Probabilistic Life-Cycle Cost Analysis of Pavements

Drivers of Variation and Implications of Context

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Significant research has been conducted over the past decade to enhance probabilistic pavement life-cycle cost analysis (LCCA) models, yet the drawing of broad conclusions from different studies is difficult because of the significant variation in scope and sources of uncertainty. Specifically, these two issues make it difficult to infer from existing research (*a*) which parameters are significant contributors to uncertainty for a specific context and (*b*) how context affects the analysis. The goal of this research was to address this problem by implementing an LCCA model in a range of scenarios that vary in location, traffic conditions, design life (e.g., year to first rehabilitation), analysis period, maintenance schedule, and discount rate. Results from the analysis indicated that, in relation to the drivers of variation, uncertainty about initial cost was the principal driver of variation across the case studies. Other parameters, such as the predicted performance of pavement over time, could also be important drivers of variation and in particular a matter for lower-volume roads, for which thinner pavement designs are used. In terms of contextual decisions, some decisions, such as whether to use mechanistic–empirical pavement designs instead of the paving design manual of a state department of transportation to determine future maintenance events, seem to have a larger impact than do others. For example, analysis period and design life, though important, affect the final results significantly less, although in some instances they can play a role in differentiating between alternative designs.

Life-cycle cost analysis (LCCA) is an analytical framework to assess the most economically prudent investment from a set of alternatives over their respective lifetimes (*1*). Frequently, decision makers are faced with significant uncertainty in estimating future costs, in both the short term and long term; this uncertainty motivates a probabilistic perspective. As a result, different governmental agencies, such as the FHWA and the Government Accountability Office (GAO), have strongly recommended a probabilistic approach be implemented in order to overcome the limitations of a deterministic analysis (*1, 2*).

With that said, the majority of departments of transportation (DOTs) implement LCCAs by treating inputs as single-point estimates despite the availability of FHWA's RealCost software to conduct a probabilistic analysis (*3, 4*). Clearly, practitioners appreciate the simplicity of the deterministic approach, which only requires considering one set of conditions that may arise in the future. This leaves decision makers, however, susceptible to comparing values that may not be appropriate if future conditions unexpectedly alter (*5*). This is an important issue given that cost overruns are a common characteristic across transportation projects (*6–8*).

One understandable reason that may explain the tendency to implement deterministic analyses is the significant time and effort to characterize the uncertainty for each input. Given that previous studies have primarily focused upon characterizing uncertainty for a limited set of parameters and applying models to a single case study, it is difficult for practitioners to extrapolate such results to their own particular scenario. The goal of this research, therefore, is to identify which parameters are important depending upon context, allowing practitioners to have a stronger sense of which parameters will likely matter for their particular analysis.

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LITERATURE REVIEW

The National Highway System Designation Act of 1995, which required states to conduct an LCCA for projects costing more than $25 million, is the major piece of legislation that sparked significant research efforts to improve the pavement LCCA methodology (*9*). Since then, the FHWA has played a lead role in promoting and funding LCCA research and efforts, leading to significant advancements (*3*). This includes the development of FHWA's RealCost software that a large number of DOTs currently use in some capacity according to a recent survey by the GAO (*10, 11*).

Scope and Context Across Previous Pavement LCCA Studies

Table 1 synthesizes some of the major contributions to pavement LCCA over the past decade. While not exhaustive, it provides a representative sample of recent research efforts. Most of these studies implemented LCCA to support decisions when alternative strategies were being compared, and these strategies may include different materials [e.g., asphalt concrete (AC) versus portland cement concrete (PCC) pavements] or the same material (e.g., AC overlay versus full-depth AC reconstruction).

