Material Diversification in Pavement Management: A Technique to Proactively Deal with an Uncertain Future

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ABSTRACT

Pavement management systems are important tools that planning agencies depend upon for the effective maintenance of roadway systems. Although uncertainty is an inherent trait of these systems, the current approaches generally exclude its consideration from the analysis. Consequently, decision-makers disregard opportunities to embed sources of flexibility that may be advantageous to deploy if future conditions unfold differently from expectations. One potential source of flexibility available to planners is the incorporation of a broader range of paving materials and designs as part of their pavement preservation strategy. More specifically, this thesis hypothesizes that the inclusion of concrete-based maintenance alternatives by an agency can act as an insurance policy that protects planners at moments of spiraling costs for other paving commodities.

To test the hypothesis set forth, this dissertation develops a stochastic simulation model that incorporates uncertainty as it relates to roadway deterioration and the future cost of maintenance actions. Its greedy heuristic algorithm addresses the inability of the current methods to (a) account for the heterogeneous (e.g., material, design, traffic) nature of pavements (b) scale for the type of real-world contexts that planners intend to use pavement management systems and/or (c) allow decisions to be made sequentially over time. The algorithm provides a high fidelity solution that generally falls within 2% of the global optimum for low-dimensional and deterministic problems. Subsequently, the model is applied to the Commonwealth of Virginia's interstate system, whose department of transportation (VDOT) traditionally only maintains their pavements with asphalt-based technologies, to minimize traffic-weighted roughness over a 50-year analysis period.

A comparison of the solution for Virginia demonstrates that the DOT could achieve its desired performance goals, on average, at a cost reduction of 10% by incorporating multiple paving materials as part of their pavement management strategy. Results from the simulations indicate that much of the expected benefit from the concrete-based designs stems from their ability to mitigate poor performance at times where asphalt prices are significantly higher than expected. These results suggest that the benefit from incorporating a larger range of paving materials and designs by a planning agency could be much higher than agencies realize using the current deterministic approach for pavement management.

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SYNTHESIS

Part I provides a general overview of the goals and objectives of this dissertation. Chapter 1 begins by presenting an abbreviated synthesis of the evolution of science and engineering over the last four centuries. This chapter posits that engineering in today's world requires sound technical design that must also meet ex-ante returns of relevant stakeholders. Planners and designers of complex engineering systems are frequently unable to fulfill the latter requirement, at least in part, because they design under the assumption of a known and deterministic future. As a result, this thesis postulates, similar to others, that designers must leave room for the doubt in order to (a) recognize the risk of the status-quo and (b) appreciate the value of embedding flexibility to proactively deal with the unknown.

Chapter 2 subsequently details the existing paradigms used by both practitioners and academics for pavement management systems, the focus of this thesis. Such systems are another example of analytical tools used by planners to guide multi-billion dollar investments that overlook uncertainty in the decision-making process. Consequently, this chapter hypothesizes that the exclusion of uncertainty causes the current methods to underestimate the value of incorporating a broader range of pavement materials and designs as part of a planning agency's pavement maintenance strategy. A high-level summary is presented at the end of this chapter of the modeling approach used to test the hypothesis of this dissertation.

CHAPTER 1: INTRODUCTION

> "The scientist has a lot of experience with ignorance and doubt and uncertainty, and this experience is of very great importance, I think. When a scientist doesn't know the answer to a problem, he is ignorant. When he has a hunch as to what the result is, he is uncertain. And when he is pretty damn sure of what the result is going to be, he is still in some doubt. We have found it of paramount importance that in order to progress we must recognize the ignorance and leave room for doubt. Scientific knowledge is a body of statements of varying degrees of certainty – some most unsure, some nearly sure, but none absolutely certain."
>
> -Richard Feynman (1918-1988)

The scientific revolution, and the 400 years of discovery that followed the early findings of Galileo in the late 16th century, facilitated the creation of the modern society for which we know today. Our avidity to explore the unknown allowed for the creation of new technologies, such as the automobile and computer, that have transformed our everyday lives. Over time, however, there has been a subtle yet tremendous shift in how society views and values scientific discovery. A prime example of this change can be found in *Science: The Endless Frontier*, a report authored by Vanevar Bush, director of the Office of Scientific Research and Development following World War II, to President Harry Truman. The report, which outlined the need for strong government support of science and engineering research for the sake of "the war against disease, our national security, and public welfare", illustrates the evolution of public perception towards science from a field of intellectual curiosity to one that enables economic efficiency and security in an increasingly complex world (Bush 1945). This profound change in how we view science and engineering has spurned the introduction of a new class of metrics and paradigms, such as cost-benefit analysis, to measure the value of new engineering technologies.

