Probabilistic Characterization of Uncertain Inputs in the Life-Cycle Cost Analysis of Pavements

Omar Swei, Jeremy Gregory, and Randolph Kirchain

Life-cycle cost analysis (LCCA) is an important tool for evaluating the merits of alternative investments. Inevitably, inputs for an LCCA are subject to a high level of uncertainty in both the short and long term. However, the way LCCA is currently implemented in the field treats LCCA inputs as static, deterministic values. Conducting an analysis in this way, though computationally simpler, hides the underlying uncertainty of the inputs by only considering a few possible permutations. The results of such an analysis could potentially lead a decision maker to the incorrect pavement selection. One methodology that has gained traction in the past decade is describing uncertain parameters probabilistically and allowing the analysis to consider a range of possible outcomes. Although this methodology is recommended by FHWA, practitioners still generally conduct deterministic LCCAs. One of the major reasons is that further work must be conducted to characterize uncertainty statistically for input parameters. This research attempted to build on previous work by probabilistically characterizing several input parameters for which empirical data were and were not readily available. This paper characterizes uncertainty and variability in the LCCA of pavements and then applies the methodology presented to two case studies to understand the implications of a probabilistic LCCA for the pavement selection process.

Life-cycle cost analysis (LCCA) is an analytical tool for assessing the value of alternative investments. It includes the total cost of ownership, operation, and maintenance for a given project (*1*). For pavement projects, these costs encompass the costs associated with initial construction, the costs of maintenance and rehabilitation and user costs (i.e., vehicle operation costs). Despite LCCA's merits, a recent survey showed highway officials place a greater emphasis on initial costs than on life-cycle costs (*2*). One likely reason for this emphasis is that it is generally more plausible that costs predicted in the near term will have a much higher level of precision than costs predicted 20, 30, or even 50 years into the future. It is likely that decision makers will only weigh life-cycle costs more heavily in decision making if more advanced analytical models are constructed to account for such uncertainties (*3*).

Despite the recognized uncertainty in constructing an LCCA, practitioners have implemented it in the field by treating inputs as static, deterministic values (*4*). Using static values to model an LCCA hides the underlying uncertainty of the inputs but makes the pavement selection process simple: one chooses the pavement alternative with the lowest total life-cycle cost. The issue with this deterministic analysis is that a pavement alternative is selected on the basis of only a few considered scenarios. It is highly likely, therefore, that the values being compared are not what the actual life-cycle costs will be. This observation suggests that although the answer from the deterministic analysis is computationally simpler, it may lead the decision maker to select a pavement design with a higher life-cycle cost. One methodology for accounting for the uncertainty in an LCCA is conducting a probabilistic LCCA that can account for a range of possible outcomes in the analysis (*5*).

The idea of conducting a probabilistic LCCA is not particularly novel; FHWA has recommended the use of a probabilistic LCCA for almost 15 years (*1*). Nevertheless, implementation of a probabilistic LCCA has been limited in practice for many reasons. First, because the LCCA of pavement alternatives is a large-scale problem with many input parameters with a high level of uncertainty, implementation of the methodology is challenging. Second, there is currently a gap in the literature with regard to the statistical quantification of uncertainty for input values, the need for which often results from uncertainty regarding the quantity of inputs and the quality of data (*5*). If a decision maker incorrectly quantifies the underlying uncertainty of input parameters, the results of the analysis are rendered useless.

This research aimed to build on previous work to move probabilistic LCCA methodology into practice by statistically quantifying input parameters in the LCCA of pavements. Specifically, this research characterizes uncertainty related to the unit cost of construction activities, the frequency and timing of maintenance events, and the evolution of material prices over time and characterizes uncertainty in the absence of empirical data.

LITERATURE REVIEW

Following the National Highway System Designation Act of 1995, which required states to conduct an LCCA for projects costing more than $25 million, state departments of transportation (DOTs) and researchers focused their efforts on improving the overall LCCA process. FHWA has played a major role in both promoting and funding LCCA research that has led to significant advancements in the past 15 years (*4*).

Early research by 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 (*6*). Huang et al.

O. Swei, Department of Civil and Environmental Engineering, E38-435, and J. Gregory, E38-424, and R. Kirchain, E38-432, Engineering Systems Division, Materials Systems Laboratory, Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA 02139. Corresponding author: O. Swei, oaswei@mit.edu.

