PROBABILISTIC LIFE-CYCLE COST OF PAVEMENTS: CHARACTERIZATION AND APPLICATION OF PARAMETER INPUT VARIATION FOR SCENARIOS

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Life Cycle Cost Analysis (LCCA) evaluates the economic performance of alternative pavement investments. Currently, practitioners treat input parameters as static, deterministic values, which although computationally simpler, will hide the implicit uncertainty underlying the analysis. Over the past decade, an emphasis has been placed upon accounting for uncertainty by treating input parameters as probabilistic, rather than deterministic, values. This research builds upon existing pavement LCCA work by probabilistically characterizing several sources of uncertainty, including unit-cost of construction activities, pavement deterioration, and forecasting of future material prices. The probabilistically characterized input parameters have subsequently been implemented in three concrete pavement case studies which vary in terms of analysis period. For each case study, uncertainty has been propagated to characterize the difference in life-cycle costs and has been used to elicit which input parameters are significant contributors to the overall life-cycle cost uncertainty in each scenario. From the analysis, uncertainty surrounding unit-cost is the dominant driver of variation across all scenarios, significantly outweighing the impact of the many other input parameters considered; this suggests practitioners should focus their efforts on deriving statistical characterization methods to reduce its variation, if possible, rather than focusing their efforts on more trivial uncertain parameters

KEY WORDS: CONCRETE PAVEMENTS / LIFE CYCLE COST ANALYSIS / RISK ANALYSIS / SCENARIO ANALYSIS / STATISTICAL CHARACTERIZATION / UNCERTAINTY PROPOGATION

1. INTRODUCTION

Life Cycle Cost Analysis (LCCA) is an analytical tool to assess the economic value of alternative investments over their respective lifetimes. For pavement projects, this encompasses costs associated with initial construction, maintenance and rehabilitation, and user costs (i.e. vehicle operation costs) (Smith, 1998). Despite its merits, a recent report prepared for the Federal Highway Administration (FHWA) highlighted that highway officials prioritize structural and functional conditions as well as initial costs over life-cycle costs (Flintsch & Bryant, 2006). Besides the political pressure placed upon a Department of Transportation (DOT) to maintain their pavement assets to a certain performance metrics, one of the other reasons LCCA takes a backseat to these other measures is the difficulty in predicting costs into the future. As such, decision-makers will likely only consider life-cycle costs if advanced analytical models are developed which account for the difficulties in predicting future costs (Frangopol et al., 2001).

This recognition of uncertainty would naturally incline one to view things from a probabilistic standpoint, which several governmental agencies in the United States have strongly recommended for several years, in order to overcome the limitations of a deterministic approach (Smith, 1998). Despite this, however, practitioners have typically implemented LCCA in the field by treating inputs as static, deterministic values (Chan et al., 2008). Modeling an LCCA using static values hides the underlying uncertainty of the inputs, but makes the pavement selection significantly simpler. Of course, one is only comparing alternatives under one set of conditions which may arise in the future, implicitly ignoring the full range of possible conditions which may arise in the future. As such, although computationally simpler, the answer from the deterministic analysis may lead the decision-maker to select the incorrect (in-terms of economic cost).

The implementation of probabilistic LCCA to overcome this has been limited in practice, however, in large part due to the large-scale complexity of modeling a system with many input parameters with a high-level of uncertainty, making its implementation both time-consuming and challenging. This research, therefore, sets forth the goal of developing a comprehensive LCCA model which characterizes a full range of sources of uncertainty and applying it to multiple case studies in order to a) develop an understanding of which parameters are the major sources of variation in an LCCA and b) apply the model to multiple case studies to characterize if the major sources of uncertainty change as a function of context c) understand if the cost competitiveness of concrete roads alters for certain contexts.

2. LITERATURE REVIEW

Following the National Highway System Designation Act of 1995, which required states to conduct an LCCA for project costing over $25 million, state DOTs and researchers have focused their efforts on improving the overall LCCA process (FHWA, 1995). Of the major governmental institutions, the Federal Highway Administration (FHWA), in particular, has played a major role in both promoting and funding LCCA research and efforts, leading to significant advancements this past decade (Chan, Keoleian et al., 2008). This includes the development of FHWA's RealCost software, a significant contribution to the pavement LCCCA domain as a large number of DOTs in the United States currently use it in some capacity according to a recent survey by the GAO (FHWA, 2002; GAO, 2013).