Consequently, there have been several technologically innovative projects over the last half century that can be viewed as failures not because of poor engineering but, rather, because they did not meet ex-ante returns. One well-documented example of this phenomenon is Motorola's Iridium satellite infrastructure that was launched in the late 1990's (de Weck and de Neufville 2004). From a pure engineering perspective, the project was a great success; it provided global satellite phone coverage with significant quality gains as compared to competitors. With that said, between the time of inception and project completion consumer preferences shifted towards more lightweight and cheaper telecommunication alternatives. Demand was much less than expected and, within just 9 months of launching, the founding company had already filed for bankruptcy (de Weck and de Neufville 2004). Motorola's Iridium technology is just one example of a recurring theme found across a range of applications, from oil drilling to copper mining, where solid *technical* engineering is not suffice to meet today's needs (Cardin, de Neufville et al. 2008; Lin, de Weck et al. 2013). Rather, engineers of today must also carefully consider (and meet) performance goals for relevant stakeholders in the design process.

One approach that researchers are just beginning to utilize to maximize expected performance of large-scale engineering systems is real options analysis (Hastings and McManus 2004; Eckert, de Weck et al. 2009). Real option analysis (ROA) applies the principles of financial options to engineering design by explicitly accounting for uncertainty and embedding flexibility in the design process (de Neufville and Scholtes 2011). The ROA approach for engineering design is a stark contrast to the conventional method that assumes a fixed, deterministic future (Dixit and Pindyck 1994). In some ways, part of our hesitancy to adopt ROA in engineering design is tied to our natural tendency as humans to search for *the* optimal solution to the problem at hand. However, ignoring the existence of uncertainty leads us to be both overconfident in our solution and constrains our decision space; for the more we recognize the doubt, the more cognizant we are about the possibility of underperformance and the more appreciative we are of the value to adapt. As an example, if Motorola explicitly accounted for demand uncertainty, a more judicious strategy would have been to deploy satellites in stages so that (a) losses could be mitigated if demand did not materialize while (b) the capability would still exist to capitalize should the future have been more prosperous (Lin, de Weck et al. 2013).

Pavement management systems, the focus of this thesis, are another example of decision-making tools that assume a deterministic future. The importance of such systems continues to grow as state departments of transportation (DOTs) and municipality planning organizations (MPOs) search for effective ways to maintain an aging infrastructure network that spans more than 8.5 million lane-miles and supports over 3 trillion vehicle-miles per year in the United States (Kuhn and Madanat 2005; FHWA 2013; Zhang, Keoleian et al. 2013). Unfortunately, similar to the cited examples, the deterministic approach of existing tools come with several drawbacks. First, current pavement management systems do not provide a mechanism to quantify risk, the consequence of that which is uncertain, in the decision-making process (Hastings and McManus 2004). Second, and perhaps more importantly, the deterministic approach causes pavement engineers to be *reactive*, rather than *proactive*, towards uncertainty as it evolves. Consequently, system managers disregard of opportunities to embed sources of flexibility in such systems that may be advantageous to deploy if future conditions unfold differently from expectations. Therefore, the goal of this dissertation is to demonstrate that the explicit consideration of uncertainty not only provides a mechanism to capture risk of pavement preservation strategies, but also allows planners to quantify the value of potential sources of flexibility to increase system-wide performance.