Transportation Research Record: Journal of the Transportation Research Board, No. 2366, Transportation Research Board of the National Academies, Washington, D.C., 2013, pp. 71–77.
DOI: 10.3141/2366-09

created a decision support system for identifying optimal repairs of concrete bridge decks (*7*). Fagen and Phares compared the life-cycle costs of steel beam precast, concrete beam precast, and continuous concrete slab bridge decks for a low-volume roadway (*8*). Zimmerman and Peshkin used LCCA to identify optimal timings for preventative maintenance procedures (*9*). Although these are major contributions, a drawback associated with all of these studies is that input parameters were treated as deterministic values. Recognizing this drawback, research in the past decade has focused on developing a probabilistic approach to dealing 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 that for many of the input parameters, a lognormal distribution fit the data best (*5*). Osman developed a risk-based methodology by considering uncertainty only with respect to pavement performance over time, which was described with a Weibull distribution (*10*). Li and Madanu created a life-cycle cost–benefit model by characterizing cost uncertainty with a beta distribution (*11*). Salem et al. characterized uncertainty related to the occurrence of pavement failure and future life-cycle events with a Weibull distribution (*12*). Despite the progress, state DOTs still mostly conduct deterministic LCCAs (*4*). The aim of the present study was to build on some of the previously mentioned work to accelerate the inclusion of probabilistic LCCAs in practice.

First, the previously mentioned studies characterize uncertainty and variability in an LCCA but do not reduce it by considering likely drivers of it. For example, Herbsman showed there is a direct correlation between bid volume and the unit cost of bid items (*13*). One potential way to reduce the uncertainty and make the results of the analysis more realistic is to account for such relationships. Second, the *Mechanistic–Empirical Pavement Design Guide* (MEPDG) is a major breakthrough in the pavement selection process (*14*). The present study integrated the MEPDG with a probabilistic LCCA model to project future maintenance events and understand the MEPDG's implications for conducting an LCCA. Third, the previous studies have not accounted for projecting future prices. Not only will the real price of construction costs change over time, but different inputs will change differentially. Last, all of the previous studies make use of empirical data in characterizing input parameters. It is likely, however, that there are many input parameters for which there are no readily available data. A methodology should be introduced to account for such uncertainties.

METHODOLOGY

The most common reference for practitioners conducting an LCCA is FHWA's 1998 report *Life-Cycle Cost Analysis in Pavement Design: Interim Technical Bulletin* (*1*). The present study followed the same five major steps outlined in the report: identify the structure of the problem, quantify uncertainty, perform simulations, interpret results, and make a consensus decision.

Identify the Structure of the Problem

This research quantified the probabilistic economic cost of building and maintaining a new roadway. The study focused only on the cost of financing a project and ignored user costs associated with traffic delays, which previous studies have explored (*15–17*). The study also assumed that a decision had already been made to build a new roadway. Underlying policies and the impacts a roadway has on existing infrastructure, although important, were ignored to reduce the complexity of the problem at hand (*18*). Figure 1 is a simplified flowchart of all phases considered within the system boundary of this research. The four general life-cycle phases are materials, construction, maintenance, and end of life.

This study was a comparative assessment of pavement alternatives, and, as such, it ignored costs incurred apart from pavement selection. If land had to be cleared for a new roadway, for example, the costs of clearing the land were independent of the pavement selection and, consequently, were outside the scope of this work. To allow for fair comparison between pavement alternatives with likely different cash flows, all costs were converted into a net present value to allow for an equivalent time perspective.

Quantify Uncertainty

The LCCA in this research was structured to allow for the incorporation of uncertainty related to the unit cost of construction, occurrence of maintenance activities, future material prices, and quantity of inputs.

Unit Cost of Construction Activities

Basic economic theory postulates that it is likely that the average cost of production will decrease as production increases; this principle is known as economy of scale. Therefore, it is likely more reasonable to model cost as a function of bid volume than to characterize uncertainty with a best-fit distribution.

Substantial historical bid data, including bid volume and total bid cost, are made publicly available by state DOTs. The total bid cost provided by DOTs typically convolves manufacturing of materials, labor and overhead, and other costs into one number. This practice makes it difficult to differentiate the relative contribution of variable and fixed costs to the total bid price. Nevertheless, one way to quantify the relationship between cost and quantity is to evaluate

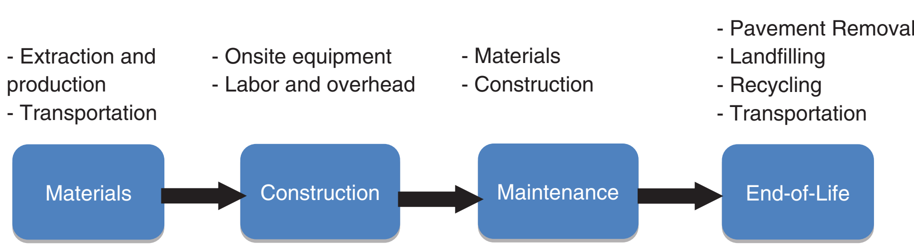

FIGURE 1 Simplified scope and boundary of LCCA study.

the average unit cost (total cost divided by quantity) with respect to bid volume. It is likely that for most relevant construction activities, a statistically significant relationship will exist between the two. To test whether the relationship is in fact statistically significant, a univariate regression analysis between average unit cost and bid volume can be conducted.

