Evaluation of probabilistic underspecification as a method for incorporating uncertainty into comparative life cycle assessments

by

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Abstract

Life cycle assessments are quickly becoming a crucial method through which the environmental impacts of products or processes are evaluated. A concern with current practice, however, is that the use of deterministic values for inputs and final results only represent a single scenario, not all possible values and outcomes, or even a real-world situation. By incorporating uncertainty, an LCA can account for inherent variation and the use of proxy data, both of which are common occurrences in LCA implementation. In a comparative LCA, this uncertainty allows a decision to be made between alternatives with a certain level of confidence. While uncertainty is necessary for credible results, its implementation can also be time consuming. As LCAs grow more common, methods of streamlining are being explored to reduce both the effort and cost. One such streamlining method that also incorporates uncertainty is probabilistic underspecification. This method evaluates environmental parameters by dividing them into different material and process categories. The lowest level of specification, Level 1, is defined by the type of material or process, such as metal or freight transportation. This category is then subdivided based on different characteristics of the material or process. The highest level of specification, Level 5, consists of the individual database processes used by traditional LCAs.

This thesis compares the streamlining method of probabilistic underspecification to the more common method of incorporating uncertainty, termed here as individual probabilistic specification. A case study on alternative pavement designs is used to demonstrate and compare both the methodologies. The effort required for each methodology is compared by the percentage of processes specified at Level 5, which is 100% for individual probabilistic specification, but much less for probabilistic underspecification. The results of the case study showed that as little as 32% or less of the processes need to be specified at Level 5 in order to have the required level of confidence in the decision being made. It can be seen that, as a streamlining method to estimate the results of comparative LCAs, probabilistic underspecification is a viable option.

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1 INTRODUCTION

As a result of the demand for environmentally friendly products, life cycle assessments (LCAs) are being utilized to determine inefficiencies within a system, allowing the highest emitting phases to be targeted. As LCAs gain prominence, however, researchers need to ensure that they are leading to credible conclusions. Significant variation between results from different LCAs on similar products or systems have led to doubts in the accuracy and reliability of LCAs in general (Williams et al. 2009).

Generally, a single value is used to represent a quantity or an emission factor for a material in an LCA. In real life, however, inventory values will vary significantly due to measurement inaccuracies, inefficiencies in manufacturing, human error, or simply inherent variation. The amount of coal required to produce cement, for example, will vary depending on the type of manufacturing used at the plant, the location, the efficiency of the kilns, etc., and therefore finding a single value for the average amount of coal required by a U.S. cement plant will not necessarily be representative of a real-world situation. These ranges of values are represented by probability distributions, which are established through empirical data or external data quality quantification methods. Incorporation of these ranges allows an assessment to attempt to account for all possible real-world values for the total, establishing a quantifiable level of confidence for this final value.

Recently there has been a push to provide more information to consumers on the environmental impact of the products they are buying. Environmental product declarations (EPDs) are being developed within most industries. The sheer magnitude of products that need to be evaluated, however, is overwhelming. Additionally, including uncertainty in a traditional LCA is a time-consuming and therefore cost-intensive process. The LCA community has begun to look into streamlining processes in order to increase the usage of LCAs (Hunt et al. 1998). By making it faster and therefore cheaper to perform an LCA, the usage can become far more widespread and accessible. The results are only credible, however, if uncertainty is incorporated into these streamlined methodologies. Therefore, a streamlined method that accounts for uncertainty needs to be developed.

One example of an often-studied genre of LCAs is that of pavements. As a significant contributor to both material use and emissions within the U.S., the environmental impacts attributable to different pavement designs needs to be accurately assessed and compared so that reductions can be made. At present, pavement LCAs typically use deterministic values, comparing the average impact without accounting for the real-life variation that occurs. Through the incorporation of uncertainty into a pavement LCA, the decision-maker, often a state or federal agency, can associate a certain level of confidence or reliability with their decision. Additionally, pavements are products that change significantly depending on contextual conditions, such as climate, traffic, and soil type. This means that a new LCA must be performed for each scenario being assessed – and the U.S. alone has over two million miles of paved roads (BTS 2010). This thesis presents a comparative pavement analysis for three scenarios, which explores two different methodologies to evaluate the efficacy of the streamlined methodology.

The validation of methodologies that streamline and/or incorporate uncertainty is ongoing. Particularly, the efficacy of using them to evaluate comparative LCAs remains to be seen. This thesis aims to explore different methodologies of analyzing uncertainty to determine their efficacy and efficiency in performing comparative LCAs. Chapter 2 discusses the current literature available on the incorporation of uncertainty within LCAs, the use of uncertainty in comparative LCAs, and the methodologies being explored later in the thesis. Then, Chapter 3 provides a detailed explanation of the key methodologies being compared in this thesis, individual probabilistic specification (IPS) and probabilistic underspecification (PU). The case study presented in Chapter 4 compares alternative pavement designs evaluated using each of the methods discussed previously. Chapter 5 then evaluates the efficacy and effort required for each methodology within the context of the pavement LCA. Finally, the last chapter discusses the conclusions that can be drawn from the case study and their greater application, as well as opportunities for future work.

2 LITERATURE REVIEW

The results of a life cycle assessment (LCA) are only as reliable as the method used to conduct the analysis. Though there are standards for performing an LCA, they can lead to unreliable results if further assessments on data quality, sensitivity and uncertainty are not performed (Bjorklund 2002). Within uncertainty alone, however, there are a variety of types and methodologies that can be considered (Ross et al. 2002 ; Heijungs and Huijbregts 2004 ; Heijungs and Frischknecht 2005). Key sources that discuss uncertainty in LCAs are presented below, followed by a discussion of uncertainty in comparative LCAs and literature introducing the method of probabilistic specification.

2.1 Uncertainty in LCA

The incorporation of uncertainty is a relatively new addition to the field of life cycle assessment. In the last two decades especially, researchers have realized that LCAs have been lacking this key aspect, which would allow for greater credibility and application of their results. While many of the methods for this incorporation stem from other fields and earlier ideas, this integration with LCA is still a young field and requires greater evaluation. The following sources have successfully summarized the concept of uncertainty in LCAs and present methods and case studies for evaluation.

An early work describing uncertainty in LCAs is a paper by Huijbregts (1998a), in which the author discusses different types of uncertainty and variability, and presents probabilistic simulation as the tool to incorporate them into an LCA. To better understand his assertions, it is first important to clarify the difference between uncertainty and variability. Variability refers to values that change in a way that is known or can be found, and is inherent in the product or process being represented. Uncertainty, on the other hand, refers to changes that are not or cannot be known, whether due to lack of data, inaccurate measurements, or incorrect assumptions. Huijbregts presents three types of uncertainty: parameter, model, and uncertainty due to choices. Parameter uncertainty can be due to inaccurate measurements, lack of data, or outdated data. It is best analyzed using stochastic modeling – either Monte Carlo or Latin Hypercube simulations. Model uncertainty is due to misrepresentation of the mathematical relationships within the model, especially focusing on characterization factors. The author's solution is to include the fate of substances and environmental sensitivity in the impact assessment model. He recommends that uncertainty due to choices be dealt with through scenario analysis. Huijbregts also names three types of variability: spatial, temporal, and variability between sources and objects. Spatial and temporal variability concern the differences in measurement due to location or year. Finding data that represent the exact location and year to be modeled is ideal, but this is impossible when making predictions about the lifecycle of a product. Incorporating a probability distribution that represents available years and locations is the most feasible way of representing this variation. Finally, variability between sources and objects deals with the appropriateness of the inventory to assess the real world impacts of a product or process. This can also be dealt with through the application of a probability distribution. Due to the difficulty of incorporating all six types of uncertainty and variability, the author addresses only parameter uncertainty and uncertainty due to choices in an example, presented in a second paper. Huijbregts (1998b) utilizes the Latin Hypercube method of stochastic sampling, using arbitrary uncertainty factors to determine the minimum and maximum of a value. First, a broad assessment of the system being assessed is performed with the standard uncertainty factors and then, based on a sensitivity analysis, the overall uncertainty is reduced through the refinement of key parameters. For the scenario analysis the author suggests incorporating only the extremes of scenarios, creating a range that other variations of a scenario will most likely fall within. Finally, the author suggests that using ranges of all possible values within a defined category can also be an effective way of incorporating parameter uncertainty when combined through a stochastic simulation.

Similar to Huijbregts (1998a ; 1998b), a more recent paper by Lloyd and Ries (2007) refers to three types of uncertainty: parameter, scenario, and model. They survey twenty-four LCAs that include quantitative uncertainty analyses and assess them based on a variety of categories, including the methodology used and the types of uncertainty included. Parameter uncertainty is associated with the values used in a model that may be measured imprecisely, vary over time, or are unavailable. Scenario uncertainty deals with the "normative choices" within an LCA, such as method of allocation or geographic location. Finally, model uncertainty has to do with the LCA model's structure and the appropriateness of a mathematical relationship to represent a specific process. For example, uncertainty would be introduced if a linear equation was used to represent what was actually an exponential growth of emissions within a process. To determine which studies to asses in their paper, Lloyd and Reis looked at over 100 easily-accessible and relatively recent LCAs, 24 of which incorporated some form of quantitative uncertainty. Of those 24, all incorporated parameter uncertainty, nine considered scenario uncertainty, and eight included model uncertainty. Only seven of the 24 looked at all three types of uncertainty. A variety of methods were used to assess the uncertainty: stochastic modeling, scenarios, fuzzy data sets, interval calculations, and uncertainty propagation. Stochastic modeling was used by two-thirds of the studies, ten of which used a Monte Carlo simulation. Probability distributions were most often used in model and parameter uncertainty, the top four of which were normal, triangle, uniform, and lognormal. The information used to characterize the uncertainty varied, including supporting information, LCI data, data quality indicators, expert judgment, and arbitrary values. Finally, correlation between parameters was included in only four of the studies. The authors conclude that detailed standards within the LCA community concerning the types of uncertainty and methodologies for incorporation need to be identified, evaluated, and agreed upon.

While the previous studies use conventional LCA methodologies, Williams et al (2009) discuss methods for the incorporation of uncertainty into a hybrid method of economic input-output (EIO) and process LCA for generating life cycle inventories. The sources of uncertainty and methods of incorporation, however, can be applied to all LCA methodologies. The authors emphasize that uncertainty must be incorporated to preserve the reliability of LCAs. As LCAs have become more commonplace, the results of studies done on the same product have begun to disagree due to issues ranging from scope to data source. This disagreement can discredit the results of all LCAs. By incorporating uncertainty, however, the range of all possible values can be determined. Uncertainty has traditionally been separated into two categories, epistemic and aleatory. Epistemic deals with imperfect knowledge and can be decreased through greater data quality. Aleatory refers to the inherent variability of a system. An example of epistemic uncertainty is data uncertainty, which concerns both quality and representativeness of the data. It can be addressed through a stochastic analysis. Aggregation uncertainty, another example of epistemic uncertainty, is caused by the combining of many similar processes into one data set, whether due to the availability of data or concerns about releasing proprietary information. This uncertainty is a particular problem for EIO-LCI because data is confined to the specificity of the economic sectors. If aggregation uncertainty is recognized, it can be dealt with through further specification of the process or product being represented. Examples of aleatory uncertainty are temporal and geographic uncertainty, which are caused by the representativeness of the data to the time and area being modeled. They can often be quantified by modeling the historical trend of the data to predict for future time periods, and by using international data to determine the potential geographic variation.

All these studies, and the vast majority of LCAs, reference the International Organization for Standardization (ISO) 14040-14044 (ISO 1997 ; ISO 2006) standards, which outline a methodology for performing a life cycle assessment. At present, however, there is very little discussion in the standard about the incorporation of uncertainty. The standards state that uncertainty should be quantified "due to cumulative effects of model imprecision, input uncertainty and data variability" (5). It goes on to state that probability distributions or ranges can be used to quantify this uncertainty, but little attention is paid to the implementation of an uncertainty assessment throughout the rest of the standards.

As seen in the above sources, the degree to which uncertainty is included and the methodology by which it is done varies significantly from study to study. At present, there is no guideline that provides a definitive methodology. Focusing on which sources of uncertainty are the most prevalent and crucial to the outcome of the study, as well as the accessibility of data to quantify that uncertainty, is key to establishing definitive methods for assessment. There is a growing consensus, however, that uncertainty assessment is valuable, and nowhere is this more apparent than in comparative LCAs.

2.2 Uncertainty in Comparative LCAs

While the previous references show that it is not uncommon for an LCA to incorporate uncertainty, there are fewer examples of uncertainty being incorporated into comparative LCAs. Huijbregts et al (2003) presents an example of a comparative LCA that incorporates uncertainty. The case study is of two insulation alternatives for a Dutch single-family home. The authors account for parameter, scenario, and model uncertainty. For parameter uncertainty, an initially conservative range of values were established for each parameter. A sensitivity analysis was performed and any parameter that contributed more than 1% to the final uncertainty was further analyzed for a more detailed uncertainty distribution, which was then incorporated into a final Monte Carlo simulation. A lognormal distribution was chosen "because it avoids negative values, it captures a large value range, and the uncertainty in many processes and parameters follows a skewed distribution" (Huijbregts et al. 2003, p. 2602). Scenario uncertainty was included by establishing six different scenarios, including different allocation, waste treatment, and impact assessment methods. They were then given equal probability and combined into a single outcome. Finally, model uncertainty looked at two sources, lack of spatial variability and adequate characterization factors for certain materials. The model uncertainty was evaluated using equal probability between alternatives as well. To compare the two alternatives, a comparison indicator was used, which divided the output of option A by option B for each iteration. If 95% were above or below one then they were considered significantly different. The authors concluded that these three sources of uncertainty did affect the final result and therefore are necessary within an LCA.

A second example of a comparative LCA that includes uncertainty is de Koning et al. (2010). This example compares the carbon footprint of two types of detergent. The authors also include parameter, scenario, and model uncertainty. However, they look at three different comparison situations and the effect they have on the uncertainty. The first situation is the intrapractitioner comparison, in which both products are assessed at the same time by the same person. In this case, the processes that are the same between the two products are fully correlated. This correlation is addressed either by using correlated inputs or by neglecting the uncertainty on those processes that are shared, because it should not affect the final comparison. The second comparison situation is if the LCA method is standardized, but each assessment is performed by a different practitioner (multipractitioner). This means that different data sources will most likely be used. The third situation is if there is no standardized method, apart from ISO 14044 (2006), and the assessment is performed separately for each product. This means the system boundary, allocation method, data sources, and any assumptions will most likely be different between the two, and therefore comparisons will be highly inaccurate. The authors concluded that the intrapractitioner comparison produced the most confident result, with the least spread on the final uncertainty distribution. If the same boundaries, data, assumptions, etc. are not used within a comparative LCA, the conclusion is not reliable.

The incorporation of uncertainty in a comparative LCA provides a level of confidence for the conclusion. The above sources make it clear, however, that uncertainty in comparative LCAs is useless if the systems being compared are not assessed by the same practitioner, or at least use the same scope and data sources. As regulatory rules are further refined and established concerning the implementation of LCAs including uncertainty, this process will become simpler.

2.3 Probabilistic Underspecification

Patanavanich (2011) introduces the methodology of structured underspecification to account for the uncertainty in an LCA, both in calculations and user specification. This method uses varying levels of categorization to account for the use of proxy data in an assessment, which enables streamlining of the LCA process. This streamlining process has become necessary recently due to the increased demand to produce environmental product declarations (EPDs) and other forms of labeling for manufactured items. Patanavanich reviews the current state of methods for streamlining LCAs and using surrogate data, as well as incorporating the uncertainty acquired due to both. This method involves categorizing processes into five different levels of specificity. Level 1 is the least specified, grouping materials by general categories such as metals or chemicals. It therefore has the largest range of possible values and corresponds to higher uncertainty. The next level up of specification is the material property level, which divides the material category by a primary characteristic. The author gives the example of defining metals by ferrous, non-ferrous, and metal alloys. The next two levels continue to split the previous level definition by common characteristics. Finally, level five is composed of the individual database entries that are being categorized. As the levels become more specific, their associated uncertainty decreases and the range of values becomes smaller. For example, steel rebar manufactured using a blast furnace could be defined at its broadest level of specification, Level 1 (L1), as a metal. Level 2 (L2), a narrower level of specification, would be used to define it as a ferrous metal. At Level 3 (L3) it would be defined as steel, separating it from iron. Finally, Level 4 (L4) would categorize it as steel rebar, which would combine all the rebar data that utilize different manufacturing processes, such as blast furnace, electric arc furnace, or a combination of both. Level 5 (L5) would be the most specified, the steel rebar made using a blast furnace, which is the level at which all the processes in individual probabilistic specification method are defined. The idea is that as more information is obtained about a specific material or process, the less uncertainty there will be in the assessment. The author evaluates the efficacy of the method through the degree of confidence, level of precision, and the degree of streamlining. He compares the highest level of specification to the lowest, as well as to the combination of levels of specification (L1/L5 hybrid) for three different consumer products. This evaluation shows that as a method of estimation, the use of underspecification is accurate. Section 3.3 in the methodology chapter of this thesis further expands on the methodology used by Patanavanich.

Probabilistic underspecification is unique in that it combines both uncertainty and streamlining into LCA – both of which are categories that have not yet been fully implemented in the LCA community. Studies such as Kennedy et al (1997) and Chevalier and Téno (1996) discuss the idea of specifying range endpoints, an idea similar to underspecification. Even more similar is the use of fuzzy sets, which gives probabilities to specific sub-intervals, acknowledging that some values are more likely than others (Lloyd and Ries 2007).

Other stream-lined methodologies are discussed in the literature review performed by Patanavanich. One, presented by Chen and Wai-Kit (2003), is a pattern-based qualitative approach. It groups products into six categories and makes the assumption that products developed using similar methods will have similar characteristics and thus environmental impacts. It does not, however, quantify those environmental impacts. An example of a quantitative method discussed by Patanavanich is presented by Sousa (2000). This parametric life-cycle assessment model creates a neural network that analyzes previously conducted LCAs and distinguishes impacts associated with certain product attribute descriptors. These descriptors can then be combined to quickly estimate the impacts of a product. Patanavanich's conclusion from the review of streamlining methods is that none of them are effective in including uncertainty.

2.4 Gap Analysis

While a variety of different streamlining methods exist, many do not begin to approach the accuracy of full LCAs (Hunt et al. 1998). This is caused, in part, by the lack of uncertainty incorporation in these methods. Not incorporating uncertainty is clearly widespread in the LCA community, but when making an approximation via a streamlining method it becomes even more crucial. The method of probabilistic underspecification presented by Patanavanich is unique in the streamlining category because it does quantify the associated uncertainty. It has yet to be used in a comparative LCA, however. Because the most important consideration in a comparative LCA is that the alternatives are evaluated with the same goal and scope, the potential for probabilistic underspecification as a streamlining method for comparative LCAs is great.

2.5 Research Question

The incorporation of uncertainty into a comparative LCA is crucial for credible results. It allows a level of confidence to be applied to the decision, as well as a greater ability to represent real world scenarios. The feasibility of this extended LCA, however, is restricted both by time and the reliability of the conclusions. This thesis discusses the advantages and disadvantages of two different methodologies for uncertainty incorporation. The first, labeled here as *individual probabilistic specification*, is based on existing literature and is the more rigorous and detailed of the two methods. The second, *probabilistic underspecification*, is a relatively new method that defines uncertainty for all parameters but only details the uncertainty of the key contributors, reducing the time and effort required.

While existing literature agrees that individual specification is an inclusive way of considering uncertainty in an LCA, its time-intensive nature limits its feasibility and accessibility. Probabilistic underspecification is a method of streamlining the LCA process so as to encourage a greater consideration of uncertainty. It takes a material or process input and determines its probability distribution at different levels of specification.

Probabilistic underspecification is only a useful streamlining technique if it allows accurate decisions to be made early enough in the design phase of a product that changes can be made to reduce its environmental impact. Therefore, a means of evaluating the two methodologies must be determined to evaluate the efficacy of probabilistic underspecification. The following research question is thus proposed: *Does the method of probabilistic underspecification allow for a decision to be made with an equal level of confidence to, and less effort than, the method of individual probabilistic specification?* This thesis evaluates the following areas during the comparison of the two methods:

- Reliability/risk of the conclusion drawn, based on the probability distribution of a comparison variable;
- Portion of processes that need to be specified based on percentage of contribution to total uncertainty, and
- Variation in the final result

3 METHODOLOGY

The two methodologies of individual probabilistic specification and probabilistic underspecification are used to quantify the parameter uncertainty in a life cycle inventory (LCI). Other forms of uncertainty discussed in the literature review, such as model and scenario uncertainties, are beyond the scope of this thesis. Additionally, uncertainty about the characterization factors used to transform an LCI to a life cycle impact assessment (LCIA) is neglected.

While measurement uncertainty has been described and included by other sources, *inventory quantity application* and *intermediate flow application uncertainty* (defined in section 3.1) are terms coined specifically for this study and are used to quantify the appropriateness of specific data sources. Additionally, *individual probabilistic specification* is a new term used to describe the more established (albeit erstwhile unnamed) method to assess uncertainty and to differentiate that approach from the other methodology of probabilistic underspecification. Finally, the method of probabilistic underspecification comes directly from Patanavanich (2011), though further expansion and definition of the underspecification data set was performed for this assessment. The two methods presented below have not been previously evaluated in terms of their effectiveness and effort in the context of a comparative LCA example before, nor have they been analyzed within the context of non-consumer goods.

3.1 Types of Uncertainty

This study considers three types of uncertainty that fall under the general umbrella term of parameter uncertainty. The first is *measurement uncertainty*, which is termed basic uncertainty by ecoinvent (Weidema et al. 2011). It refers to errors collected due to the inability to precisely measure a value, whether due to human error, improperly calibrated equipment, or inherent variation of the value within the population being studied. For example, the amount of CO_2 emitted by the combustion of coal is not necessarily a constant because it depends on the quality of the coal and the consistency of the product within a particular shipment. The rate of emission (kg CO_2/kg coal) can be represented by an average, but this value has an inherent distribution associated with it.

The second type of uncertainty is *inventory quantity application uncertainty*. This type addresses the appropriateness of the data source used to represent the amount of a given material or process in the product or system being represented. If, for example, the amount was measured or specified directly for the LCA model, then there would be no quantity application uncertainty. Alternatively, if proxy data were used, uncertainty would be incorporated depending on the applicability of the data in terms of geographic, temporal, and spatial correlation as well as reliability and completeness. Similarly, Lloyd and Reis (2007) include this within their definition of parameter uncertainty variation over time, while Huijbregts (1998a ; 1998b) defines three different types of variability that would be akin to this application uncertainty. However, he does not include them in the scope of his assessment.

Finally, the third type of uncertainty within parameter uncertainty is *intermediate flow application uncertainty*. Across all LCAs, finding appropriate data for the environmental impacts of a certain material or process can be difficult due to limited data availability and/or quality. Flow application uncertainty accounts for the use of proxy flows as a best representation when more precise information is unavailable. A simplified example would be the use of cement data from Switzerland to represent cement made in the United States. There are clearly similarities between these two sources, but there are also differences in the energy sources, electricity grid, and the technology used that would lead to a change of impact between the two locations, and these must be accounted for. This use of proxy flows can be accounted for within the associated probability distribution using uncertainty factors. Huijbregts (1998a ; 1998b) refers to this type of uncertainty as variability between sources and objects.

Quantifying the applicability of both quantity and intermediate flow data is difficult because it is essentially a subjective decision. The two methods presented below are different approaches for characterizing intermediate flow application uncertainty: the first is individual probabilistic specification, which uses data quality indicators, and the second is probabilistic underspecification. They both, however, evaluate inventory quantity application uncertainty in the same way, using data quality indicators, the process of which is discussed in section 3.2.3.1.

3.2 Individual Probabilistic Specification

There are five steps to performing individual probabilistic specification:

1. Data collection
2. Uncertainty quantification
    a. Measurement uncertainty
    b. Inventory quantity application uncertainty quantified using data quality indicators
    c. Intermediate flow application uncertainty quantified using data quality indicators
3. Model creation
4. Monte Carlo simulation
5. Evaluation and interpretation of results

The following sections detail the steps outlined above. Step 5 is presented in section 3.4, after probabilistic underspecification is described, as the same method of evaluation is used within the two methodologies.

3.2.1 Data Collection

The initial data collection required for individual probabilistic specification is the same as that of a standard LCA. Deterministic values are required for all the quantities of materials and processes necessary to assess the systems under study. This includes both the inputs and outputs of materials and processes as well as their associated emissions to air, land, and water. Empirical data is the highest quality and least uncertain source used to detail the specific system. Proxy data can also be used to estimate quantities, but will increase the associated uncertainty.

There are a variety of databases that contain life cycle inventories. These databases include ecoinvent (Swiss Centre for Life Cycle Inventories 2012), PE International (2012), and the US Life Cycle Inventory (USLCI) database (NREL 2012). There are software programs, such as SimaPro (PRe Consultants 2010) and GaBi (PE International 2012) that have incorporated established LCIA methods to transform the database inventories into environmental impacts. Additionally, literature contains many already-characterized values for impacts such as global warming potential and energy use, whether published through academia or organizations like the US Environmental Protection Agency (EPA) (U.S. EPA 2012).

3.2.2 Measurement Uncertainty

Measurement (or basic) uncertainty can be determined through the evaluation of empirical data or expert estimates. While the ideal source is empirical data, they are often quite difficult to obtain due to the scope of data needed and concerns over proprietary information. Empirical data assessment involves the collection of information from all the individual sources that went into the aggregated data, which results in the final averaged value presented by most databases. An example would be assessing the environmental impact of a kilogram of Portland cement from each manufacturer in the United States. A statistical analysis performed on these results creates a distribution around the average from which a variance can be calculated. This variance must then be transformed to the variance of an underlying normal distribution in order to be combined with the other types of uncertainty (DQIs), which are discussed in the following sections. The difficulty in this process, however, is that there are at least eighty-eight cement factories in the U.S., making data collection from all these sources a time-intensive project (PCA 2010). Additionally, the information needed, such as fuel use and total production quantity, is considered proprietary information, which means that few manufacturers will readily release it.

In the absence of readily available empirical information, one can use expert estimates. ecoinvent (Weidema et al. 2011) provides their own set of expert estimates categorized by process or material type as well as type of emissions. See Table 3.1 for the complete list of basic uncertainty factors.

Table 3.1 Basic Uncertainty Factors (Weidema et al. 2011)

Input / output group	c	P	A
demand of:			
thermal energy, electricity, semi-finished products, working material, waste treatment services	0.0006	0.0006	0.0006
transport services (tkm)	0.12	0.12	0.12
Infrastructure	0.3	0.3	0.3
resources:			
primary energy carriers, metals, salts	0.0006	0.0006	0.0006
land use, occupation	0.04	0.04	0.002
land use, transformation	0.12	0.12	0.008
pollutants emitted to water:			
BOD, COD, DOC, TOC, inorganic compounds (NH_4, PO_4, NO_3, Cl, Na etc.)		0.04	
Individual hydrocarbons, PAH		0.3	
heavy metals		0.65	0.09
Pesticides			0.04
NO_3, PO_4			0.04
pollutants emitted to soil:			
oil, hydrocarbon total		0.04	
heavy metals		0.04	0.04
Pesticides			0.033

Input / output group	c	p	a
pollutants emitted to air:			
CO_2	0.0006	0.0006	
SO_2	0.0006		
NMVOC total	0.04		
NO_X, N_2O	0.04		0.03
CH_4, NH_3	0.04		0.008
Individual hydrocarbons	0.04	0.12	
PM>10	0.04	0.04	
PM10	0.12	0.12	
PM2.5	0.3	0.3	
Polycyclic aromatic hydrocarbons (PAH)	0.3		
CO, heavy metals	0.65		
Inorganic emissions, others		0.04	
Radionuclides (e.g., Radon-222)		0.3	

These factors represent the variance of the underlying normal distribution, meaning they are normalized to be applicable to any factor. The following section explains how to incorporate the basic uncertainty factor with the other types of uncertainty.

3.2.3 Application of Data Quality Indicators

The use of data quality indicators (DQIs) is one option to quantify the uncertainty due to data quality and appropriateness. Lloyd and Ries (2007) found that of the 24 LCAs they investigated that incorporated uncertainty, seven make use of data quality indicators. Of those seven, five use DQIs directly to quantify the value of the uncertainty, while two use DQIs indirectly to indicate which inputs need to be focused on and further refined. ecoinvent is one source that has established their own set of data quality indicators using a pedigree matrix approach adapted from Weidema and Wesnaes (1996) and Weidema (1998) (see Table 3.2).

Table 3.2 Definitions of Pedigree Matrix scores (Weidema et al. 2011)

Indicator score	1	2	3	4	5 (default)
Reliability	Verified[5] data based on measurements[6]	Verified data partly based on assumptions *or* non-verified data based on measurements	Non-verified data partly based on qualified estimates	Qualified estimate (e.g. by industrial expert)	Non-qualified estimate
Completeness	Representative data from all sites relevant for the market considered, over an adequate period to even out normal fluctuations	Representative data from >50% of the sites relevant for the market considered, over an adequate period to even out normal fluctuations	Representative data from only some sites (<<50%) relevant for the market considered *or* >50% of sites but from shorter periods	Representative data from only one site relevant for the market considered *or* some sites but from shorter periods	Representativeness unknown or data from a small number of sites *and* from shorter periods
Temporal correlation	Less than 3 years of difference to the time period of the dataset	Less than 6 years of difference to the time period of the dataset	Less than 10 years of difference to the time period of the dataset	Less than 15 years of difference to the time period of the dataset	Age of data unknown or more than 15 years of difference to the time period of the dataset
Geographical correlation	Data from area under study	Average data from larger area in which the area under study is included	Data from area with similar production conditions	Data from area with slightly similar production conditions	Data from unknown *or* distinctly different area (North America instead of Middle East, OECD-Europe instead of Russia)
Further technological correlation	Data from enterprises, processes and materials under study	Data from processes and materials under study (i.e. identical technology) but from different enterprises	Data from processes and materials under study but from different technology	Data on related processes or materials	Data on related processes on laboratory scale *or* from different technology

The pedigree matrix in Table 3.2 considers five different categories in assessing data quality: reliability, completeness, temporal correlation, geographical correlation, and technological correlation. Depending on the score assigned for each category, evaluated based on the descriptions given in the matrix, indicator scores are assigned according to Table 3.3, providing a variance (σ^2) of the underlying normal distribution.

Table 3.3 Indicator Score (Weidema et al. 2011)

Indicator score	1	2	3	4	5
Reliability	0.000	0.0006	0.002	0.008	0.04
Completeness	0.000	0.0001	0.0006	0.002	0.008
Temporal correlation	0.000	0.0002	0.002	0.008	0.04
Geographical correlation	0.000	2.5e-5	0.0001	0.0006	0.002
Further technological correlation	0.000	0.0006	0.008	0.04	0.12

The five categories within the matrix, along with the measurement uncertainty from Table 3.2, are combined using the following equations (Weidema et al. 2011):

$$\sigma^2(X+Y)=\sigma^2(X)+\sigma^2(Y)+2\operatorname{cov}(X,Y) \qquad [3\text{-}1]$$

$$\sigma^2=\sum_{n=1}^{6}\sigma_n^2 \qquad [3\text{-}2]$$

In equation 4-1, the variables X and Y, which are characterized by the same type of distribution but with different properties, are assumed to be independent, and therefore the covariance is equal to zero, allowing the variances to simply be summed for all categories as in equation 3-2. The variable n represents the five pedigree matrix categories plus the measurement uncertainty from the previous section.

The indicator score values assigned to the DQIs (Table 3.3) were used directly as the quantification of the uncertainty because they provide a consistent method of valuation across all inputs. Therefore, the contribution of uncertainty due to different parameters and types of uncertainty can be accurately compared.

3.2.3.1 Inventory Quantity Application

The inventory quantity application uncertainty is quantified using the DQIs by evaluating the source of inventory data based on the five categories in the pedigree matrix (Table 3.2). If the values are adapted from sources not wholly applicable to the systems being assessed, then they will score higher within the pedigree matrix and have a greater uncertainty. If they are, however, directly specified for each of the parameters, then the uncertainty will be zero. For example, a certain pavement design for a concrete road dictates that the diameter of the dowel bars (steel) should be 1.5" but does not specify the length. The quality of the data for the diameter is very high, as it is specified precisely for the pavement being studied. Therefore, "ones" are awarded for all five categories of the pedigree matrix for the inventory quantity application uncertainty. The length and material density values, however, have to be specified using alternate sources. A design for a similar road could be used to specify the length at 12 inches. Depending on the date and location of the proxy design, in reference to the road being assessed, the categories of temporal and geographical correlation will have a higher value of uncertainty. Additionally, depending on the source of the proxy design, the completeness and reliability categories may have to increase in uncertainty as well. Finally, the material density is taken from a textbook as the typical value for steel. This value might be confident temporally and geographically, but technological correlation may be off if a less refined type of steel could be used for rebar.