This dissertation presents one type of real option, the integration of a broader set of pavement materials and designs as part of a planning agency's pavement preservation strategy. Historically, DOTs across the nation have maintained and preserved their roadway networks by using asphalt-based technologies almost exclusively. Although effective, the cost of these actions are susceptible to large price swings from year to year due to the volatile nature of the underlying commodities (Swei, Gregory et al. 2016). Consequently, planners, who are responsible for prioritizing roadway projects subject to available resources, are exposed to the downside risk should asphalt prices be well above their typical levels. Alternatively, concrete-based pavement treatments, despite their extra cost, tend to exhibit less volatility and, generally, require less frequent maintenance activities. As a result, the integration of concrete-based maintenance alternatives by an agency could potentially act as an insurance policy (more formally referred to as a put option) that planners can exercise at moments of spiraling asphalt prices coupled with stable/suppressed concrete prices (Black and Scholes 1973; Dixit and Pindyck 1994).

To evaluate whether or not concrete-based maintenance and reconstruction alternatives are an effective put option for planning agencies, this thesis develops a stochastic simulation model that incorporates uncertainty as it relates to the deterioration of a roadway segment and the future cost of maintenance actions. The future prices of commodities relevant for pavements are probabilistically projected through a hybrid forecasting model that convolves conventional forecasts for underlying constituent prices and a long-term price equilibrium relationship between commodities. The existing pavement management approaches described in the literature, as will be discussed at great length in Chapter 2, tend to be (a) computationally costly and not scalable to realistic problem sizes and/or (b) simplify a pavement system by removing material, traffic, and other roadway-specific information. Because this research seeks to account for flexibility that arises from incorporating multiple paving materials within a pavement management program, a simple heuristic is needed that can account for heterogeneity amongst pavement segments and scale to real world contexts. As such, this research uses a greedy algorithm for project prioritization. The fidelity of the greedy algorithm is measured in Chapter 6 by comparing its solution for a series of small, deterministic case studies to that of a mixed-integer non-linear program (MINLP) solved with a branch and bound (B&B) algorithm that can find the global optimum. Of course, a benefit besides the reduced computational complexity of the former algorithm is its ability to make sequential decisions over time as information becomes available to the decision-maker.

The full model is subsequently applied to the state of Virginia's interstate system, whose DOT traditionally maintains their pavement network with asphalt-based technologies only. The objective of this case study is to minimize traffic-weighted roughness, a common metric of system performance, over a 50-year analysis period subject to a resource constraint. Projected performance of the system with/without concrete-based technologies is presented via the cumulative distribution function (CDF) of outcomes. Such an output allows one to compare the difference in system-level performance in terms of its expectation and Value at Risk (VaR). The latter metric, as will be discussed in Chapter 7, provides a mechanism to quantify the ability of concrete-based alternatives to act as an insurance policy for a planning agency. Additionally, Chapter 7 reports the reduction in annual budget needed by a planning agency to achieve the level of performance with a multiple pavement material system as it would need if it continued the status-quo maintenance policy. Such a metric provides a mechanism to quantify the added value from the proposed source of flexibility.

This dissertation is divided into four parts. The following chapter of Part I reviews the current state of pavement management systems implemented by both practitioners and academics. A focus is placed upon broadly understanding the key methodological and contextual differences of existing optimization-based approaches. Part II, subsequently, develops novel approaches to estimate the exogenous information and system model that underlies the decision-making process for pavement management systems. These approaches lead to representative estimates of uncertainty for each input that influences the decision-making process. Part III presents the heuristic algorithm implemented to determine the optimal allocation of resources in each year. The solution of the heuristic approach is compared to that of a globally optimal solver for small, deterministic case studies to comment on its relative fidelity and computational complexity. Part IV integrates the findings from Part II and Part III for the large-scale stochastic simulation model that tests the hypothesis set forth in this dissertation. Lastly, Part V synthesizes the key conclusions and contribution of this work and sets forth a series of recommendations for future research activities amongst the pavement management community.