As Table 1 shows, a large portion of these studies have centered around rehabilitation and reconstruction rather than new pavement construction, a response to a general movement from system expansion toward system preservation. Although all studies incorporate agency cost, less than half (seven of the 16) consider user

TABLE 1 Summary of Scope of Analysis for Some Recent Pavement LCCA Studies

	Scope						Probabilistic LCCA						
	Project Type						Sources of Variation						
Study	New	M&R	User Cost	AP (years)	Traffic	Location	Agency Cost	Input Quantity	DR	Pavement Degradation	Traffic	User Cost	AP
Gransberg and Molenaar (*12*)	✓			35	13,693 AADT	British Columbia, Canada; Washington							
Chan et al. (*13*)		✓		25	27,000–53,000 AADT	Michigan							
Khurshid et al. (*14*)		✓	✓	na	873 AADTT	Indiana							
Lee et al. (*15*)		✓	✓	60	60,000 AADT	California							
Lee et al. (*16*)		✓	✓	60	137,500 AADT	California							
Pittenger et al. (*17*)		✓		5–20	Unknown	United States							
Gschosser and Wallbaum (*18*)	✓			75	3,000 ESALs per day	Switzerland							
Lee et al. (*19*)	✓		✓	50	Unknown	Wisconsin							
Tighe (*5*)	✓			30	Low to medium	Ontario, Canada	✓	✓	—	—	—	—	—
Salem et al. (*20*)		✓		30	872 ESALs per day	Alberta, Canada	—	—	—	✓	—	—	—
Huang et al. (*21*)		✓	✓	70	Unknown	Wisconsin	—	—	✓*	✓*	—	—	—
Whiteley et al. (*22*)	✓			30	Medium to high	Ontario, Canada	—	✓	—	✓	✓	—	—
Guo et al. (*23*)		✓	✓	48	30,000 AADT	Jiangsu, China	✓	—	✓*	—	✓*	✓	—
Harvey et al. (*24*)		✓		1–20	30 to 2,100 AADTT	California	—	—	✓	✓	✓	—	✓
Pittenger et al. (*25*)		✓	✓	2–12	na	United States	✓*	—	✓*	✓*	—	—	—
Swei et al. (*26*)	✓			50	8,000 AADT, 300 AADTT	Missouri	✓	✓	—	✓	—	—	—

NOTE: Blank cell = item was not covered in study; ✓ = item was covered in study; ✓* = parameter is a major driver of variation (by calculation); — = parameter is deterministic; shaded area denotes deterministic studies for which uncertainty is ignored; M&R = maintenance and rehabilitation; AP = analysis period; DR = discount rate; AADT = annual average daily traffic; na = not applicable; AADTT = annual average daily truck traffic; ESAL = equivalent single axle load.

cost (which is measured only by estimating the number of hours lost to users during road construction), illustrating the tendency to emphasize agency cost over cost to users (*21, 23, 25*). Last, and particularly important to this research, the context of the previous LCCA studies varies considerably, inhibiting one's ability to draw any conclusions that find a consensus. This variation includes the analysis period (AP) (30 to 75 years for new construction and reconstruction), traffic volumes (e.g., annual average daily traffic from slightly over 10,000 to over 100,000), metric of choice to measure traffic (qualitative descriptions, annual average daily traffic, annual average daily truck traffic, equivalent single axle loads), and climatic locations. The pervasiveness of pavement LCCAs that vary measurably in scope and context is a testament to the complexity of pavement LCCAs, which explains the focus on methodological and characterization issues rather than on implementing a model in a range of contexts (*13, 18, 20*).

Probabilistic LCCAs: What Are the Drivers of Variation?

Although all previously mentioned studies are significant contributions to the pavement LCCA literature, only some treat input values as probabilistic. Of those studies, a portion have calculated the drivers of variation by a sensitivity analysis or through the correlation between input parameters and final life-cycle cost (LCC) through Monte Carlo simulations. The former presents a computationally simple (yet oftentimes effective) approach in which each input parameter is altered individually while the overall change in LCC is noted. The obvious drawback here is that any joint effects between multiple parameters are completely ignored, a situation with which the latter approach can deal (although, as expected, it adds a level of complexity). Interestingly, across those latter studies, uncertainties about discount rate and predicted service life tend to be key contributors when they are considered (*5, 16, 24*). Nevertheless, it is clear that the scope and sources of uncertainty considered are inconsistent, presenting an issue when the results are synthesized.