3.2.3.2 Intermediate Flow Application

Intermediate flow application uncertainty is addressed in much the same way as inventory quantity application uncertainty. Instead of assessing the appropriateness of the data source of the quantity, however, the quality of data used for the impact flow is quantified. The rebar used previously as an example also has a unit weight associated with it that translates the material volume into a mass. While this has an inventory quantity application uncertainty it also serves as the connection between the inventory and the impact. The appropriateness of the intermediate flow is again evaluated based on the five pedigree matrix categories in Table 3.2. Using an impact factor for rebar made in the U.S. might be the most appropriate, but only information for rebar made in Europe is available, and therefore has to be used as a substitute.

The variance values for inventory quantity application uncertainty, measurement uncertainty, and intermediate flow application uncertainty are combined into a single variance using equation 3-2. As long as they all are based on the same distribution, in this case normal, then they can be summed, otherwise they need to be transformed first into equivalent distributions. This total variance is then applied to the inventory quantity input, creating a probability distribution on that value, as seen in Figure 3.1(a). Figure 3.1 presents a simplified version of the methodology. In actuality, a Monte Carlo simulation is performed with 10,000 runs, which when combined create the final probability distribution. This thesis automatically assigns a lognormal distribution to the data so as to ensure a value above zero (Huijbregts et al. 2003). Figure 3.2 summarizes the different types of uncertainty.

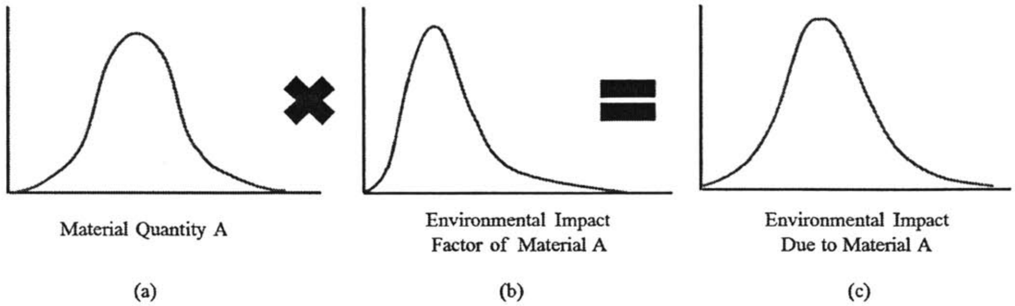

Figure 3.1 Visual of uncertainty application depicting the distributions for: (a) material quantity, (b) the environmental impact factor, and (c) the total environmental impact attributed to the material

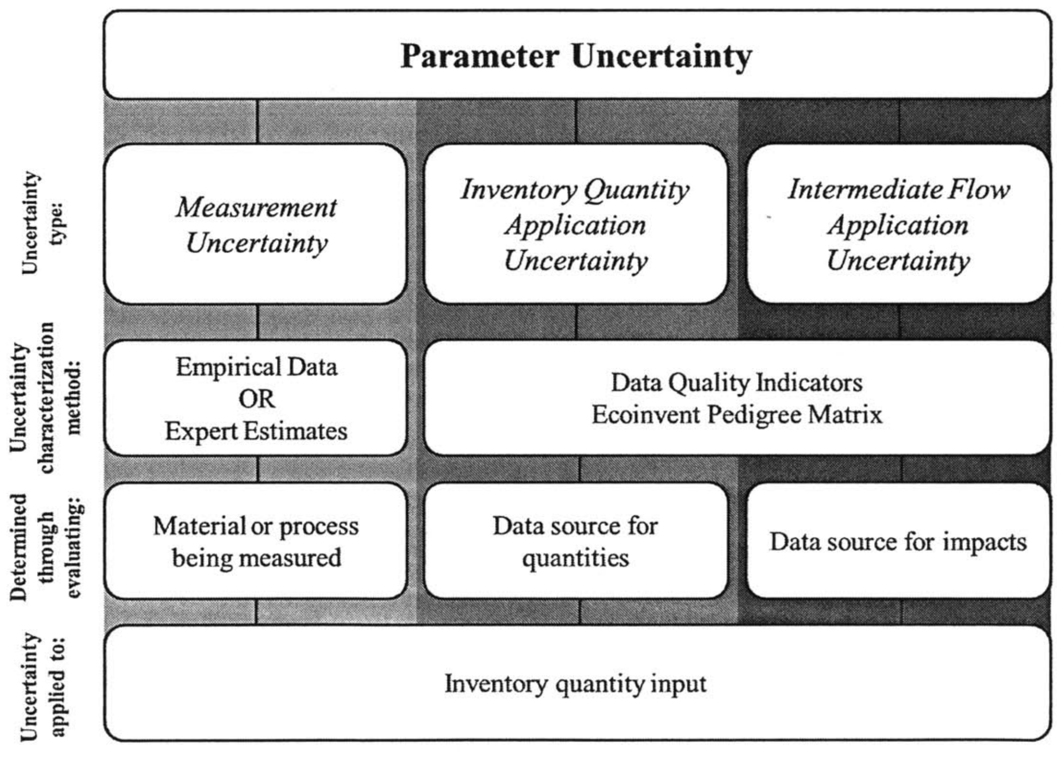

Figure 3.2 IPS Uncertainty characterization method

3.2.3.3 Upstream Uncertainty

Measurement and application uncertainties should be applied to all upstream data as well, from mineral extraction to the gate of the processing plant. As an LCA practitioner, however, this is infeasible due to the vast magnitude of data it would be necessary to evaluate. The benefit of using both the ecoinvent impact data and ecoinvent DQI methodology (Swiss Centre for Life Cycle Inventories 2012 ; Weidema et al. 2011) is that the database records its own application of the DQIs and basic uncertainty. This allows for an estimate of the aggregate upstream measurement and inventory quantity application uncertainties, which can then be applied as a distribution to the relevant impact factor, as seen in Figure 3.1 (b).

3.2.4 Monte Carlo Simulation

Once the uncertainty has been quantified for all parameters, they are incorporated into individual probability distributions, assigned either to the quantity input or the impact factor. This allows for a Monte Carlo simulation to be performed. Tools like Crystal Ball (Oracle 2012), which work within Microsoft Excel, allow for this direct random sampling from the assigned distributions. A Monte Carlo simulation is used because it allows for the incorporation of probability distributions, which acknowledges that some values are going to be more likely than others. Within a Monte Carlo simulation values are chosen at random, based on the assigned distribution of each parameter, for a specified number of iterations. Depending on the model setup, parameter values are combined resulting in an output value for each run, which then creates a probability distribution for the final result. Another benefit of using a Monte Carlo simulation is that it can consider correlation between parameters within the model. It should be noted, however, that one aspect neglected in the scope of this thesis, due to feasibility, is the exclusion of certain combinations of parameters that may represent impossible scenarios. Future work should attempt to include this area of study.

De Koning et al (2009) conclude in their paper that "calculations for products can only provide a fair comparison if the LCA background system used for the two products is the same" (79). This means the same constants must be used for factors between the two systems being compared, such as environmental impact factors. Within the authors' comparison of laundry detergents, this refers to water temperature, washing machine electricity mix, efficiency of the washing machine, and transportation distance from the manufacturer, among others. When performing a Monte Carlo assessment, one needs to ensure that for each run the appropriate constants are the same between the systems being compared in order to allow for accurate comparisons.

3.3 Probabilistic Underspecification

In contrast to individual probabilistic specification, probabilistic underspecification allows the practitioner to broadly define a material or process category depending on the contribution to the total uncertainty. As mentioned in Section 2.3, probabilistic underspecification was first introduced by Patanavanich (2011). The following sections will briefly summarize Patanavanich's methodology, but for further information see the original literature. The steps below represent the methodology for probabilistic underspecification.

1. Data collection
2. Pedigree matrix application and upstream uncertainty
3. Designation of underspecification levels
4. Monte Carlo simulation
5. Evaluation and interpretation of results

Step 4 has already been described in section 3.2.4, because it does not vary from the IPS methodology. Additionally, step 5 is presented in section 3.4 as it is the same between the two methodologies.

3.3.1 Data Collection

Probabilistic underspecification is based on the significant availability of a variety of generic processes in established databases, such as ecoinvent (Swiss Centre for Life Cycle Inventories 2012) and PE (PE International 2012). It may be unclear when performing an LCA whether a specific process is appropriate for the system being studied, or if the appropriate process is even available. Often, proxy data is used as a best guess by the practitioner. By instead gathering all the data within a given category and sampling using a Monte Carlo analysis, a descriptive probability distribution can be determined for a given category. The categories are defined at different levels of specification according to different material or process characteristics (see Figure 3.3).

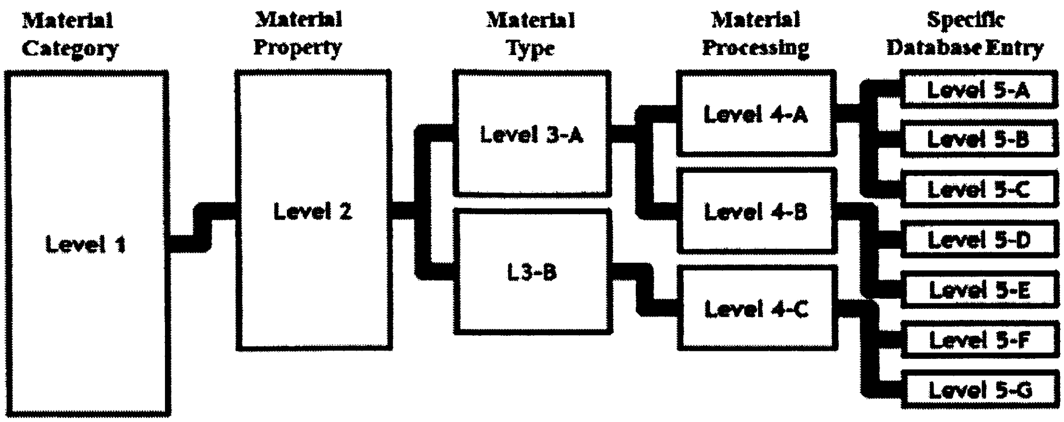

Figure 3.3 Underspecification Hierarchy (Patanavanich 2011)

At the broadest level is the material category, which is the least specific. An example would be all metals (L1), which would include materials like copper or steel. It is important to make sure that all processes within a given material category are defined by the same units. Freight transportation, for example, is in units of ton-kilometers (tkm), which is different from person transportation, defined by person-kilometers (person-km). As there is no way to convert between the two, they cannot be combined into a single transportation category. The next level up of specification (L2) is the material property, which divides the material category according to the most basic of characteristics. Metals can be divided into ferrous, non-ferrous, and alloys, while freight transportation can be divided into ground, water, and air transport. One can continue specifying further within these categories until level 5 (L5) is reached, which is the specific database entry. See Appendix A for a detailed list of transportation underspecification levels established for this study. Because further specification is needed for an individual process within an LCA, more effort is required to accurately label it and characterize its uncertainty.

3.3.2 Pedigree Matrix Application and Upstream Uncertainty

There is a median level of uncertainty applied through the pedigree matrix that accounts for the upstream data quality uncertainty at L5 data specification. Additionally, the pedigree matrix is applied to the inventory quantity application uncertainty, and measurement uncertainty is included, as in individual probabilistic specification. Figure 3.4 summarizes the types of uncertainty included in the methodology. The differences between this figure and Figure 3.2 are in the uncertainty characterization method for inventory quantity and intermediate flow application uncertainties. Additionally, the factor to which the intermediate flow application uncertainty is applied to changes from the inventory quantity input to the intermediate flow impact factor.

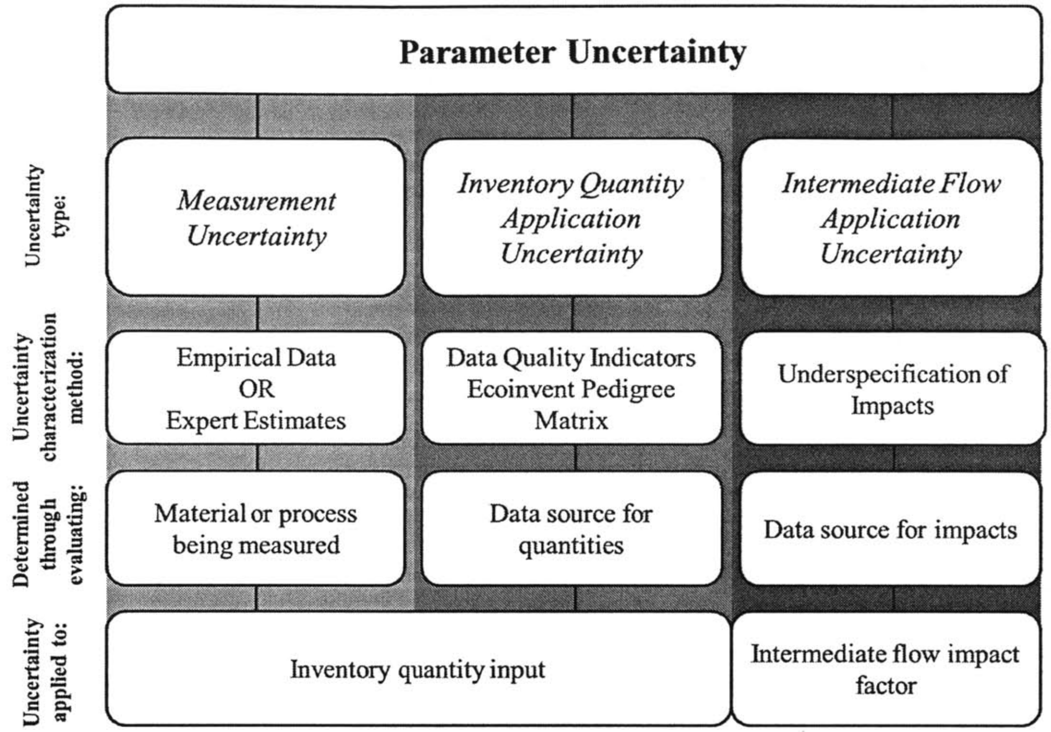

Figure 3.4 PU Uncertainty characterization method

3.3.3 Designation of Underspecification Levels

The aim of probabilistic underspecification is to be able to limit the number of processes that must be specified in detail, while still being able to draw a conclusion from the comparison. Initially, all the processes are defined at the lowest level of specification, L1. Then, a Monte Carlo simulation is run, just as in the method of individual probabilistic specification. The environmental factors that are defined at L1 contribute a certain amount to the uncertainty of the total. Those that contribute more than 5% (an arbitrary value that may be adjusted) need to be defined at a greater specificity, L5. These processes can be determined through a sensitivity analysis. While there a variety of ways to conduct a sensitivity analysis, Crystal Ball (Oracle 2012) does so by computing the rank correlation between each input parameter (that has an associated uncertainty distribution), the assumption, and the final total value, the forecast (EPM Information Development Team 2010). Essentially, this process quantifies the amount that each assumption can change the forecast. These rank correlation coefficients are then transformed to a contribution to variance value by "squaring the rank correlation coefficients and normalizing them to 100%" (EPM Information Development Team 2010, 170). This method is not without faults, as it may not capture correlated results and non-monotonic relationships. It is, however, only used as a method to pinpoint which parameters need to be further specified so that a decision can be made between the two alternatives.

While the levels are defined from 1 through 5, this methodology is only concerned with specified and unspecified, which in this case is L1 and L5, respectively. If defining processes at L5 does not significantly decrease the number of processes that need to be specified then there is little point in exploring the other levels, which have higher uncertainties than L5. In future applications of this methodology if the L5 information is unavailable, L4, L3, or L2 data presents a viable proxy if further specification is needed.

After changing the necessary parameters to L5, another Monte Carlo simulation is performed. If a decision can then be made according to the evaluation methodology presented in section 3.4, the assessment is complete. If not, the sensitivity analysis will show which of the remaining parameters need to be further specified. This cycle of parameter specification, Monte Carlo simulation, and sensitivity analysis is repeated until the results meet the adequate levels of confidence or until a threshold value for the median absolute deviation coefficient of variation (MAD-COV) is reached. In the case study presented in the following chapter, this value is 10%, though this is arbitrarily chosen.

3.4 Evaluation of Results

In order to account for the correlation between the two systems being evaluated, an indicator variable is used to compare the alternatives for each run of the Monte Carlo simulation. This comes from the comparison indicator variable used by Huijbregts (2003):

$$CI_u = \frac{r_{u,A}}{r_{u,B}} \qquad [3\text{-}3]$$

Where:

CI_u = comparison indicator for impact category, u

$r_{u,A}$ and $r_{u,B}$ = impact total of product A or B for impact category, u

When the value is less than one, the impact of product A is less than that of product B. The output from each run allows a probability distribution to be determined for the likelihood of product A being less than, equal to, or greater than product B. In order to determine if the two products can be considered statistically different, CI_u must be less than or greater than a specified value, δ, with a certain level of confidence, α. The value, δ is termed the ratio of alternatives and is specified by the practitioner and represents the amount by which design A must be less than design B. The term α is akin to a one-sided confidence interval. If the value of the CI and its associated confidence interval, α, falls below δ, then design A can be accepted as having a lower impact than design B with the associated level of confidence. If not, then more information is needed to make the decision. This further information includes data quality for parameters or the consideration of another impact assessment method, such as cost. The values presented in Table 3.4 are used in the case study below when evaluating the results of each methodology.

Table 3.4 Values used to evaluate statistical significance of results

Ratio of Alternatives	δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	α	50%	75%	90%	95%	99%		

4 CASE STUDY OF PAVEMENTS

A case study comparing three pairs of alternative pavement designs is presented below to evaluate the two methodologies presented in the previous section. As a significant portion of most countries' infrastructure, pavements are an important field of study to evaluate and better define the associated environmental impacts. First, a literature review discusses current pavement LCAs, followed by the goal and scope of the LCA being performed. Finally, the results are presented for each methodology.

4.1 Pavement LCA Literature Review

Santero (2010) provides a comprehensive overview of existing pavement LCAs and the modeling techniques used to perform them. He reviews twelve papers that conduct a pavement LCA and three pavement LCA models that have been developed. Finally, he identifies gaps and inconsistencies between them. A significant variation between the studies concerns which phases were included in the studies' scopes. This lack of consistency does not allow for comparisons to be made between results. Santero concludes his overview by listing recommendations for improvements and greater equivalency across pavement LCAs. One of these recommendations is the inclusion of an uncertainty analysis that considers errors both in data accuracy and the implementation of the model because it is neglected by all of the studies.

One of the conclusions drawn by Santero (2010) is that the pavement-related activities included in the boundary of the LCA varies significantly by study. This includes the phases of the LCA, materials, construction, use, maintenance, and end-of-life, as well as the scope of those phases. The use phase, for example, can include rolling resistance, albedo, carbonation, lighting, leachate, and tire wear, and any combination thereof. In Santero and Horvath (2009), the authors include eight categories in their LCA: materials, transportation, construction, carbonation, lighting, albedo, and rolling resistance. By exploring the literature values on the probable ranges and extreme values of the global warming potential, the authors determine the potential portion of the total that could be attributed to each phase. This method allows a pavement LCA practitioner to focus effort on collecting data for the phases that contribute the most.

4.2 Goal

This study compares two pavement alternatives for three locations in southern California representing low, medium, and high-volume traffic conditions. Each location involves a comparison between a hot-mix asphalt (HMA) pavement design and a jointed plain concrete pavement (JPCP) design. The intent is to assess the three different scenarios using both the methodologies of individual probabilistic specification and probabilistic underspecification to compare the effectiveness of probabilistic underspecification at accounting for uncertainty while streamlining the LCA process. The intended audience is both the LCA and pavement communities, as this study provides an example of a pavement LCA that incorporates uncertainty as well as a process to reduce the time, and thus cost, required to perform a comparative LCA, while still incorporating uncertainty.

4.3 Scope

The primary energy use and global warming potential of two alternative designs in southern California are calculated in each of the three scenarios. The scope includes only the components that can be attributed to the pavement design itself, rather than the decision to build a road in the first place. The functional unit, system boundary, and impact assessment are presented in the following sections.

4.3.1 Functional Unit

The functional unit for this study is one kilometer of pavement under a given traffic condition. It must be noted that the functional equivalence of different pavement designs is a significant source of controversy within pavement LCAs. The designs used in this study are considered to be equivalent because they were created using California Department of Transportation (Caltrans) specifications for the same location (Caltrans 2012). By using designs that are regulated by an authority for a specific region and range of traffic, one can imagine a scenario where a choice would be made between the two alternatives. The designs are detailed in Table 4.1, while Table 4.2 describes their associated maintenance schedules. The time horizon of the study is 55 years, and therefore includes any maintenance necessary for it to remain functional throughout that time. This time horizon was chosen because Caltrans uses this time period for its

LCAs and life cycle cost assessments (LCCA), so its pavements and maintenance schedules are designed to make the pavements function for 55 years (Caltrans 2007).

Table 4.1 Pavement scenarios (Caltrans 2012 ; Mack 2012)

		Low Volume	Medium Volume	High Volume
Location		Oxnard, CA	Ramona, CA	Oxnard, CA
AADT (*vehicles/day*)		3,400	23,400	139,000
AADTT (*trucks/day*)		150	1,357	6,672
Lanes		2	4	6
Lane Width (*m*)		3.70	3.70	3.70
Paved Shoulders		0	4	4
Shoulder Width (*m*)		3.05	3.05	3.05
CALTRANS DESIGNS				
Concrete (JPCP)	Concrete thickness (mm)	215	245	275
	Dowel bar diameter (mm)	32	32	38
	Lean concrete base thickness (mm)	110	120	150
	Aggregate subbase thickness (mm)	150	180	215
Asphalt (HMA)	Asphalt thickness (mm)	120	170	200
	Aggregate base thickness (mm)	215	270	320
	Aggregate subbase thickness (mm)	150	215	245

Table 4.2 Maintenance schedule (Caltrans 2012 ; Mack 2012)

Low Volume		Medium Volume		High Volume	
Year	*Activity*	*Year*	*Activity*	*Year*	*Activity*
Concrete Pavement					
25	2% Patch, DG	25	2% Patch, DG	45	2% Patch, DG
30	4% Patch, DG	30	4% Patch, DG	50	4% Patch, DG
40	6% Patch, DG	40	6% Patch, DG		
45	3" Asphalt Overlay	45	3" Asphalt Overlay		
Asphalt Pavement					
20	3" Asphalt Overlay	20	3" Asphalt Overlay	20	3" Asphalt Overlay
30	Mill / 3" AC Overlay	25	Mill / 4" AC Overlay	25	Mill / 4" AC Overlay
40	Mill / 2.5" AC Overlay	35	Mill / 3" AC Overlay	35	Mill / 3" AC Overlay
45	Mill / 3" AC Overlay	45	Mill / 4" AC Overlay	45	Mill / 4" AC Overlay
		50	Mill / 3" AC Overlay	50	Mill / 3" AC Overlay

*DG = Diamond Grinding

4.3.2 System Boundary

Based on Santero (2010) it was clear that all five phases of the lifecycle of a pavement should be included to encompass the entire impact of the pavement design. Figure 4.1 depicts the system boundary of the LCA, which includes material extraction, construction of the pavement, impacts during the use phase, maintenance and rehabilitation requirements, and end-of-life.

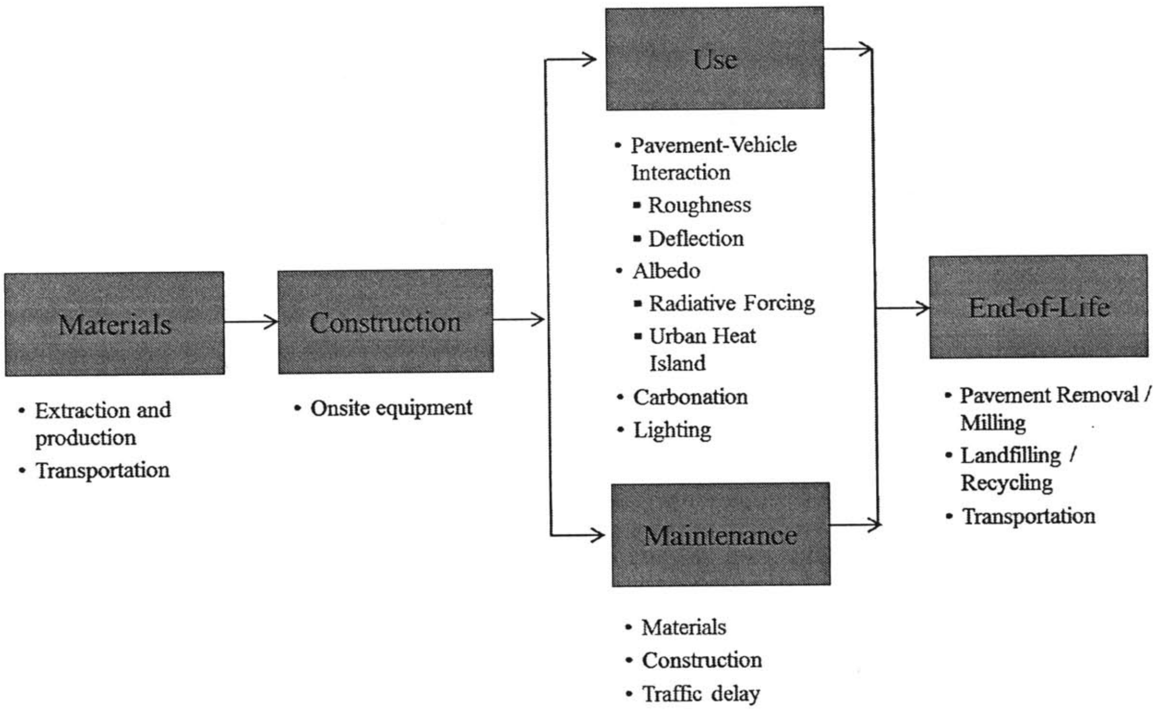

Figure 4.1 LCA System Boundary

Within each of these phases are subcategories. The use phase includes impacts that depend on the pavement design itself. This accounts for anything that would change between the two designs. Lighting requirements, for example, change depending on whether the pavement is asphalt or concrete, as do albedo impacts. Pavement-vehicle interaction depends both on how the roughness of the road changes with time and the deflection of the pavement due to material properties of the layers, which impacts the fuel consumption of the cars and trucks using the road. The scope accounts only for the change in fuel consumption, however, as compared to the initial condition of the pavement. Therefore the roughness and deflection fuel consumption impacts do not include the entire fuel consumption that could be attributed to vehicles driving over the one kilometer of road. Additionally, albedo and lighting impacts are only calculated as the difference between the two pavements, taking into account the additional requirements or properties that one design may have. These are then added to the asphalt design totals, whether they end up being negative or positive.

The end-of-life activities could encompass anything from complete disposal through landfilling to 100% recycling of the material being removed. Both methods have their complexities, but the rate of recycling is so variable from project to project that it requires far more assumptions by the practitioner. Santero (2010) points out that landfilling is the simplest approach, and because this case study is primarily meant to compare methodologies, the method of landfilling is thus applied.

4.3.3 Life Cycle Inventory

The data sources and methods used for the inventory quantities and process impacts are detailed in the following sections.

4.3.3.1 Bill of Activities

The pavement designs come from the Caltrans specifications for southern California roads (Caltrans 2012). Their effectiveness and future characteristics were evaluated using the mechanistic empirical pavement design guide (MEPDG) combined with the DARWIN-ME software, which implements the calculations specified by MEPDG (ARA 2009 ; National Cooperative Highway Research Program et al. 2004). MEPDG is specified by the Federal Highway Administration (FHWA) as an improvement to the previous design manual, which did not account for variations in climate, increased truck loads, or variations in rehabilitation requirements and material properties, along with other deficiencies. It allows for optimization of the pavement design in order to reduce material usage and cost. The designs were run through the Darwin-ME software by Jim Mack of CEMEX (2012). The inventory quantities were derived from the MEPDG output file, which contains the material type and quantity specifications from Caltrans.

Transportation data for most materials were obtained from the US Bureau of Transportation Statistics, while cement transportation information was calculated from the PCA environmental surveys discussed previously (PCA 2010 ; BTS 2007).

Pavement-vehicle interaction consists of two parts: fuel losses due to changes in roughness and fuel losses due to deflection of the pavement. The deflection losses are calculated by Mehdi Akbarian according to the method published by Akbarian and Ulm (2012), which takes into account the increased fuel loss, over time, due to the decay of material properties, such as stiffness. Additionally, data quality evaluations via the pedigree matrix are incorporated to account for uncertainty. The roughness is an output in meters per kilometer (inchers per mile) calculated by MEPDG, based on pavement and traffic properties specified by the engineer. To calculate fuel loss, the roughness average for each month is compared to a baseline of 1 m/km (60 in/mi). This is the default minimum roughness used by MEPDG and is the typical best that a contractor can achieve in terms of smoothness for a pavement. This roughness is then combined with the average daily traffic for trucks and cars and their associated gas mileage. Finally, Zaabar and Chatti (2010) have established estimates for fuel loss due to an increase in roughness for a variety of vehicles, which allows for a final inventory of additional fuel consumption required due to changes in roughness over the given time horizon. The roughness is reset to the starting value after each maintenance activity. See Appendix B for detailed calculations.

Albedo relates to the reflectivity of the pavement. Concrete has a high value of reflectivity and asphalt has a low value. Higher reflectivity reduces the impact of the urban heat island effect and the radiative forcing capability of the area. The method used to calculate the carbon dioxide equivalents (CO_2e) offset comes from Santero and Horvath (2009). The difference is compared between asphalt and concrete, with the additional CO_2e due to this difference added to the asphalt pavement. An aspect neglected both in their methodology and this study is the change of albedo with the age of the pavement because there is inadequate information available on the topic. Additionally, the method of calculating the CO_2e offset due to carbonation of concrete is also based on Santero and Horvath (2009), who adapt it from Lagerblad (2005). Finally, the electricity required for lighting, which varies based on state DOT specifications, is also calculated using the methodology detailed in Santero and Horvath (2009).

See Appendix C for a detailed list of inventory quantities.

4.3.3.2 Unit Process Inventory Data

Environmental impact quantity data was obtained from the ecoinvent and United States life cycle inventory (USLCI) databases (NREL 2012) using SimaPro software (PRe Consultants 2010). Additionally, the environmental impact of cement was calculated using confidential energy and material usage surveys for individual cement plants obtained from the Portland Cement Association (PCA) (2010).

4.3.4 Impact Assessment

The environmental impacts assessed by this study are primary energy use and global warming potential (GWP). They are calculated using the Impact 2002+ midpoint category characterization method (Jolliet et al. 2003). Primary energy, also known as non-renewable energy (NRE), refers to both the feedstock (embodied) and combustion energy due to fossil fuel use, and is an important metric to quantify because asphalt is a co-product of crude oil refining and therefore uses a large amount of embodied fossil fuel energy. The units used for NRE are megajoules (MJ). GWP is defined as kilograms of carbon dioxide equivalents (CO_2e). The characterization factors for other greenhouse gases (GHG) to be converted into CO_2e come from the International Panel on Climate Change (IPCC) global warming potentials (IPCC 2001).

4.4 Individual Probabilistic Specification

The results for the individual probabilistic specification methodology are presented below for the environmental impacts of GWP and NRE, respectively. First, the results from the low-volume road are discussed in detail, then the results for the medium- and high-volume roads are summarized.

4.4.1 Low-Volume Scenario Results

The graph in Figure 4.2 depicts the median GWP of the asphalt and concrete designs for the low-volume traffic road being assessed. The error bars represent the 5^{th} and 95^{th} percentile GWP values. The median absolute deviation coefficient of variation (MAD-COV) for the asphalt and concrete designs are 5.5% and 6.6%, respectively. This graph shows that while the variation of each is relatively equivalent, the asphalt design has a greater GWP than the concrete design.

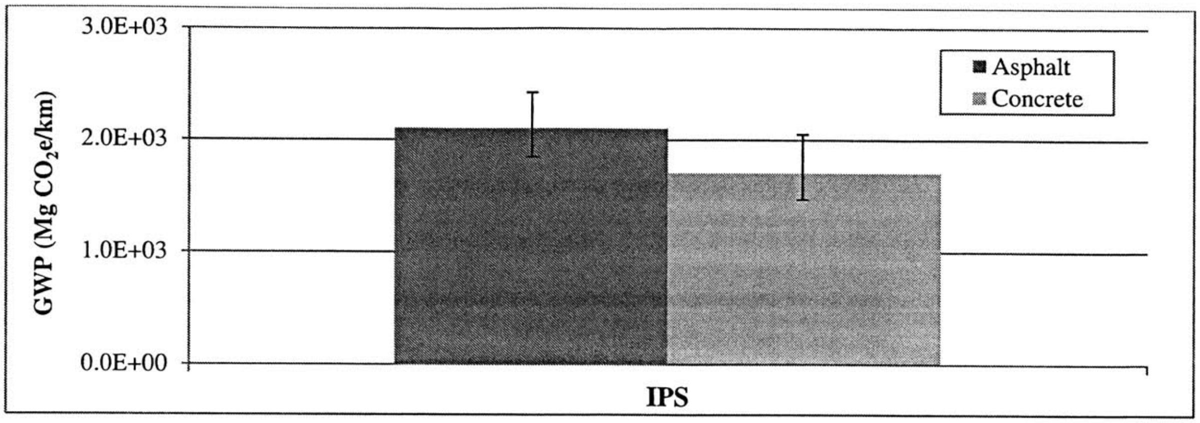

Figure 4.2 IPS GWP: Results depicting the 5th percentile, median (50th percentile), and 95th percentile

Figure 4.3 details the same GWP results broken down by life cycle phase. It can be seen that while the initial construction phase dominates for the concrete design, asphalt dominates significantly for the use phase. The use phase accounts for the increased impacts due to albedo in asphalt and the decreased impacts due to carbonation in concrete, which increase the difference between the two. The pavement-vehicle interaction (PVI) also has a greater impact for the asphalt design than the concrete. The construction impacts for the concrete design can primarily be attributed to the impacts from cement.