CHAPTER 2: REVIEW OF LITERATURE

Motivation to integrate pavement management systems (PMS) in practice

Federal and state transportation agencies currently stand at a crossroad. Decreasing transportation funds, increasing maintenance needs, and a growing understanding of the relationship between design and the environment has led to a push for major reform within agencies to take a long-term perspective to transportation investments (Zhang, Keoleian et al. 2010; Santero, Masanet et al. 2011). Such concerns, which have haunted transportation agencies for decades, have historically only pushed a few departments of transportation (DOT) towards adopting asset management, the use of quantitatively based support tools in the planning and prioritization of infrastructure facilities (Markow 1995; Madanat, Park et al. 2006; Zhang, Keoleian et al. 2013). These exceptions have included the states of Washington, which first began using simplified heuristics for allocation decisions in the early 1970's, and Arizona, which introduced the first optimization-based approach a decade later (Golabi, Kulkarni et al. 1982; FHWA 2006). The importance to integrate such systems within state DOTs has magnified, however, following the enactment of the Moving Ahead for Progress in the 21st Century (MAP-21) Act that now compels all state agencies to develop performance and outcome-based programs for the management of the national highway system (U.S. Congress 2012). The goal of such legislation is to push DOTs to cost-effective allocation choices that provide a means to meet national transportation goals.

Since the earliest management systems of the late 1960's, which only processed and stored pavement condition information, pavement management systems as a whole have witnessed staggering developments (Markow 1995). In general, the overarching theme across these studies is to search for a near-optimal, computationally tractable, allocation policy across a pavement network (de Neufville and Mori 1970; Medury and Madanat 2014). Despite this commonality, the approaches, scopes, and objectives of some of the influential work in the field diverges in many directions. As such, this chapter aims to benchmark the status-quo of current academic research in pavement management to facilitate a better understanding of the gaps and contribution of this dissertation.

A brief overview of pavement management

As mentioned previously, pavement management is broadly defined as the planning, management, and preservation of a pavement segment (oftentimes denoted as facility and is used interchangeably in this thesis) or network using quantitative information (Mbwana 2001). For a pavement network, AASHTO asserts that a pavement management system should determine a set of network priorities by making use of budget requirements, pavement distress data, and structural adequacy information (AASHTO 1990). In many instances, pavement management systems follow a top-down approach in which pavement facilities are aggregated into groups with similar characteristics (Zimmerman 1995). The goal of such an approach is to determine the appropriate budget-level for a planning agency to meet its long-term performance objectives. Increasingly, however, researchers have recognized the limitations of the top-down methodology in determining which pavement facilities should receive treatments, leading to the emergence of facility-specific models (Sathaye and Madanat 2012; Yeo, Yoon et al. 2013; Medury and Madanat 2014). Such models, theoretically, have an additional advantage of being able to account for the heterogeneous nature of pavement segments; however, as will be discussed later in this chapter, studies to date have yet to exploit this property.

The following sections review over 30 years of academic research to facilitate an understanding of the contextual and methodological differences across existing studies. This review includes both the earlier top-down studies and the more predominant facility-specific models of today. In particular, this review focuses upon better understanding the role of uncertainty in pavement management given (a) the aims of this thesis and (b) that MAP-21 legislation now stipulates state DOTs to develop *risk-based* management plans for the effective maintenance of the national highway system (U.S. Congress 2012).

Contextualization of previous research: objectives, constraints, and dimensionality

Table 2-1 synthesizes the existing literatures as it relates to differences across four attributes, namely (a) objective functions (b) network constraints (c) number of facilities and (d) analysis period. Studies presented are, for the most part, multi-period decision models that allow for the consideration of network performance over multiple years. For that reason, many studies that have evaluated important issues, such as the coordination of maintenance activities across multiple facilities, have been removed from this chapter (Fwa, Cheu et al. 1998; Ma, Cheu et al. 2004).

