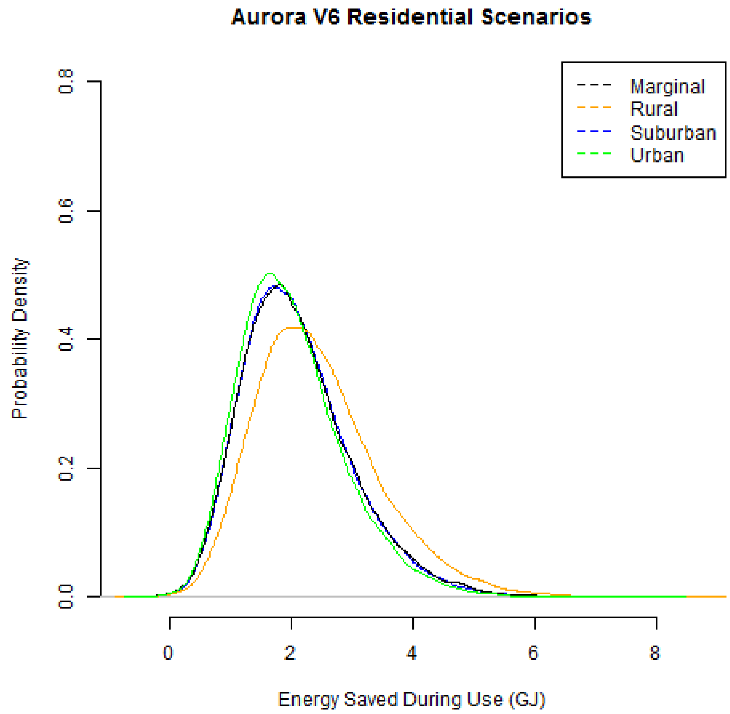

Figure C.17: Residential Density Scenarios Exhibit Significant Effects on Energy Savings for the Aurora V6

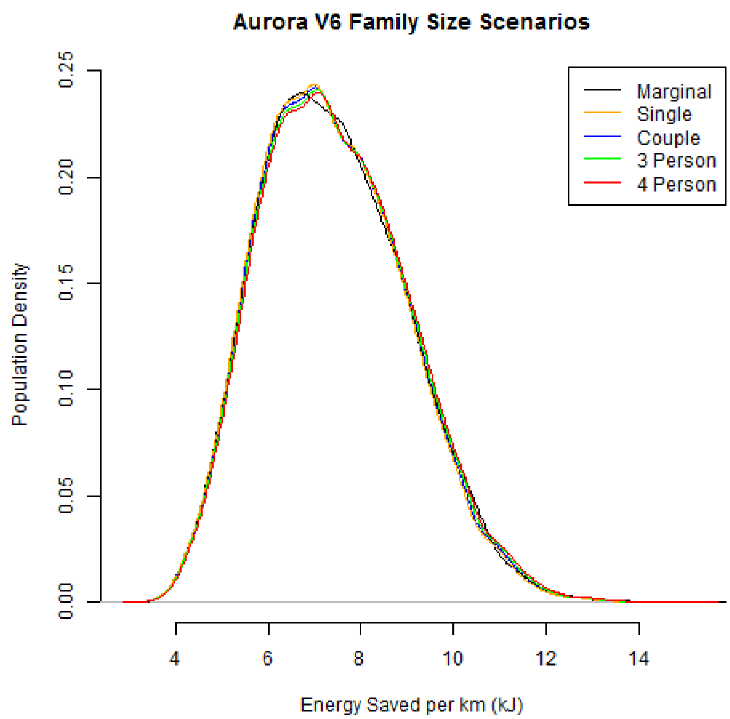

Figure C.18: Family Size Scenarios Exhibit Insignificant Effects on Distance Normalized Energy Savings for the Aurora V6