In a regression analysis, both average unit cost and bid volume undergo a log transformation to allow the data to meet the assumptions of a linear regression analysis, which will report the p-value of the dependent variable. The p-value represents a statistical measure, which ranges from 0 to 1, for evaluating whether a parameter can be classified as statistically significant (*19*). If the p-value is less than a threshold value (α), the confidence that the parameter is statistically significant is $1 - \alpha$. Typical p-values used in statistics can range between .1 and .01, meaning 90% to 99% confidence that the dependent variable—bid volume in this case—is statistically significant. For this particular research, a threshold p-value of .05 was used.

For all construction activities that showed a statistically significant relationship between average unit cost and bid volume, regression analysis was used to project initial costs. Other factors not captured by this relationship, such as construction site variability or daytime versus nighttime construction, were modeled by using the standard error of the univariate regression equation in conducting Monte Carlo simulations. For construction activities in which there is a statistically insignificant relationship between average unit cost and bid volume, a chi-square best-fit lognormal distribution was fitted to the data, consistent with the approach of previous LCCA studies (*5*).

Timing of Future Maintenance on Basis of Predicted Pavement Distress

To predict both the number and timing of maintenance activities, this research integrated the pavement design process with the recently developed MEPDG (*14*). The MEPDG transforms a set of design conditions (e.g., pavement type and thickness) and contextual conditions (e.g., climate, predicted traffic) into predicted performance with models that have been calibrated and validated with data from the Long-Term Pavement Performance program (*20*). The process of design with MEPDG software is iterative; the pavement designer initially selects a pavement, and if that pavement does not meet a required level of performance, the designer will make the necessary amendments to the initial design. Pavement performance is measured through outputs of distress data, which include factors such as roughness, bottom-up cracking, and surface-down cracking.

The developed probabilistic LCCA model leveraged the MEPDG outputs of predicted pavement performance at the 50th and 90th percentile reliability levels. From the two outputs, a Gaussian distribution was formed to represent the distress at any reliability level with respect to time. For each uncertainty simulation, the year in which maintenance would be performed was selected by choosing the first distress criteria that failed to meet the required performance threshold level (e.g., if the international roughness index were to exceed a desired threshold of 160).

Future Material Cost

Research has shown that concrete and asphalt are two commodities with historically different price growth rates and volatilities and that this differential behavior is likely to continue into the future (*21*). Nevertheless, decision makers tend to avoid consideration of this difference when conducting an LCCA because of the difficulty in projecting prices over such a long time horizon, especially given the lack of significant historical price data for the commodities. Therefore, to understand the price link between concrete and asphalt, the price of each was probabilistically forecast by testing for cointegration between paving materials (e.g., cement, aggregate) and their relevant price inputs. Concrete and asphalt prices were then forecast by projecting future constituent prices and using the derived long-run price equilibrium to forecast future paving material prices. This research followed the same approach as Swei (*21*), but incorporated more recent data in the price projections.

Quantification of 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 none of the historical data that are required for statistical characterization. Because an acceptable methodology for quantifying such uncertainty was not found in the LCCA literature, this study adopted a methodology practiced by the life-cycle assessment community known as the pedigree matrix approach (*22*). A pedigree matrix is a framework of analysis for quantifying uncertainty related to the data quality of input parameters in the absence of empirical data.

The Ecoinvent pedigree matrix recognizes two extremely general types of uncertainty: basic uncertainty and additional uncertainty (*22*). Basic uncertainty is defined as values with variation and stochastic error resulting from process variation. For example, the pavement thickness prescribed by a pavement engineer will not be perfectly met in the field. Additional uncertainty is defined as uncertainty resulting from temporal, geographic, or technological correlation as well as completeness and reliability in the underlying data. If a construction activity is estimated on the basis of 5-year-old data, for example, there is temporal uncertainty related to the data in use. The power of the pedigree matrix approach is that it allows for the quantification of uncertainty by qualitatively evaluating the input parameters (*23*). Quality indicator scores are used to assess the input values being used and are transformed into variances that are applied to the input parameters in the form of a lognormal distribution.