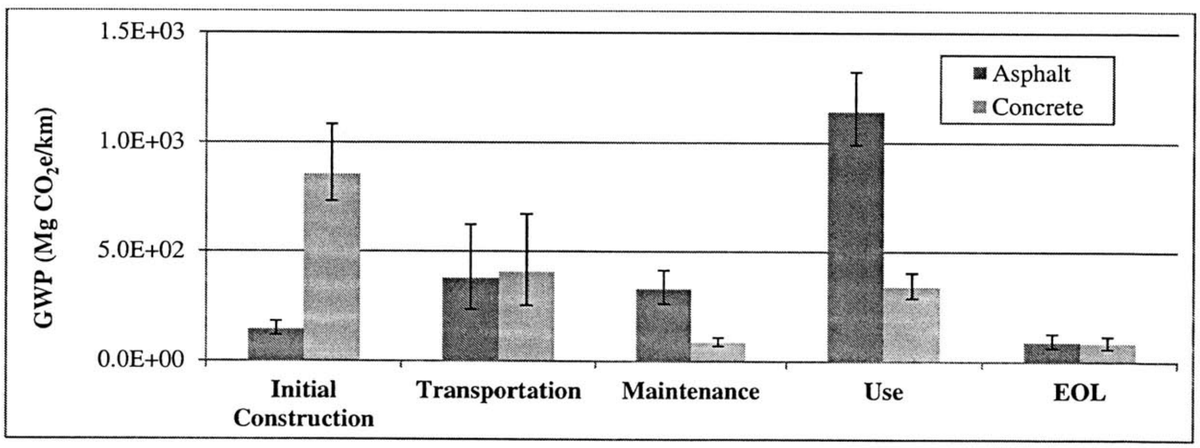

Figure 4.3 IPS GWP: Results by phase depicting the 5th percentile, median (50th percentile), and 95th percentile

Figure 4.4 is a histogram showing the frequency of the asphalt and concrete results from the Monte Carlo simulation. There is significant overlap between the results. In order to make a decision that accounts for the correlation between the two alternatives, the designs must be compared to each other after each run within the Monte Carlo simulation.

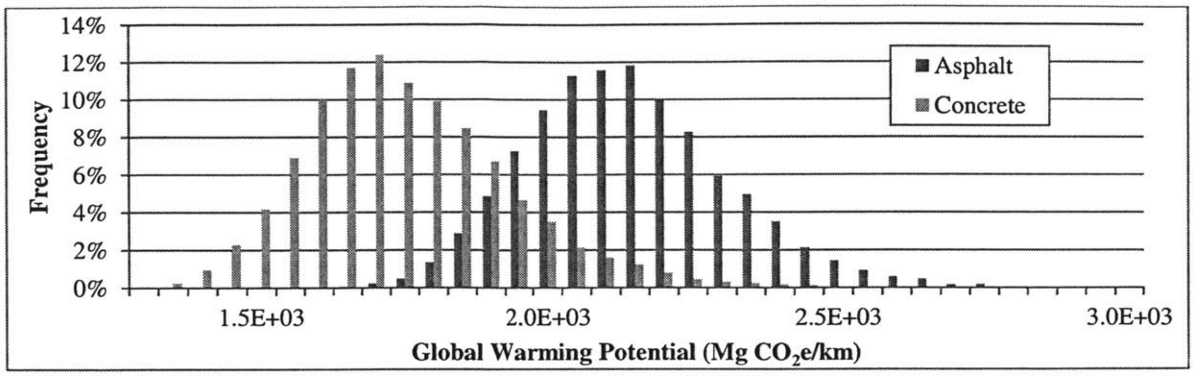

Figure 4.4 IPS GWP: Results histogram

To account for the correlation between the designs, the indicator variable, discussed previously in section 3.4, is presented in Figure 4.5. While the concrete design appears to have less of an impact than the asphalt design because the majority of the values of the histogram fall below one, the confidence interval and difference between the two must still be evaluated.

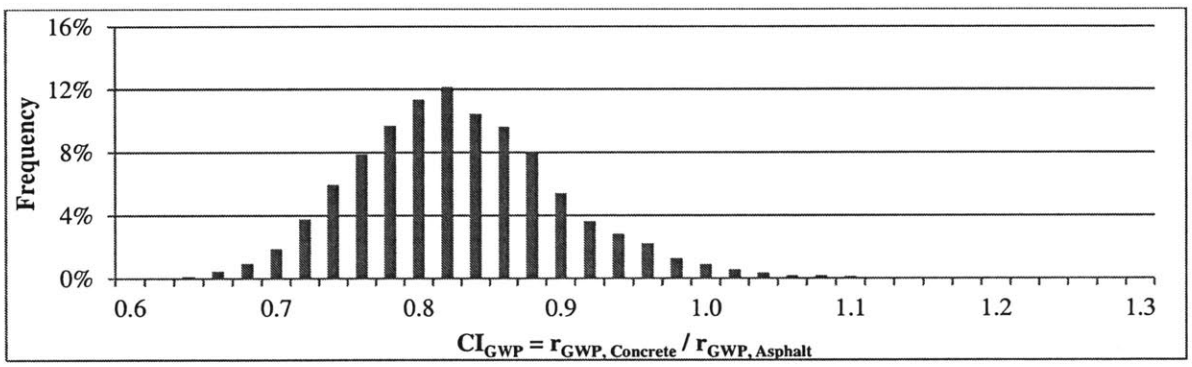

Figure 4.5 IPS GWP: Indicator variable histogram

Table 4.3 presents a statistical analysis of the differences between the two designs. The values of δ represent the magnitude of that difference. When δ is equal to or less than 1.00, the concrete design is equal in impact, or less than, the impact of the asphalt design. If, instead, the ratio of alternatives is equal to 0.95, then the concrete design impact is 95% the impact of the asphalt design, or more. Alternatively, one could say that the concrete design has at least 5% less of an impact than the asphalt. The values of α depict the level of confidence that the indicator variable is less than δ, based on the probability distribution of the indicator variable. It can be seen in Table 4.3 that with a low level of confidence (50%) one can say that the concrete design impact will be less than the impact of the asphalt design by at most 15%. Higher levels of confidence (90% or 95%) show the difference would be at most 5%.

Table 4.3 IPS GWP: Statistical analysis of indicator variable

	α | δ	Ratio of Alternatives						
		1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	90%	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	95%	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	99%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive

The results for NRE are much more extreme than for GWP, with Figure 4.6 showing that the asphalt design is approximately twice the impact of the concrete design. The MAD-COV of the asphalt and concrete designs NRE impact are 4.6% and 6.9%, respectively.

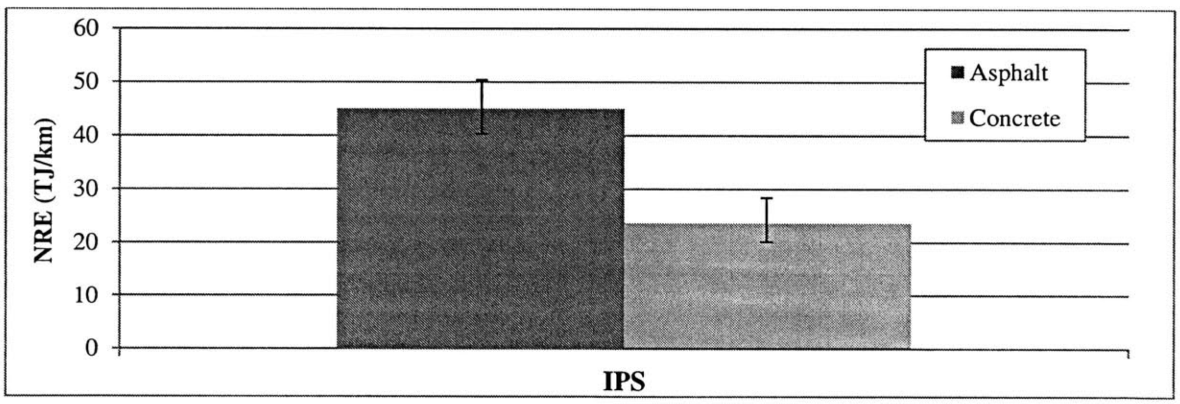

Figure 4.6 IPS NRE: Results depicting the 5th percentile, median (50th percentile), and 95th percentile

The difference between the designs is shown mainly in the embodied energy of asphalt because it is a co-product of oil refining, and therefore most of this difference can be seen during the maintenance phase (see Figure 4.7) due to the additional material requirements required for repair over the asphalt pavement's lifetime.

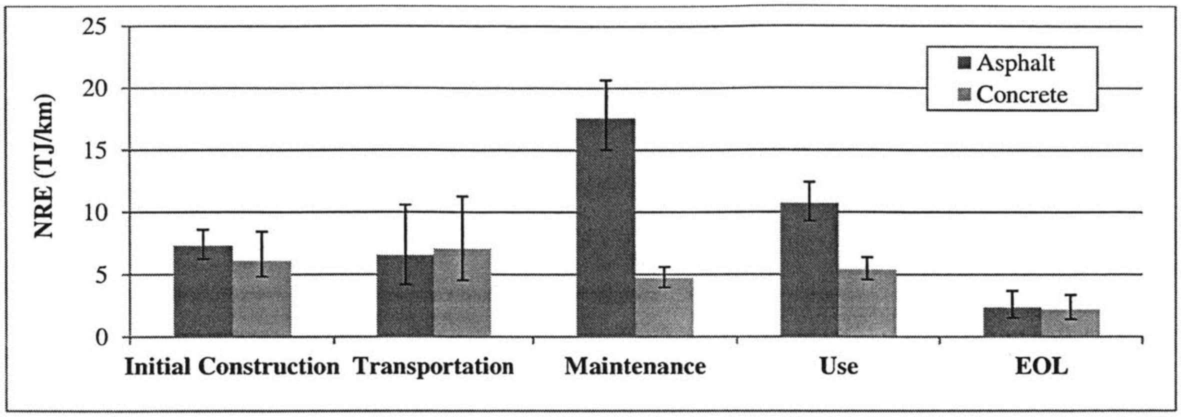

Figure 4.7 IPS NRE: Results by phase depicting the 5th percentile, median (50th percentile), and 95th percentile

Both the histograms in Figure 4.8 and Figure 4.9 depict the drastic difference between the NRE impacts of the two designs. In Figure 4.8 there is almost no overlap between the asphalt and concrete distributions, implying their significant difference.

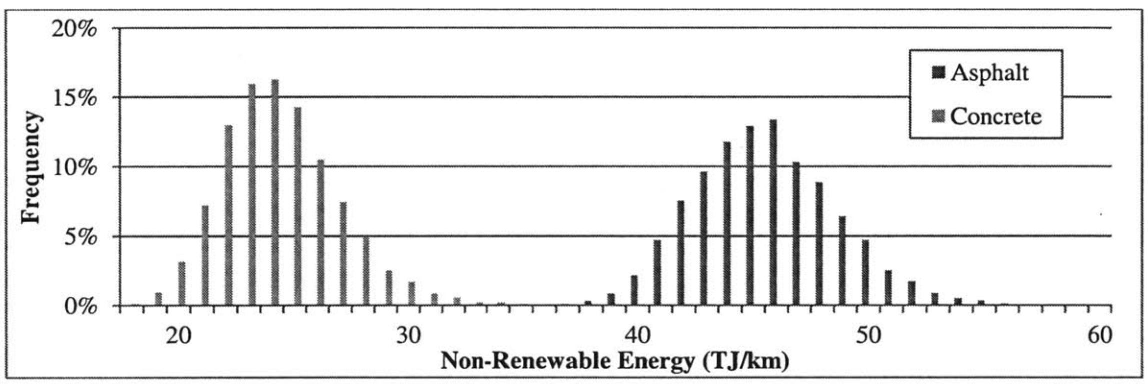

Figure 4.8 IPS NRE: Results histogram

Meanwhile, Figure 4.9 shows that the indicator variable distribution is entirely below one, which translates to the concrete design impact being less than the asphalt impact.

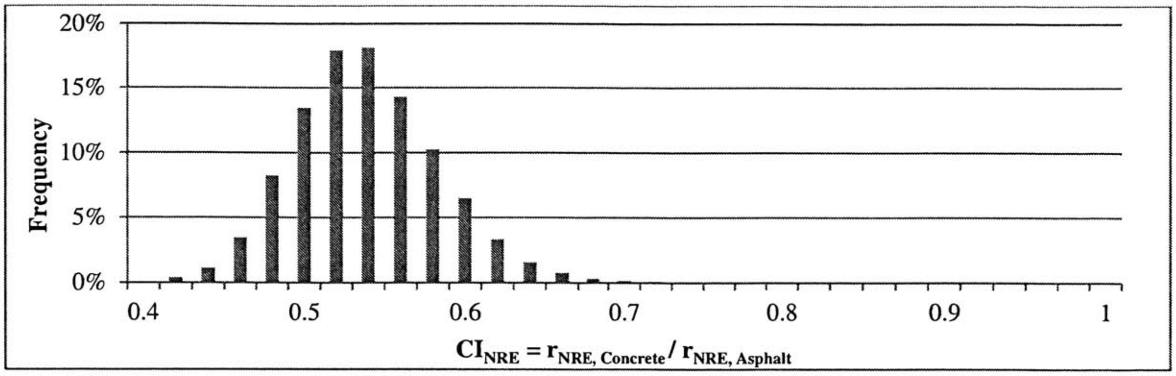

Figure 4.9 IPS NRE: Indicator variable histogram

Table 4.4 shows just how much better, and with how much confidence, the concrete design is than the asphalt design. One can say with 99% confidence that the concrete design impact will be at least 30% less than the impact of the asphalt design, where 30% is equal to 1-δ.

Table 4.4 IPS NRE: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α | δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	90%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	95%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	99%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**

4.4.2 Medium-Volume Scenario Results Summary

The IPS results for the medium-volume pavement are presented below. The MAD-COVs for the GWP of the asphalt and concrete results, presented in Figure 4.10, are 4.7% and 6.0%, respectively.

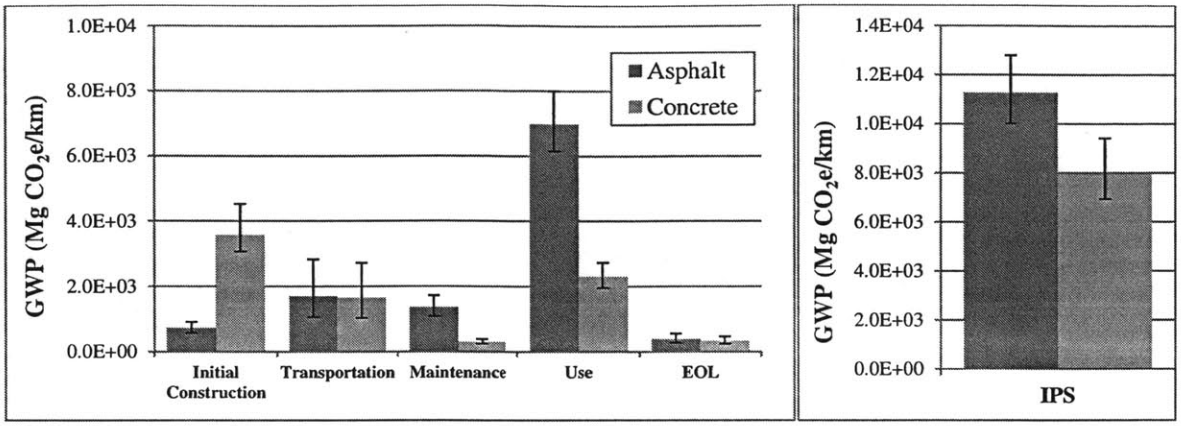

Figure 4.10 Medium-Volume GWP: Results depicting the 5th, 50th, and 95th percentiles by phase, followed by the total

Table 4.5 shows that at the 99% confidence level the concrete design will have a lesser impact than the asphalt alternative by at least 10%.

Table 4.5 Medium-Volume GWP: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α | δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive
	90%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive
	95%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive
	99%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive	Inconclusive

The medium-volume results for the NRE impact category are presented in Figure 4.11. The MAD-COVs are 4.5% and 6.5% for the asphalt and concrete designs, respectively.

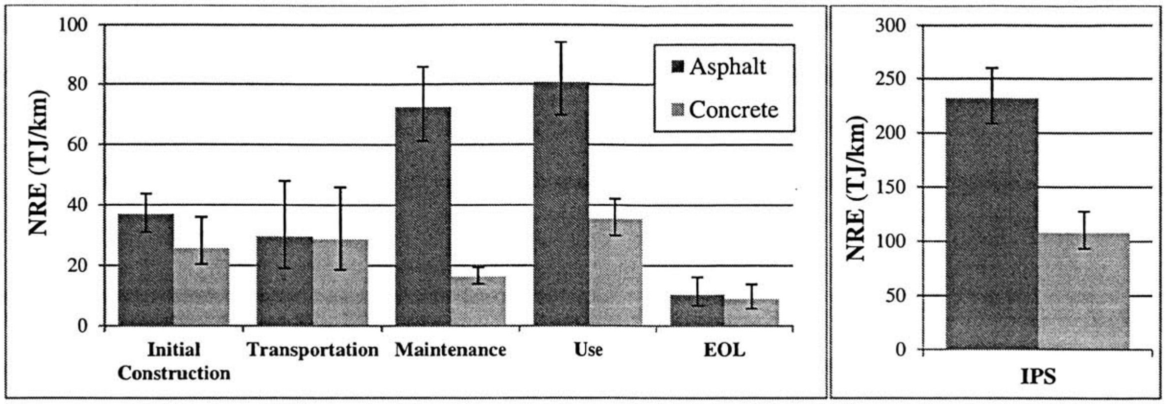

Figure 4.11 Medium-Volume NRE: Results depicting the 5th, 50th, and 95th percentiles by phase, followed by the total

Table 4.6 shows that at all levels of confidence and ratios of alternatives, the concrete design has a lower impact than the asphalt design.

Table 4.6 Medium-Volume NRE: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α | δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	90%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	95%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	99%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**

See Appendix E for further graphs relating to the medium-volume scenario.

4.4.3 High-Volume Scenario Results Summary

The IPS results for the high-volume road are presented below. Figure 4.12 shows the GWP results by phase and total. The MAD-COVs for the total impact of the asphalt and concrete designs are 5.2% and 5.5%, respectively.

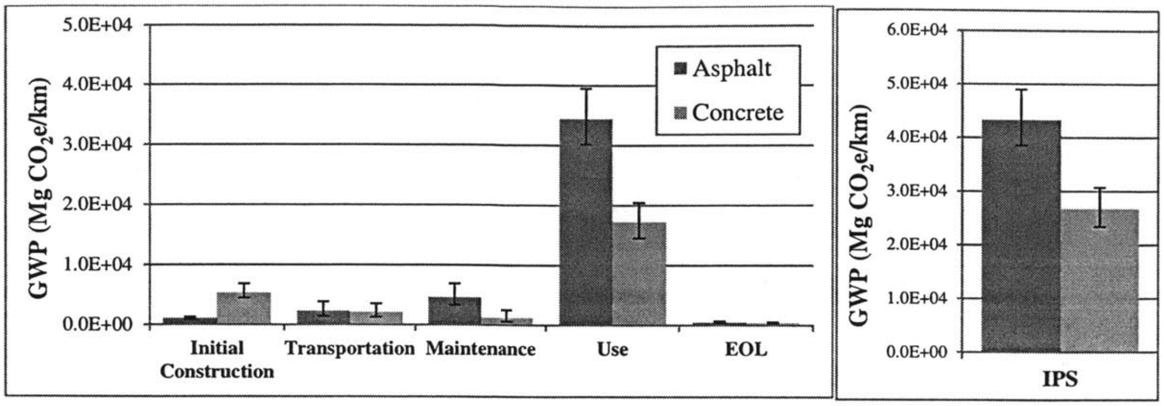

Figure 4.12 High-Volume GWP: Results depicting the 5th, 50th, and 95th percentiles by phase, followed by the total

Table 4.7 shows conclusively that the GWP totals of the high-volume scenario are lower in the concrete design than in the asphalt design.

Table 4.7 High-Volume GWP: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α | δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	90%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	95%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	99%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**

Figure 4.13 shows the phase and total results for the NRE impact assessment of the high-volume scenario. The MAD-COVs of the asphalt and concrete designs are 4.7% and 6.2%, respectively.

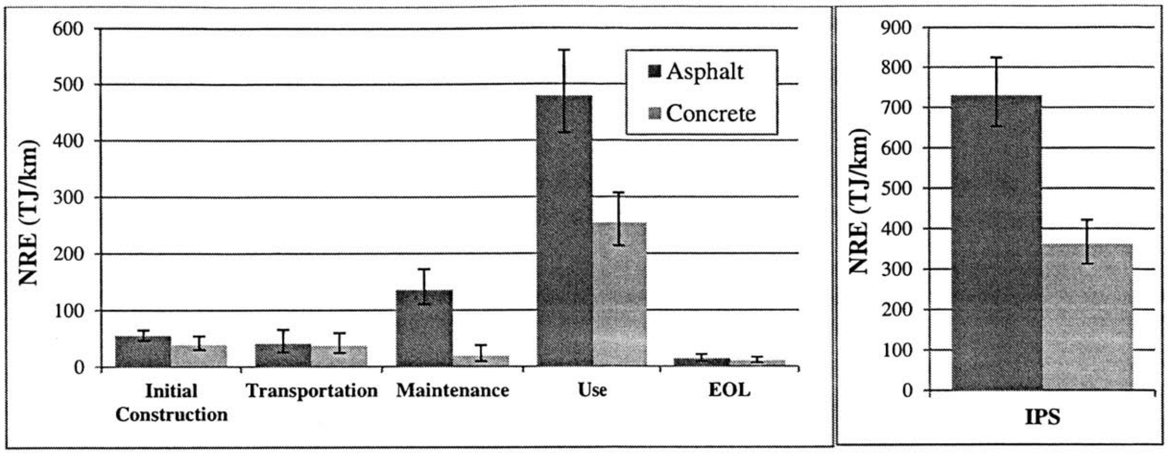

Figure 4.13 High-Volume NRE: Results depicting the 5th, 50th, and 95th percentiles by phase, followed by the total

Finally, the analysis of the indicator variable in Table 4.8 shows that for this scenario, the concrete design has a smaller NRE impact than the asphalt alternative.

Table 4.8 High-Volume NRE: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α | δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	90%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	95%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	99%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**

See Appendix D for further details of the high-volume results.

The results presented above demonstrate the methodology of individual probabilistic specification and the associated results from the pavement case study. The next section demonstrates the probabilistic underspecification methodology and its relevant results.

4.5 Probabilistic Underspecification

The results for the probabilistic underspecification methodology are presented below for the environmental impacts of GWP and NRE. Details on the categories of specification are discussed first, followed by the results of the first run of probabilistic underspecification for the low-volume scenario. The first run results are followed by the results for the second and third runs, which are required to complete the probabilistic underspecification methodology. Additionally, the PU results for the high and medium-volume scenarios are summarized at the end of this chapter.

4.5.1 Material Classification Data

As discussed in section 3.3.3, there is a hierarchy of material and process specification levels within probabilistic underspecification. Figure 4.14 presents an example of the hierarchy within freight transportation and is modeled after Figure 3.4. The processes in black depict the flow from least specified process on the left, L1, to the most specified on the right, L5.

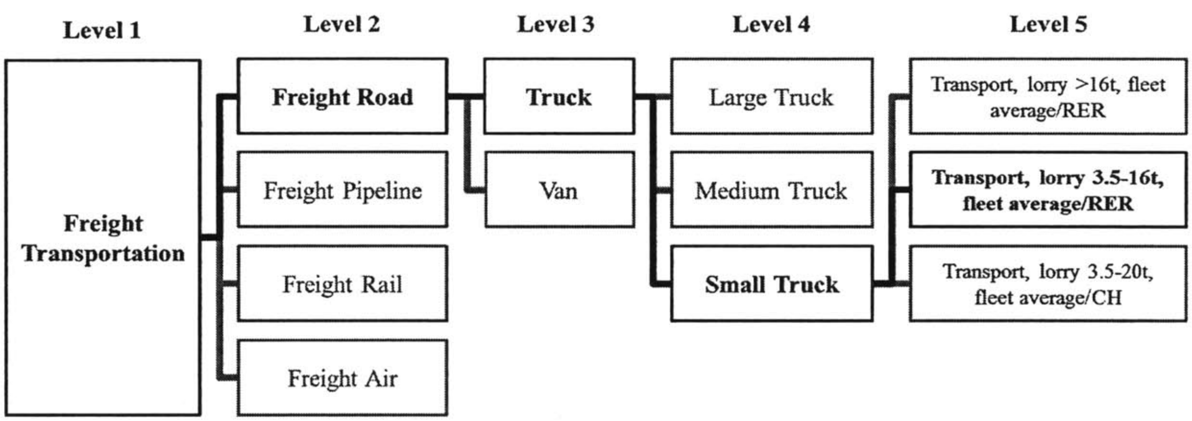

Figure 4.14 Example of Underspecification Level Hierarchy within Freight Transportation

Table 4.9 details the different levels of underspecification for each environmental impact parameter used in the analysis. Additionally, the mean and standard deviation are presented for the L1 and L5 data. Because the distributions come from direct sampling of the data, the types of distributions vary amongst the levels. This explains why the standard deviations seem to cause the values to go below zero, though the values are actually always positive across the distributions. The numbers instead are there to emphasize the relative variation within each category, as well as the difference in variation between L1 and L5.

Table 4.9 Levels of Underspecification, the numbers represent the relative mean and standard deviation

Level 1 (L1)	Level 2 (L2)	Level 3 (L3)	Level 4 (L4)	Level 5 (L5)
Freight Transportation 2.5E-01 ± 5.8E-01	Freight Road	Truck	Small Truck	Transport, lorry 3.5-16t, fleet average/RER 2.5E-01 ± 7.1E-02
	Freight Rail	Freight Rail - Diesel	Freight Rail - Diesel	Transport, freight, rail, diesel/US 5.0E-02 ± 1.1E-03
	Freight Water	Barge	Barge	Transport, barge, average fuel mix/US 4.5E-02 ± 3.4E-03
Transport Fuel Combustion 3.8 ± 0.5	Diesel Combustion	Diesel Low-Sulphur Combustion	Diesel Low-Sulphur Combustion	Operation, lorry 16-32t, EURO3/RER 3.7 ± 0.1
	Gasoline Combustion	Gasoline Combustion	Gasoline Combustion	Operation, passenger car, petrol, fleet average 2010/RER 3.9 ± 0.1
Construction 1.4 ± 3.0	Binders	Cement	Cement unspecified	[PCA Cement Data] 1.1 ± 2.6E-02
	Sealing	Bitumen	Bitumen - refinery	Bitumen, at refinery/CH 4.1E-01 ± 7.5E-02
Electricity 1.6E-01 ± 9.5E-02	N. America Mix	US Mix	Medium Voltage NA	Electricity, medium voltage, at grid/US 2.0E-01 ± 9.0E-03
Heat Fuel (MJ) 8.7E-02 ± 9.8E-02	Fuel Oil (MJ)	Light Fuel Oil (MJ)	Light Fuel Oil (MJ)	Heat, light fuel oil, at industrial furnace 1MW/RER 8.6E-02 ± 6.2E-03
Ores/Concentrates Minerals 2.0E-01 ± 1.9	Rock - Ore	Gravel	Gravel, crushed, at mine/CH U	Gravel, crushed, at mine/CH 4.3E-03 ± 6.3E-04
Construction Fuel Combustion (MJ) 9.2E-02 ± 1.2E-02	Diesel (MJ) - Construction Fuel	Diesel (MJ) - Construction Fuel	Diesel (MJ) - Construction Fuel	Diesel, burned in building machine/GLO 9.1E-02 ± 8.0E-03
Metal 1.1E+01 ± 2.9E+01	Ferrous metals	Steel	Steel rebar	Reinforcing steel, at plant/RER 1.4 ± 9.3E-02
Water 6.2E-03 ± 3.8E-02	Industry Water	Further treated water	Further treated water	Water, ultrapure, at plant/GLO 6.6E-04 ±1.3E-04
Disposal 1.7 ± 1.9E+01	Construction Waste	Mineral Waste	Concrete Waste	Disposal, building, concrete gravel, to final disposal/CH S 1.2E-02 ± 2.6E-03

4.5.2 Low-Volume Scenario Results

The figures and tables presented below show the results for the first run of probabilistic underspecification. Figure 4.15(a) shows the median results for the two designs, with the error bars depicting the 5th and 95th percentiles. All parameters are defined at the lowest level of specification, L1, for this run, as seen in Figure 4.15(b). The asphalt and concrete bars in the graph show the number of parameters specified within each design, divided by the total number of parameters used by each design. The combined analysis considers the total number of specified parameters divided by the total number of parameters between the two designs. The MAD-COV for the asphalt and concrete designs are 61% and 39%, respectively. While the asphalt design has a higher median than the concrete, it also has a greater range of uncertainty.

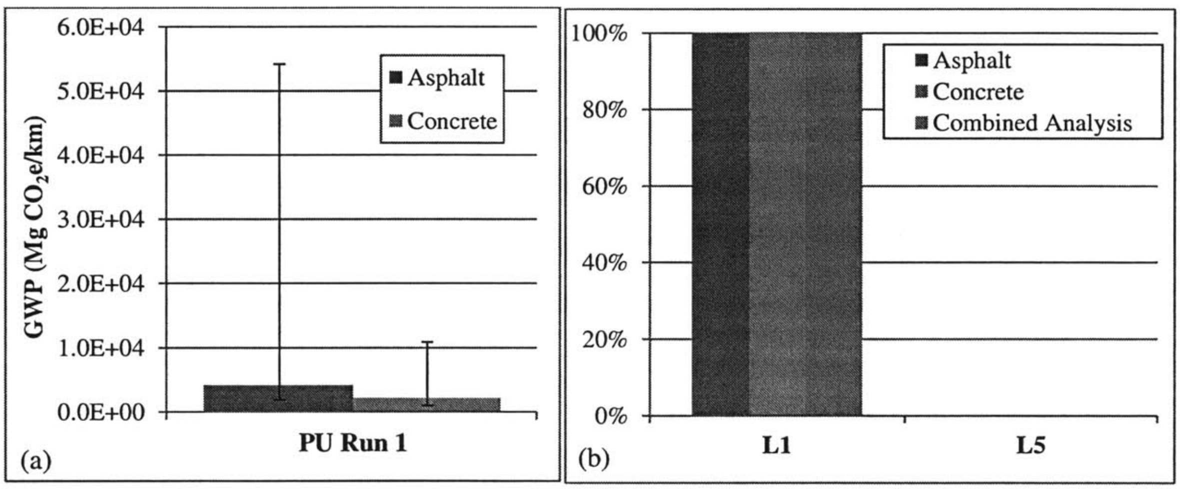

Figure 4.15 PU Run 1 GWP: (a) Results depicting the 5th percentile, median (50th percentile), and 95th percentile; and (b) parameter specification

Figure 4.16 shows that uncertainty is seen in all categories, but most significantly in the EOL impacts. The disposal category at L1 encompasses everything from inert landfilling to hazardous waste disposal, which accounts for the large variation in this phase.