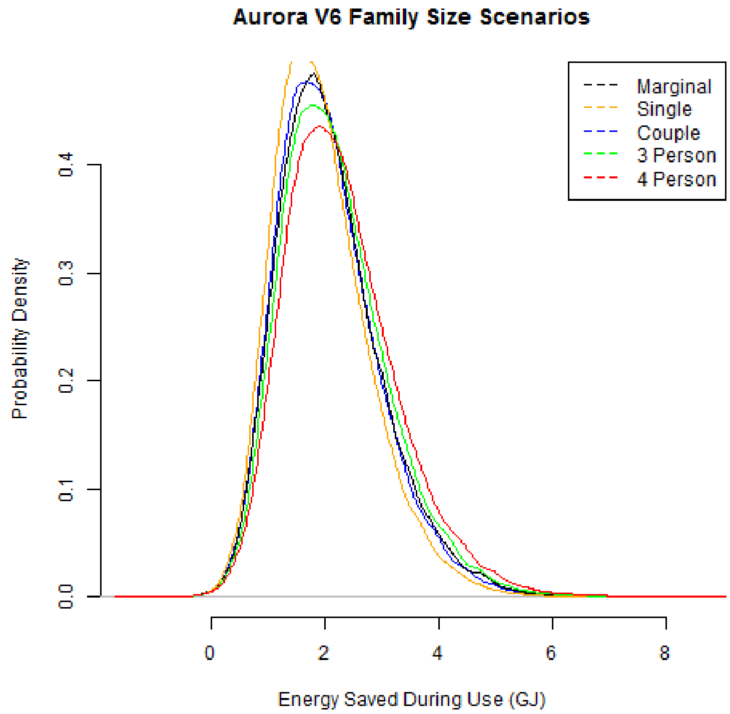

Figure C.19: Family Size Scenarios Exhibit Significant Effects on Energy Savings for the Aurora V6

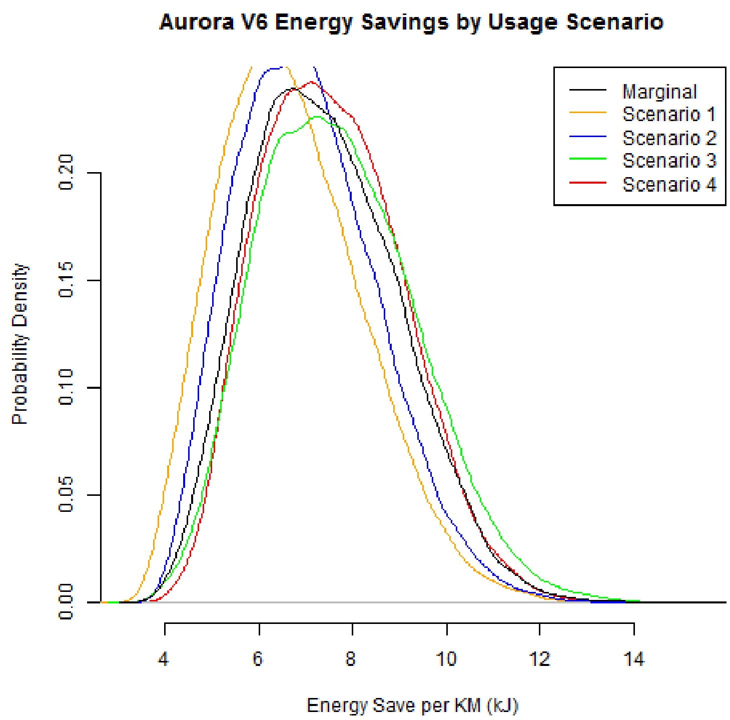

Figure C.20: Four Usage Scenarios Exhibit Unique Effects on Distance Normalized Energy Savings for the Aurora V6

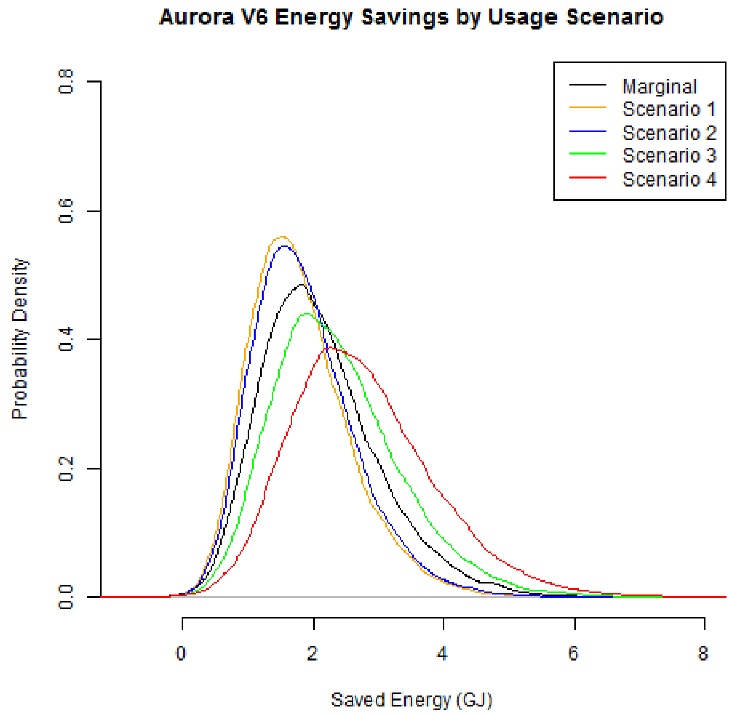

Figure C.21: Four Usage Scenarios Exhibit Unique Effects on Energy Savings for the Aurora V6

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