Perform Simulations

In conducting a Monte Carlo simulation, random values are sampled from probability distributions thousands of times to form a distribution of possible outcomes. An important factor in performing a Monte Carlo simulation is ensuring that the values selected, although random, make sense structurally. Therefore, in accounting for uncertainty, it is paramount that the analysis consider both correlation and dependencies between input parameters. Dependencies represent statistical relationships between multiple variables. For example, the timing of a second maintenance depends on what occurred during the first maintenance activity. Correlation is the common inputs shared by each alternative. 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.

Interpret Results and Make a Consensus Decision

One way to visualize the results from a Monte Carlo simulation is to examine the results in the form of a cumulative distribution function (CDF); this is the integral of the more commonly used probability density function. The usefulness of a CDF is that a decision maker can select an alternative on the basis of his or her risk perspective. It is expected that a decision maker is not necessarily interested in the expected cost of a project, but potentially more interested in limiting his or her losses. From this risk-averse perspective, a decision maker would use a CDF to select a pavement that has a high probability of costing less than a certain threshold.

CASE STUDY

The methodology described above was applied to estimating the probabilistic life-cycle cost in two case studies, both located in Joplin, Missouri. The selection of the location was based on local calibration efforts that were conducted with the recently developed MEPDG software. Pavement designs were developed independently by Applied Research Associates, which sought to use the MEPDG to develop equivalent hot-mix asphalt (HMA) and jointed plain concrete pavement (JPCP) alternatives for each scenario. Alternative pavements were designed for (*a*) a major roadway with three lanes of traffic in each direction and expected initial annual average daily truck traffic (AADTT) of 8,000 and (*b*) a local roadway with one lane of traffic in each direction and an expected initial AADTT of 300. Life-cycle costs were calculated for a 50-year analysis period, and future maintenance costs were discounted by using a real discount rate of 4% to stay consistent with FHWA's suggestion for conducting an LCCA (*1*). Tables 1 and 2 present the HMA and JPCP designs and maintenance schedules, respectively, for the 90th percentile reliability level.

Statistical Characterization of Data

This section presents the statistical characterization of uncertainty for the LCCA model. This paper presents only the results for characterizing the unit cost and pavement mechanistic performance with respect to time uncertainty. The price projections and pedigree matrix uncertainty factors used in this probabilistic analysis can be found in Swei (*21*).

TABLE 1 MEPDG-Based JPCP and HMA Pavement Designs for Urban Interstate and Local Road Case Studies

Layer	Thickness [in. (cm)]
Urban Interstate Road (Initial AADTT of 8,000)	
JPCP design	
JPCP	11 (27.9)
Aggregate base	6 (15.2)
HMA design	
Surface HMA PG 76-22	2 (5.1)
Intermediate HMA PG 76-22	3 (7.6)
Base HMA PG 76-22	7 (17.8)
Rock base	24 (61.0)
Local Road (Initial AADTT of 300)	
JPCP design	
JPCP	7.5 (19.1)
Aggregate base	4 (10.2)
HMA design	
Surface HMA PG 76-22	1.75 (4.4)
Intermediate HMA PG 76-22	4 (10.2)
Aggregate base	4 (10.2)

TABLE 2 Maintenance Schedule for JPCP and HMA Pavement Designs at MEPDG-Specified 90% Reliability for Urban Interstate and Local Road Case Studies

Maintenance Number	Year of Occurrence	Type of Rehabilitation
Urban Interstate Road (Initial AADTT of 8,000)		
JPCP design		
1	30	100% diamond grinding and full-depth repair
2	na	na
HMA design		
1	20	2-in. mill, overlay and patching
2	37	2-in. mill, overlay and patching
Local Road (Initial AADTT of 300)		
JPCP design		
1	20	Full-depth repair
2	40	Full-depth repair
HMA design		
1	20	1.75-in. mill, overlay and patching
2	37	1.75-in. mill, overlay and patching

NOTE: na = not applicable.

Unit Price of Construction Activities

Figure 2 presents a univariate regression analysis of the unit price of JPCP pavements versus bid quantity over a 36-month span in Missouri; the Oman Systems BidTabs database was used in the analysis (*24*). For this particular data set, the coefficient of determination was 0.70, which implied that 70% of the variation could be described by this simple analysis. As shown in Table 3, this result generally holds true for many of the major cost inputs for the LCCA model. Some of the inputs, however, such as the removal of material for patching, show no statistically significant relationship between cost and quantity, and are therefore characterized with a best-fit probability distribution.