Early research amongst the pavement LCCA community focused on comparative assessments for a range of different applications. Embacher and Snyder compared the life-cycle cost of asphalt and concrete pavements for low-volume roadways (Embacher & Snyder, 2001). Huang et al. created a decision support system for identifying optimal concrete bridge deck repairs (Huang et al., 2004). Fagen and Phares compared the life-cycle costs of steel beam precast, concrete beam precast, and continuous concrete slab bridge deck for a low-volume roadway (Fagen & Phares, 2000). Zimmerman and Peshkin used LCCA to identify optimal timings for preventative maintenance procedures (Zimmerman & Peshkin, 2003). Although these are major contributions, a drawback associated with all of these studies is that input parameters were treated as deterministic values. Recognizing this, research in the past decade has focused on developing a probabilistic approach to deal with uncertainty.

The majority of probabilistic LCCAs have focused on statistically characterizing a select few input parameters by characterizing historical data with a variety of best-fit probability density functions. Tighe collected historical experimental data and found for many of the input parameters a log-normal distribution best fit the data (Tighe, 2001). Osman developed a risk-based methodology by considering uncertainty only with respect to pavement performance over time, which was described with a Weibull distribution (Osman, 2005). Li and Madamu created a life-cycle cost/benefit model by characterizing cost uncertainty with a Beta distribution (Li & Madanu, 2009). Salem et al. characterized uncertainty related to the occurrence of pavement failure and future life-cycle events with a Weibull distribution (Salem et al., 2003). Despite the progress, deterministic LCCAs are still mostly conducted by state DOTs (Chan, Keoleian et al., 2008). This research aims to build upon some of the previously mentioned work to accelerate the inclusion of probabilistic LCCAs in practice by filling in three gaps.

2.1. GAPS OF PREVIOUS RESEARCH

From the previous discussion, there are several opportunities to build upon the existing literature a probabilistic LCCA for pavements. First and foremost, the previously discussed studies have focused their efforts around characterizing a select group of sources of uncertainty and variation. Although such studies are useful in terms of helping researchers and practitioners understand ways of characterizing input parameters, they provide no insight regarding the relative importance of any one parameter compared to the host of other input parameters. This importance will obviously vary depending upon the scenario (which depends upon factors such as location or traffic volume) and when in the course of the decision-making process the LCCA model is utilized (for example, whether the analysis conducted prior to or following the collection of bids). This, of course, is another gap in the previous work, as a comparative analysis has been traditionally implemented for a single scenario. Conducting such an analysis provides little insight regarding how uncertainty and/or the decision will change as a function of scenario (which is, of course, naturally large) or the defined scope of the analysis.

2.2. Research Question

Two key gaps have been identified surrounding the LCCA of pavements: what are the principal drivers of uncertainty and how do the scope and/or scenario impact the final results of a comparative assessment? This research aims to takes the first steps at addressing these questions by developing a comprehensive LCCA model, characterizing sources of uncertainty and variation, and applying it to case studies which vary in terms of analysis period in order to address one of those contextual decisions.

3. METHODOLOGY

To answer the questions set forth in the previous section, a probabilistic LCCA model is constructed consistent with the methodology developed and presented by Swei et al. (2013) by characterizing uncertainty only in the agency cost. The following section will, in more brevity, describe the model developed. This model will be applied to three concrete pavement alternatives developed for different analysis periods. The insights the analysis aims to understand are:

- What are the principal drivers of variation across the scenarios, and does it remain consistent as the scope of analysis changes?
- How does the economic cost competitiveness of concrete pavement alternatives change as a function of the scope of analysis?

3.1. Sources of Uncertainty Quantified

The LCCA analysis in this research is structured to allow for the incorporation of several sources of uncertainty, including the unit-cost of construction activities, future material prices, number of maintenance events and their years of occurrence, and the consideration of uncertainty in the absence of empirical data.