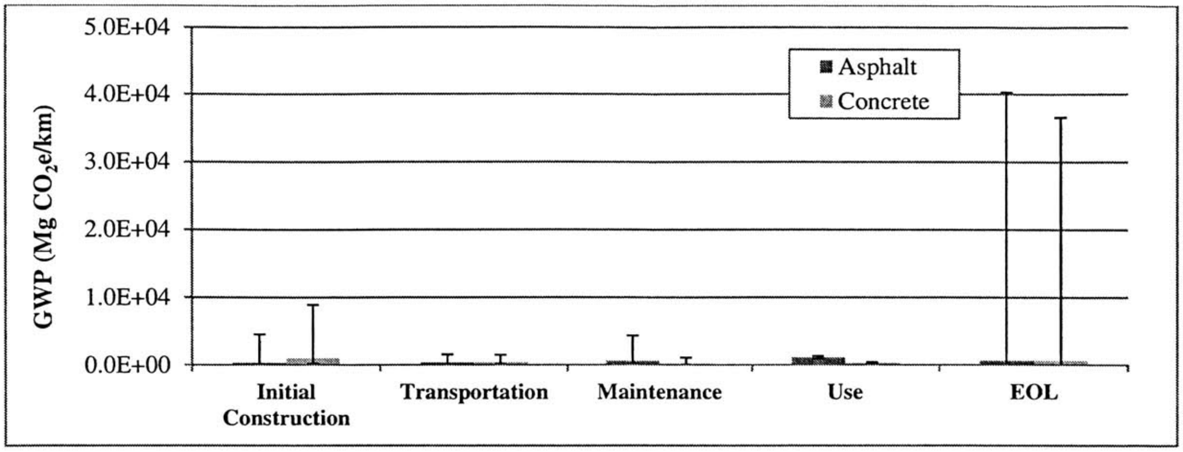

Figure 4.16 PU Run 1 GWP: Results by phase depicting the 5th percentile, median (50th percentile), and 95th percentile

The histogram results in Figure 4.17 show significant overlap between the distributions of the two designs. The results of the indicator variable in Figure 4.18 show that to differentiate between the two designs is inconclusive because its value spans all the way from almost zero to two, which translates to the concrete design being anywhere from 100% less than the asphalt design all the way to twice the impact of the asphalt design.

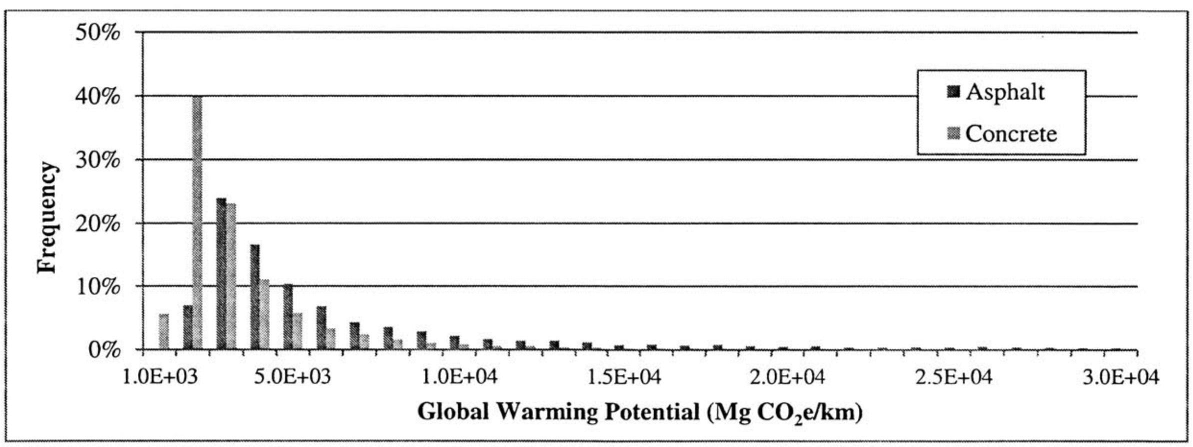

Figure 4.17 PU Run 1 GWP: Results histogram

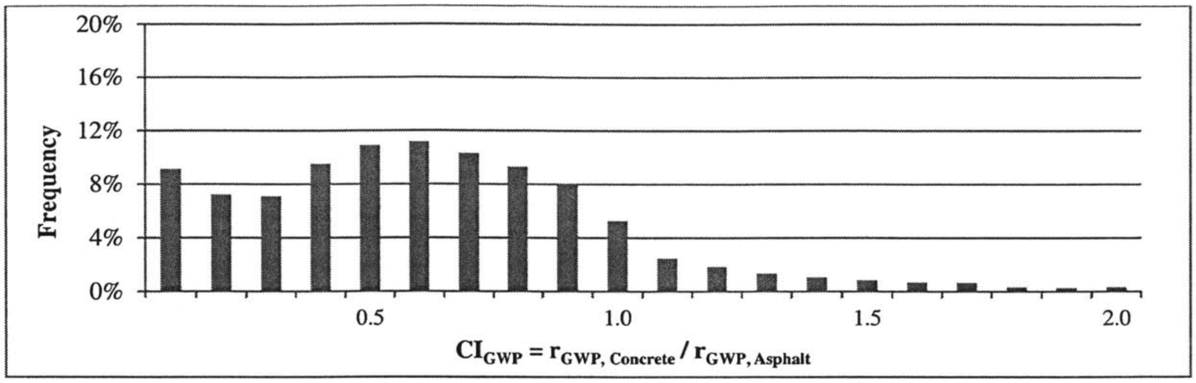

Figure 4.18 PU Run 1 GWP: Indicator variable histogram

The assessment of the indicator variable is shown in Table 4.10. At a 50% level of confidence, one can say that the concrete impact is less than that of asphalt, but when the required level of confidence is increased, it is clear that a decision for the GWP impact results after the first run of probabilistic underspecification cannot be made between the two designs with the given information. The level of confidence required by a decision maker can vary, but it is generally accepted that state and federal transportation departments in charge of road building are risk-averse, meaning that they would want higher levels of confidence, ones at which the above result is inconclusive.

Table 4.10 PU Run 1 GWP: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α | δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive
	90%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	95%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	99%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive

The figures below depict the NRE impact results from the first run of probabilistic underspecification. Figure 4.19(a) shows that while the asphalt design has a higher median impact, the variation in the total is significant for both alternatives. The MAD-COV for the asphalt and concrete designs is 42% and 46%, respectively. All parameters are defined at the lowest level of specification, L1 (Figure 4.19(b)).

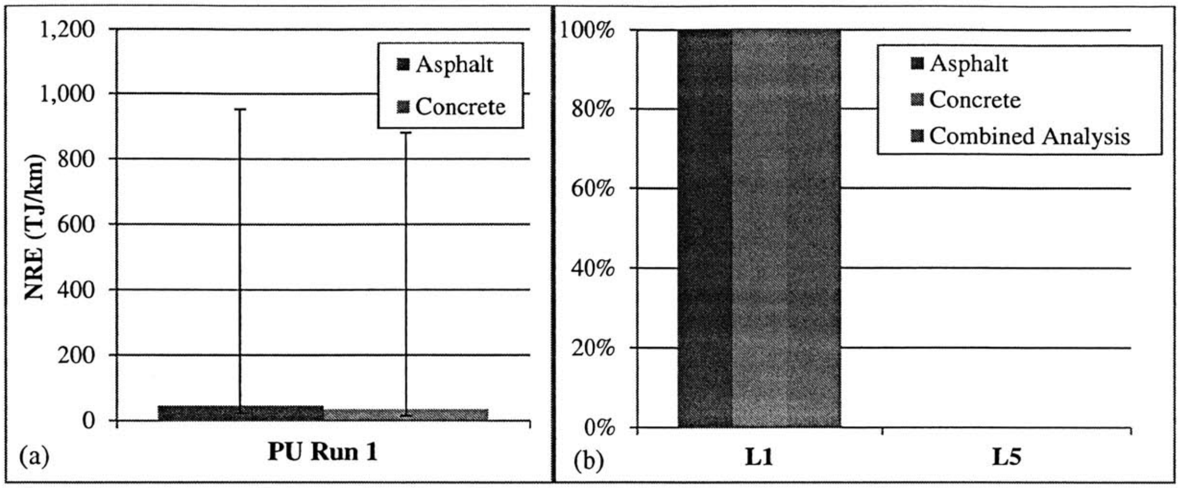

Figure 4.19 PU Run 1 NRE: (a) Results depicting the 5th percentile, median (50th percentile), and 95th percentile; and (b) parameter specification

For the first run of the NRE assessment, the majority of the uncertainty lies in the initial construction and maintenance phases (Figure 4.20).

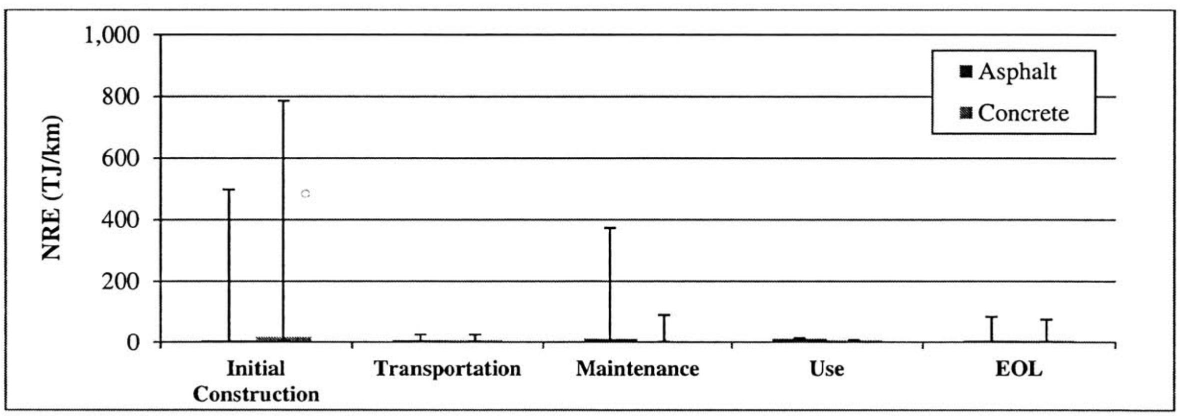

Figure 4.20 PU Run 1 NRE: Results by phase depicting the 5th percentile, median (50th percentile), and 95th percentile

The histogram of results presented in Figure 4.21 shows significant overlap between the two distributions, which does not allow for a conclusive differentiation between the two designs.

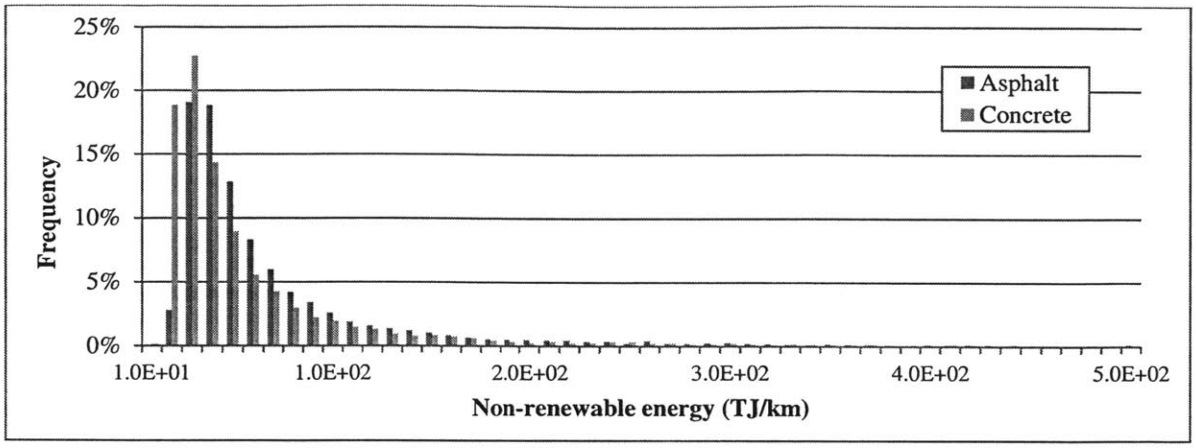

Figure 4.21 PU Run 1 NRE: Results histogram

Finally, the indicator variable results in Figure 4.22 are also inconclusive because they range all the way up to three. This inconclusiveness can be further seen in Table 4.11 because a decision is only capable of being made at the low confidence level of 50%. If higher confidences are required, as is often the case, then there would not be enough information to make a decision between the two designs.

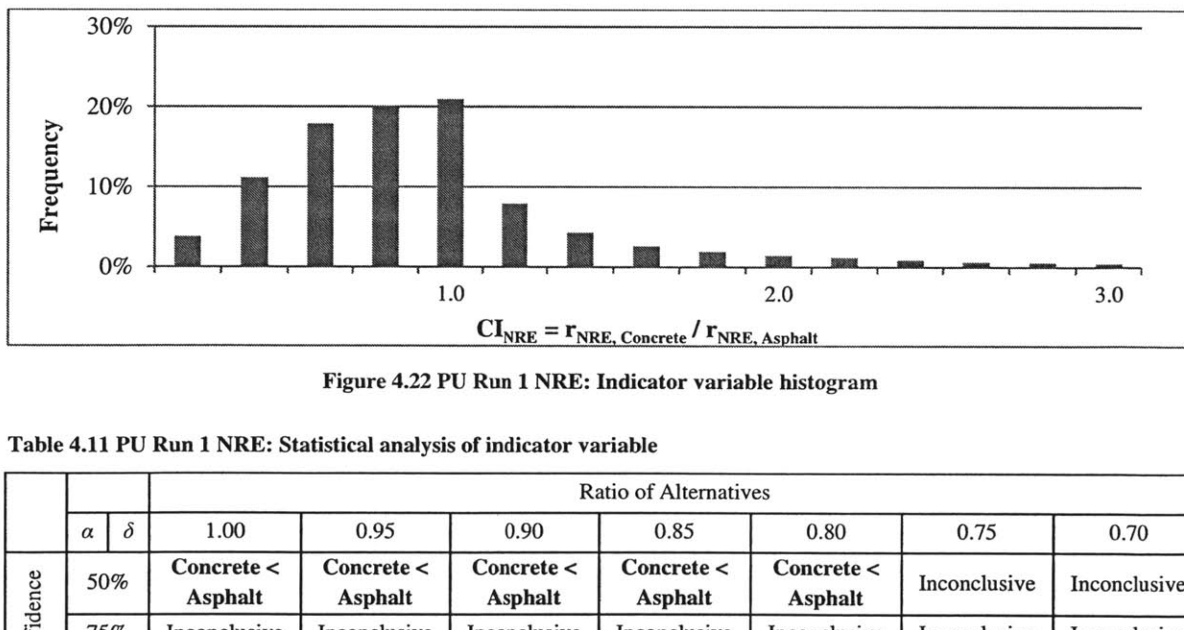

Figure 4.22 PU Run 1 NRE: Indicator variable histogram

Table 4.11 PU Run 1 NRE: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α | δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive
	75%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	90%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	95%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	99%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive

The following figures and tables represent the second run for probabilistic underspecification. Because the results presented previously did not allow for a decision to be made between the alternative designs, further specification is required for either impact category. A sensitivity analysis is performed on the final results from the first run to determine each parameter's contribution to the total variance of the results. The parameters that contribute to more than 5% of the total variance are then changed from an L1 specification to an L5 specification. The processes now specified at L5 for both the GWP and NRE impact categories are listed in Table 4.12. Depending on the designs, certain processes only affect the concrete or asphalt pavements, but not both. For example, cement happens to not be needed in this particular asphalt design, and neither does bitumen in this particular concrete design. Therefore, the process specification for each design is presented separately; however, as the comparison itself is essentially a single analysis, all the parameters must be correlated. For example, the aggregate truck transportation L5 specification may only be required in the asphalt design, but as this has the same impact between the two designs, it is therefore also specified at L5 for the concrete design. In the parameter specification charts presented in this section there are therefore different series for asphalt, concrete, and for the overall combined analysis.

Table 4.12 Processes specified at L5 for PU Run 2

GWP		NRE	
Asphalt	*Concrete*	*Asphalt*	*Concrete*
• Aggregate • Aggregate Truck Transportation • Landfilling/Disposal	• Cement • Aggregate • Aggregate Truck Transportation • Landfilling/Disposal	• Aggregate • Asphalt/Bitumen • Landfilling/Disposal	• Cement • Aggregate • Landfilling/Disposal

Figure 4.23(a) shows a significant reduction in uncertainty compared to Figure 4.15. Asphalt still has a higher median value, but the uncertainty ranges overlap significantly for both concrete and asphalt. The MAD-COV for the asphalt and concrete designs are 13% and 11%, respectively, compared with 61% and 39% in Figure 4.15. Figure 4.23(b) shows that 14% and 15% of the asphalt and concrete designs parameters, respectively, are now specified at L5, which accounts for 13% of the parameters in the combined analysis

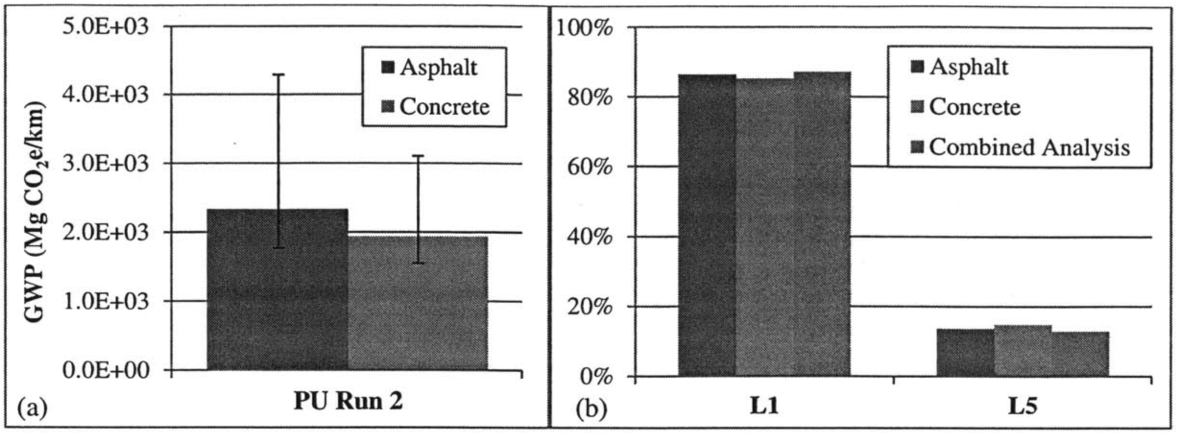

Figure 4.23 PU Run 2 GWP: (a) Results depicting the 5th percentile, median (50th percentile), and 95th percentile; and (b) parameter specification

The uncertainty which in Figure 4.16 lay mostly in the EOL phase is reduced drastically and now is distributed among the first three phases, initial construction, transportation, and maintenance (Figure 4.24).

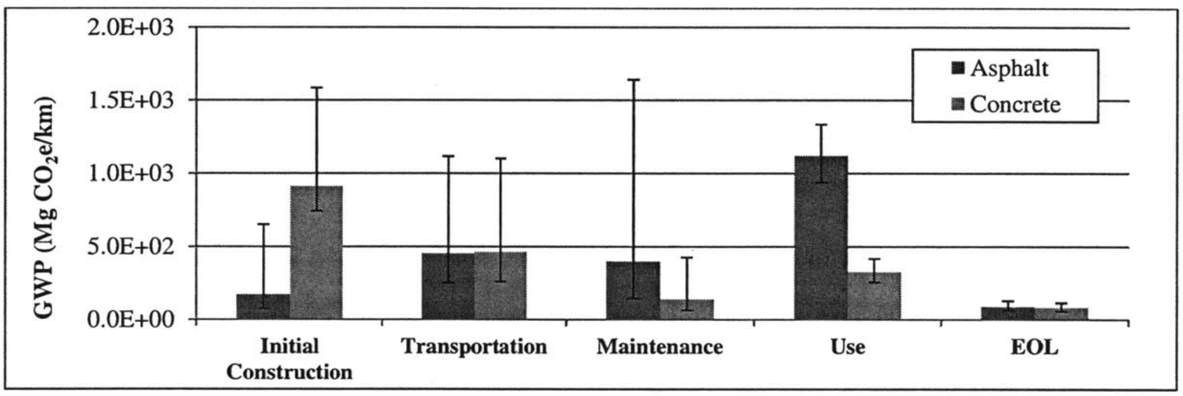

Figure 4.24 PU Run 2 GWP: Results by phase depicting the 5th percentile, median (50th percentile), and 95th percentile

The histogram of the results (Figure 4.25) shows significant overlap between the two distributions, while the indicator variable histogram (Figure 4.26) shows that a majority of the runs demonstrate that the concrete design's impact is less than the asphalt design's impact.

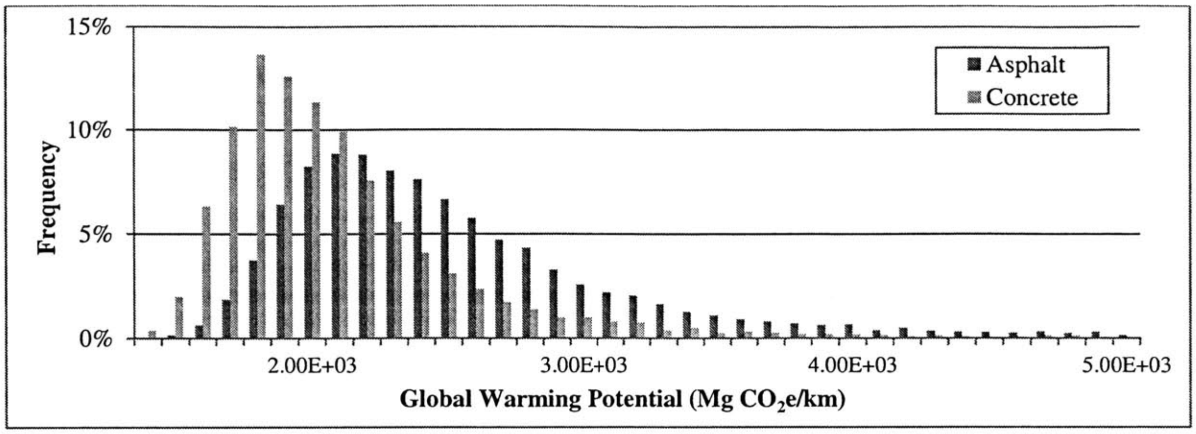

Figure 4.25 PU Run 2 GWP: Results histogram

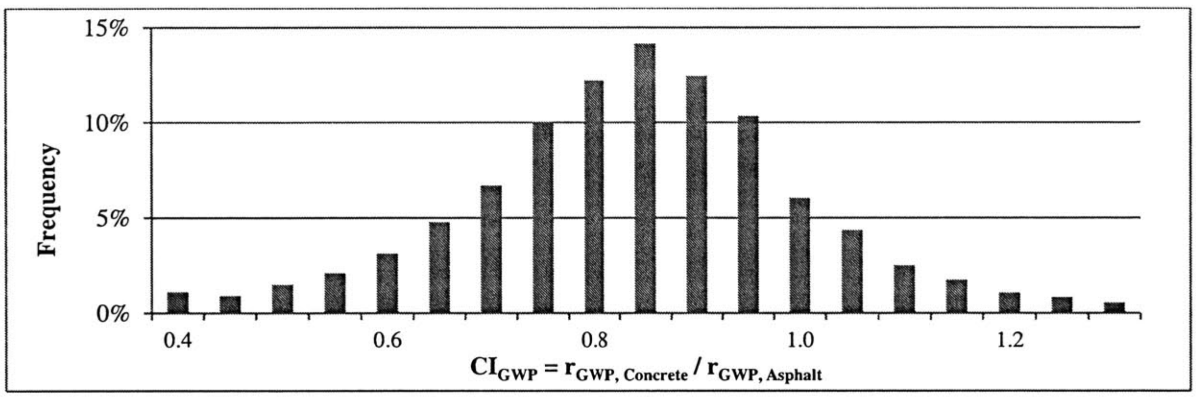

Figure 4.26 PU Run 2 GWP: Indicator variable histogram

The statistical significance of the results is evaluated in Table 4.13. At a 75% confidence interval, there is enough information to accept that the concrete design impact is greater than or equal to 95% of the impact of the asphalt design. At higher levels of difference and confidence, however, the results are inconclusive. Compared to Table 4.10 there are more inconclusive results but the MAD-COV has decreased significantly, indicating less uncertainty in the results.

Table 4.13 PU Run 2 GWP: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α | δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	90%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	95%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	99%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive

The second run for the probabilistic underspecification of the NRE impact also significantly reduces the uncertainty. Figure 4.27(a) shows that while there is overlap of the uncertainty ranges of the two designs, the median value for the asphalt design is higher. The MAD-COV is 9.5% and 16% for the asphalt and concrete designs, respectively, compared to 42% and 46% in Figure 4.19. Figure 4.27(b) shows that just about 14% of the parameters have been specified at L5 for the asphalt design, while only 11% have been for the concrete design. This results in a total of 13% of the parameters specified at L5 for the overall analysis.

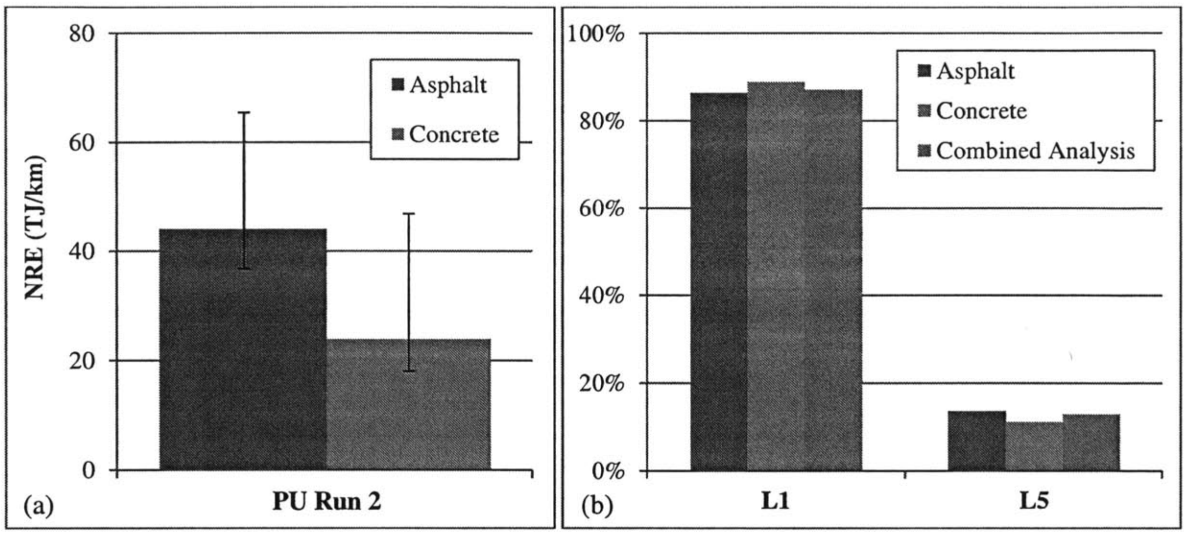

Figure 4.27 PU Run 2 NRE: (a) Results depicting the 5th percentile, median (50th percentile), and 95th percentile; and (b) parameter specification

The majority of the impact within the asphalt design occurs during the maintenance period (Figure 4.28), which is expected because bitumen has a high embodied energy value. This leads to a large difference between the two designs during the maintenance phase. Additionally, there is a significant difference between the two designs during the use phase, which is due to the increased impacts from PVI.

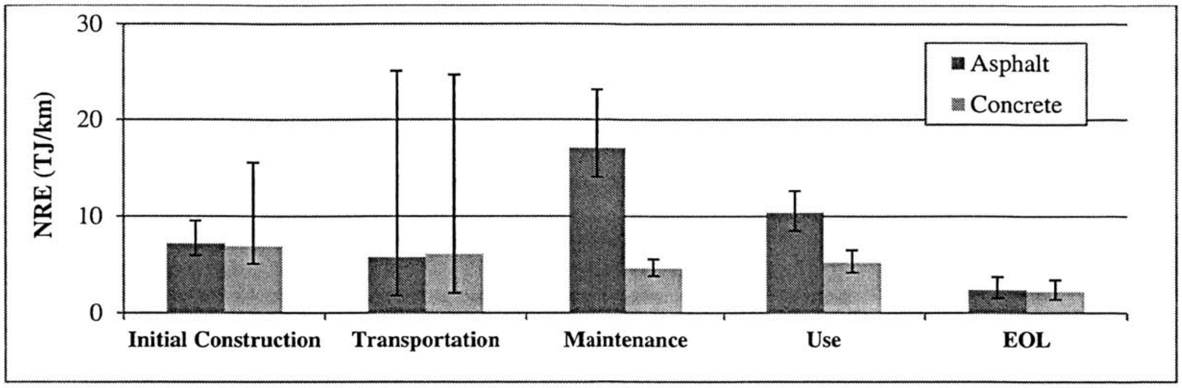

Figure 4.28 PU Run 2 NRE: Results by phase depicting the 5th percentile, median (50th percentile), and 95th percentile

The two histograms of the second-run results overlap slightly, as seen in Figure 4.29. When correlation is accounted for through the indicator variable (Figure 4.30), however, it can be seen that the value is consistently less than one, implying that the concrete design has a lesser impact than the asphalt.

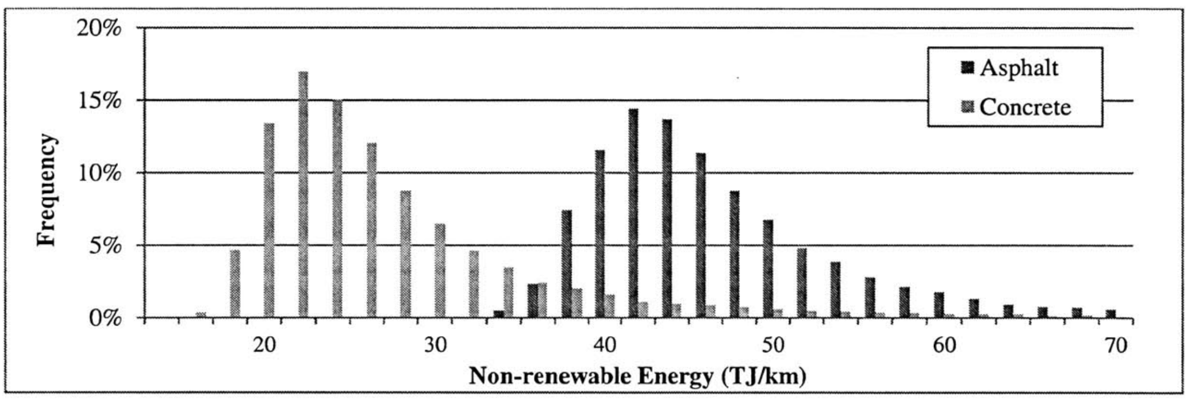

Figure 4.29 PU Run 2 NRE: Results histogram

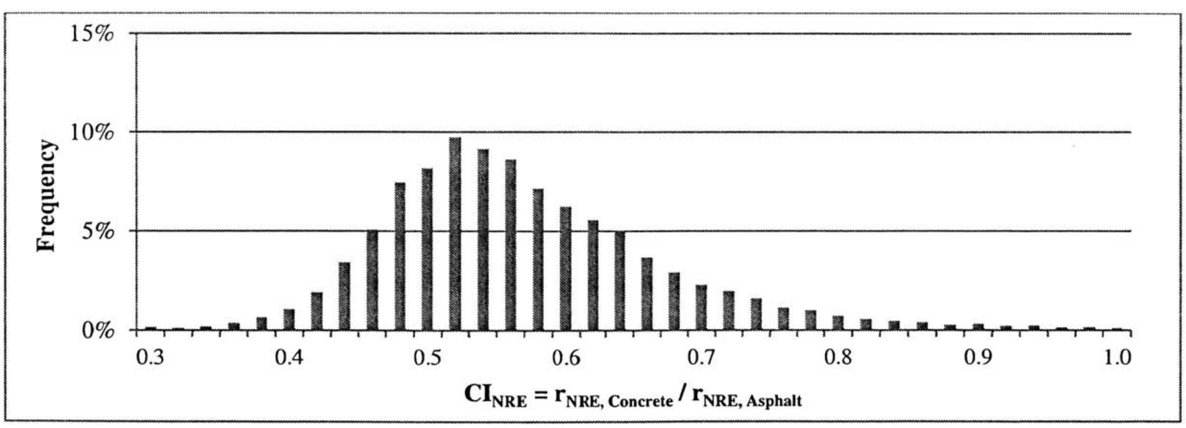

Figure 4.30 PU Run 2 NRE: Indicator variable histogram

Table 4.14 shows that the indicator variable is conclusive up to confidence levels of 95%. At a 99% confidence level, however, the results are inconclusive. The ability to make a decision at this level again depends on the requirements of the decision maker. If higher confidence is required, then further runs must be performed until either that confidence level is reached or the MAD-COV is less than 10%.

Table 4.14 PU Run 2 NRE: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α | δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	90%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive
	95%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive
	99%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive

For both the GWP and NRE results, a decision was incapable of being made at the highest level of confidence, 99%. Additionally, some of the MAD-COV values were above the threshold value of 10%. Therefore, a third run is required to either increase the confidence of the decision and/or reduce the MAD-COV value until it is below 10%. The following figures and tables represent the third run for probabilistic underspecification. The additional processes specified at L5 are listed in Table 4.15.