In conducting the deterministic cost analysis described in the following section, either the mean values of the best-fit distributions or a univariate regression analysis was used, depending on whether the relationship between cost and quantity was statistically significant.

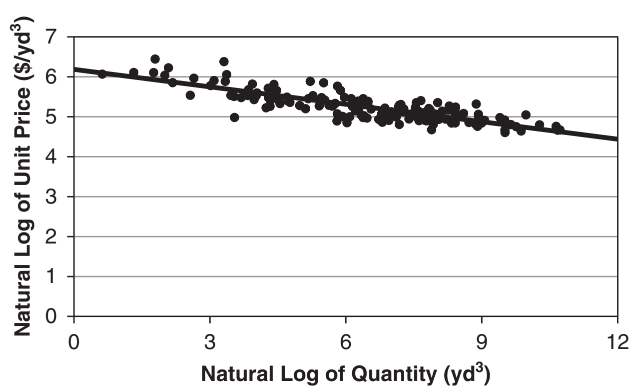

FIGURE 2 Regression analysis of unit price of JPCP winning pavement bids with respect to bid volume (*24*).

TABLE 3 Quantification of Unit Cost Uncertainty for Significant Input Parameters

Input	Unit of Measurement	*P*-Value	R^2	Regression Equation $\ln(P) = a * \ln(Q) + b$	Best-Fit Lognormal Distribution
Initial JPCP Design Inputs					
JPCP	yd^3	<.0001	.70	$a = -0.15$ (0.0076) $b = 6.19$ (0.052)	na
Type 5 aggregate base	yd^3	<.0001	.49	$a = -0.17$ (0.014) $b = 5.02$ (0.091)	na
Initial Asphalt Design					
Surface mixture SP125 (PG 76-22 binder)	Tons	<.0001	.49	$a = -0.11$(0.017) $b = 5.49$ (0.15)	na
Surface mixture BP1 (PG 64-22 binder)	Tons	<.0001	.62	$a = -0.18$ (0.0083) $b = 5.50$ (0.062)	na
Base mixture (PG 64-22 binder)	Tons	<.0001	.55	$a = -0.16$ (0.0044) $b = 5.29$ (0.035)	na
Type 5 aggregate base	yd^3	<.0001	.49	$a = -0.17$ (0.014) $b = 5.02$ (0.091)	na
Placing rock base	yd^3	<.0001	.38	$a = -0.26$ (0.086) $b = 4.44$ (0.70)	na
Maintenance-Specific Input Parameters					
Diamond grinding	yd^2	<.0001	.78	$a = -0.33$ (0.034) $b = 3.50$ (0.33)	na
Cold milling	yd^2	<.0001	.70	$a = -0.39$ (0.013) $b = 4.27$ (0.12)	na
Patching, additional material	yd^3	<.0001	.53	$a = -0.38$ (0.070) $b = 7.30$ (0.20)	na
Patching, removal of material	yd^3	.08	na	na	Mean = 4.65 SD = 0.93

NOTE: SD = standard deviation. In the regression equation, P = unit price, Q = quantity, and a and b = regression coefficients. Values in parentheses represent standard error of regression coefficient.

To account for other factors driving the variability, the probabilistic analysis incorporated the standard error of the regression equations.

Timing of Future Maintenance and Rehabilitation

As discussed, both the number and timing of maintenance events were characterized by leveraging the outputs of the MEPDG software. With the predicted pavement deformation curves at the 50th and 90th percentile reliability levels, a curve can be developed for all reliability levels if the assumption is that the pavement deformation in each month follows an underlying normal distribution. Because the random variable in the probabilistic analysis is the selected reliability level, the model assumes that the performance in each year implicitly depends on previous performance (i.e., if the pavement performance in Month 1 is the 75th percentile, the performance in Month 100 will also be the 75th percentile). When Monte Carlo simulations were conducted, reliability levels could only be selected between 25% and 98%, as it was found that using the full range of reliability levels could lead to unrealistic results. For different reliability levels, the controlling performance criteria (e.g., international roughness index, cracking) may switch, and so the model developed allows for that flexibility during each simulation.