Unit-Cost of Construction Activities

Basic economic theory tells one it is likely that the average cost of production will decrease as production increases, otherwise known as economies-of-scale. Therefore, rather than characterizing uncertainty with a best-fit distribution, it is likely more reasonable to model cost as a function of bid volume. One method to go about quantifying the likely relationship between cost and quantity is to conduct a univariate regression analysis of average unit-cost (total cost divided by quantity) with respect to bid volume. The p-value of the estimated coefficients, a statistical measure ranging from zero to one, can be used to answer the question of whether the estimated relationship is in fact statistically significant (Selke et al.). More specifically, if we assume that there is no statistically significant relationship between the dependent variable (unit-cost) and the independent variable (volume), the p-value tells us what is the probability of observing the correlation between the two parameters at least as large as was actually observed from the data. This means small p-values would suggest the difference observed would occur rarely during random sampling. Typical p-values used in statistics can range between 0.1 and 0.01; for this particular research, a threshold p-value of 0.05 is used. In order to account for the other factors not captured by this relationship, such day versus night construction, the standard error of the univariate regression equation is used when conducting Monte Carlo simulations. On the other hand, if a given activity shows a statistically insignificant relationship exists between average unit-cost and bid volume, a chi-square best-fit log-normal distribution is fitted to the data, consistent with the approach of previous LCCA studies (Tighe, 2001).

Future Maintenance Years Based Upon Predicted Pavement Distress

In order to predict both the number of maintenances and their respective years of occurrence, this research integrates the pavement design process with the recently developed Mechanistic-Empirical Pavement Design Guide (MEPDG) (Hallin et al., 2011). From a set of design (i.e. pavement type, thickness) and contextual (i.e. climate, predicted traffic) conditions, MEPDG transforms this information into a predicted performance via models that have been calibrated and validated by using empirical data collected by the Long-Term Pavement Performance (LTPP) program (Baus & Stires, 2010). The design process is oftentimes iterative when using the MEPDG software, as a pavement is initially selected, and if it does not meet a required level of performance, a pavement designer will make necessary amendments to the initial design. Pavement performance is measured through distress data outputs, which includes factors such as roughness, bottom-up cracking, surface-down cracking, etc.

Uncertainty is characterized, and implemented, in the developed probabilistic LCCA model by leveraging the MEPDG outputs of predicted pavement performance at the 50^{th} and 90^{th} percentile reliability levels. From the two outputs, a Gaussian distribution is formed to represent the distress at any reliability level with respect to time, with reliability treated as the random variable. In the uncertainty simulations, the maintenance year for each simulation is selected by choosing the first distress criteria that fails to meet the required performance threshold level (e.g. if the International Roughness Index factor were to exceed a desired threshold of 160 inches per mile). It is important to note that the decision to treat reliability as the random variable implicitly makes the evolution of distress over time path dependent, which may not necessarily be completely true.

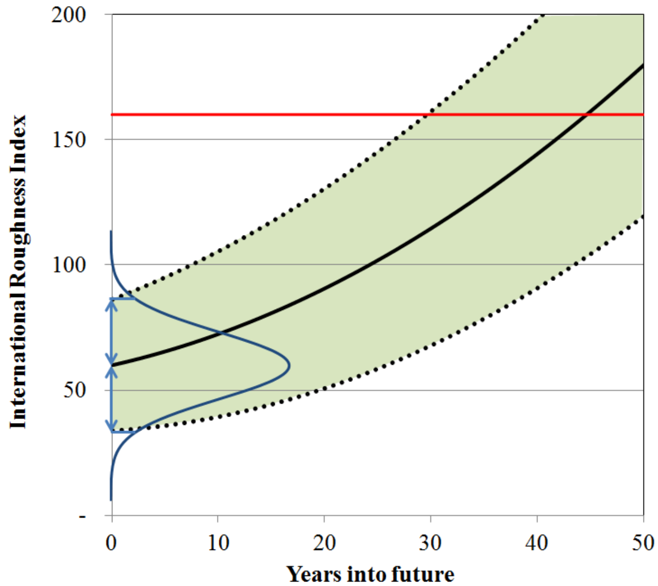

Figure 1 – Sample MEPDG prediction of the evolution of IRI for a pavement alternative at a reliability of 90% (top dashed line) 50% (solid line) and 10% (bottom dashed line)

Future Material Cost
Research has shown concrete and asphalt are two commodities with historically different price growth rates and volatilities, and that differential behavior is likely to continue going into the future (Swei, 2012). Despite this, decision-makers tend to avoid its consideration when conducting an LCCA due the difficulty in projecting prices over such a long time-horizon, especially given the lack of significant historical price data for the commodities. Therefore, the researchers of this work have probabilistically forecasted the price of concrete and asphalt by testing for “cointegration” between paving materials and their relevant price inputs (i.e. cement, aggregate) in order to understand the price-link between the two. Concrete and asphalt prices have then been forecasted by projecting future constituent prices, and using the derived long-run price equilibrium to forecast future paving material prices. The authors of this research have submitted a paper devoted solely to the characterization of this input parameter (Swei et al., 2013).