Table 4.15 PU Run 3, Processes Specified at Level 5 (bold indicates processes that differ from Run 2)

GWP		NRE	
Asphalt	*Concrete*	*Asphalt*	*Concrete*
• Aggregate • **Asphalt/Bitumen** • Landfilling/Disposal • **Aggregate Rail Transportation** • **Waste/Landfilling Truck Transportation** • **Fuel oil for asphalt mixing**	• Cement • Aggregate • Landfilling/Disposal • Aggregate Truck Transportation • **Steel Dowel Bars** • **Aggregate Rail Transportation** • **Waste/Landfilling Truck Transportation**	• Aggregate • Asphalt/Bitumen • Landfilling/Disposal • **Aggregate Truck Transportation** • **Aggregate Rail Transportation** • **Waste/Landfilling Truck Transportation** • **Fuel oil for asphalt mixing**	• Cement • Aggregate • Landfilling/Disposal • **Aggregate Truck Transportation** • **Steel Dowel Bars** • **Aggregate Rail Transportation** • **Waste/Landfilling Truck Transportation**

The median value of the asphalt design continues to be higher than that of the concrete design, but there remains significant overlap between their ranges of uncertainty. The MAD-COV for the results in Figure 4.31(a) is 6.6% and 7.3% for the asphalt and concrete designs, respectively. Figure 4.31(b) shows that just fewer than 30% of the parameters for the combined analysis are specified at L5. Of the concrete and asphalt design parameters, 32% and 26% are specified at L5, respectively.

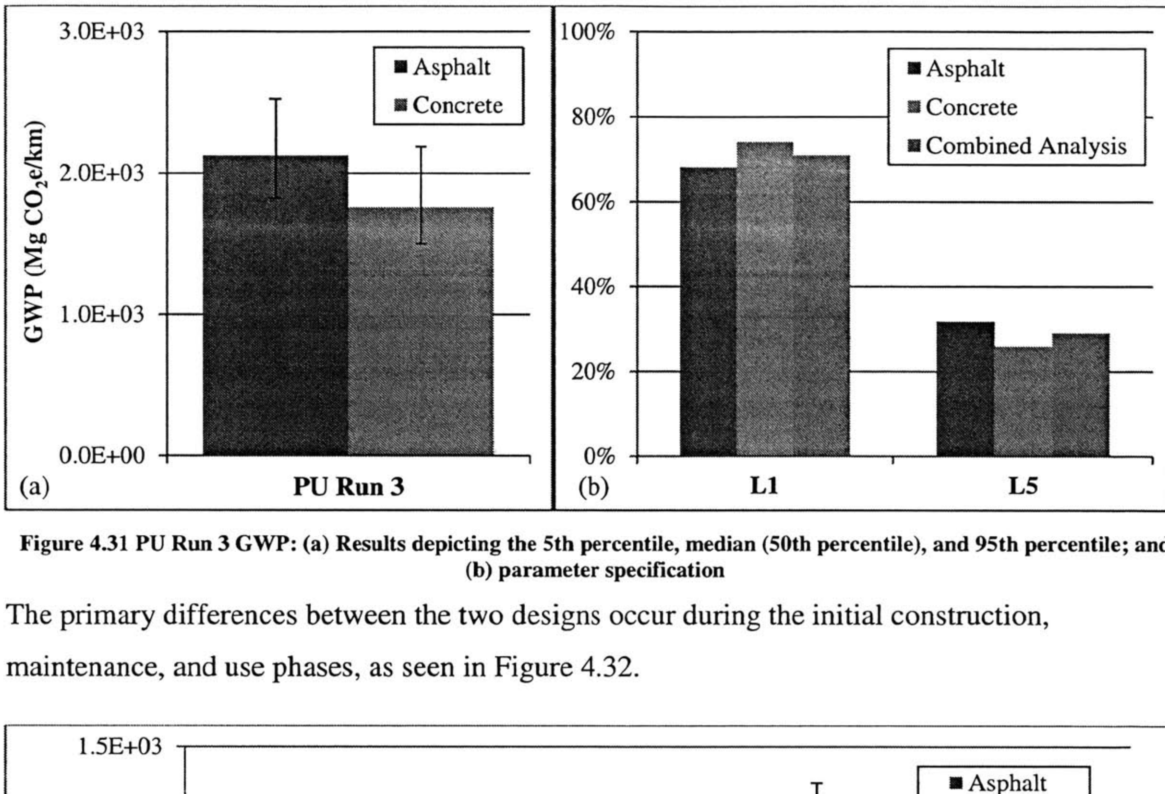

Figure 4.31 PU Run 3 GWP: (a) Results depicting the 5th percentile, median (50th percentile), and 95th percentile; and (b) parameter specification

The primary differences between the two designs occur during the initial construction, maintenance, and use phases, as seen in Figure 4.32.

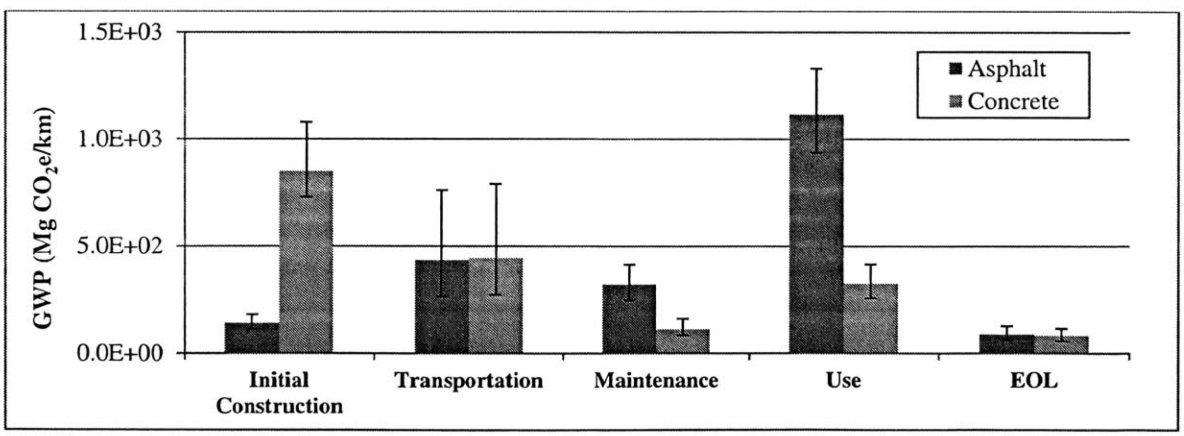

Figure 4.32 PU Run 3 GWP: Results by phase depicting the 5th percentile, median (50th percentile), and 95th percentile

The two distributions within the histogram in Figure 4.33 still overlap significantly. Once the correlation is accounted for in Figure 4.34, however, the majority of the Monte Carlo runs fall below one.

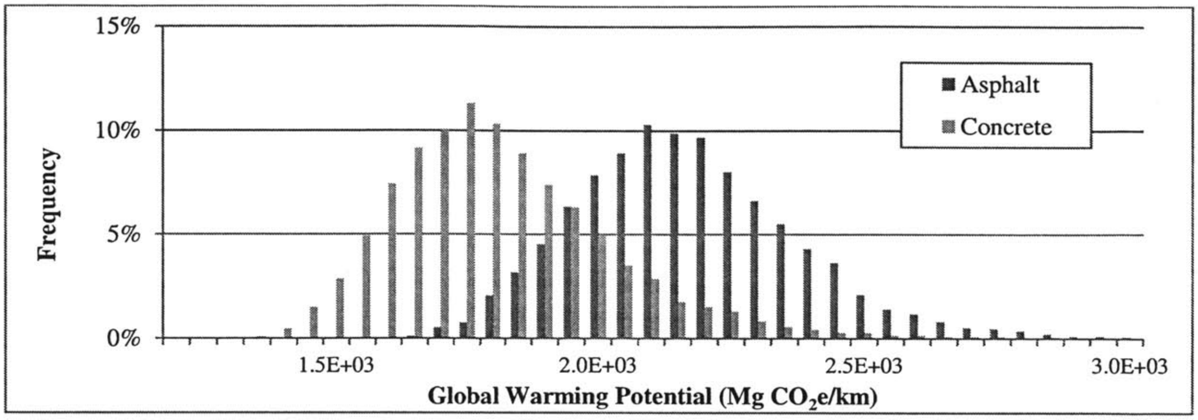

Figure 4.33 PU Run 3 GWP: Results histogram

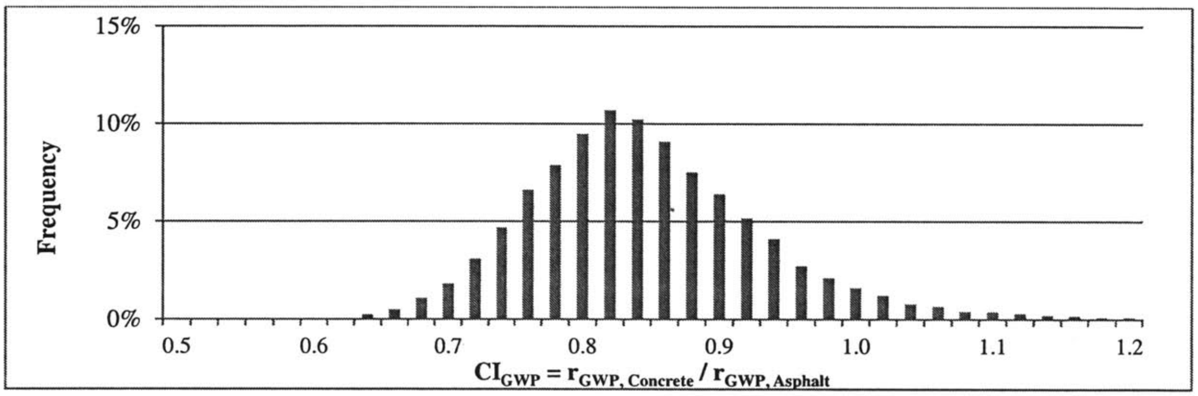

Figure 4.34 PU Run 3 GWP: Indicator variable histogram

When the statistical significance of the indicator variable is evaluated in Table 4.16, it can be seen that at the high levels of confidence often required, 90% and 95%, the concrete design impact is only equal to or less than 5% of the asphalt impact. Because the MAD-COVs are both less than 10%, however, further specification will not significantly alter the results. Therefore, depending on the difference and level of confidence required, it may be determined that the GWP of the concrete design is slightly less than that of the asphalt design, or additional factors must be assessed to provide more information with which to make a reliable decision. More often than not, the other factor evaluated is cost.

Table 4.16 PU Run 3 GWP: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α | δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	90%	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	95%	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	99%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive

The results from the third run of the NRE impact category are much more conclusive than the GWP results. It can be seen in Figure 4.35(a) that the ranges of uncertainty do not overlap at all between the two designs. Only about 30% of the parameters are specified at L5 (Figure 4.35(b)), and as with the GWP results, 32% and 26% of the asphalt and concrete parameters, respectively. The MAD-COVs of the asphalt and concrete designs are 5.1% and 7.3%, respectively.

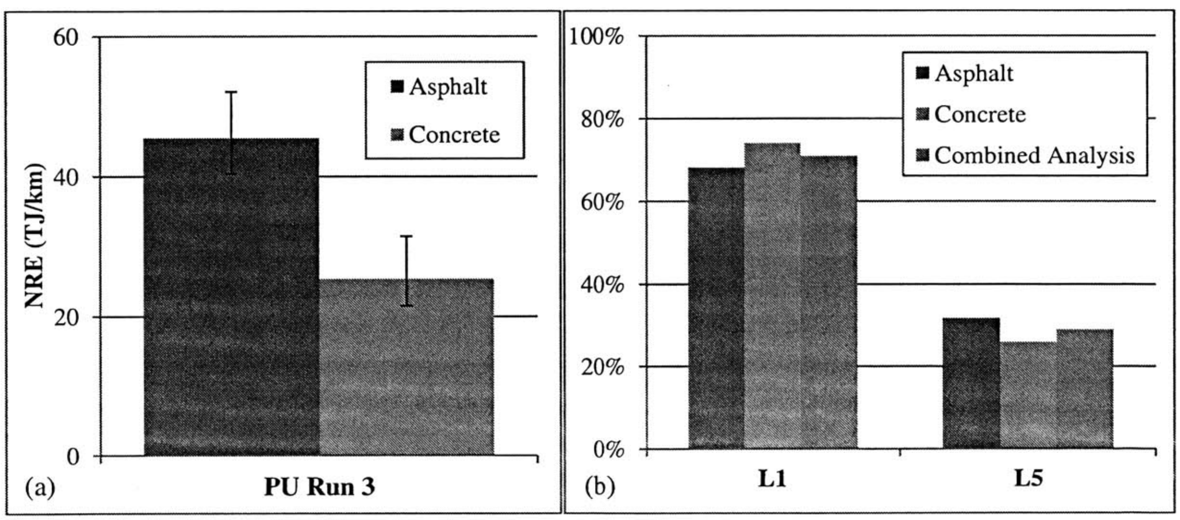

Figure 4.35 PU Run 3 NRE: (a) Results depicting the 5th percentile, median (50th percentile), and 95th percentile; and (b) parameter specification

The significant difference between the two designs occurs during the maintenance and use phases (Figure 4.36). Again, this is due to the increased material requirements during the maintenance of the asphalt design, as well as the increased fuel loss during the use phase due to differences in the PVI effects.

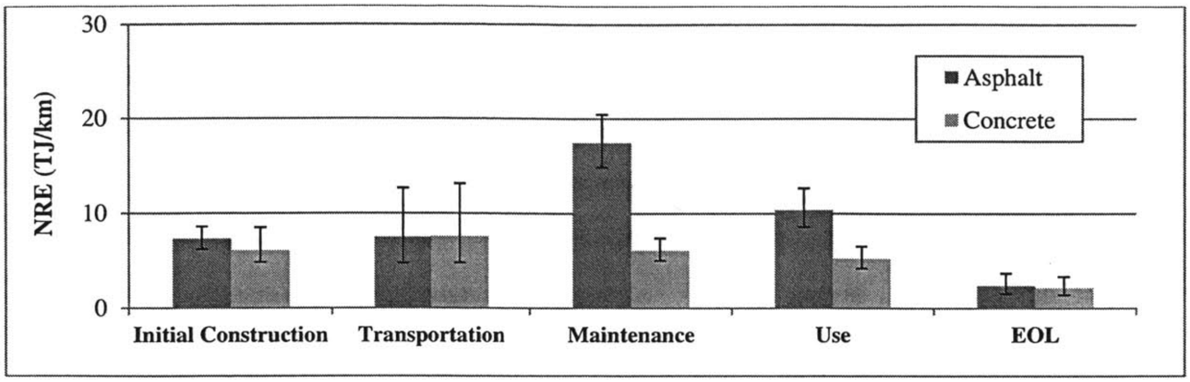

Figure 4.36 PU Run 3 NRE: Results by phase depicting the 5th percentile, median (50th percentile), and 95th percentile

As with the IPS results, there is very little overlap between the two distributions in the histogram, which is presented in Figure 4.37.

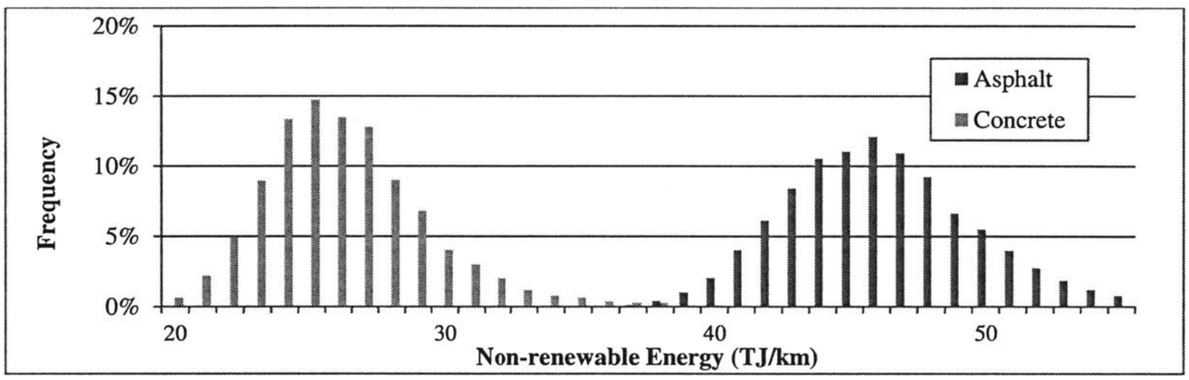

Figure 4.37 PU Run 3 NRE: Results histogram

The indicator variable, presented in Figure 4.38, shows that all the values are well below one.

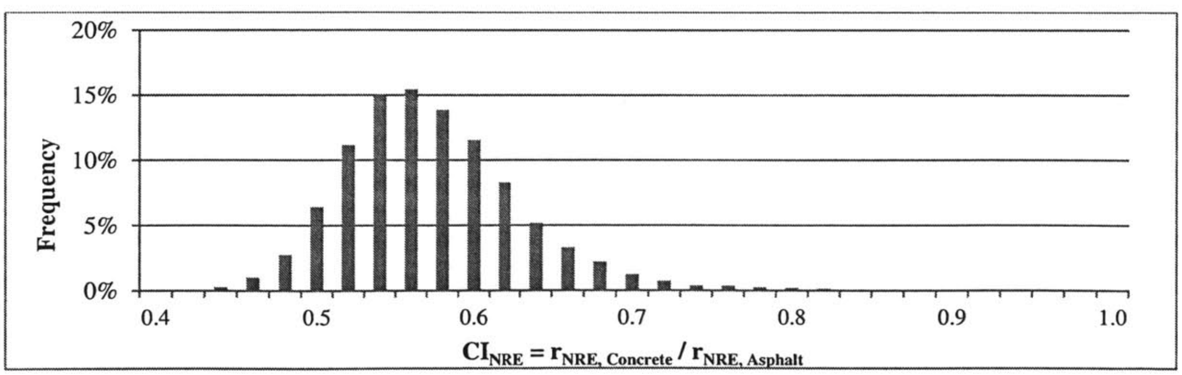

Figure 4.38 PU Run 3 NRE: Indicator variable histogram

The statistical analysis of the indicator variable in Table 4.17 shows that a decision can be made between the two alternatives. At all but the highest level of confidence for the lowest ratios of alternatives, the concrete design can confirmed as having less of an impact than the asphalt design. Additionally, the threshold value of less than 10% for the MAD-COV has been reached, so further specification of parameters most likely would not make a significant difference, and is unnecessary unless an even higher reliability is required for a decision to be made.

Table 4.17 PU Run 3 NRE: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α | δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	90%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	95%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	99%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive

4.5.2.1 Low-Volume GWP Run 3 Sensitivity Analysis

The contribution to variance plots presented below show the impact on the total caused by increasing a parameter. Positive values will increase the final value, while negative values will reduce the total. This allows the practitioner to assess which parameters most affect the total, leading to possible areas of impact reduction. It is also the method by which it is determined which parameters need to be specified at L5 in the PU methodology. Figure 4.39 shows the parameters within the concrete design that had the largest contributions to variance within the GWP impact assessment, after all the necessary processes have been specified at L5. The most significant parameter is the truck impact factor, which is applied to both the aggregate and waste transportation. This is followed by the cement content of the cement stabilized layer, which, if increased, will increase the total. The amount of cement, however, is inextricably linked with the aggregate content, which is shown to have a negative contribution to variance. Since the unit weight of the cement stabilized layer is constant, should the content of cement decrease then the aggregate content would increase; therefore, the aggregate content increase is linked to a reduction in the total impact.

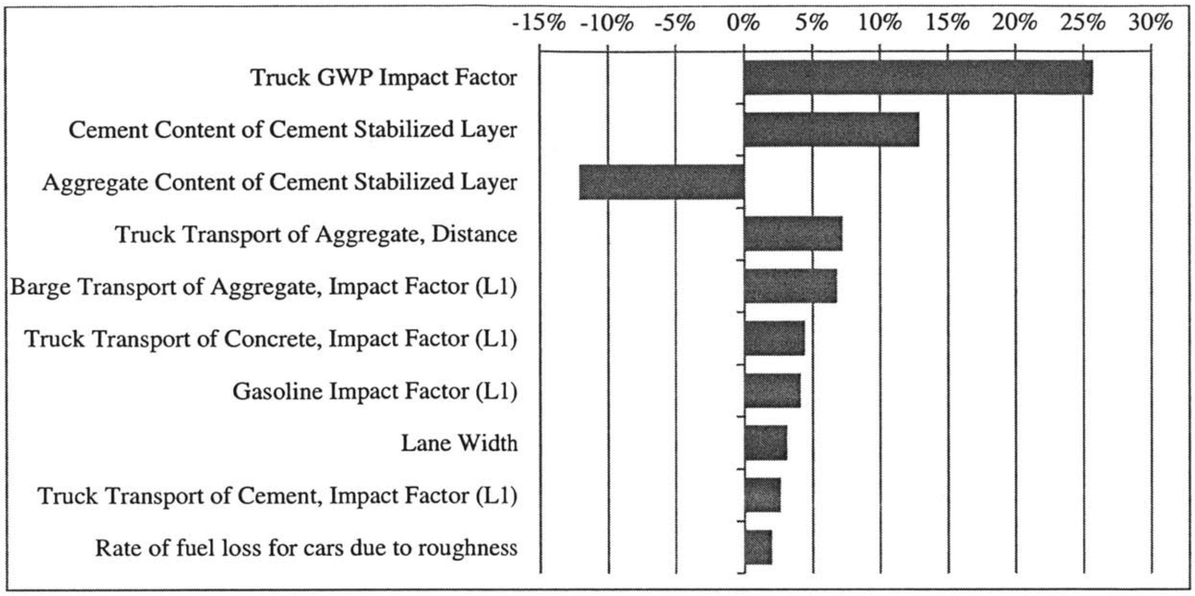

Figure 4.39 Low-Volume PU Run 3 GWP: Concrete design parameter contributions to variance; environmental parameters not labeled as L1 are specified at L5

There are similarities in the list of parameters that contribute most to the variance, in the asphalt and concrete designs. Figure 4.40 shows that once again the truck impact factor has a significant effect on the total, and again this is due to the large masses of aggregate and waste that must be transported. The second highest contribution to variance is the albedo value of concrete. The higher this value the higher the albedo difference is between the two pavements; therefore, more GWP is attributed to the asphalt design.

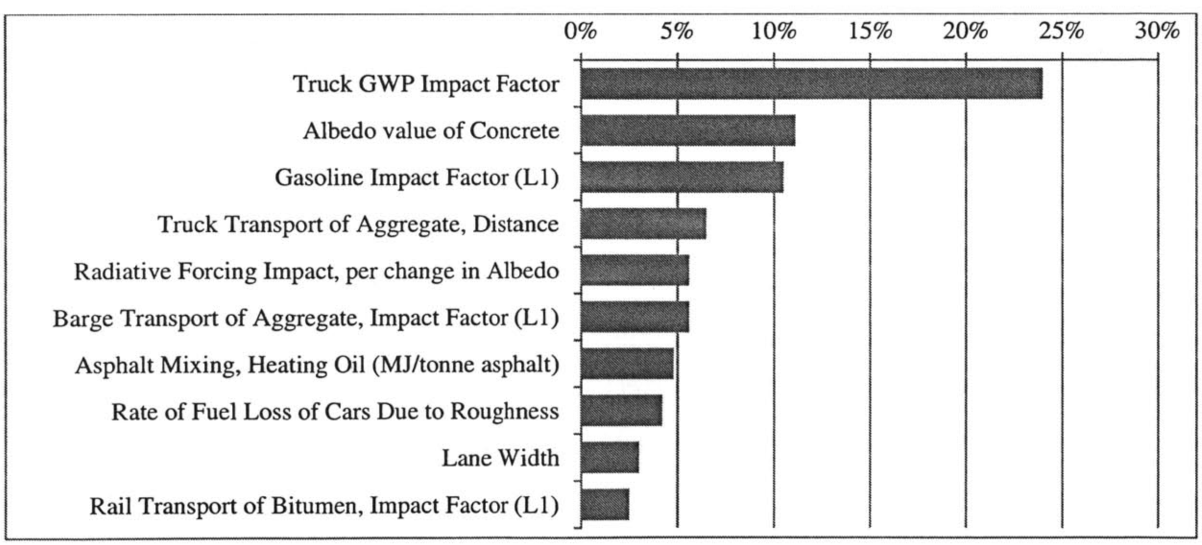

Figure 4.40 Low-Volume PU Run 3 GWP: Asphalt design parameter contributions to variance; environmental parameters not labeled as L1 are specified at L5

The final contribution to variance graph, Figure 4.41, is the sensitivity analysis of the indicator variable. The indicator variable is the ratio of the concrete design to the asphalt design; therefore, anything that has a negative contribution to variance would decrease the value of the indicator variable through the decrease of the concrete total or the increase of the asphalt total. Conversely, should the contribution to variance be positive, the indicator variable would increase through either the increase of the concrete total or the decrease of the asphalt total. It is interesting to note here that though the truck impact factor significantly contributed to the variances of both the asphalt and concrete designs, it does not affect the indicator variable. This is because if the truck impact factor were to increase then both designs would increase proportionally, leaving the ratio between the two close to the same, and therefore it would not alter the indicator variable significantly.

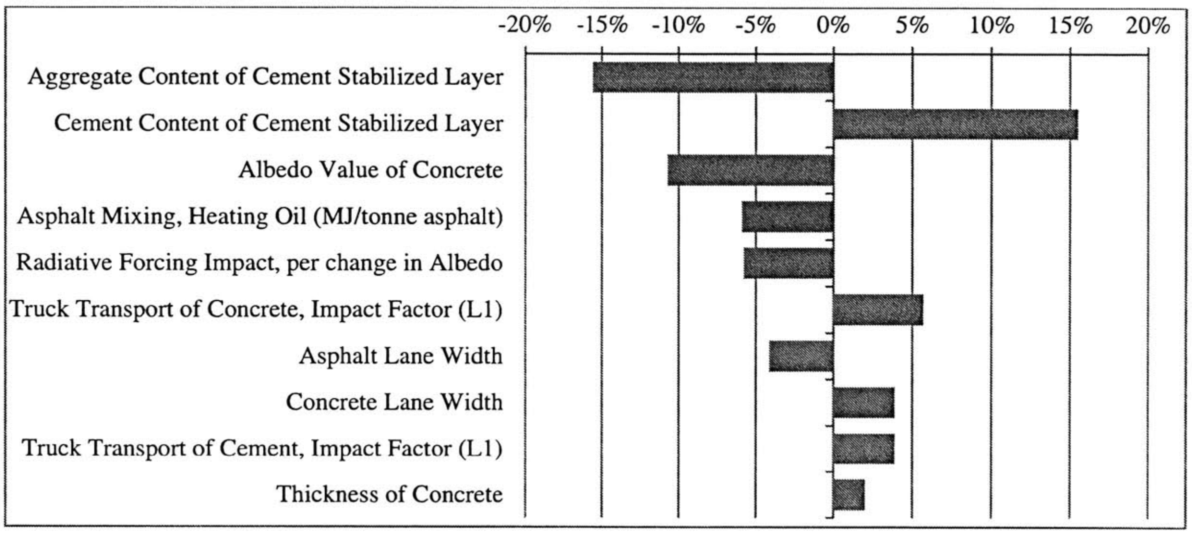

Figure 4.41 Low-Volume PU Run 3 GWP: Indicator variable parameter contributions to variance; environmental parameters not labeled as L1 are specified at L5

Connections between the indicator variable's parameter contribution to variance and the designs' parameter contributions to variance can also be seen. For example, the cement content of the cement stabilized layer would increase the concrete total and leave the asphalt total unaffected; therefore, the indicator variable would increase. In contrast, should the albedo value of the concrete increase, the asphalt design total would increase, thus decreasing the value of the indicator variable.

Contribution to variance is a useful tool within LCA, and necessary within probabilistic underspecification. It can be seen in the above graphs that L1 processes still have an impact on the total variation. Further specification would allow for reduction in the final uncertainty, though not a significant amount, as the MAD-COV is already below 10%.

4.5.3 Medium-Volume Scenario Results Summary

The results for the first run of the medium volume road are presented below. Additional information on the results can be found in Appendix E. Figure 4.42 shows the significant variation in the final value, most of it falling within the EOL category. The MAD-COVs of the asphalt and concrete designs for the first run are 47% and 36%, respectively.

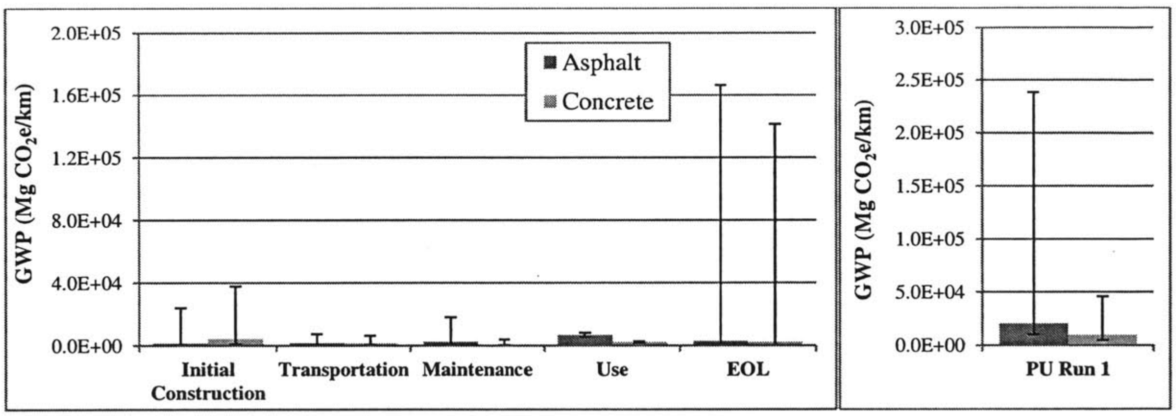

Figure 4.42 Medium-Volume Run 1 GWP: Results depicting the 5th, 50th, and 95th percentiles by phase, followed by the total

The statistical analysis of the indicator variable (Table 4.18) shows that at 90% confidence, a decision can be made between the two alternatives, a relatively high value for a first run result.

Table 4.18 Medium-Volume Run 1 GWP: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α | δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive
	90%	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	95%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	99%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive

The NRE results for the first run of the medium-volume road, in Figure 4.43, show that much of the uncertainty occurs during the initial construction phase. The MAD-COVs are 36% and 42% for the asphalt and concrete designs, respectively.

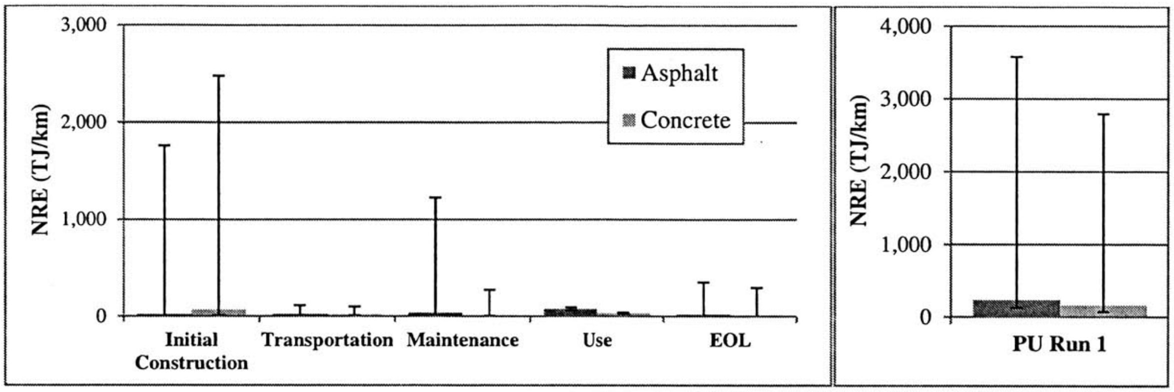

Figure 4.43 Medium-Volume Run 1 NRE: Results depicting the 5th, 50th, and 95th percentiles by phase, followed by the total

At a 50% confidence level the concrete design is significantly less than the asphalt; however, at higher levels of confidence this distinction cannot be made.

Table 4.19 Medium-Volume Run 1 NRE: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α / δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	90%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	95%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	99%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive

The results for the second run of the medium volume road are presented below. The MAD-COVs for the asphalt and concrete results in Figure 4.44 are 13% and 11%, respectively.

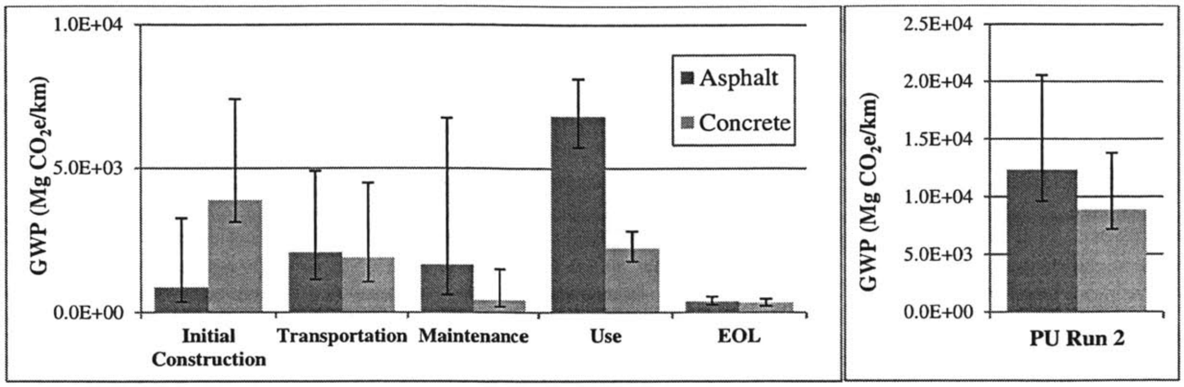

Figure 4.44 Medium-Volume Run 2 GWP: Results depicting the 5th, 50th, and 95th percentiles by phase, followed by the total

The indicator variable results (Table 4.20) show differentiation is possible at the 50%, 75% and 90% levels of confidence. The MAD-COVs, however, are above the threshold value of 10%, so further specification is required.