Gap Analysis

The preceding discussion makes clear that earlier probabilistic LCCA studies have revolved around characterizing a select group of sources of uncertainty and variation. Although those studies are useful in helping researchers and practitioners understand ways of characterizing input parameters, they provide minimal insight about their relative importance compared with the host of other input parameters. This importance, naturally, should vary in relation to (*a*) the context (e.g., traffic), (*b*) the time at which the LCCA model is used in the decision-making process (e.g., before the collection of bids), and (*c*) the selection of discretionary inputs (e.g., AP), which have no fundamentally correct values yet define the scenario. Therefore, the important contribution from this work is numerical quantification of the parameters that matter as scope and context varies.

Research Questions

The key questions this research explores in pavement LCCAs are these: What are the principal drivers of uncertainty? How sensitive are those drivers to the scenario and context? And how do decisions when the scope of analysis is being framed affect the results of a comparative assessment? This research addresses these questions by developing a comprehensive LCCA model, characterizes sources of uncertainty and variation, and applies these values to a range of case studies.

METHODOLOGY

To answer the questions asked in the previous section, a probabilistic LCCA model is constructed consistent with the methodology developed and presented by Swei et al., as shown in Figure 1 (*26*). First, the case studies presented consider only the cost to finance a project, ignoring all user costs previously analyzed (*27–29*). Second, the analysis implicitly assumes that a decision has already been made to build a new roadway, ignoring the underlying policies and impacts of a roadway on existing infrastructure (*30*). Last, because this study is a comparative assessment of pavement designs, all costs incurred irrespective of pavement design are ignored (e.g., land clearing).

Uncertainty around parameters related to the unit cost of construction, future material prices, quantities of materials, and pavement degradation has been characterized here similarly to those in Swei et al. (*26*), except that a more in-depth forecasting methodology has been implemented to estimate future material prices (*31*). In addition, the implications of contextual variation in pavement LCCAs, including traffic volume, climate, initial design life (DL), and AP (which will be defined for this paper later), and discount rate are explored in this analysis by applying the model to a range of scenarios to quantify the following items:

1. The implications of a life-cycle perspective–probabilistic perspective,

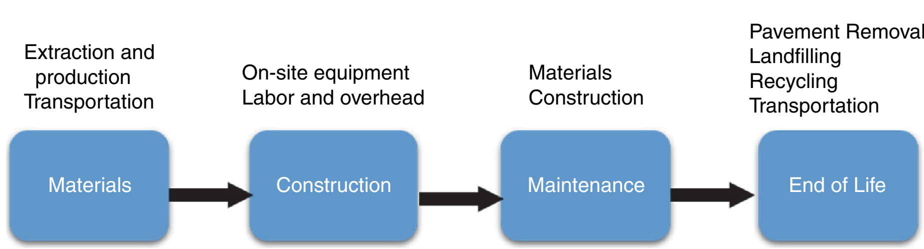

FIGURE 1 Simplified scope and boundary of LCCA study.

TABLE 2 Scenarios in Case Study Analysis

	DL, AP by Long-Term Pavement Performance Climate Zone			
Traffic Level	Wet–Freeze (Missouri)	Dry–No Freeze (Arizona)	Dry–Freeze (Colorado)	Wet–No Freeze (Florida)
Local street–highway (rural), AADTT = 300	20, 50	na	na	na
	30, 50			
State highway (rural), AADTT = 1,000	20, 50	30, 50	30, 50	30, 50
	30, 50	na	na	na
	40, 50	na	na	na
Interstate (urban), AADTT = 8,000	20, 30	30, 50	30, 50	30, 50
	20, 50	na	na	na
	30, 50	na	na	na
	30, 75	na	na	na
	50, 75	na	na	na
	50, 100	na	na	na

2. The principal drivers of variation in LCCA in relation to context, and
3. The implications of scenario context in comparative assessments.