Quantify uncertainty for input parameters that lack historical data
Many inputs in an LCCA, such as the thickness of a pavement layer or density of a mixture, have variability but potentially no historical data required for statistical characterization. In the absence of an acceptable methodology to quantify such uncertainty in the LCCA literature, this work has adopted a methodology practiced by the life cycle analysis (LCA) community, known as the pedigree matrix approach (Weidema et al., 2011). The pedigree matrix is a framework of analysis to quantify uncertainty related to the data quality of input parameters in the absence of empirical data. The power of the pedigree matrix approach is it allows for the quantification of uncertainty by qualitatively evaluating the input parameters (Weidema & Wesmaes, 1996). Quality indicator scores are used to assess the input values being used and are transformed into variances which are applied to the input parameters in the form of a log-normal distribution.

3.2 Application to Case Studies

Having statistically quantified different sources of uncertainty relevant to the LCCA of pavements, this research now evaluates the probabilistic cost to build and maintain a new roadway for a single case study. Such an analysis allows for an understanding of which sources of uncertainty significantly impact the final results, and therefore, are of tremendous importance for practitioners to focus their efforts around the parameters which drive the decision at hand. Given one prevalent issue in LCCAs is the results are generally context specific, meaning the results for one case study may not be representative of another case study, multiple case studies have been analyzed which vary in terms of the analysis period used. Future research will have to go beyond this and evaluate several contexts which will vary based upon location, traffic levels, maintenance schedule, and more.

The present research only focuses on the cost to finance a project and ignores user costs associated with traffic delays previous studies have explored (Vadakpat et al., 2000; Lee, 2002; Temple et al., 2004). It also assumes that a decision has already been made to build a new roadway, ignoring the underlying policies and impacts a roadway has on existing infrastructure (Stamatiadis et al., 2010). Although these are important considerations, they are ignored to reduce the complexity of the problem at hand. The four general life-cycle phases include: materials, construction, maintenance, and end-of-life. Since LCCA is typically implemented in a comparative pavement assessment, although this research only calculates the life-cycle cost (LCC) of a single concrete road, the scope of the analysis is reduced such that it ignores costs incurred irrespective of pavement selection. For example, if land had to be cleared for a new roadway, for example, costs to clear land are independent of the pavement selection, and are subsequently outside the scope of this work. All costs are converted into a net present value (NPV) to allow for an equivalent time perspective of cash flows, a metric suggested by the FHWA in the United States.

The probabilistic economic cost is estimated through Monte Carlo simulations, where random values are sampled from probability distributions thousands of times to formulate a distribution of possible outcomes. An important factor when performing a Monte Carlo simulation is to ensure that the values selected, although random, structurally make sense. Therefore, it is paramount when accounting for uncertainty that the analysis considers both correlation and dependencies between input parameters. Dependencies represent statistical relationships between multiple variables. For example, the year of occurrence for a second maintenance is clearly dependent upon what occurred during the first maintenance activity. Correlation is the common inputs that each alternative shares. For instance, the source of materials for two asphalt designs is expected to be the same. Considering dependencies and correlation allows for a Monte Carlo simulation to select values that are reasonable and not completely random and unrealistic.

The results of the LCCA analysis is examined first by visualizing the Monte Carlo simulations in the form of a cumulative distribution function (CDF). The usefulness of a CDF is a decision-maker can select an alternative based upon his or her risk-perspective. To characterize which parameters significantly contribute to the overall variance of the final results, the contribution to variance for the total life-cycle cost is estimated by use of the Pearson correlation coefficient ($\rho_{x,y}$), a statistical measure of the dependency between two variables. From the Monte Carlo simulations, the correlation between each input variable and the final output (in this case, the total life-cycle cost of an alternative) can be calculated through the following equation:

$$\rho_{x,y} = \frac{\sum_{i=1}^{n}(x_i - m_x)(y_i - m_y)}{\sqrt{\sum_{i=1}^{n}(x_i - m_x)^2}\sqrt{\sum_{i=1}^{n}(y_i - m_y)^2}} \tag{1}$$

where x_i and y_i are the numerical values of input x and the total life-cycle cost (y) for each Monte Carlo simulation and m_x and m_y are the average values of x and y across the full sample of simulations. To estimate the contribution to variance for each input variable, the Pearson correlation coefficient is squared ($\rho_{x,y}^2$), followed by normalizing $\rho_{x,y}^2$ such that the summation of $\rho_{x,y}^2$ across all inputs sums to one. Again, it should be emphasized that this is an approximation of the contribution to variance and is not precisely a variance decomposition. With that said, such information is tremendously useful in determining which input parameters are the true drivers of uncertainty and deserve further attention, and which parameters have a negligible impact on the final results and, therefore, can be ignored by practitioners to reduce the complexity of the problem at hand.