Deterministic Analysis

The current procedure adopted by state DOTs and a model created in Microsoft Excel were used to construct a deterministic analysis to estimate the likely pavement selection. Historical bid data were collected between 2010 and 2012 for the state of Missouri by using the Oman BidTabs database, which includes all cost components except mobilization (*24*). Therefore, an additional 10% was added to each bid item in the deterministic case, consistent with what the California DOT suggests is the approximate cost of mobilizing materials (*25*). Uncertainty regarding this value was incorporated in the probabilistic analysis with the pedigree matrix approach. As mentioned in the methodology section, only differential costs were considered in this analysis, and costs such as engineering fees, traffic, and lighting were therefore excluded from the scope of the analysis.

Figure 3 presents the initial, discounted rehabilitation and discounted life-cycle costs for the HMA and JPCP designs for the two case studies. In each case study, the superior alternative in terms of life-cycle costs was also superior in terms of initial costs. However, it is difficult to assert with certainty that one alternative was superior to another, given the significant uncertainty underlying all of the input parameters.

Probabilistic Analysis

Figure 4 presents the results when all input parameters were treated as probabilistic. When uncertainty is taken into account, the expected life-cycle cost of the JPCP design is 10% superior in the case of the urban Interstate but 33% more expensive for the local road. The change in expected net present value can be attributed to the deterministic analysis that used the 90th percentile reliability from the MEPDG—a more risk-averse perspective that is typically used in

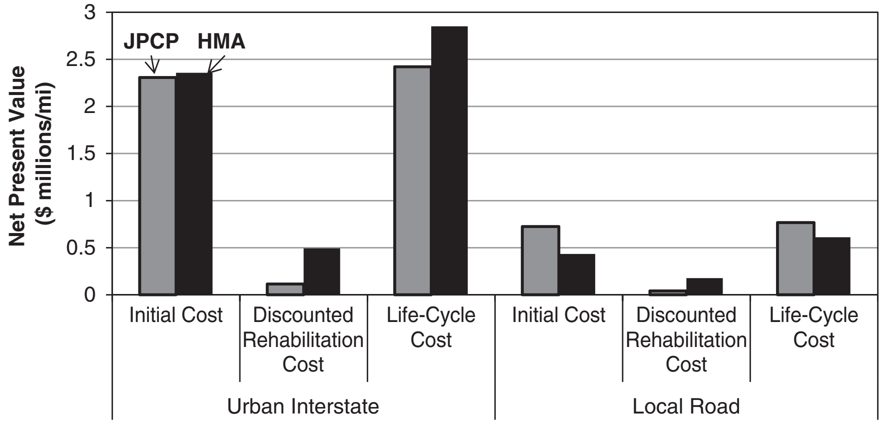

FIGURE 3 Initial, discounted rehabilitation, and life-cycle costs of JPCP and HMA pavement designs for two scenarios.

pavement designs. Given that the probabilistic approach considers all reliability levels and that a larger portion of the total life-cycle cost of HMA pavements is from rehabilitation, a probabilistic LCCA could potentially favor the HMA alternative as compared with a deterministic analysis when the mean values are evaluated. That being said, the discrepancy between the alternatives for the urban Interstate case tended to increase as the cumulative probability increased, as shown in Table 4. This indicates that in this particular scenario, the JPCP pavement design would be more likely to be selected if the decision maker had a more risk-averse perspective. On the other hand, for the local road, the relative difference for different risk profiles does not change. This finding likely can be attributed in part to the uncertainty surrounding the initial cost inputs, as the regression analysis for the surface HMA mixture for the local road fit the data better than that for the urban Interstate, as can be seen in Table 3.

CONCLUSIONS AND FUTURE WORK

This research probabilistically quantified uncertainty in the LCCA of pavements for input parameters with empirical data—specifically, the unit price of bid items, timing of maintenance events, and forecasting of material prices—and accounted for uncertainty for inputs without empirical data. The majority of unit cost inputs showed a statistically significant relationship with quantity, indicating that such explanatory variables should be accounted for in an LCCA. The development of a model that fits within the MEPDG framework characterized the probabilistic evolution of pavement distress over time to account for that distress in conducting an LCCA. By applying the characterized uncertainties in two case studies, this research reinforced the benefit of probabilistic LCCAs and of viewing the results in the form of a CDF, as FHWA has pointed out (*1*).

One of the major limitations of the analysis done in this study is that the methodology was applied to a scenario that assumes that future rehabilitation activities are fixed irrespective of future market conditions. It is likely, for example, that a future rehabilitation activity would either be changed or be delayed if material prices were significantly higher than expected. The LCCA model should account for a decision maker's flexibility in changing future actions in response to future events (known as real options); not doing so is a drawback of the analysis presented in this paper. Additionally, the scope of the analysis focused only on the cost of financing a roadway. The model should be expanded to include the user cost associated with a pavement decision.