Description of Scenario Space Analyzed

After each source of variation and uncertainty is statistically quantified consistent with the methodology discussed in Swei et al. (*26*), the values are incorporated into 34 case studies. These case studies, presented in Table 2, vary in traffic volume (ranging in annual average daily truck traffic from 300 to 8,000) and in climatic regions (four). And within Missouri, both the DL (e.g., years until first major rehabilitation) and AP (e.g., number of years of the analysis) are varied. Furthermore, discount rate is varied by a sensitivity analysis to quantify its impact. For each scenario in Table 2, two analyses are conducted: one with a maintenance schedule derived from the DOT and a second based on a maintenance schedule derived from the AASHTOWare Pavement ME software.

For each one of these scenarios, two pavement rehabilitation schedules are considered: one that is consistent with current DOT practice for each state and another that is based on mechanistic–empirical (pavement M-E) designs. The major difference between these two schedules generally is the expected year of rehabilitation, with the former (DOT) generally predicting more frequent or earlier rehabilitations than do the pavement M-E designs. For example, the jointed plain concrete pavement (JPCP) for the design covering an urban Interstate highway with a 30-year DL actually has an expected first rehabilitation at Year 25 under current DOT practice. The four states (Arizona, Colorado, Florida, and Missouri) were selected not only because of climactic differences but also because of local calibration efforts of pavement M-E through use of sections from FHWA's Long-Term Pavement Performance program. For each scenario, a hot-mix asphalt (HMA) and a JPCP alternative considered functionally equivalent are compared, as defined by Applied Research Associates, who developed the designs (*31*). The intention of the comparison is to understand which parameters are consistently the major sources of variation in analyses involving the two paving materials across the scenario space (and not necessarily to draw conclusions about which paving material is lower cost). Further information about the designs and LCCA input data used in the analysis can be found in supplementary information provided on the Concrete Sustainability Hub website (*31*).

Comparative Assessment

To allow a fair comparison between pavement alternatives with likely different cash flows, all costs are converted to a net present value to allow equivalent time perspectives. The probabilistic economic cost is estimated through Monte Carlo simulations, by which random sampling is used to formulate a probability distribution of outcomes that accounts for correlation and dependencies, as described by Swei et al. (*26*). Results about total LCCs are compared on the basis of three metrics (Table 3). These metrics provide insight into (*a*) the relative mean difference between the alternatives, denoted as $\Delta\mu$, (*b*) the difference between the alternatives from a risk-averse perspective, expressed as α_{90}, and (*c*) the probability that one can be certain about which design has a lower–higher cost, symbolized as β. Figure 2 presents the graphical representation of the three comparison metrics. For each analysis, the JPCP and HMA alternatives have been designated as Designs A and B, respectively.

To characterize the parameters that significantly contribute to the overall variance, the contribution to variance to the total LCC for each parameter is estimated by use of the Pearson correlation coefficient ($r_{x,y}$), a statistical measure of the dependency between two

TABLE 3 Metrics Used for Comparative Assessment

Metric	Meaning
$\Delta_\mu = \dfrac{\text{mean cost}_B - \text{mean cost}_A}{\text{mean cost}_A}$	Relative mean difference between Design A and Design B
$\alpha_{90} = \dfrac{90\%\ \text{cost}_B - 90\%\ \text{cost}_A}{90\%\ \text{cost}_A}$	Relative 90th percentile difference between Design A and Design B
$\beta = \text{probability}\left(\dfrac{\text{cost}_B - \text{cost}_A}{\text{cost}_A} > 0\right)$	Percentage of Monte Carlo simulation in which Design B has a higher cost than Design A. Values greater than 0.9 (or less than 0.1) indicate Design A (or Design B) cost less with statistical significance.