4. CASE STUDY

The described methodology is applied to estimate the probabilistic life-cycle cost for three concrete pavement case studies, located in Joplin, Missouri. The selection of the location is based upon local calibration efforts that have been conducted with the recently developed MEPDG software. Pavement designs were developed independently by Applied Research Associates (ARA) who strived to develop "appropriate" pavement designs for the given scenarios. Alternative pavements have been designed for a major roadway with three lanes of traffic in each direction with an expected initial Average Annual Daily Truck Traffic (AADTT) of 8,000. The scenarios vary as the designs and maintenance schedules have been developed using an analysis period of 30, 50, and 100-years, respectively. Future maintenance costs have been discounted using a real-discount rate of 4% to stay consistent with what FHWA has suggested be used when conducting an LCCA (Walls & Smith, 1998). **Error! Reference source not found.** Table 1**Error! Reference source not found.** presents the Joint Plain Concrete Pavement (JPCP) designs and maintenance schedules for the 90th percentile reliability level.

Table 1 – JPCP initial pavement designs for the three scenarios and projected maintenance schedules at MEPDG specified 90% reliability

Initial Design						
Layer	**30 – year Analysis Period**		**50 – year Analysis Period**		**100 – year Analysis Period**	
JPCP	10.5 in (26.7 cm)		11 in (27.9 cm)		12 in (30.5 cm)	
Aggregate Base	6 in (15.2 cm)		6 in (15.2 cm)		6 in (15.2 cm)	
Maintenance Schedule						
	30 – year Analysis Period		**50 – year Analysis Period**		**100 – year Analysis Period**	
Maintenance Number	Year	Rehab Type	Year	Rehab Type	Year	Rehab Type
1	20	100% diamond grinding and 0.14% slab replacement	30	100% Diamond Grinding	40	100% diamond grinding and 10% slab replacement
2	N/A	N/A	N/A	N/A	60	100% diamond grinding and 15% slab replacement
3	N/A	N/A	N/A	N/A	75	100% diamond grinding and 20% slab replacement
4	N/A	N/A	N/A	N/A	90	100% diamond grinding and 30% slab replacement

4.1. Statistically Characterize Data

The following section presents the statistical characterization of uncertainty for the LCCA model. This paper only presents the results to characterize the unit-cost and the projection of future pavement prices. Pedigree matrix uncertainty factors and pavement design information can be found in (Swei, 2012).

Unit-Price of Construction Activities

Figure 2 presents a univariate regression analysis of the unit-price of JPCP pavements over a 36-month span in Missouri. For this particular dataset, the coefficient of determination is 0.70, implying 70% of the variation can be described by this simple analysis. As can be seen in Table 2, this result generally holds true for many of the major cost inputs for the LCCA model. Some of the processes, however, such as the removal of material for patching, show no statistically significant relationship between cost and quantity, and are therefore characterized using a best-fit probability distribution.