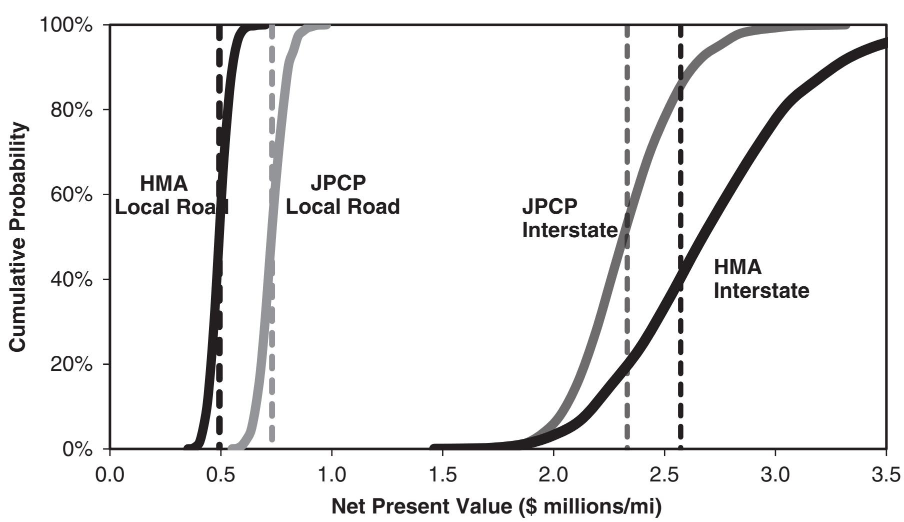

FIGURE 4 Probabilistic life-cycle cost of urban Interstate and local road alternatives (dashed lines = mean value from analysis).

TABLE 4 Results from Probabilistic Analysis for Three Potential Risk Profiles

Cumulative Distribution Value	HMA Design ($ millions/mi)	JPCP Design ($ millions/mi)	$\frac{\text{JPCP} - \text{HMA}}{\text{JPCP}}$ (%)
Urban Interstate			
Mean value	2.57	2.33	−9
75th percentile	2.84	2.48	−13
95th percentile	3.32	2.74	−17
Local Road			
Mean value	0.49	0.73	33
75th percentile	0.52	0.77	32
95th percentile	0.57	0.83	31

NOTE: Column 4 is cost of JPCP design for percentile minus cost of HMA design for percentile, divided by cost of JPCP design for percentile.

Last, the described methodology showed that a probabilistic analysis could potentially change a decision maker's selection of pavement. This finding ignores the underlying political and nontechnical factors that drive a decision. The study also did not test whether such a model would actually lead to economically smarter investment decisions. To validate the methodology presented in this paper, a future study comparing the cost expectancy of historical pavement projects with the actual costs should be conducted to assess whether the model leads to the correct selection.

ACKNOWLEDGMENTS

This research was carried out as part of the Concrete Sustainability Hub at the Massachusetts Institute of Technology and was supported by the Portland Cement Association and the Ready Mixed Concrete (RMC) Research & Education Foundation. The authors are grateful to Applied Research Associates, Inc., which helped develop the pavements used in the case studies, and to James Mack for his technical input.