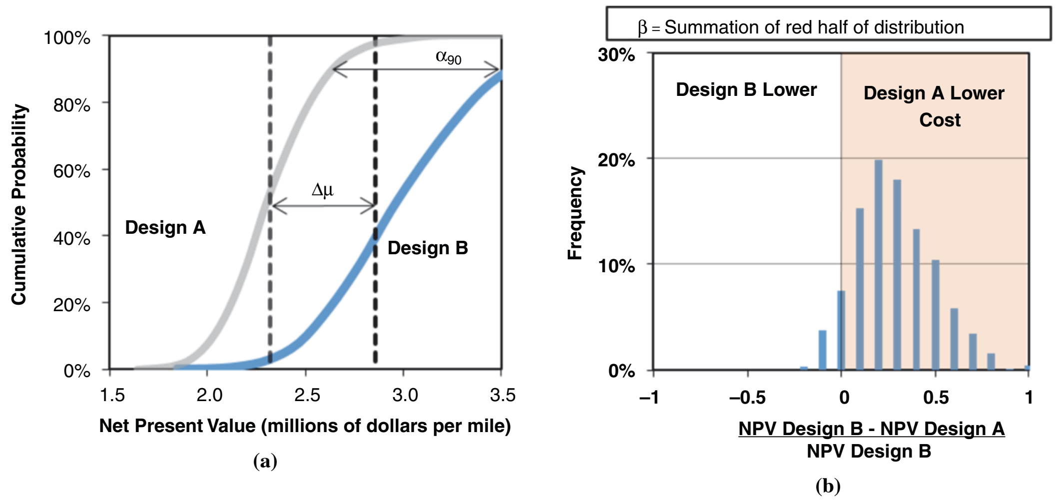

FIGURE 2 Plot of (*a*) cumulative distribution LCC of two pavements (with dashed lines representing mean values) and (*b*) probability distribution of β for same cumulative distribution.

variables, for each input. From the Monte Carlo simulations, the correlation between each input variable and the final output can be calculated as

$$r = \frac{\sum_{i=1}^{n}(x_i - m_x)(y_i - m_y)}{\sqrt{\sum_{i=1}^{n}(x_i - m_x)^2}\sqrt{\sum_{i=1}^{n}(y_i - m_y)^2}} \quad (1)$$

where x_i and y_i are numerical values of an input (x) and total LCC (y) for simulation i and m_x and m_y are average values of x and y across the full sample.

The contribution to variance for each input variable is estimated by squaring the Pearson correlation coefficient ($r^2_{x,y}$) and normalizing $r^2_{x,y}$ such that the summation across all inputs equals one. This result is an approximation of the contribution to variance and is not precisely a variance decomposition.

SCENARIO ANALYSIS RESULTS

Implications of Life-Cycle–Probabilistic Perspective

Table 4 presents the comparative results for initial cost and LCC (on the basis of pavement M-E and DOT) for the HMA pavement and the JPCP that assume a 30-year DL and a 50-year AP. The results clearly show the magnitude of the impact that both the inclusion of maintenance costs and the methodology have on the results. For example, on the basis of initial cost, only three instances with a statistically significant difference between the designs (e.g., $\beta > .9$ or $\beta < .1$) favor the HMA alternatives, whereas implementing an LCC

TABLE 4 Initial and LCC Results for Each Scenario with DL of 30 Years and AP of 50 Years on Basis of Pavement M-E and DOT Schedule