Table 4.20 Medium-Volume Run 2 GWP: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α | δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive
	90%	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	95%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	99%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive

The NRE results for the second run are presented in Figure 4.45. The MAD-COVs of the asphalt and concrete designs are 8.7% and 14%, respectively.

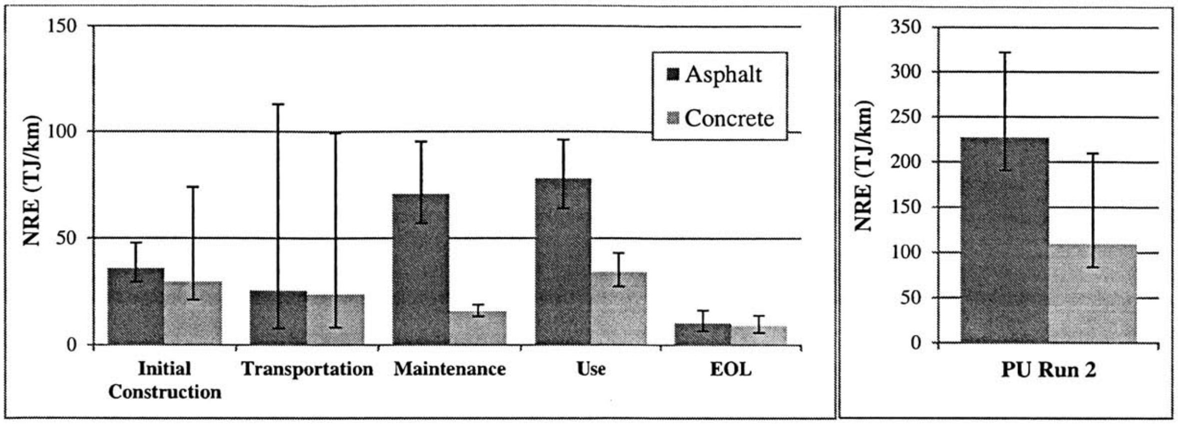

Figure 4.45 Medium-Volume Run 2 NRE: Results depicting the 5th, 50th, and 95th percentiles by phase, followed by the total

The statistical analysis of the indicator variable in Table 4.21 shows that at up to a 95% confidence level, a decision can be made between the two alternatives. Because the MAD-COV of the concrete design is above 10%, however, a third run is performed.

Table 4.21 Medium-Volume Run 2 NRE: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α | δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	90%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	95%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive
	99%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive

The results for the third and final run of the probabilistic underspecification for the medium volume road are presented below. The MAD-COVs for the asphalt and concrete designs presented in Figure 4.46 are 6.0% and 6.8%, respectively.

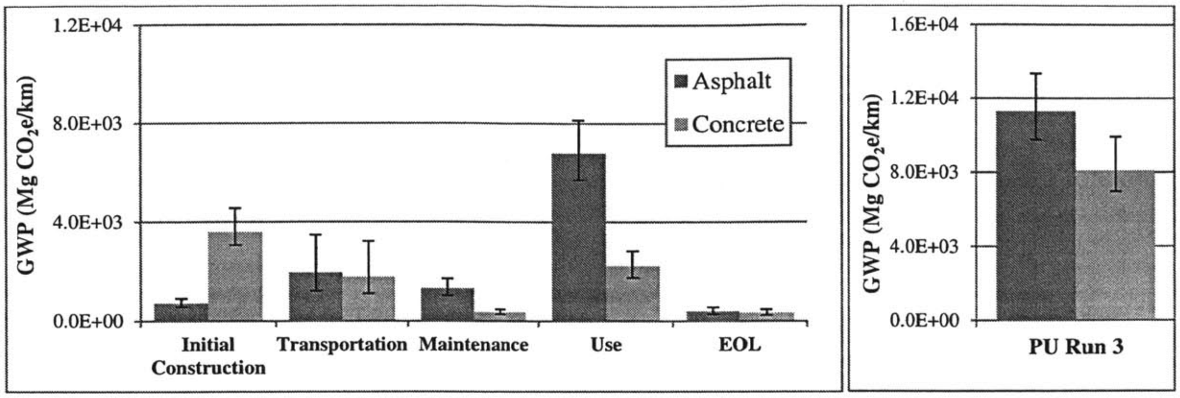

Figure 4.46 Medium-Volume Run 3 GWP: Results depicting the 5th, 50th, and 95th percentiles by phase, followed by the total

Table 4.22 shows that at a 99% level of confidence, a decision can be made between the alternatives, though the concrete design is not much more than 5% better than the asphalt. Whether this is enough of a difference to validate choosing the concrete design would be up to the final decision-maker, who would consider other factors as well.

Table 4.22 Medium-Volume Run 3 GWP: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α | δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive
	90%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive
	95%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive
	99%	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive

The NRE results for the third run of the medium-volume road are presented in Figure 4.47. The MAD-COVs are 4.8% and 7.0% for the asphalt and concrete designs, respectively.

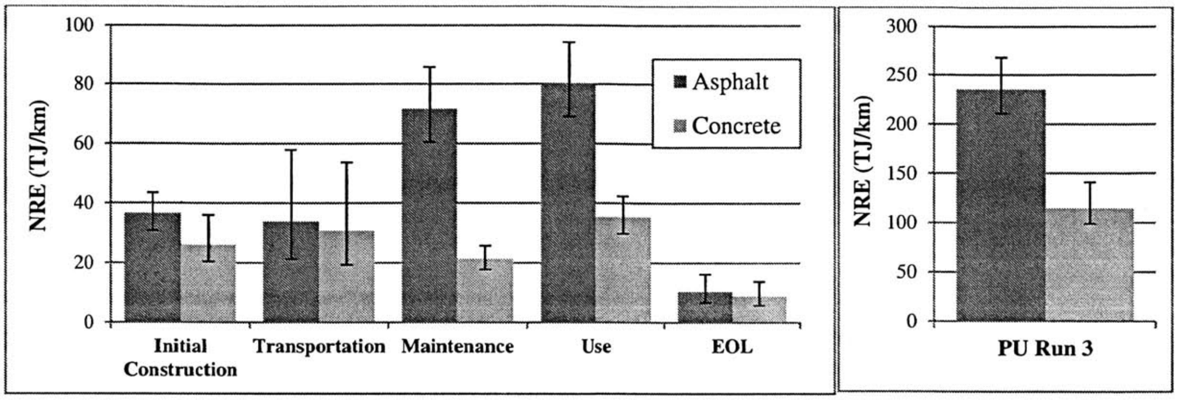

Figure 4.47 Medium-Volume Run 3 NRE: Results depicting the 5th, 50th, and 95th percentiles by phase, followed by the total

The analysis of the indicator variable for the NRE results presented in Table 4.23 shows conclusively that the concrete design has a lower impact than the asphalt alternative.

Table 4.23 Medium-Volume Run 3 NRE: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α | δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	90%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	95%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	99%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**

4.5.4 High-Volume Scenario Results Summary

The following results depict the first run of the probabilistic underspecification for the high-volume road. Additional information on the results can be found in Appendix E. Figure 4.48 shows the uncertainty in the results for each phase and the total, the MAD-COV of which is 20% and 19% for the asphalt and concrete designs, respectively.

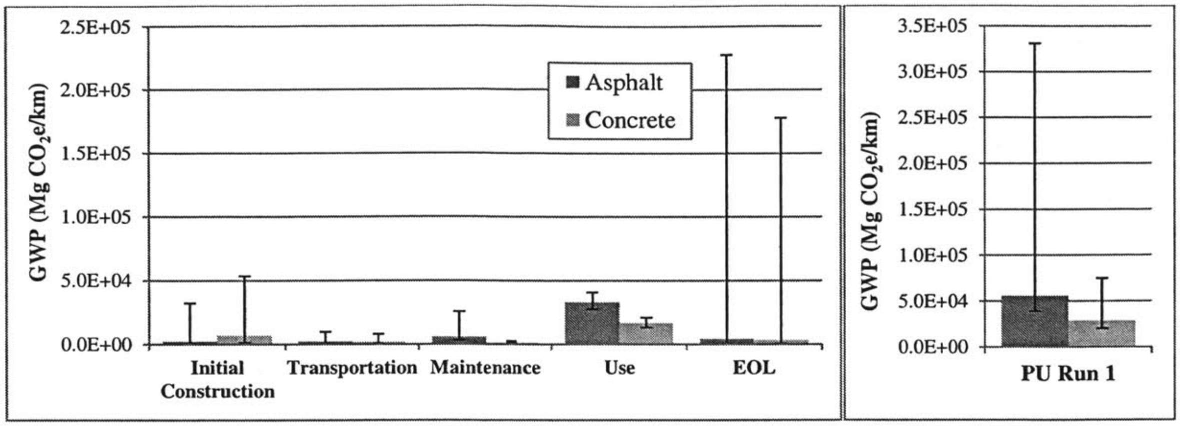

Figure 4.48 High-Volume Run 1 GWP: Results depicting the 5th, 50th, and 95th percentiles by phase, followed by the total

Table 4.24 shows that at the relatively high confidence level of 95%, one can already distinguish between the two alternatives, with the concrete design impact at least 10% less than that of the asphalt.

Table 4.24 High-Volume Run 1 GWP: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α | δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	90%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive
	95%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	99%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive

Figure 4.49 shows the uncertainty for the NRE results of the first run of the high-volume scenario. The MAD-COVs for the asphalt and concrete designs are 18% and 23%, respectively.

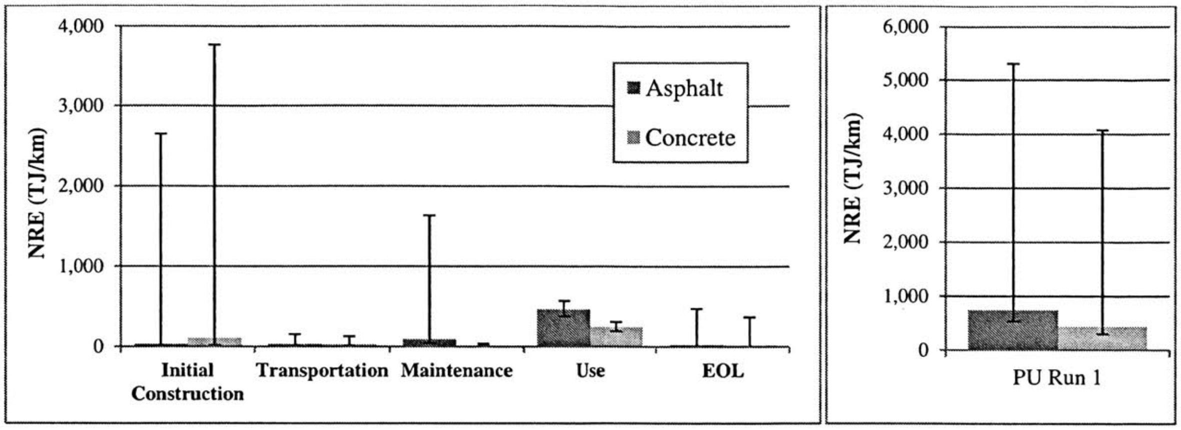

Figure 4.49 High-Volume Run 1 NRE: Results by phase depicting the 5th, 50th, and 95th percentiles, and the total

The statistical analysis in Table 4.25, however, shows that a decision between the alternatives can be made with at most 90% confidence.

Table 4.25 High-Volume Run 1 NRE: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α | δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive
	90%	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	95%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive
	99%	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive

The results of the second and final run for the probabilistic underspecification of the high-volume road are presented below. Figure 4.50 shows the uncertainty for the phases and totals of the final GWP run. The MAD-COVs for the asphalt and concrete totals are 9.1% and 7.0%, respectively.

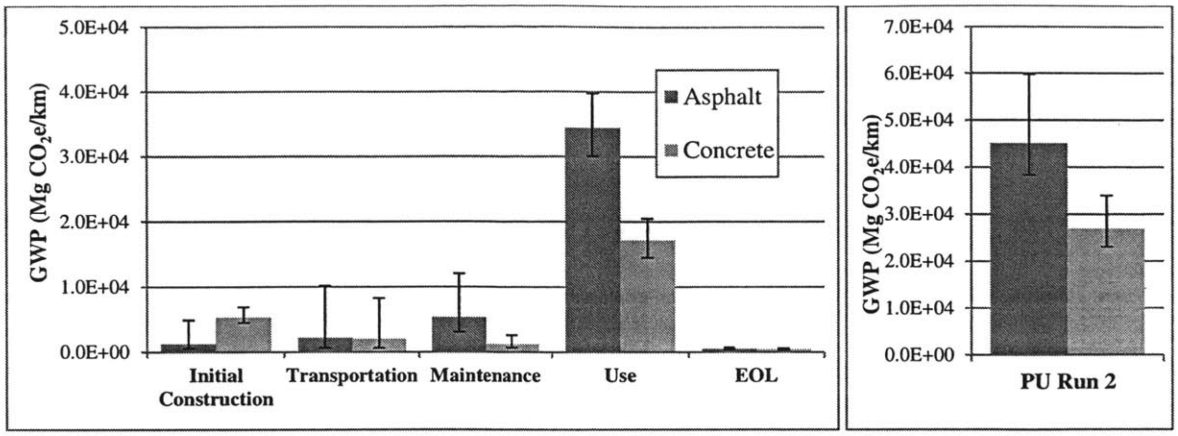

Figure 4.50 High-Volume Run 2 GWP: Results depicting the 5th, 50th, and 95th percentiles by phase, followed by the total

The analysis of the indicator variable in Table 4.26 shows that at almost all levels of confidence and ratios of alternatives, the concrete design has a lesser impact than the asphalt alternative.

Table 4.26 High-Volume Run 2 GWP: Statistical analysis of indicator variable

		Ratio of Alternatives						
	α | δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	90%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	95%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	99%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive

Figure 4.51 shows the results for the final NRE run for the high-volume road. The MAD-COVs for the asphalt and concrete designs are 6.2% and 9.1%, respectively.

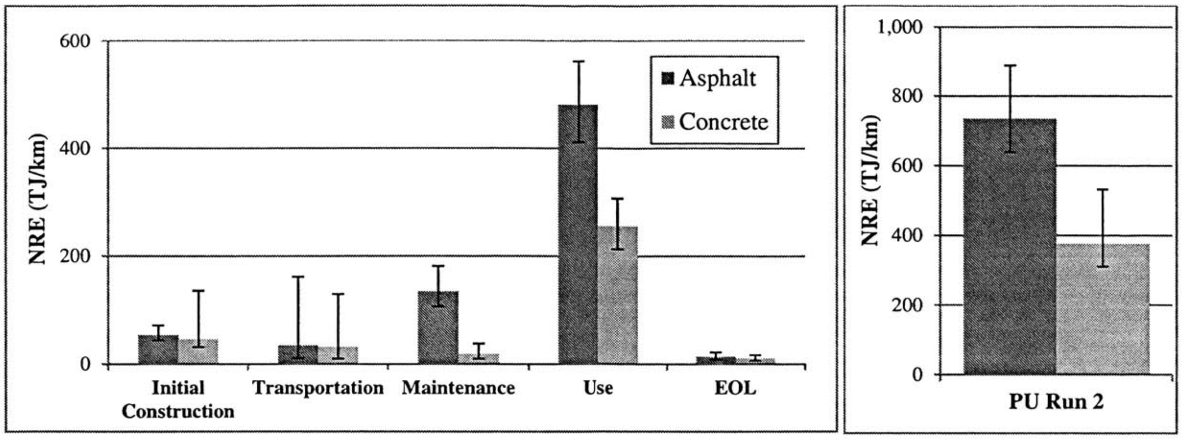

Figure 4.51 High-Volume Run 2 NRE: Results depicting the 5th, 50th, and 95th percentiles by phase, followed by the total

Finally, Table 4.27 shows the analysis of the indicator variable for the final run of the NRE impact category for the high-volume road. At the 99% level of confidence it can be seen that the concrete design impact is at least 10% less than that of the asphalt alternative.

Table 4.27 High-Volume Run 2 NRE: Statistical analysis of indicator variable

	α \ δ	Ratio of Alternatives						
		1.00	0.95	0.90	0.85	0.80	0.75	0.70
Level of Confidence	50%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	75%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	90%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	95%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**
	99%	**Concrete < Asphalt**	**Concrete < Asphalt**	**Concrete < Asphalt**	Inconclusive	Inconclusive	Inconclusive	Inconclusive

4.6 Conclusion

The results presented above demonstrate first the methodology of individual probabilistic specification and then the method of probabilistic underspecification. Both methodologies resulted in similar conclusions, showing that the concrete design had a lower impact than the asphalt, for some combinations of levels of confidence and ratios of alternatives, but for other combinations the results were inconclusive. The next section compares and contrasts the results from these two methodologies.

5 RESULTS AND DISCUSSION

The sections below discuss the accuracy and effort required of the two different methodologies in comparing the global warming potential and non-renewable energy impacts of the alternative pavement designs presented in the case study.

5.1 Degree of Uncertainty Comparison

Table 5.1 displays the MAD-COV results of each assessment. As expected, the level of uncertainty is the lowest for the IPS results because all the parameters are defined at their most specific, L5. The MAD-COV of the final runs for both the GWP and NRE PU results, however, are very close to the IPS results.

Table 5.1 Low-Volume: MAD-COV of results

	GWP		NRE	
	Asphalt	**Concrete**	**Asphalt**	**Concrete**
Run 1	61%	39%	42%	46%
Run 2	13%	11%	9.5%	16%
Run 3	6.6%	7.3%	5.1%	7.3%
IPS	5.5%	6.6%	4.6%	6.9%

To compare the ranges of uncertainty in each run, Figure 5.1 shows the median values, with the error bars representing the 5^{th} and 95^{th} percentiles, of the last two runs of the PU assessment and the IPS assessment for the GWP impact category. The first run is omitted because of the extreme range in values that makes viewing the details of the graph difficult. It can be seen that while the median values and ranges of uncertainty for the results are higher for run two, the IPS results and run three results are quite similar.

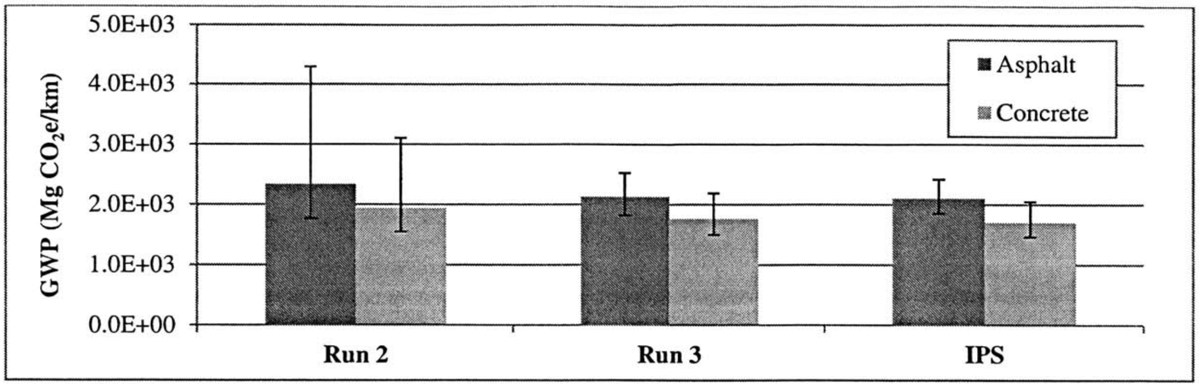

Figure 5.1 Low-Volume GWP: Comparison of results for IPS and PU Runs - 5th, 50th, and 95th percentiles

Figure 5.2 shows this same trend for the NRE results – the final PU and IPS results are in agreement.

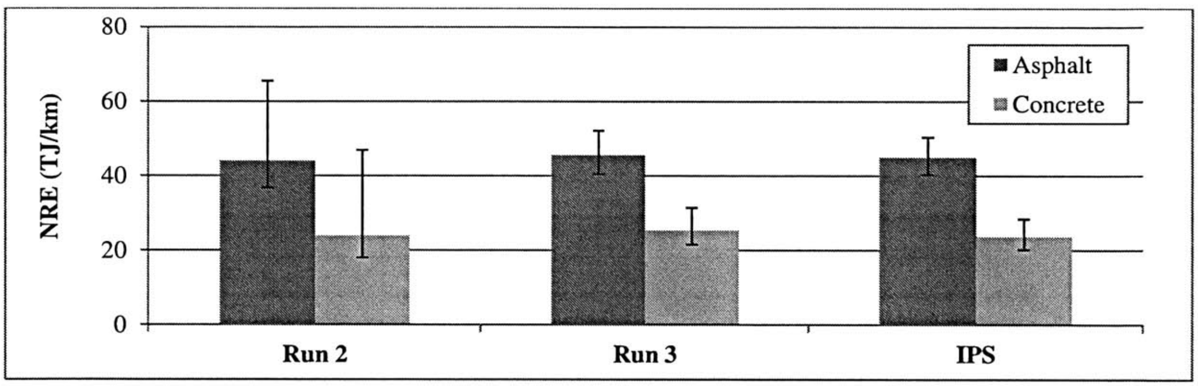

Figure 5.2 Low-Volume NRE: Comparison of results for IPS and PU runs - 5th, 50th, and 95th percentiles

The purpose of using these two methodologies in the context of a comparative LCA was, ultimately, to be able to make a decision between the two alternatives with a certain level of confidence. The tables below are similar to the statistical analysis tables presented in the previous chapter but instead of assigning standard confidence levels of 99%, 95%, and so on, the maximum level of confidence for the given ratios of alternatives is calculated. This allows for a comparison in the ability of each method to make a decision between the two designs. Table 5.2 shows the results for the low-volume GWP assessment. It can be seen for all but the final ratio, the IPS method provides more confidence in the decision that the concrete design has less of an impact than the asphalt. The difference between the two, however, is small – at most 9 percentage-points. The only time the PU result has a greater confidence than the IPS result is for the 0.70 ratio. This can be attributed to the broader range of the PU distribution, which has a longer tail than the IPS distribution and therefore a greater cumulative confidence level can be seen at the beginning of the distribution.

Table 5.2 Low-Volume GWP: Comparison of maximum levels of confidence, for each ratio of alternatives, of final PU run and IPS results (bold refers to highest, or equivalent, level of confidence)

	δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
α_{MAX}	IPS	**98%**	**95%**	**88%**	**70%**	**42%**	**17%**	3.4%
	PU	95%	90%	79%	61%	35%	14%	**3.8%**

The NRE results presented in Table 5.3 shows that the confidence levels are quite similar, though they decrease for the PU results at lower ratios. The drastic difference between the concrete and asphalt totals is what allows for this equivalent confidence.

Table 5.3 Low-Volume NRE: Comparison of maximum levels of confidence, for each ratio of alternatives, of final PU run and IPS results (bold refers to highest, or equivalent, level of confidence)

	δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
α_{MAX}	IPS	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
	PU	**100%**	**100%**	**100%**	**100%**	99%	99%	98%

Ultimately, for the low-volume results, the PU methodology is able to make a decision between the alternatives with only slightly less confidence than the IPS results.

The medium-volume results are similar to the low-volume scenario in that the MAD-COVs of the final PU run and the IPS results are very close in magnitude (Table 5.4).

Table 5.4 Medium-Volume MAD-COV of results

	GWP		**NRE**	
	Asphalt	**Concrete**	**Asphalt**	**Concrete**
Run 1	47%	36%	36%	42%
Run 2	13%	11%	8.7%	14%
Run 3	6.0%	6.8%	4.8%	7.0%
IPS	4.7%	6.0%	4.5%	6.5%

Figure 5.3 and Figure 5.4 compare the ranges of uncertainty for the final runs of the PU assessment with the IPS results for the GWP and NRE impact categories, respectively. Again, the final PU results and IPS results agree, while the second PU run has a wider range of uncertainty.

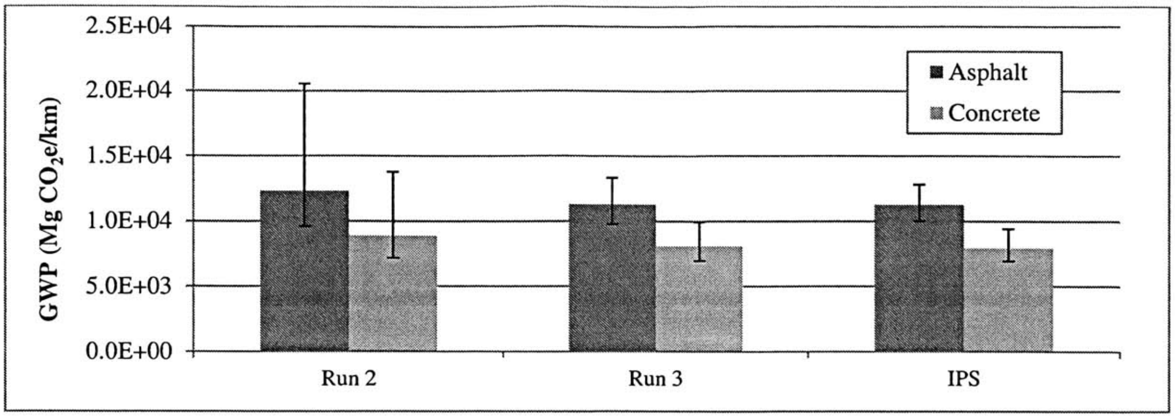

Figure 5.3 Medium-Volume GWP: Comparison of IPS and PU results - 5th, 50th, and 95th percentiles

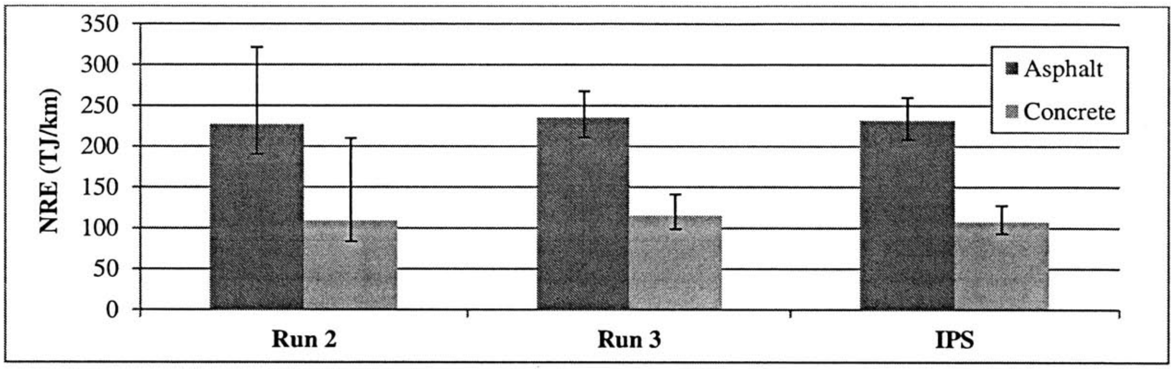

Figure 5.4 Medium-Volume NRE: Comparison of IPS and PU results - 5th, 50th, and 95th percentiles

As seen in the low-volume results, the maximum levels of confidence for the medium-volume GWP assessment (Table 5.5) show that the IPS method produces a slightly higher level of confidence; however, the difference between the two is again small.

Table 5.5 Medium-Volume GWP: Comparison of maximum levels of confidence, for each ratio alternative, of final PU run and IPS results (bold refers to highest, or equivalent, level of confidence)

	δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
α_{MAX}	IPS	**100%**	**100%**	**100%**	**99%**	**94%**	**80%**	**46%**
	PU	99%	99%	98%	96%	89%	71%	40%

Due to the significant difference between the asphalt and concrete NRE distributions, both methods can decide between the alternatives with almost 100% confidence, as seen in Table 5.6.

Table 5.6 Medium-Volume NRE: Comparison of maximum levels of confidence, for each ratio alternative, of final PU run and IPS results (bold refers to highest, or equivalent, level of confidence)

	δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
α_{MAX}	IPS	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
	PU	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	99%

The high-volume scenario was different from the other two scenarios in that it only required two PU runs to be below the threshold MAD-COV value of 10%. Despite this, the IPS and run 2 MAD-COVs do not differ by much (Table 5.7).

Table 5.7 High-Volume MAD-COV of Results

	GWP		NRE	
	Asphalt	**Concrete**	**Asphalt**	**Concrete**
Run 1	20%	19%	18%	23%
Run 2	9.1%	7.0%	6.2%	9.1%
IPS	5.2%	5.5%	4.7%	6.2%

Only the uncertainty ranges for the final run of the PU assessment are compared with the IPS assessment in Figure 5.5 and Figure 5.6 for GWP and NRE, respectively. Fewer processes are specified within this final run than within the final runs for the other scenarios, so the uncertainty for the PU results is slightly more than for the IPS results for this scenario.

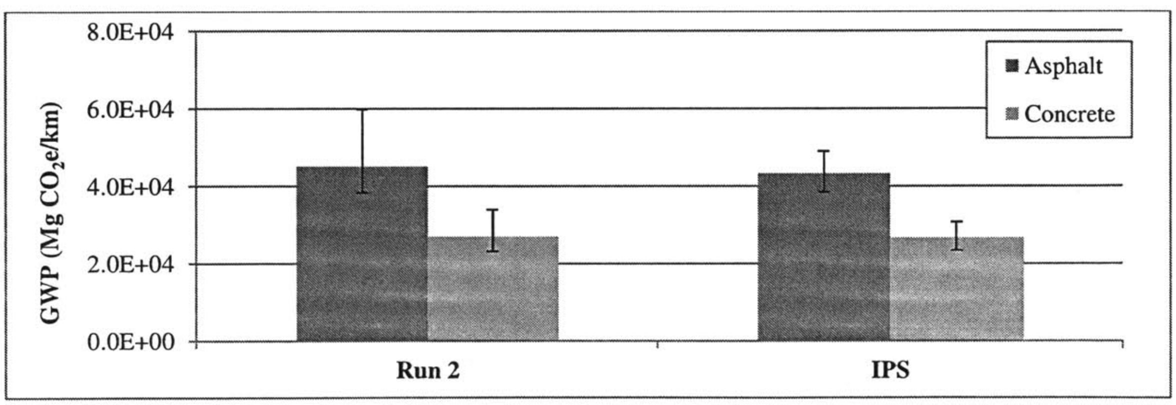

Figure 5.5 High-Volume GWP: Comparison of IPS and PU results - 5th, 50th, and 95th percentiles

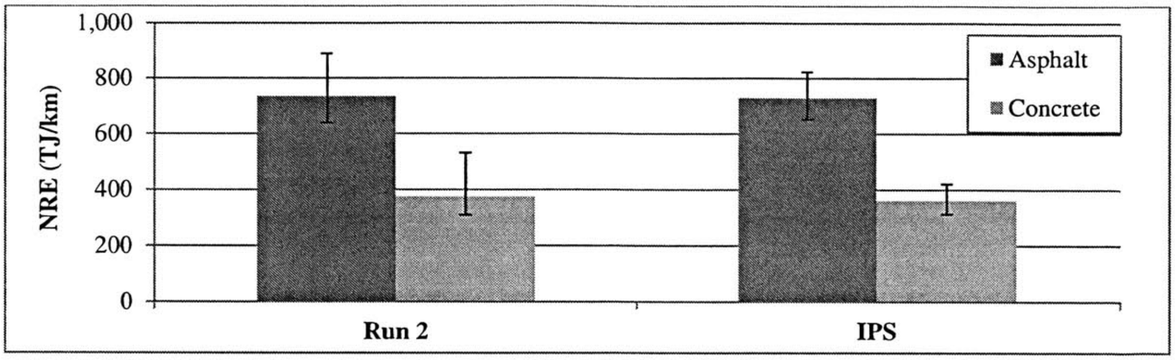

Figure 5.6 High-Volume NRE: Comparison of IPS and PU results - 5th, 50th, and 95th percentiles

Finally, the results presented in Table 5.8 and Table 5.9 show almost equivalent confidence levels between the two methods, for both the GWP and NRE assessments.

Table 5.8 High-Volume GWP: Comparison of maximum levels of confidence, for each ratio alternative, of final PU run and IPS results (bold refers to highest, or equivalent, level of confidence)

	δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
α_{MAX}	IPS	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
	PU	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	98%

Table 5.9 High-Volume NRE: Comparison of maximum levels of confidence, for each ratio alternative, of final PU run and IPS results (bold refers to highest, or equivalent, level of confidence)

	δ	1.00	0.95	0.90	0.85	0.80	0.75	0.70
α_{MAX}	IPS	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
	PU	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

The above tables show that the ranges of the uncertainty distributions are comparable between the two methodologies. Additionally, the graphs show that the median values are very similar, and often the uncertainty range of the final PU run encompasses the uncertainty range of the IPS assessment.