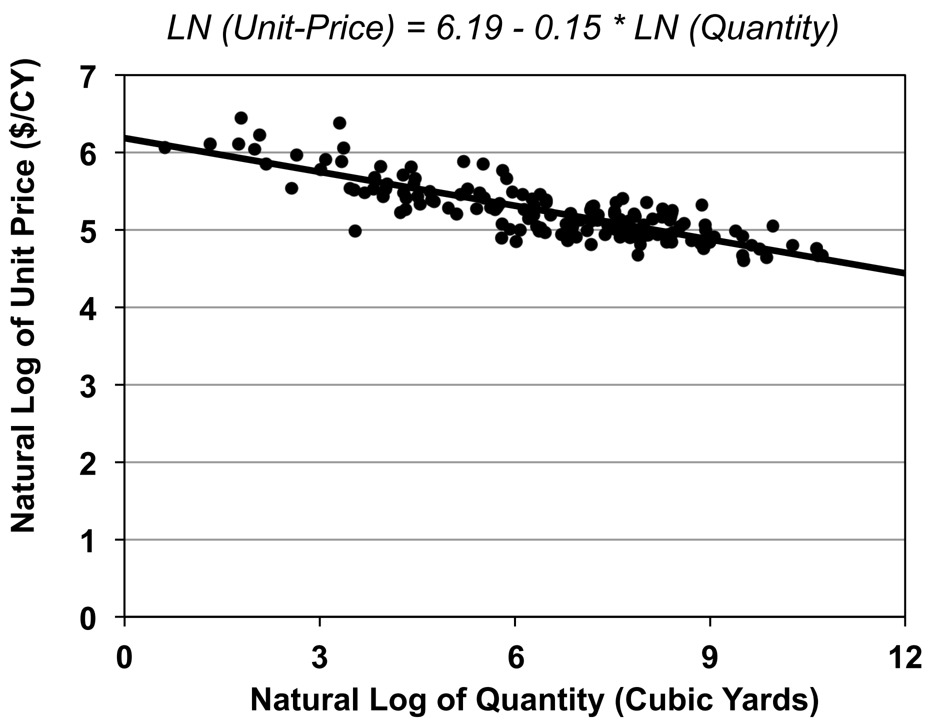

Figure 2 – Regression analysis of unit-price of JPCP winning pavement bids with respect to bid volume

When conducting the deterministic cost analysis in the following section, either the mean values of the best-fit distributions or the univariate regression analysis will be used, depending upon if the relationship between cost and quantity is "statistically significant". To account for other factors driving the variability, the probabilistic analysis will incorporate the standard error of the regression equations.

Table 2 – Quantification of unit-cost uncertainty for significant input parameters. Values in parenthesis represent the standard error of the regression coefficients

Input	Units	R^2	Regression Equation *Ln(P)=a*Ln(Q)+b*	Best-fit Log-Normal Distribution
Initial Concrete Design				
JPCP	Cubic Yards	0.70	a = -0.15 (0.0076) b = 6.19 (0.052)	N/A
Type 5 Aggregate Base	Cubic Yards	0.49	a = -0.17 (0.014) b = 5.02 (0.091)	N/A
Maintenance Specific Input Parameters				
Diamond Grinding	Square Yards	0.78	a = -0.33 (0.034) b = 3.50 (0.33)	N/A
Patching - Additional Material	Cubic Yards	0.53	a = -0.38 (0.070) b = 7.30 (0.20)	N/A
Patching – Removal of Material	Cubic Yards	N/A	N/A	Mean = 4.65 St. Dev. = 0.93

Future Material Costs

In the absence of significant empirical data for projecting future paving material prices, this research has established a long-run price equilibrium between paving materials and its constituents, and leveraged that information to probabilistically project future paving prices, as illustrated in Swei et al., which has more detailed information regarding the methodology and data sources used to construct future price projections (Swei, Greene et al., 2013). Figure 3 presents the probabilistic price projections for concrete and asphalt characterized and implemented in the subsequent case study.