		Percentage by LTPP Climate Zone and Metric											
		Wet–Freeze (Missouri)			Dry–No Freeze (Arizona)			Dry–Freeze (Colorado)			Wet–No Freeze (Florida)		
Traffic Level	Scope	Δμ	α_{90}	β	Δμ	α_{90}	β	Δμ	α_{90}	β	Δμ	α_{90}	β
Local street–highway, AADTT = 300	Initial	–40	–37	0	na	na	na	na	na	na	na	na	na
	LCC—M-E	–32	–33	0	na	na	na	na	na	na	na	na	na
	LCC—DOT	–20	–20	1	na	na	na	na	na	na	na	na	na
State highway (rural), AADTT = 1,000	Initial	–22	–24	3	–33	–35	8	16	29	71	–41	–64	22
	LCC—M-E	–12	–14	17	–14	–20	29	27	29	82	–29	–49	33
	LCC—DOT	–4	–3	48	9	6	69	50	54	95	11	–18	68
Interstate (urban), AADTT = 8,000	Initial	15	29	76	–1	–7	49	18	22	69	16	–14	62
	LCC—M-E	22	30	86	15	10	70	23	36	75	23	–6	71
	LCC—DOT	30	36	95	34	24	91	42	42	93	63	21	90

NOTE: Δμ = percentage of difference at mean; α_{90} = percentage of difference at 90th percentile; β = percentage of simulations in which Design B (HMA in scenarios) has a higher cost; black background = HMA has statistically significant lower impact; gray background = JPCP has statistically significant lower impact; LCC = life-cycle cost; M-E = pavement M-E methodology.

with a DOT-based maintenance schedule leads to five instances for which the difference is statistically significant, but these all now favor the JPCP alternatives. In contrast, when the mean differences are compared, four instances show that HMA has a lower cost on the basis of initial costs, four instances when LCC is used with the pavement M-E methodology, but only two instances when LCC is calculated with the DOT rehabilitation schedule. On average, the mean difference between the initial cost alternative and when LCC with pavement M-E and DOT maintenance schedules was used was 11% (M-E) and 32% (DOT); these results indicate that both a life-cycle perspective alters decisions, and, furthermore, that the degree of change depends on the pavement performance methodology. The reasons for this difference are that (*a*) pavement M-E estimated, on average, that fewer rehabilitations were needed for both alternatives relative to the DOT estimates, and (*b*) rehabilitation costs were significantly larger for the HMA alternatives. Future research should evaluate the optimal way to balance initial cost expenditures and frequency of future rehabilitations by an optimization-based approach to gain a better understanding of this relationship.

An added value of a probabilistic analysis is that it allows a decision maker to evaluate alternative pavement designs on the basis of their risk profiles. Ten instances (italicized) in Table 4 display shifts of at least 10% in the difference between the alternatives when the comparison from the mean difference ($\Delta\mu$) to the 90th-percentile difference (α_{90}) is modified. Six of those instances occur in Florida and, as will be noted later, have significant uncertainty surrounding initial cost characterization for the JPCP alternatives, which results from the lack of available historical empirical data. Therefore, for cases with a high level of uncertainty for a particular significant input, the competitiveness of an alternative can considerably shift in relation to the risk profile.

Principal Drivers of Variation in LCCA That Depend on Context

Table 5 presents the parameters with the highest contribution to the cost variation of each alternative and the differential LCC when correlation (by using the approach based on pavement M-E)

TABLE 5 Parameters for Major Sources of Variation for 50-Year AP, 30-Year DL, and Pavement M-E Scenarios