REFERENCES

1. Walls, J. III, and M. L. Smith, *Life-Cycle Cost Analysis in Pavement Design: Interim Technical Bulletin.* FHWA-SA-98-079. FHWA, U.S. Department of Transportation, 1998.
2. Rangaraju, P. R., S. Amirkhanian, and Z. Guven. *Life Cycle Cost Analysis for Pavement Type Selection.* FHWA-SC-08-01 2008. South Carolina Department of Transportation, Columbia.
3. Frangopol, D. M., J. S. Kong, and G. Emhaidy. Reliability-Based Life-Cycle Management of Highway Bridges. *Journal of Computing in Civil Engineering,* Vol. 15, No. 1, 2001, pp. 27–34.
4. Chan, A., G. Keoleian, and E. Gabler. Evaluation of Life-Cycle Cost Analysis Practices Used by the Michigan Department of Transportation. *Journal of Transportation Engineering,* Vol. 134, No. 6, 2008, pp. 236–245.
5. Tighe, S. Guidelines for Probabilistic Pavement Life Cycle Cost Analysis. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1769,* TRB, National Research Council, Washington, D.C., 2001, pp. 28–38.
6. Embacher, R. A., and M. B. Snyder. Life-Cycle Cost Comparison of Asphalt and Concrete Pavements on Low-Volume Roads: Case Study Comparisons. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1749,* TRB, National Research Council, Washington, D.C., 2001, pp. 28–37.
7. Huang, Y.-H., T. M. Adams, and J. A. Pincheira. Analysis of Life-Cycle Maintenance Strategies for Concrete Bridge Decks. *Journal of Bridge Engineering,* Vol. 9, No. 3, 2004, pp. 250–258.
8. Fagen, M. E., and B. M. Phares. Life-Cycle Cost Analysis of a Low-Volume Road Bridge Alternative. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1696,* TRB, National Research Council, Washington, D.C., 2000, pp. 8–13.
9. Zimmerman, K. A., and D. G. Peshkin. Applying Pavement Preservation Concepts to Low-Volume Roads. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1819,* Vol. 1, Transportation Research Board of the National Academies, Washington, D.C., 2003. pp. 81–87.
10. Osman, H. Risk-Based Life-Cycle Cost Analysis of Privatized Infrastructure. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1924,* Transportation Research Board of the National Academies, Washington, D.C., 2005, pp. 192–196.
11. Li, Z., and S. Madanu. Highway Project Level Life-Cycle Benefit/Cost Analysis Under Certainty, Risk, and Uncertainty: Methodology with Case Study. *Journal of Transportation Engineering,* Vol. 135, No. 8, 2009, pp. 516–526.
12. Salem, O., S. AbouRizk, and S. Ariaratnam. Risk-Based Life-Cycle Costing of Infrastructure Rehabilitation and Construction Alternatives. *Journal of Infrastructure Systems,* Vol. 9, No. 1, 2003, pp. 6–15.
13. Herbsman, Z. Model for Forecasting Highway Construction Costs. In *Transportation Research Record 1056,* TRB, National Research Council, Washington, D.C., 1986, pp. 47–54.
14. Hallin, J. P., S. Sadasivam, J. Mallela, D. K. Hein, M. I. Darter, and H. L. Von Quintus. *NCHRP Report 703: Guide for Pavement Type Selection.* Transportation Research Board of the National Academies, Washington, D.C., 2011.
15. Vadakpat, G., S. Stoffels, and K. Dixon. Road User Cost Models for Network-Level Pavement Management. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1699,* TRB, National Research Council, Washington, D.C., 2000, pp. 49–57.
16. Temple, W. H., Z. Zhang, J. Lambert, and K. M. Zeringue. Agency Process for Alternate Design and Alternate Bid of Pavements. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1900,* Transportation Research Board of the National Academies, Washington, D.C., 2004, pp. 122–131.
17. Lee, D. B., Jr. Fundamentals of Life-Cycle Cost Analysis. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1812,* Transportation Research Board of the National Academies, Washington, D.C., 2002, pp. 203–210.
18. Stamatiadis, N., A. Kirk, D. Hartman, and J. Pigman. Practical Solution Concepts for Planning and Designing Roadways. *Journal of Transportation Engineering,* Vol. 136, No. 4, 2010, pp. 291–297.
19. Selke, T., M. J. Bayarri, and J. O. Berger. Calibration of p-Values for Testing Precise Null Hypotheses. *The American Statistician,* Vol. 55, No. 1, pp. 62–71.
20. Baus, R. L., and N. R. Stires. *Mechanistic-Empirical Pavement Design Guide Implementation.* Report No. FHWA-SC-10-01. Department of Civil and Environmental Engineering, University of South Carolina, Columbia, 2010.
21. Swei, O. A. Accounting for Uncertainty in the Life-Cycle Cost Assessment of Pavements. MS thesis. Massachusetts Institute of Technology, Cambridge, 2012.
22. Weidema, B. P., C. Bauer, R. Hischier, C. Mutel, T. Nemecek, C. O. Vadenbo, G. Wernet. *Overview and Methodology: Data Quality Guideline for the Ecoinvent Database Version 3.* Ecoinvent Report 1(v3). Ecoinvent Centre, Saint Gallen, Switzerland, 2011.
23. Weidema, B. P., and M. S. Wesmaes. Data Quality Management for Life Cycle Inventories: An Example of Using Data Quality Indicators. *Journal of Cleaner Production,* Vol. 4, No. 3–4, 1996, pp. 167–174.
24. BidTabs Professional. Oman Systems, Inc., Nashville, Tenn., 2013. http://www.omanco.com/bidtabspro.asp.
25. Life-Cycle Cost Analysis. California Department of Transportation, Sacramento. http://www.dot.ca.gov/hq/maint/Pavement/Offices/Pavement_Engineering/LCCA_index.html.

The Pavement Management Systems Committee peer-reviewed this paper.