5.2 Level of Effort Comparison

The benefit of the probabilistic underspecification methodology is its ability to streamline the process of evaluating the appropriateness of the environmental factor. Additionally, when incorporating uncertainty, it greatly simplifies the quantification of appropriateness for the intermediate flow. Figure 5.7 shows the percentage of GWP parameters specified at L5 for the low-volume scenario. The IPS methodology requires that all the parameters be specified at L5, while PU begins with no parameters specified at L5. As increased specification becomes necessary, the number of parameters defined at L5 increase with each PU run. The fewer parameters that need to be defined at L5, the less effort required to determine the appropriateness of an intermediate flow and its associated uncertainty. It should be noted that "effort" does not refer to the overall effort required to perform the entire LCA, but rather just the effort in quantifying the intermediate flow application uncertainty. It is used here as a proxy metric for effort, but is not intended to quantify the effort required to conduct a complete comparative LCA. This is especially true given that multiple simulations are required for the PU methodology, and only one for the IPS. The eventual aim of the PU methodology, however, is to determine, on average, how many processes need to be specified within a given product or category so that fewer runs are required.

It can be concluded from Figure 5.7 that PU requires just 29% of the intermediate flow effort that IPS requires for the intermediate flow assessment within the GWP impact calculation. If less reliability is required, and a smaller final difference between the two alternatives, then only 13% of the effort of IPS is required.

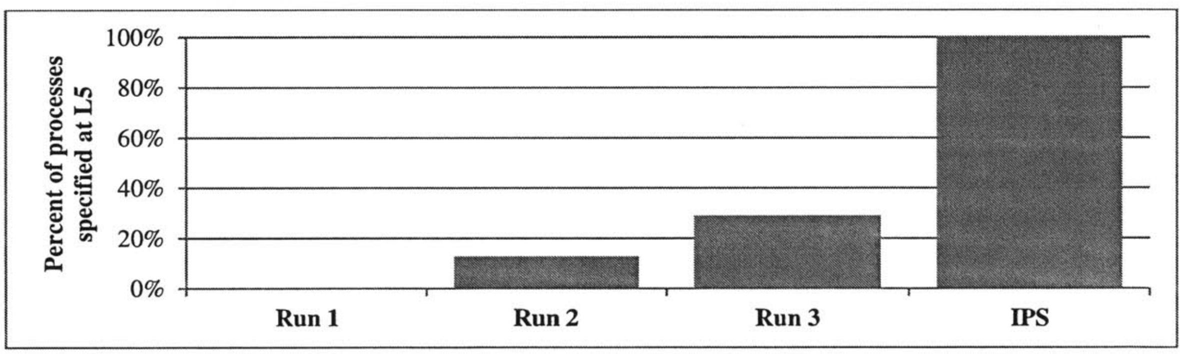

Figure 5.7 Low-Volume GWP: Percent of processes specified at L5, combined analysis

Due to the large difference in embodied energy between concrete and asphalt pavements, the same amount of effort is required for the NRE calculations (Figure 5.8). Again, only 29% of the effort required for the IPS method is required for the intermediate flow assessment in order to give enough information to make a decision between the two alternatives.

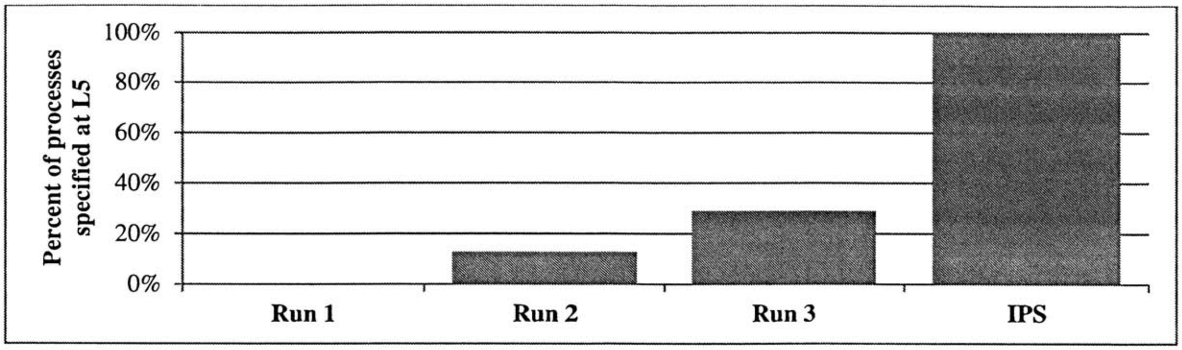

Figure 5.8 Low-Volume NRE: Percentage of processes specified at L5, combined analysis

The comparison of the results from the final runs of the probabilistic underspecification method with the results from the individual probabilistic specification method show that the same conclusions can be reached, but with less effort.

Figure 5.10 and Figure 5.11 show the percentage of processes specified at L5 for the medium-volume scenario, for the GWP and NRE impact categories, respectively. The GWP PU assessment requires only 29% of the effort for intermediate flow assessment that the IPS assessment requires, while the NRE assessment requires 32%.

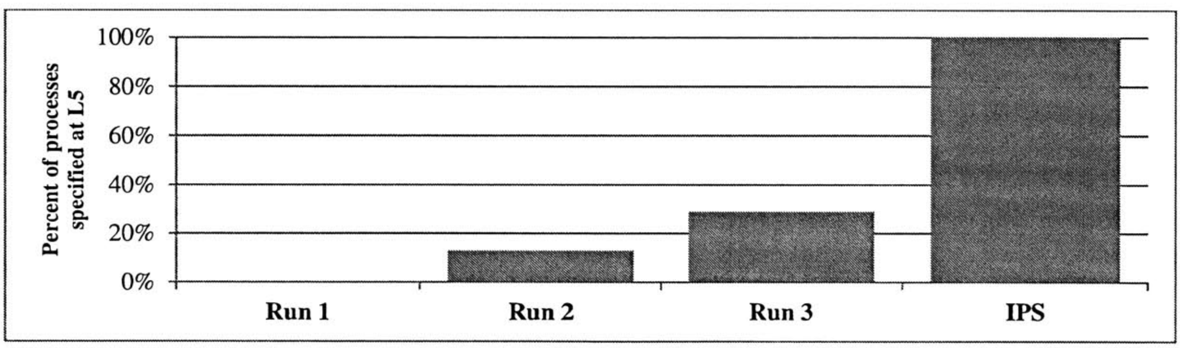

Figure 5.9 Medium-Volume GWP: Percentage of processes specified at L5, combined analysis

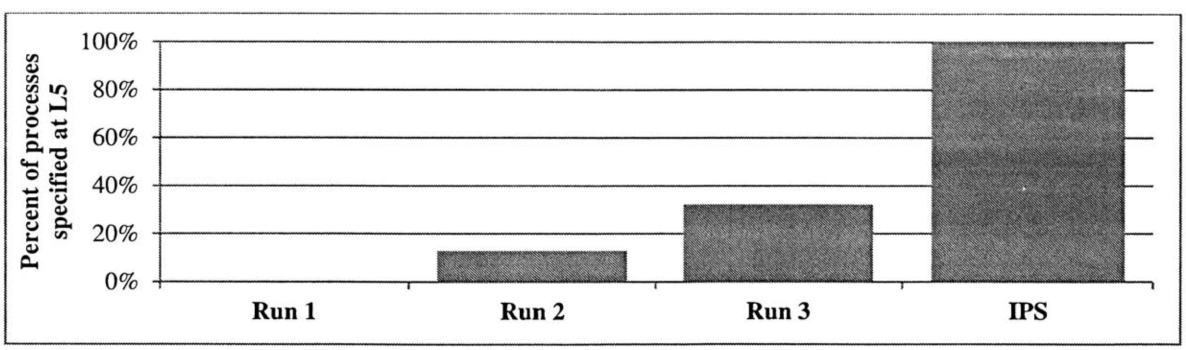

Figure 5.10 Medium-Volume NRE: Percentage of processes specified at L5, combined analysis

For the high-volume scenario, Figure 5.11 and Figure 5.12 show the percentage of processes specified at L5. The GWP and NRE PU assessments are the same, with both requiring only 16% of the effort the IPS assessment requires for the intermediate flow assessment.

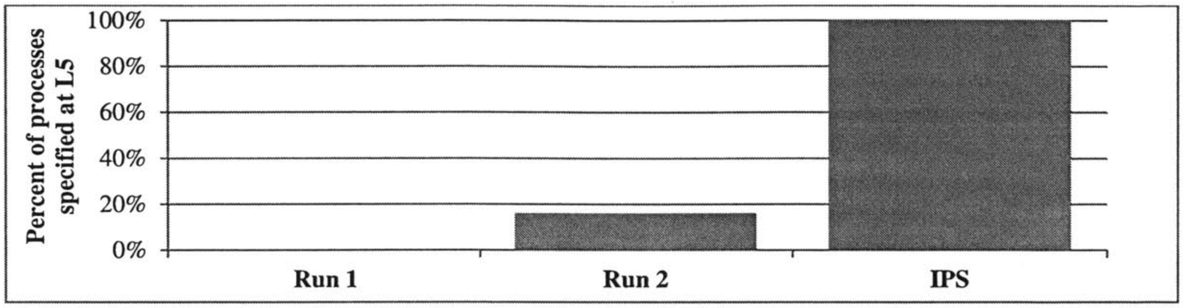

Figure 5.11 High-Volume GWP: Percentage of processes specified at L5, combined analysis

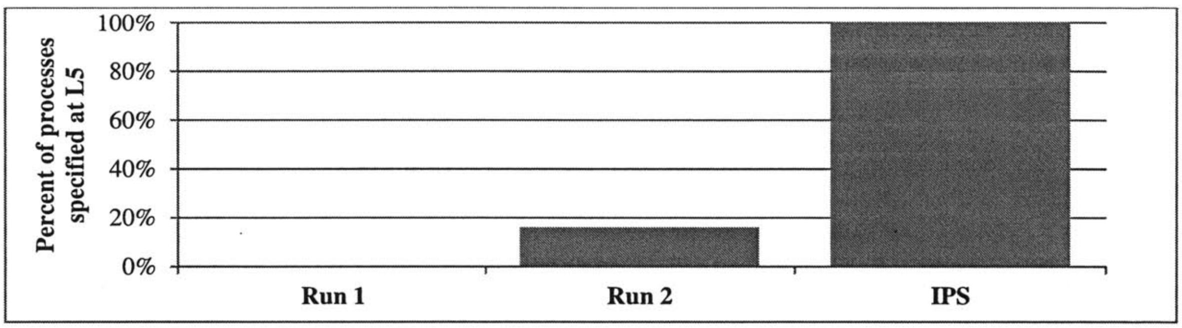

Figure 5.12 High-Volume NRE: Percentage of processes specified at L5, combined analysis

It can be seen from the above graphs that no more than 32% of the processes needed to be specified in order for a decision to be made between the alternatives. This translated to a lower amount of effort required to determine the appropriateness of intermediate flows and their associated uncertainties.

This chapter demonstrates that the method of probabilistic underspecification is capable of accurately evaluating the environmental impact of a pavement with a relatively low degree of uncertainty, and it performs this evaluation with less effort than the alternative method of individual probabilistic underspecification.

6 CONCLUSION

The incorporation of uncertainty into a comparative life cycle assessment is crucial to the credibility of any conclusions drawn. Through the literature review presented, the importance of incorporating uncertainty into LCAs is emphasized, especially within comparative LCAs. With increased use of LCAs, however, a focus must be made to incorporate this uncertainty through streamlined methods so as to reduce time and cost requirements.

This thesis presents two alternative methodologies for including uncertainty in a comparative LCA. The first, individual probabilistic specification (IPS) incorporates measurement, quantity application, and intermediate flow application uncertainties through the use of empirical data, expert estimates, and data quality indicators. Though IPS is presented as time-intensive, it is an import method for in-depth analysis because it identifies and combines existing forms of uncertainty into a single methodology that can be implemented by other practitioners in the future. In contrast, the second method, probabilistic underspecification (PU), while incorporating measurement and quantity application uncertainties in the same way as IPS, addresses intermediate flow application uncertainty in a different manner that requires less effort. This process involves the structured underspecification of different material and process categories. By underspecifying the impact parameter, less effort is required to determine the appropriate intermediate flow and uncertainty quantification.

A case study is presented to compare these two methodologies. Alternative asphalt and concrete pavement designs are evaluated for three different roads in southern California using the impact assessment methods of global warming potential and non-renewable energy. It should be emphasized that these are only three of a practically infinite number of scenarios that could be assessed, and in no way represent all cases in which this comparison between asphalt and concrete alternatives would be made. The emphasis of this thesis is on the validity of probabilistic underspecification within comparative LCAs. The focus is not on the final values, but rather the ranges of uncertainty and the ability to differentiate between two alternatives. With that said, the median values of the results from the two methodologies do not differ significantly, and the IPS median value always falls within the uncertainty range predicted by the PU assessment.

The original research question stated: *Does the method of probabilistic underspecification allow for a decision to be made with an equal level of confidence to, and less effort than, the method of individual probabilistic specification?* The final conclusion is that though the confidence levels are slightly less when applied to this case study, probabilistic underspecification is able to assess the impact and associated uncertainty of a comparative LCA with less effort than traditional methods. The following points summarize the results of this case study:

- While the two methods do not always result in the same level of confidence when deciding between the alternative designs, they are comparable, with no more than a 9 percentage-point difference between the two. Additionally, at a minimum ratio of alternatives of 1.00, all three scenarios were able to differentiate between the two alternatives with a high level of confidence.
- For this example, no more than 32% of the processes need to specified at L5 in order to allow for a decision to be made between alternatives, with a high level of confidence.
- The method of probabilistic underspecification is able to produce results with less than 10% variation (MAD-COV values), which are comparable to the IPS results. While PU results in a slightly higher spread of the data, this spread does not impact the diagnostic power of the assessment.

6.1 Future Work

The method of probabilistic underspecification is in an early stage of exploration. Further case studies will be required to prove its efficacy, both for individual and comparative LCAs. While this thesis explores pavements, they are just one category of products and systems that require an environmental assessment. Patanavanich (2011) explores electronics in his study; there are many more categories that should be assessed before this streamlining method can be fully validated.

This thesis neglects the exclusion of certain potentially impossible parameter combinations within the Monte Carlo simulations due to time constraints. A more accurate result could be obtained by including this aspect. Another area for potential work is the threshold value of the MAD-COV. This thesis uses an arbitrary value, but with further investigation a more appropriate value may be determined. Additionally, the equally arbitrary value of 5% contribution to the total uncertainty in order for a process to be specified at L5 should be further researched.

Patanavanich had established his specification rules by considering the contribution to total impact, rather than uncertainty. The efficacy of using either option should be explored.

While there is significant work that needs to be done to further validate the method of probabilistic underspecification, the results of this assessment show that it is promising. Further investigation could potentially lead to the adoption of this method as a viable LCA streamlining option.

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Appendix A – Freight Transportation Underspecification Levels

Level 1	Level 2	Level 3	Level 4	Level 5
Freight Transportation	Freight Air	Freight Air	Freight Air	Plane, technology mix, cargo, 68 t payload RER
Freight Transportation	Freight Air	Freight Air	Freight Air	Transport, aircraft, freight/RER
Freight Transportation	Freight Air	Freight Air	Freight Air	Transport, aircraft, freight/US
Freight Transportation	Freight Air	Freight Air - Continental	Freight Air - Continental	Transport, aircraft, freight, Europe/RER
Freight Transportation	Freight Air	Freight Air - Intercontinental	Freight Air - Intercontinental	Transport, aircraft, freight, intercontinental/RER
Freight Transportation	Freight Pipeline	Natural Gas Pipeline	Natural Gas Pipeline - Long Distance	Transport, natural gas, pipeline, long distance/RU
Freight Transportation	Freight Pipeline	Natural Gas Pipeline	Natural Gas Pipeline - Long Distance	Transport, natural gas, pipeline, long distance/RER
Freight Transportation	Freight Pipeline	Natural Gas Pipeline	Natural Gas Pipeline - Long Distance	Transport, natural gas, pipeline, long distance/NL
Freight Transportation	Freight Pipeline	Natural Gas Pipeline	Natural Gas Pipeline - Long Distance	Transport, natural gas, pipeline, long distance/DE
Freight Transportation	Freight Pipeline	Natural Gas Pipeline	Natural Gas Pipeline - Offshore	Transport, natural gas, offshore pipeline, long distance/NO
Freight Transportation	Freight Pipeline	Natural Gas Pipeline	Natural Gas Pipeline - Offshore	Transport, natural gas, offshore pipeline, long distance/DZ
Freight Transportation	Freight Pipeline	Natural Gas Pipeline	Natural Gas Pipeline - Onshore	Transport, natural gas, onshore pipeline, long distance/NO
Freight Transportation	Freight Pipeline	Natural Gas Pipeline	Natural Gas Pipeline - Onshore	Transport, natural gas, onshore pipeline, long distance/DZ
Freight Transportation	Freight Pipeline	Oil Pipeline	Oil Pipeline - Offshore	Transport, crude oil pipeline, offshore/OCE
Freight Transportation	Freight Pipeline	Oil Pipeline	Oil Pipeline - Onshore	Transport, crude oil pipeline, onshore/RER
Freight Transportation	Freight Rail	Freight Rail - Coal	Freight Rail - Coal	Transport, coal freight, rail/CN
Freight Transportation	Freight Rail	Freight Rail - Diesel	Freight Rail - Diesel	Transport, freight, rail, diesel/US
Freight Transportation	Freight Rail	Freight Rail - Diesel	Freight Rail - Diesel	Transport, freight, rail, diesel, with particle filter/CH
Freight Transportation	Freight Rail	Freight Rail	Freight Rail - Electro/Diesel	Transport, freight, rail/RER
Freight Transportation	Freight Rail	Freight Rail	Freight Rail - Electro/Diesel	Transport, freight, rail/IT

Level 1	Level 2	Level 3	Level 4	Level 5
Freight Transportation	Freight Rail	Freight Rail	Freight Rail - Electro/Diesel	Transport, freight, rail/FR
Freight Transportation	Freight Rail	Freight Rail	Freight Rail - Electro/Diesel	Transport, freight, rail/DE
Freight Transportation	Freight Rail	Freight Rail	Freight Rail - Electro/Diesel	Transport, freight, rail/CH
Freight Transportation	Freight Rail	Freight Rail	Freight Rail - Electro/Diesel	Transport, freight, rail/BE
Freight Transportation	Freight Rail	Freight Rail	Freight Rail - Electro/Diesel	Transport, freight, rail/AT
Freight Transportation	Freight Road	Truck	Large Truck	Articulated lorry transport, Euro 0, 1, 2, 3, 4 mix, 40 t total weight, 27 t max payload RER
Freight Transportation	Freight Road	Truck	Large Truck	Transport, lorry >32t, EURO3/RER
Freight Transportation	Freight Road	Truck	Large Truck	Transport, lorry >32t, EURO4/RER
Freight Transportation	Freight Road	Truck	Large Truck	Transport, lorry >32t, EURO5/RER
Freight Transportation	Freight Road	Truck	Large Truck	Truck 40t
Freight Transportation	Freight Road	Truck	Medium Truck	Lorry transport, Euro 0, 1, 2, 3, 4 mix, 22 t total weight, 17,3t max payload RER
Freight Transportation	Freight Road	Truck	Medium Truck	Transport, combination truck, average fuel mix/US
Freight Transportation	Freight Road	Truck	Medium Truck	Transport, combination truck, diesel powered/US
Freight Transportation	Freight Road	Truck	Medium Truck	Transport, combination truck, gasoline powered/US
Freight Transportation	Freight Road	Truck	Medium Truck	Transport, lorry >28t, fleet average/CH
Freight Transportation	Freight Road	Truck	Medium Truck	Transport, lorry 16-32t, EURO3/RER
Freight Transportation	Freight Road	Truck	Medium Truck	Transport, lorry 16-32t, EURO4/RER
Freight Transportation	Freight Road	Truck	Medium Truck	Transport, lorry 16-32t, EURO5/RER
Freight Transportation	Freight Road	Truck	Medium Truck	Transport, lorry 20-28t, fleet average/CH
Freight Transportation	Freight Road	Truck	Medium Truck	Transport, lorry 28t, rape methyl ester 100%/CH
Freight Transportation	Freight Road	Truck	Medium Truck	Transport, municipal waste collection, lorry 21t/CH
Freight Transportation	Freight Road	Truck	Medium Truck	Transport, single unit truck, diesel powered/US

Level 1	Level 2	Level 3	Level 4	Level 5
Freight Transportation	Freight Road	Truck	Medium Truck	Transport, single unit truck, gasoline powered/US
Freight Transportation	Freight Road	Truck	Medium Truck	Transport, tractor and trailer/CH
Freight Transportation	Freight Road	Truck	Medium Truck	Truck 28t
Freight Transportation	Freight Road	Truck	Small Truck	Small lorry transport, Euro 0, 1, 2, 3, 4 mix, 7,5 t total weight, 3,3 t max payload RER
Freight Transportation	Freight Road	Truck	Small Truck	Transport, lorry >16t, fleet average/RER
Freight Transportation	Freight Road	Truck	Small Truck	Transport, lorry 3.5-16t, fleet average/RER
Freight Transportation	Freight Road	Truck	Small Truck	Transport, lorry 3.5-20t, fleet average/CH
Freight Transportation	Freight Road	Truck	Small Truck	Transport, lorry 3.5-7.5t, EURO3/RER
Freight Transportation	Freight Road	Truck	Small Truck	Transport, lorry 3.5-7.5t, EURO4/RER
Freight Transportation	Freight Road	Truck	Small Truck	Transport, lorry 3.5-7.5t, EURO5/RER
Freight Transportation	Freight Road	Truck	Small Truck	Transport, lorry 7.5-16t, EURO3/RER
Freight Transportation	Freight Road	Truck	Small Truck	Transport, lorry 7.5-16t, EURO4/RER
Freight Transportation	Freight Road	Truck	Small Truck	Transport, lorry 7.5-16t, EURO5/RER
Freight Transportation	Freight Road	Truck	Small Truck	Truck 16t
Freight Transportation	Freight Road	Van	Van	Delivery van <3.5t
Freight Transportation	Freight Road	Van	Van	Transport, van <3.5t/CH
Freight Transportation	Freight Road	Van	Van	Transport, van <3.5t/RER
Freight Transportation	Freight Water	Barge	Barge	Transport, barge, residual fuel oil powered/US
Freight Transportation	Freight Water	Barge	Barge	Transport, barge, diesel powered/US
Freight Transportation	Freight Water	Barge	Barge	Transport, barge, average fuel mix/US
Freight Transportation	Freight Water	Barge	Barge	Barge, technology mix, 1.228 t pay load capacity RER
Freight Transportation	Freight Water	Barge	Barge	Transport, barge/RER
Freight Transportation	Freight Water	Barge	Barge	Transport, barge tanker/RER

Level 1	Level 2	Level 3	Level 4	Level 5
Freight Transportation	Freight Water	Transoceanic	Transoceanic	Transport, ocean freighter, residual fuel oil powered/US
Freight Transportation	Freight Water	Transoceanic	Transoceanic	Transport, ocean freighter, diesel powered/US
Freight Transportation	Freight Water	Transoceanic	Transoceanic	Transport, ocean freighter, average fuel mix/US
Freight Transportation	Freight Water	Transoceanic	Transoceanic	Freighter oceanic
Freight Transportation	Freight Water	Transoceanic	Transoceanic	Container ship ocean, technology mix, 27.500 dwt pay load capacity RER
Freight Transportation	Freight Water	Transoceanic	Transoceanic	Bulk carrier ocean, technology mix, 100.000-200.000 dwt RER
Freight Transportation	Freight Water	Transoceanic	Transoceanic	Transport, transoceanic tanker/OCE
Freight Transportation	Freight Water	Transoceanic	Transoceanic	Transport, transoceanic freight ship/OCE
Freight Transportation	Freight Water	Transoceanic	Transoceanic	Transport, liquefied natural gas, freight ship/OCE
Person Transportation	Person Aircraft	Person Aircraft	Person Aircraft	Transport, aircraft, passenger, Europe/RER
Person Transportation	Person Aircraft	Person Aircraft	Person Aircraft	Transport, aircraft, passenger, intercontinental/RER
Person Transportation	Person Aircraft	Person Aircraft	Person Aircraft	Transport, aircraft, passenger/RER
Person Transportation	Person Rail	Average Train	Average Train - Electricity	Transport, average train, SBB mix/CH
Person Transportation	Person Rail	Average Train	Average Train - Electro/Diesel	Transport, average train/IT
Person Transportation	Person Rail	Average Train	Average Train - Electro/Diesel	Transport, average train/FR
Person Transportation	Person Rail	Average Train	Average Train - Electro/Diesel	Transport, average train/DE
Person Transportation	Person Rail	Average Train	Average Train - Electro/Diesel	Transport, average train/BE
Person Transportation	Person Rail	Average Train	Average Train - Electro/Diesel	Transport, average train/AT
Person Transportation	Person Rail	High Speed Train	High Speed Train	Transport, high speed train/IT
Person Transportation	Person Rail	High Speed Train	High Speed Train	Transport, high speed train/FR
Person Transportation	Person Rail	High Speed Train	High Speed Train	Transport, high speed train/DE
Person Transportation	Person Rail	Long-Distance Train	Long-Distance Train	Transport, long-distance train, SBB mix/CH

Level 1	Level 2	Level 3	Level 4	Level 5
Person Transportation	Person Rail	Short-Distance Train	Short-Distance Train	Transport, regional train, SBB mix/CH
Person Transportation	Person Rail	Short-Distance Train	Short-Distance Train	Transport, metropolitan train, SBB mix/CH
Person Transportation	Person Road	Car	Car - Alternative Fuel	Transport, passenger car, ethanol 5%/CH
Person Transportation	Person Road	Car	Car - Alternative Fuel	Transport, passenger car, methane, 96 vol-%, from biogas/CH
Person Transportation	Person Road	Car	Car - Alternative Fuel	Transport, passenger car, methanol/CH
Person Transportation	Person Road	Car	Car - Alternative Fuel	Transport, passenger car, natural gas/CH
Person Transportation	Person Road	Car	Car - Alternative Fuel	Transport, passenger car, rape seed methyl ester 5%/CH
Person Transportation	Person Road	Car	Car - Diesel/Petrol	Transport, passenger car, diesel, EURO3/CH
Person Transportation	Person Road	Car	Car - Diesel/Petrol	Transport, passenger car, diesel, EURO4/CH
Person Transportation	Person Road	Car	Car - Diesel/Petrol	Transport, passenger car, diesel, EURO5, city car/CH
Person Transportation	Person Road	Car	Car - Diesel/Petrol	Transport, passenger car, diesel, EURO5/CH
Person Transportation	Person Road	Car	Car - Diesel/Petrol	Transport, passenger car, diesel, fleet average 2010/CH
Person Transportation	Person Road	Car	Car - Diesel/Petrol	Transport, passenger car, diesel, fleet average 2010/RER
Person Transportation	Person Road	Car	Car - Diesel/Petrol	Transport, passenger car, diesel, fleet average/CH
Person Transportation	Person Road	Car	Car - Diesel/Petrol	Transport, passenger car, diesel, fleet average/RER
Person Transportation	Person Road	Car	Car - Diesel/Petrol	Transport, passenger car, petrol, 15% vol. ETBE with ethanol from biomass, EURO4/CH
Person Transportation	Person Road	Car	Car - Diesel/Petrol	Transport, passenger car, petrol, 4% vol. ETBE with ethanol from biomass, EURO4/CH
Person Transportation	Person Road	Car	Car - Diesel/Petrol	Transport, passenger car, petrol, EURO3/CH
Person Transportation	Person Road	Car	Car - Diesel/Petrol	Transport, passenger car, petrol, EURO4/CH
Person Transportation	Person Road	Car	Car - Diesel/Petrol	Transport, passenger car, petrol, EURO5/CH
Person Transportation	Person Road	Car	Car - Diesel/Petrol	Transport, passenger car, petrol, fleet average 2010/CH

Level 1	Level 2	Level 3	Level 4	Level 5
Person Transportation	Person Road	Car	Car - Diesel/Petrol	Transport, passenger car, petrol, fleet average 2010/RER
Person Transportation	Person Road	Car	Car - Diesel/Petrol	Transport, passenger car, petrol, fleet average/CH
Person Transportation	Person Road	Car	Car - Diesel/Petrol	Transport, passenger car, petrol, fleet average/RER
Person Transportation	Person Road	Car	Car - Diesel/Petrol	Transport, passenger car/CH
Person Transportation	Person Road	Car	Car - Diesel/Petrol	Transport, passenger car/RER
Person Transportation	Person Road	Car	Car - Electric	Transport, passenger car, electric, LiMn2O4, certified electricity/CH
Person Transportation	Person Road	Car	Car - Electric	Transport, passenger car, electric, LiMn2O4, city car, certified electricity/CH
Person Transportation	Person Road	Car	Car - Electric	Transport, passenger car, electric, LiMn2O4, city car/CH
Person Transportation	Person Road	Car	Car - Electric	Transport, passenger car, electric, LiMn2O4/CH
Person Transportation	Person Road	Individual Transport - Road	Individual Transport Road - Diesel	Transport, scooter/CH
Person Transportation	Person Road	Individual Transport - Road	Individual Transport Road - Electricity	Transport, electric bicycle, certified electricity/CH
Person Transportation	Person Road	Individual Transport - Road	Individual Transport Road - Electricity	Transport, electric bicycle/CH
Person Transportation	Person Road	Individual Transport - Road	Individual Transport Road - Electricity	Transport, electric scooter, certified electricity/CH
Person Transportation	Person Road	Individual Transport - Road	Individual Transport Road - Electricity	Transport, electric scooter/CH
Person Transportation	Person Road	Individual Transport - Road	Individual Transport Road - Man-power	Transport, bicycle/CH
Person Transportation	Person Road	Public Transport - Road	Public Transport Road - Electricity	Transport, tram/CH
Person Transportation	Person Road	Public Transport - Road	Public Transport Road - Electricity	Transport, trolleybus/CH
Person Transportation	Person Road	Public Transport - Road	Public Transport Road - Diesel	Transport, coach/CH
Person Transportation	Person Road	Public Transport - Road	Public Transport Road - Diesel	Transport, regular bus/CH

Appendix B - Roughness Calculations

The equations presented below briefly explain the method by which additional fuel loss due to changes in the roughness of the pavement (IRI) was calculated:

$$(Eq\ 1)\quad AADCT \times (1 + x) \times \Delta t$$

$$(Eq\ 2)\quad AADTT \times (1 + Y) \times \Delta t$$

$$(Eq\ 3)\quad C_{mpg} \times (1 + z) \times \Delta t$$

$$(Eq\ 4)\quad T_{mpg} \times (1 + z) \times \Delta t$$

$$\frac{(Eq\ 1) \times \Delta t \times \left[\frac{\Delta IRI_{t+1} - \Delta IRI_t}{2} + \Delta IRI_t\right]}{(Eq\ 3)} \times g \times \frac{l}{5280}$$

$$= additional\ gasoline\ use\ due\ to\ changes\ in\ IRI$$

$$\frac{(Eq\ 2) \times \Delta t \times \left[\frac{\Delta IRI_{t+1} - \Delta IRI_t}{2} + \Delta IRI_t\right]}{(Eq\ 4)} \times d \times \frac{l}{5280}$$

$$= additional\ diesel\ fuel\ use\ due\ to\ changes\ in\ IRI$$

IRI = international roughness index (in/mi)
AADT = average annual daily traffic
AADTT = average annual daily truck traffic
AADCT = AADT-AADTT = average annual daily car traffic
Δt = change in time (days)
x = AADCT growth factor (%)
y = AADTT growth factor (%)
C_{mpg} = average miles per gallon for cars
T_{mpg} = average miles per gallon for trucks
z = growth factor of mpg
$\Delta IRIt$ = the change in IRI over Δt
d = diesel fuel loss per change in IRI, per mile
g = gas fuel loss per change in IRI, per mile