		Percentage by LTPP Climate Zone			
Traffic Level	Parameter	Wet–Freeze (Missouri)	Dry–No Freeze (Arizona)	Dry–Freeze (Colorado)	Wet–No Freeze (Florida)
Local street (rural), AADTT = 300	HMA alternative	HMA	na	na	na
	Pavement–M-E reliability	.26	na	na	na
	Aggregate price	.16	na	na	na
	AC surface price	.00	na	na	na
	AC binder price	.16	na	na	na
	JPCP alternative	JPCP	na	na	na
	JPCP layer price	.78	na	na	na
	Difference	Difference	na	na	na
	JPCP layer price	.84	na	na	na
	Aggregate price	.00	na	na	na
	AC surface price	.02	na	na	na
	AC binder price	.05	na	na	na
State highway (rural), AADTT = 1,000	HMA	HMA	HMA	HMA	HMA
	Pavement–M-E reliability	.15	.06	.01	.13
	Aggregate price	.17	.04	.06	.01
	AC surface price	.18	.18	.11	.27
	AC binder price	.15	.52	.75	.50
	JPCP	JPCP	JPCP	JPCP	JPCP
	JPCP layer price	.91	.98	.95	.99
	Difference	Difference	Difference	Difference	Difference
	JPCP layer price	.74	.67	.29	.92
	Aggregate price	.00	.00	.00	.00
	AC surface price	.05	.09	.13	.01
	AC binder price	.07	.17	.23	.03
Interstate (urban), AADTT = 8,000	HMA	HMA	HMA	HMA	HMA
	Pavement–M-E reliability		.08	.06	.10
	Aggregate price	.16	.07	.01	.00
	AC surface price	.25	.13	.06	.31
	AC binder price	.38	.10	.16	.11
	AC base price	.01	.43	.64	.28
	JPCP	JPCP	JPCP	JPCP	JPCP
	JPCP layer price	.82	.96	.95	.99
	Difference	Difference	Difference	Difference	Difference
	JPCP layer price	.19	.56	.32	.85
	Aggregate price	.13	.01	.01	
	AC surface price	.20	.04	.03	.04
	AC binder price	.31	.04	.11	.02
	AC base price	.02	.23	.55	.04

TABLE 6 LCC Results for Each Scenario with Design Life of 30 Years and AP of 50 Years on Basis of Pavement M-E–Based Rehabilitation Schedule While Varying Discount Rate

		Percentage by LTPP Climate Zone and Metric											
		Wet–Freeze (Missouri)			Dry–No Freeze (Arizona)			Dry–Freeze (Colorado)			Wet–No Freeze (Florida)		
Traffic Level	Scope	$\Delta\mu$	α_{90}	β	$\Delta\mu$	α_{90}	β	$\Delta\mu$	α_{90}	β	$\Delta\mu$	α_{90}	β
Local street–highway, AADTT = 300	1% DR	−29	−27	0	na	na	na	na	na	na	na	na	na
	State DR	−32	−33	0	na	na	na	na	na	na	na	na	na
	7% DR	−33	−36	0	na	na	na	na	na	na	na	na	na
State highway (rural), AADTT = 1,000	1% DR	−4	−5	38	1	−4	56	31	40	87	−21	−42	41
	State DR	−12	−14	17	−14	−20	29	27	29	82	−29	−49	33
	7% DR	−14	−17	9	−26	−26	18	21	25	78	−35	−54	28
Interstate (urban), AADTT = 8,000	1% DR	27	37	91	24	19	78	33	41	80	28	5	73
	State DR	22	30	86	15	10	70	23	36	75	23	−6	71
	7% DR	17	25	81	8	0	61	22	29	73	18	17	69

NOTE: Black background = HMA has statistically significant lower impact; gray background = JPCP has statistically significant lower impact.

is taken into account. Importantly, the results clearly demonstrate that, although several parameters are sources of uncertainty, only a few affect the immediate decision. For the JPCP designs, the unit price of the JPCP layer constitutes the majority of the variance across the case studies. An obvious future area of work for a state such as Florida is evaluation of potential ways to estimate unit cost variation for paving activities that lack data. For the HMA designs, the unit price of the aggregate and asphalt layer inputs, in addition to uncertainty about the year of maintenance and the frequency (denoted as pavement M-E reliability) are all significant sources of variation, the latter the result of higher expected rehabilitation costs. When the major contributions to variance are estimated during calculation of the LCC difference, the uncertainty in material unit price across the scenarios is the most important factor driving variation in the cost difference of the alternatives. Other parameters that have been correlated, such as pavement M-E reliability, have a smaller impact.