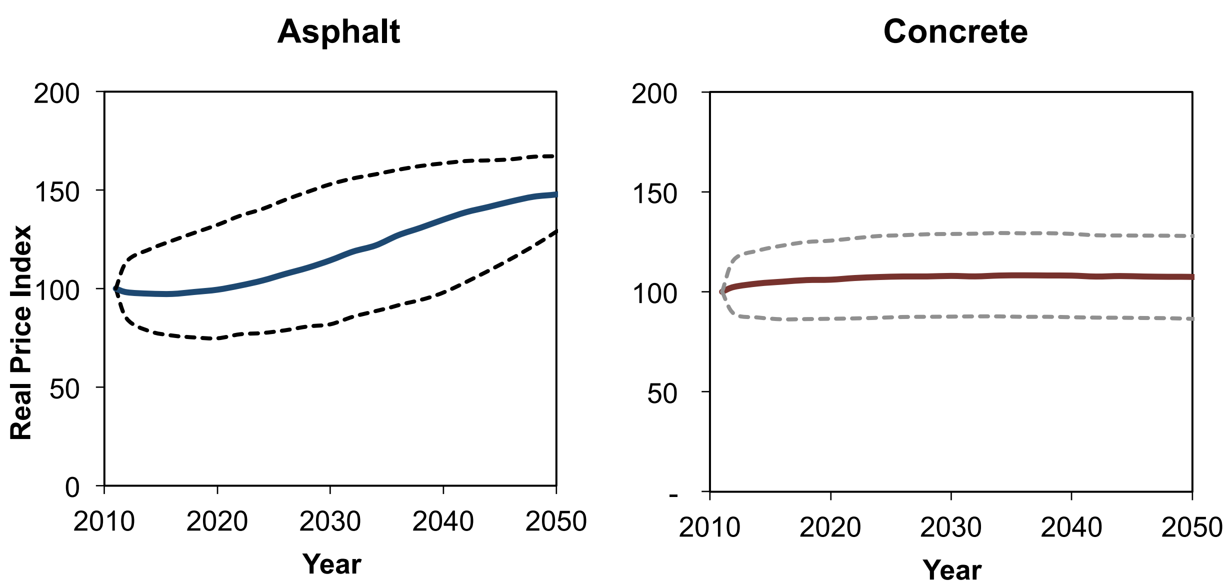

Figure 3 – Probabilistic price projections for asphalt and concrete, with the dashed lines representing the uncertainty underlying the projection (10th and 90th percentile).

4.2. Case Study Results

Figure 4 presents the results when treating all input parameters as probabilistic. Accounting for uncertainty, the expected total life-cycle cost over the entire life of the JPCP alternative is $2.28, $2.34, and $2.50 million per mile for the 30-year, 50-year, and 100-year analysis period case studies. An interesting, and unexpected, finding is that the coefficient of variation, which is a statistical measure of the spread in the distribution, is around 10% for all three scenarios. This is contrary to what one would initially expect, as one would be inclined to expect the incorporation of more years in the analysis period would increase the variation. However, given that future costs are discounted at such a rate, moving from an analysis period that is substantially longer has little impact on the final results. This, of course, can also be noted when eliciting the input parameters which are significant contributors to the uncertainty in the total life-cycle cost.

Figure 5 illustrates that despite the large number of probabilistically characterized input parameters, the unit-cost of the JPCP layer is the principal driver of variation of uncertainty. Although its relative impact decreases as analysis period increases, it never the less remains the largest contributor to variance by a significant margin. Other input parameters, such as forecasting of future prices or probabilistically characterizing input parameters without readily available empirical data via the pedigree matrix approach contribute to the overall variance in life-cycle costs insignificantly. This suggests that analysts should truly be focusing their efforts in characterizing uncertainty in initial cost for concrete pavements given its significant contribution to the total variance when considering all sources of variation.