Appendix C - Inventory Data

Concrete Designs					*Data Source*
Functional Unit	*ft*	3280.8	3280.8	3280.8	Study specific
Number of Lanes	*no.*	2	4	6	MEPDG, Caltrans 2012
Width of Lanes	*ft*	12	12	12	
No. of Shoulders	*no.*	0	4	4	(FHWA 2008)
Shoulder Width	*ft*	10	10	10	
Scenario		33 (JPCP-CA)	67 (JCP-CA)	101 (JCP-CA)	Study specific
Traffic Type		Low	Medium	High	
Location		CA	CA	CA	
Design Life	*yrs*	55	55	55	
Maintenance 1	*year*	25	25	45	MEPDG, Caltrans 2012
Type		DG	DG	DG	
Maintenance 2	*year*	30	30	50	
Type		DG	DG	DG	
Maintenance 3	*year*	40	40		
Type		DG	DG		
Maintenance 4	*year*	45	45		
Type		3" Overlay	3" Overlay		
Performance Criteria					
Initial IRI	*in/mi*	63	63	63	MEPDG, Caltrans 2012
Terminal IRI	*in/mi*	170	170	170	
Transverse Cracking	*%*	10	10	10	
Mean Joint Faulting	*in/mi*	0.1	0.1	0.1	
Traffic					
Initial Two-Way AADTT	*no.*	150	1357	6672	MEPDG, Caltrans 2012
AADTT Growth Factor	*%*	4.0%	4.0%	4.0%	
Initial Two-Way AADT	*no.*	3400	23400	139000	
AADT Growth Factor	*%*	4.0%	4.0%	4.0%	
Joint Design					
Joint Spacing	*ft*	13.5	13.5	13.5	MEPDG, Caltrans 2012
Dowel Diameter	*in*	1.25	1.25	1.5	
Dowel Bar Spacing	*in*	12	12	12	
Longitudinal Joint Spacing	*ft*	13	13	13	Other pavement designs
Tie Bar Spacing	*in*	12	12	12	
Dowel Length	*ft*	1.5	1.5	1.5	
Tie Bar Length	*ft*	0	1.5	1.5	

Concrete Designs					*Data Source*
Unit Weight	*pcf*	490	490	490	
JPCP					
Thickness	*in*	8.4	9.6	10.8	MEPDG, Caltrans 2012
Unit Weight	*pcf*	150	150	150	
Mix Properties					
Cement Type		1	1	1	MEPDG, Caltrans 2012
Cement Content	*lb/yd³*	568	568	568	
Water/Cement Ratio	-	0.42	0.42	0.42	
Aggregate	*pcf*	120	120	120	
Cement Stabilized Subgrade					
Thickness	*in*	4.2	4.8	6	MEPDG, Caltrans 2012
Unit Weight	*pcf*	150	150	150	
Mix Properties					
Cement Content	%	7%	7%	7%	Estimate
Aggregate	%	93%	93%	93%	
Aggregate Base 1					
Thickness	*in*	6	7.2	8.4	MEPDG, Caltrans 2012
Unit Weight	*pcf*	127.2	127.2	127.2	
Aggregate Base 2					
Thickness	*in*	12	12	12	MEPDG, Caltrans 2012
Unit Weight	*pcf*	97.7	97.7	97.7	
Construction Energy					
Concrete Mixing - Diesel	*MJ/tonne*	6.96	6.96	6.96	(Stripple 2001)
Concrete Mixing - Electricity	*MJ/tonne*	285	285	285	
Asphalt Mixing - Heating Oil	*MJ/tonne*	285	285	285	
Asphalt Mixing - Electricity	*MJ/tonne*	36	36	36	
Concrete Paving	*MJ/tonne*	34.00	34.00	34.00	(Stripple 2001)
Asphalt Paving	*MJ/tonne*	13.40	13.40	13.40	
Placement of Other Layers	*MJ/tonne*	6.61	6.61	6.61	
Maintenance					
Sawing of Joints	*no.*	3	3	2	MEPDG, Caltrans 2012
Sawing of Joints	*MJ/m²*	0.494	0.494	0.494	(Stripple 2001)
Diamond Grinding	*no.*	3	3	2	MEPDG, Caltrans 2012
Diamond Grinding	*gal/ln-mile*	935	935	935	(IGGA 2009)
Additional Asphalt					
Thickness	*in*	3	3	0	MEPDG, Caltrans 2012

Concrete Designs					*Data Source*
Unit Weight	*pcf*	148	148	148	(Mathew and Roa 2006)
Mix Properties					
Binder Content	%	0.116	0.116	0.116	MEPDG via (Mack 2012)
Air Voids	%	0.07	0.07	0.07	
Aggregate	%	0.814	0.814	0.814	
PVI					
Average Fuel Use	*mpg*	23.7	23.7	23.7	(FHWA 2008) -Table VM-1
Average Truck Fuel	*mpg*	6.5	6.5	6.5	
Fuel Loss - Cars	*gal/(in/mile)*	0.000166	0.000166	0.000166	(Zaabar and Chatti 2010)
Fuel Loss - Trucks	*gal/(in/mile)*	0.000111	0.000111	0.000111	
Fuel Increase -mpg	%	0.49%	0.49%	0.49%	(FHWA 2008)
Lighting					
MI Min	*lumens/m²*	3	6	6	(Mn DOT 2006)
MI Max	*lumens/m²*	5	8	10	
Tech. Efficacy Min	*lumens/W*	95	95	95	
Tech. Efficacy Max	*lumens/W*	140	140	140	
Hours/Day	*hrs*	10	10	10	
Carbonation					
k		1.58	1.58	1.58	(Lagerblad 2005)
EOL					
Removal	*MJ/m³*	3.32	3.32	3.32	(Stripple 2001)
Traffic Delay					
User Cost	*$*	0	2020	183000	(FHWA 2011)
Value of Time (Cars)	*$*	1	1	1	
Value of Time (Single Unit Trucks)	*$*	1	1	1	
Value of Time (Comb. Trucks)	*$*	1	1	1	
Percent Cars	%	0.957746479	0.94518722	0.954198473	
Percent Single Unit Trucks	%	0.028169014	0.036541853	0.030534351	
Percent Combination Trucks	%	0.014084507	0.018270927	0.015267176	
Avg Speed Through Work Zone	*mph*	35	30	55	
Fuel Loss (car)	*gal/mile*	0.0208	0.0208	0.0208	(Santero and Horvath 2009)
Fuel Loss (trucks)	*gal/mile*	0.1403	0.1403	0.1403	
Total Length	*miles*	1	1	1	(FHWA 2011)
Albedo		0.325	0.325	0.325	(Akbari et al. 2009 ; Rosenfeld et al. 2008)

Asphalt Designs					*Data Source*
Functional Unit	*ft*	3280.8	3280.8	3280.8	Study specific
Number of Lanes	*no.*	2	4	6	MEPDG, Caltrans 2012
Width of Lanes	*ft*	12	12	12	
No. of Shoulders	*no.*	0	4	4	FHWA Statistics
Shoulder Width	*ft*	10	10	10	
Scenario		33 (AC)	67 (AC)	101 (AC)	
Traffic Type					
Location		CA	CA	CA	
Design Life	*years*	55	55	55	-
Maintenance 1	*year*	20	20	20	MEPDG, Caltrans 2012
Type		3" Overlay	3" Overlay	3" Overlay	
Maintenance 2	*year*	30	25	25	
Type		Mill/3" Overlay	Mill/4" Overlay	Mill/4" Overlay	
Maintenance 3	*year*	40	35	35	
Type		Mill/2.5" Overlay	Mill/3" Overlay	Mill/3" Overlay	
Maintenance 4	*year*	50	45	45	
Type		Mill/4" Overlay	Mill/4" Overlay	Mill/4" Overlay	
Performance Criteria					
Initial IRI	*in/mi*	60	60	60	MEPDG, Caltrans 2012
Terminal IRI	*in/mi*	170	170	170	
AC Surface Down Cracking (Long. Cracking)	*ft/mi*	2000	2000	2000	
AC Bottom Up Cracking (Alligator Cracking)	*%*	25	25	25	
AC Thermal Fracture (Transverse Cracking)	*ft/mi*	1000	1000	1000	
Permanent Deformation (AC Only)	*in*	0.25	0.25	0.25	
Permanent Deformation (Total Pavement)	*in*	0.5	0.5	0.5	
Reflective Cracking	*%*	100	100	100	
Traffic					
Initial Two-Way AADTT	*no.*	150	1357	6672	MEPDG, Caltrans 2012
AADTT Growth Factor	*%*	4.0%	4.0%	4.0%	

Asphalt Designs					*Data Source*
Initial Two-Way AADT	*no.*	3400	23400	139000	(FHWA 2008)
AADT Growth Factor	*%*	4.0%	4.0%	4.0%	
Asphalt Concrete					
Thickness	*in*	4.8	6.6	7.8	MEPDG, Caltrans 2012
Unit Weight	*pcf*	150	150	150	
Mix Properties					
Binder Content	*%*	0.116	0.116	0.116	
Air Voids	*%*	0.07	0.07	0.07	
Aggregate	*%*	0.814	0.814	0.814	
Bitumen Unit Weight	*pcf*	62.12	62.12	62.12	(Mathew and Roa 2006)
Aggregate Base 1					
Thickness	*in*	8.4	10.8	12	MEPDG, Caltrans 2012
Unit Weight	*pcf*	120	120	120	
Aggregate Base 2					
Thickness	*in*	6	8.4	9.6	MEPDG, Caltrans 2012
Unit Weight	*pcf*	127.2	127.2	127.2	
Construction Energy					
Asphalt Mixing - Heating Oil	*MJ/tonne*	285	285	285	(Stripple 2001)
Asphalt Mixing - Electricity	*MJ/tonne*	36	36	36	
Concrete Paving	*MJ/tonne*	34.00	34.00	34.00	(Stripple 2001)
Asphalt Paving	*MJ/tonne*	13.40	13.40	13.40	
Placement of Other Layers	*MJ/tonne*	6.61	6.61	6.61	
Maintenance					
Asphalt Milling	*in*	9.5	11	11	(Mack 2012)
Asphalt Milling (per 1/2")	*$MJ/m^2/0.5"$*	1.56	1.56	1.56	(Stripple 2001)
Additional Asphalt					
Thickness	*in*	12.5	14	14	MEPDG, Caltrans 2012
Unit Weight	*pcf*	148	148	148	MEPDG, Caltrans 2012
Mix Properties					
Binder Content	*%*	11.6%	11.6%	11.6%	MEPDG, Caltrans 2012
Air Voids	*%*	7.0%	7.0%	7.0%	
Aggregate	*%*	81.4%	81.4%	81.4%	
PVI					
Average Fuel Use	*mpg*	23.7	23.7	23.7	(FHWA 2008) - Table VM-1
Average Truck Fuel	*mpg*	6.5	6.5	6.5	

Asphalt Designs					*Data Source*
Fuel Loss - Cars	*gal/(in/mile)*	0.000166	0.000166	0.000166	(Zaabar and Chatti 2010)
Fuel Loss - Trucks	*gal/(in/mile)*	0.000111	0.000111	0.000111	
Fuel Increase -mpg	*%*	0.49%	0.49%	0.49%	(FHWA 2008)
Lighting					
MI Min	*lumens/m²*	4	9	6	(Mn DOT 2006)
MI Max	*lumens/m²*	7	11	10	
Tech. Efficacy Min	*lumens/W*	95	95	95	
Tech. Efficacy Max	*lumens/W*	140	140	140	
Hours/Day	*hrs*	10	10	10	
EOL					
Removal	*MJ/m³*	3.32	3.32	3.32	(Stripple 2001)
Asphalt Milling (per 1/2")	*MJ/m²*	1.70	1.70	1.70	
Traffic Delay					
User Cost	*$*	0	2000	312000	(FHWA 2011)
Value of Time (Cars)	*$*	1	1	1	
Value of Time (Single Unit Trucks)	*$*	1	1	1	
Value of Time (Comb. Trucks)	*$*	1	1	1	
Percent Cars	*%*	0.957746479	0.94518722	0.954198473	
Percent Single Unit Trucks	*%*	0.028169014	0.036541853	0.030534351	
Percent Combination Trucks	*%*	0.014084507	0.018270927	0.015267176	
Avg Speed Through Work Zone	*mph*	35	30	55	
Loss of Fuel (Car)	*gal/mile*	0.0208	0.0208	0.0208	(Santero and Horvath 2009)
Loss of Fuel (Trucks)	*gal/mile*	0.1403	0.1403	0.1403	
Total Length	*miles*	1	1	1	(FHWA 2011)
Albedo	-	0.1	0.1	0.1	(Akbari et al. 2009 ; Rosenfeld et al. 2008)
Radiative Forcing	*kg CO_2e/albedo decrease*	253.3	253.3	253.3	(Akbari et al. 2009)
Urban Heat Island	*kg co2e/albedo decrease*	0.485	0.485	0.485	(Rosenfeld et al. 2008)

Appendix D - Additional IPS Results

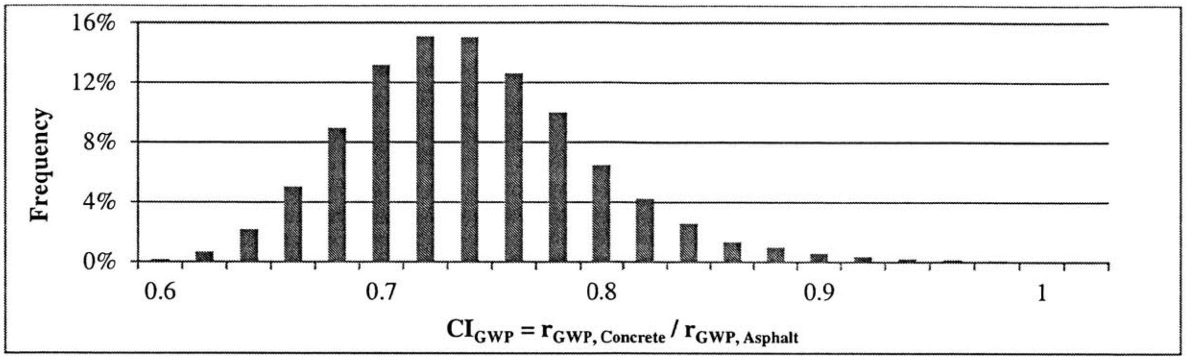

Figure D.1 Medium-Volume IPS GWP: Indicator variable histogram

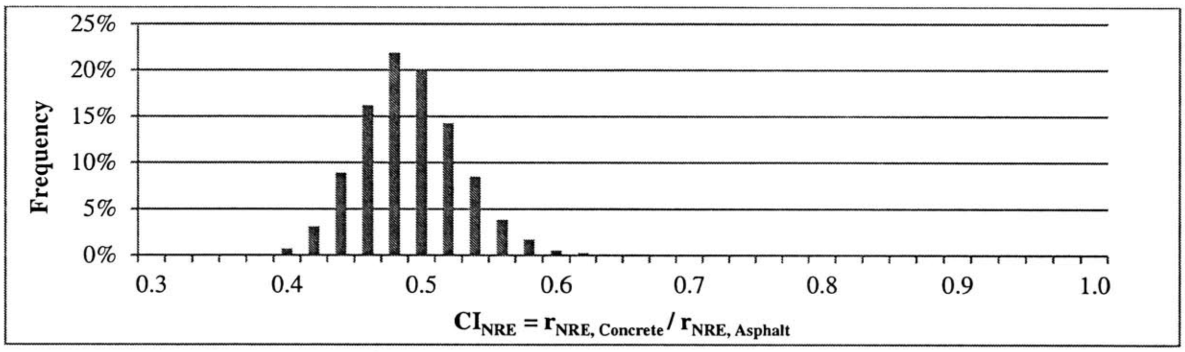

Figure D.2 Medium-Volume IPS NRE: Indicator variable histogram

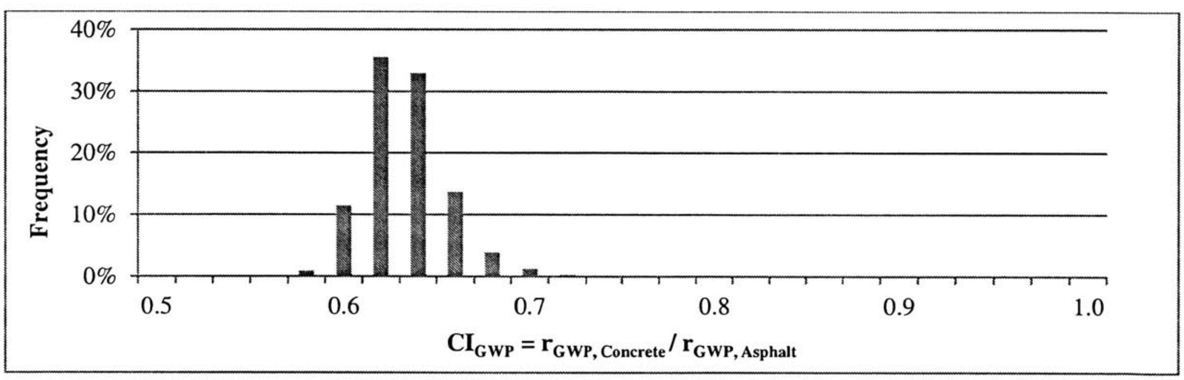

Figure D.3 High-Volume IPS GWP: Indicator variable histogram

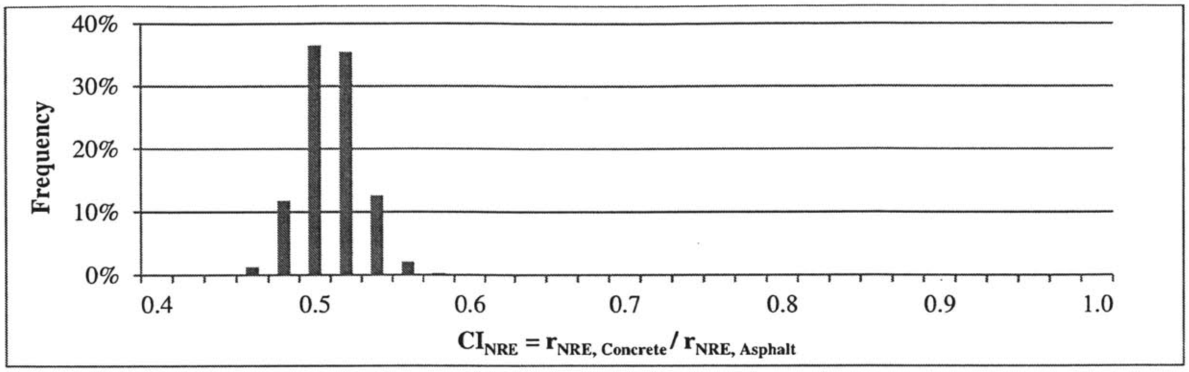

Figure D.4 High-Volume IPS NRE: Indicator variable histogram

Appendix E - Additional PU Results

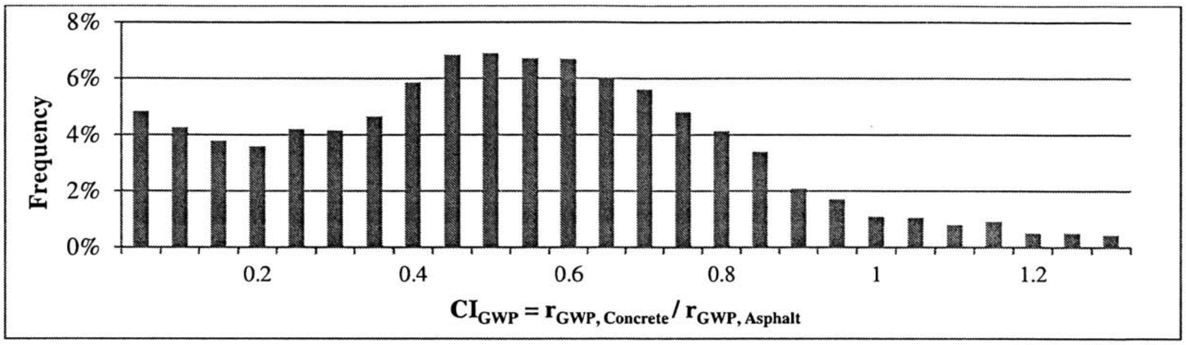

Figure E.1 Medium-Volume PU GWP Run 1: Indicator variable histogram

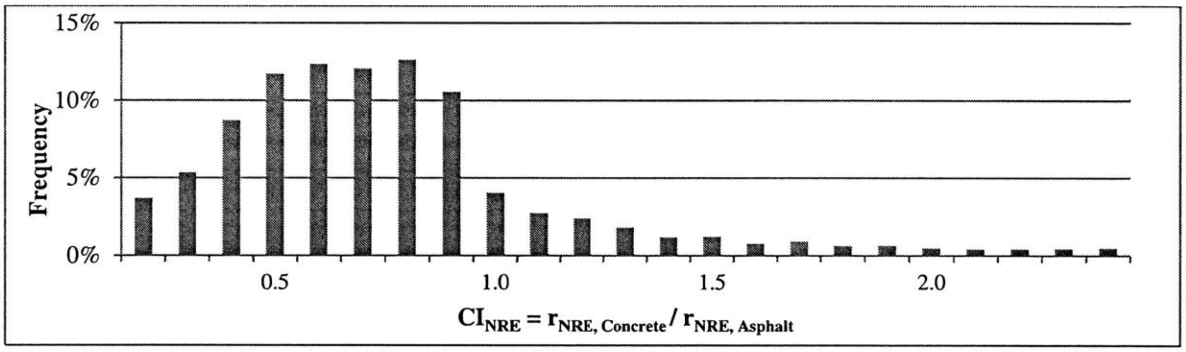

Figure E.2 Medium-Volume PU NRE Run 1: Indicator variable histogram

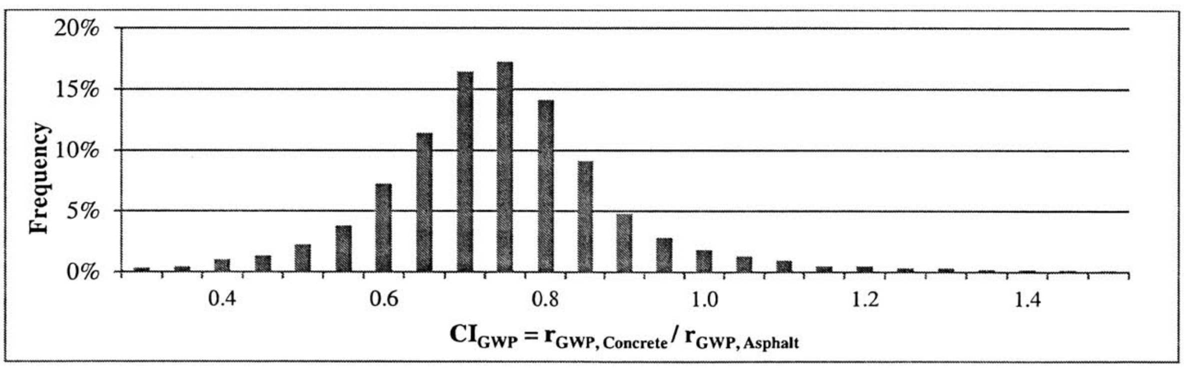

Figure E.3 Medium-Volume PU GWP Run 2: Indicator variable histogram

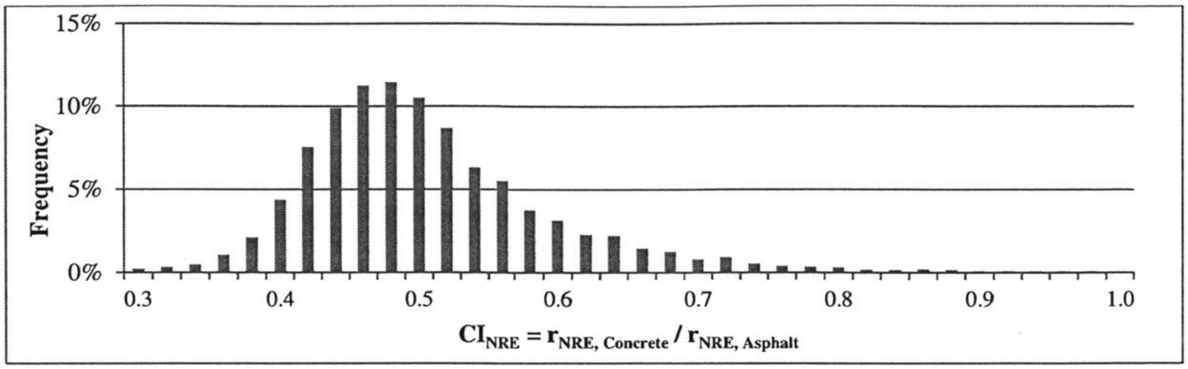

Figure E.4 Medium-Volume PU NRE Run 2: Indicator variable histogram

Run 3

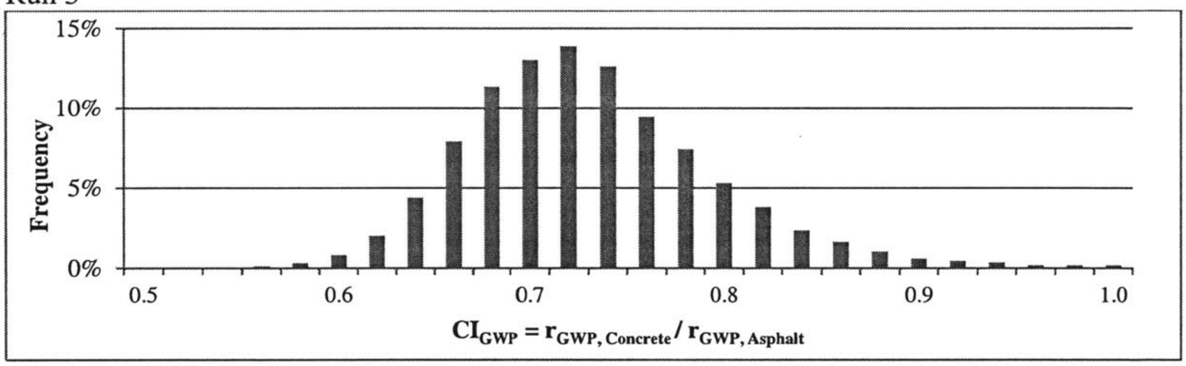

Figure E.5 Medium-Volume PU GWP Run 3: Indicator variable histogram

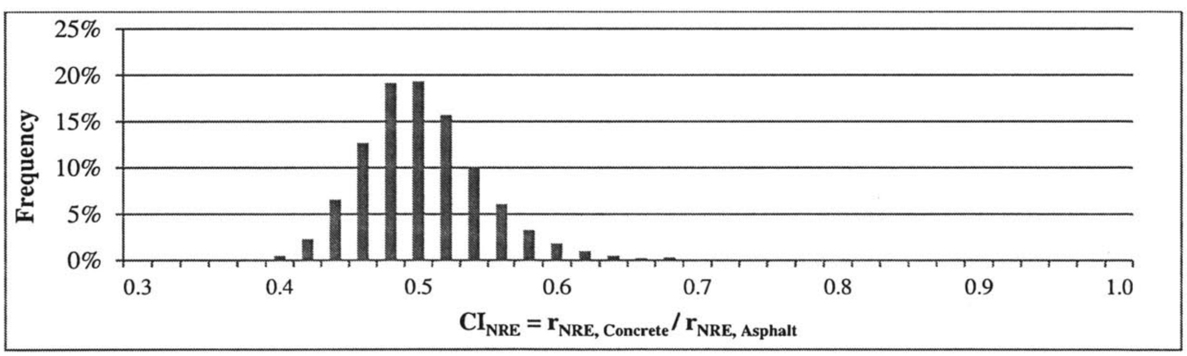

Figure E.6 Medium-Volume PU NRE Run 3: Indicator variable histogram

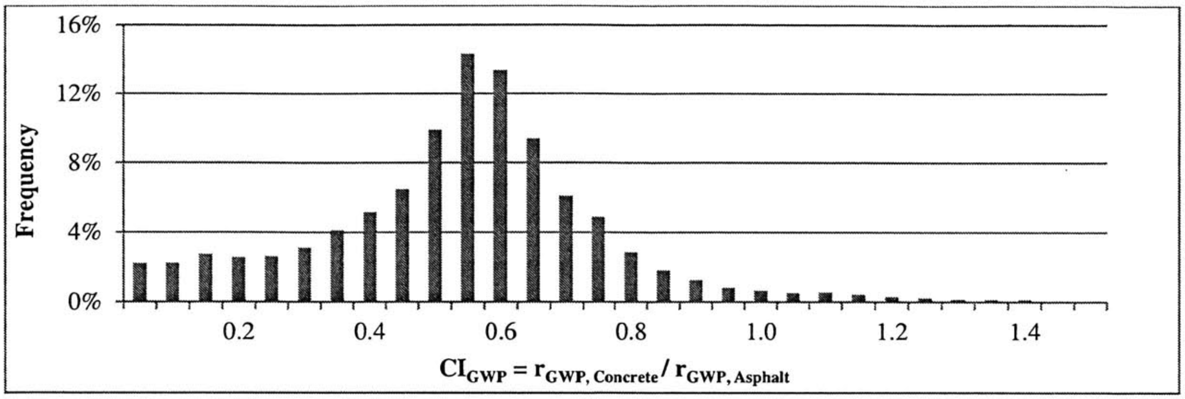

Figure E.7 High-Volume PU GWP Run 1: Indicator variable histogram

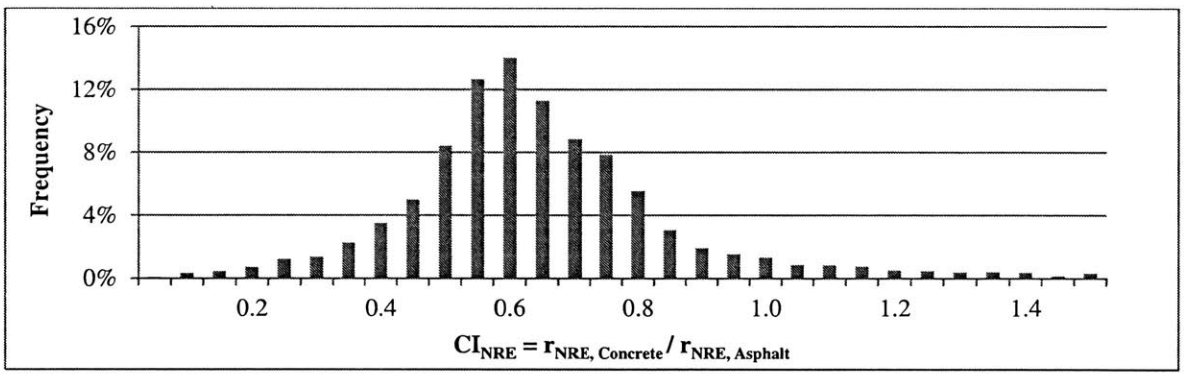

Figure E.8 High-Volume PU NRE Run 1: Indicator variable histogram

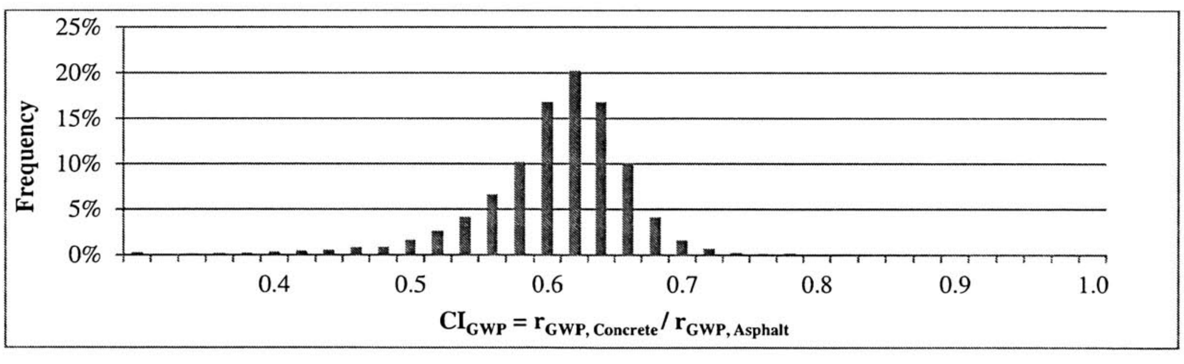

Figure E.9 High-Volume PU GWP Run 2: Indicator variable histogram

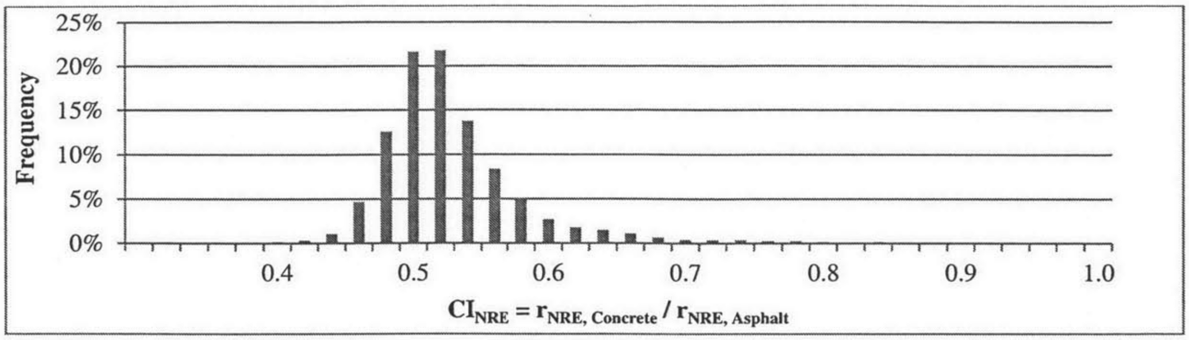

Figure E.10 High-Volume PU NRE Run 2: Indicator variable histogram