Although the previous analysis treated discount rate as a deterministic parameter, a sensitivity analysis was conducted with the discount rate varying between 1% and 7%. As Table 6 shows, the relative mean ($\Delta\mu$) and 90th-percentile (α_{90}) difference shifts, on average, by 12% and 14%, respectively, in favor of the HMA, when the discount rate is moved from its low to its high extreme.

Implications of Scenario Context

The final question is related to the impact of the scenario context on LCCA outcomes, specifically the AP and DL. As Table 7 shows, the local-street case study has a design life that leads to the largest change in the mean difference between the two designs (11%), whereas it has a smaller impact on the state highway case study (4%). As for the Interstate highway case study, the shift between the mean and the 90th-percentile differences is quite small across the DLs and APs. However, very interestingly, the frequency for which the JPCP costs less than the HMA steadily increases from 83% in the 30-year AP case study to 100% in the 100-year AP scenario (for β values). This trend suggests that increasing AP may not necessarily shift the mean difference significantly but can lead one to be more (or potentially less) confident that a design will cost less than its alternative.

CONCLUSIONS AND FUTURE WORK

This research has implemented a probabilistic LCCA model that accounts for several forms of uncertainty in the LCCA of pavements, specifically the maintenance schedules, initial and future material and construction costs, and material quantity. The model has been applied to a range of case studies that vary in scope for AP, DL, rehabilitation schedule (pavement M-E versus DOT based), location, traffic volume, and discount rate.

Results from the scenario analysis have illuminated several conclusions. First, a life-cycle approach can alter the lower-cost pavement, and if it does not, can tremendously shift the difference between alternative designs. Second, the lower-cost pavement

TABLE 7 LCC Results for Each Scenario Obtained with Pavement M-E–Based Rehabilitation Schedule While Varying Design Life and Analysis Period

Traffic Level	DL/AP	$\Delta\mu$ (%)	α_{90} (%)	β (%)
Local street–highway, AADTT = 300	20/50	−32	−34	0
	30/50	−21	−22	0
State highway (rural), AADTT = 1,000	20/50	−13	−15	11
	30/50	−12	−14	17
	40/50	−9	−11	21
Interstate (urban), AADTT = 8,000	20/30	18	25	83
	20/50	23	30	89
	30/50	22	30	86
	30/75	21	27	90
	50/75	21	27	90
	50/100	20	29	100

NOTE: Black background = HMA has statistically significant lower impact; Gray background = JPCP has statistically significant lower impact.

alternative at different risk profiles will vary; this conclusion indicates that a probabilistic approach, in some instances, will alter the decision relative to a deterministic approach. Third, in relation to the drivers of variation, for the JPCP design the estimation of the initial bid price is the major source of uncertainty. This finding was particularly true in the case of Florida because of limited empirical data and suggests that further research evaluate this topic. For the HMA designs, although uncertainty about initial cost still plays an important role, future maintenance events are also a major source of uncertainty. Fourth, certain discretionary decisions that affect the context of the analysis alter the immediate decision more than others. For example, the decision to use pavement M-E design rather than a paving design manual from a state DOT to determine future maintenance events has tremendous implications. In contrast, other decisions, such as AP and DL, although important, affect results significantly less. However, although that effect may be less, it can be sufficiently large to differentiate the alternatives in some instances (as in the urban Interstate highway case study).

Several opportunities exist to extend this research. Most important, this analysis used a comparative-assessment approach for two "functionally equivalent" pavement designs (as defined by consultants hired to perform this work). Future work should move from the traditional comparative approach to an integration of design and cost that would allow the cost consequences of pavement design alterations to be directly modeled.

Furthermore, multiple opportunities that could be a part of future work are available to enhance the model developed in this analysis. For one, a major limitation of this analysis is the application of its methodology to a scenario assuming that future rehabilitation activities are fixed, irrespective of future market conditions. For example, a future rehabilitation activity would likely 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 in response to future events, a current drawback of the analysis here. In addition, the scope of the analysis here focuses only on the cost to finance a roadway. This model should be expanded to include the user costs associated with a pavement decision.

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