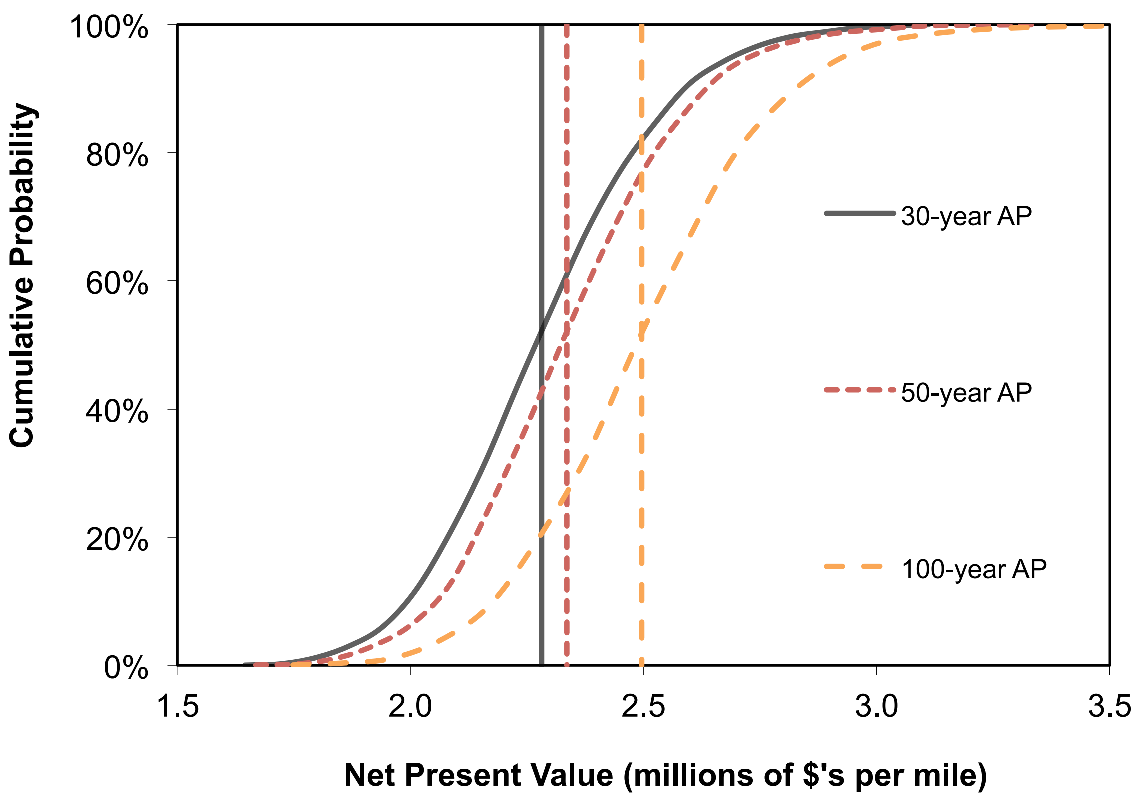

Figure 4 – Probabilistic life-cycle cost for all three scenarios (AP denotes Analysis Period). Vertical lines represent the Mean values for each scenario

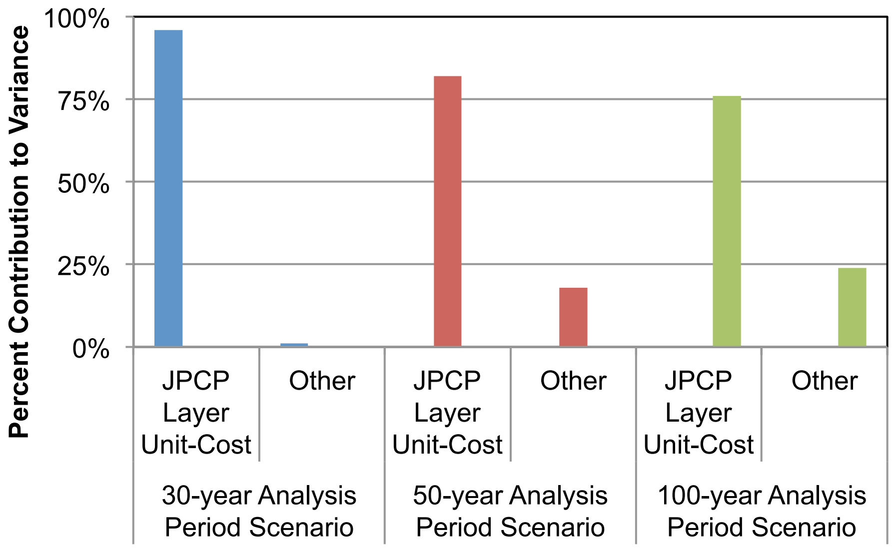

Figure 5 – Percent contribution to variance of JPCP unit-layer price compared to all other parameters for each scenario

5. CONCLUSIONS AND FUTURE WORK

This research has developed a probabilistic LCCA model which accounts for several forms of uncertainty in the LCCA of pavements, specifically the maintenance schedules and initial and future material and construction costs, in addition to accounting for uncertainty for inputs without empirical data. The developed model has been applied to three case studies to begin to understand which of input parameters truly impacts the decision-making process, in addition to understanding how one context parameter, analysis period, alters the final results. Results from the case study indicate for the JPCP design, the estimation of initial bid prices is the major source of uncertainty, despite the regression analysis to reduce it. This can partly be explained due to the fact a JPCP pavement traditionally comes at a larger up-front cost, but is expected to have significantly less rehabilitation costs than other pavement alternatives, naturally making one expect that initial cost uncertainty to inherently play a larger role.

The model developed serves as a first step to answer some of the more interesting questions set forth in the introduction and gap analysis sections. It has become clear that for concrete pavements, at least, initial cost variation is the major source of uncertainty across the scenarios. Further work, of course, should evaluate if this is the case for case studies which vary in terms of traffic levels, location, etc. Additionally, there are multiple opportunities to enhance the model developed in this analysis which could be a part of future work. For one, a major limitation of the preceding analysis is the methodology has been applied to a scenario that assumes future rehabilitation activities are fixed irrespective of future market conditions. It is likely, for example, that a future rehabilitation activity would either change, or be delayed, if material prices were significantly higher than expected. The LCCA model should account for the flexibility of a decision-maker to change future actions depending upon future events, a current drawback from the above analysis. Additionally, the scope of the above analysis only focuses on the cost to finance a roadway. The above model should be expanded upon to include the user cost associated with a pavement decision.

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