Existing research generally focuses upon maximizing pavement performance and/or minimizing costs. Although Table 2-1 differentiates between the two metrics, in reality the two objectives overlap with one another. Specifically, previous cost minimization papers search to minimize both agency costs and those costs accrued by users, with the latter computed directly from pavement condition information (Guignier and Madanat 1999; Ouyang and Madanat 2004; Kuhn and Madanat 2005; Durango-Cohen and Sarutipand 2007; Kuhn 2010; Sathaye and Madanat 2011; Yeo, Yoon et al. 2013; Medury and Madanat 2014). Although the cost minimization problem is the preferred objective function amongst the academic literature for methodological reasons, the practical value of such an approach is limited given that the primary concern of DOTs is the structural condition of existing assets (Rangaraju, Amirkhanian et al. 2008). It is worth noting that because "performance" is an ill-defined term that carries numerous connotations, several studies have interpreted its meaning differently. Examples of performance oriented objective functions include travel time to users (Ng, Lin et al. 2009), average pavement service rating (PSR) (Wu and Flintsch 2009), traffic-weighted average PSR (Li, Haas et al. 1998), greenhouse gas emissions (Zhang, Keoleian et al. 2013), safety (Melachrinoudis and Kozanidis 2002), and portion of segments in poor and/or excellent condition (Abaza, Ashur et al. 2004).

Across existing studies, researchers generally seek to optimize their selected objective function subject to an annual financial resource constraint. Slight nuances to this formulation have been proposed that allow for a decision-maker to carry over funds across years (Guignier and Madanat 1999). Although less common, some previous research constrain the decision space by only allowing a portion of pavements to be in a 'poor' state in a given year. Beyond this, studies have incorporated serviceability and physical resource constraints, albeit sparingly. Ferreira, Antunes et al. (2002), for example, allows no more than one major rehabilitation for each segment over the analysis period in order to reduce disturbances for users. Fwa, Chan et al. (1996) incorporates constraints related to material, equipment, and labor availability in a given timeframe

Table 2-1. Comparison of objectives, constraints, analysis periods (∞ indicates infinite), network size, and number of actions in the existing literature.

Study	Objective(s)			Constraint(s)			Analysis Period (years)				Number of Segments	Number of Rehabs
	Cost	Performance	Other	Budget	Condition	Other	1-10	11-20	>20	∞		
Golabi, Kulkarni et al. (1982)	✓				✓		✓				*Pavement Segments are Aggregated in Top-Down Studies*	
Carnahan, Davis et al. (1987)	✓				✓			✓				
Chen, Hudson et al. (1996)	✓	✓		✓	✓			✓				
Liu and Wang (1996)		✓		✓	✓		✓					
Wang and Liu (1997)		✓		✓	✓		✓					
Fwa, Chan et al. (1998)	✓	✓	✓				✓					
Pilson, Hudson et al. (1999)		✓		✓					✓			
Abaza, Ashur et al. (2001)		✓		✓								
Smilowitz and Madanat (2000)	✓			✓	✓			✓		✓		
Abaza, Ashur et al. (2004)	✓	✓		✓			✓					
Kuhn and Madanat (2005)	✓			✓			✓					
Abaza (2007)		✓		✓								
Wang, Nguyen et al. (2007)	✓	✓		✓	✓		✓					
Wu and Flintsch (2009)	✓	✓		✓			✓					
Gao, Xie et al. (2012)	✓	✓		✓	✓							
Gao and Zhang (2013)	✓			✓	✓							
Chan, Fwa et al. (1994)	✓	✓		✓	✓			✓			45	3
Mbwana and Turnquist (1996)	✓			✓	✓		✓				60	4
Li, Huot et al. (1997)		✓		✓			✓				18	5
Ferreira, Antunes et al. (2002)		✓		✓		✓	✓				9-254	6
Wang, Zhang et al. (2003)	✓	✓		✓	✓		✓				10	4
Ouyang and Madanat (2004)	✓			✓			✓	✓	✓		3	Continuous
Chootinan, Chen et al. (2006)	✓	✓		✓			✓				53	4
Durango-Cohen and Sarutipand (2007)	✓			✓			✓				2-5	Continuous
Ouyang (2007)	✓			✓					✓		2	Continuous
Kuhn (2010)	✓			✓					✓		3-300	6
Sathaye and Madanat (2011)	✓			✓						✓	3	Continuous
Gao and Zhang (2012)	✓		✓				✓				5-1,000	1
Sathaye and Madanat (2012)	✓			✓						✓	1,000	Continuous
Gao and Zhang (2013)		✓		✓			✓				39,018	3
Yeo, Yoon et al. (2013)	✓			✓				✓			20-2,000	2
Zhang, Keoleian et al. (2013)	✓			✓					✓		29	8
Medury and Madanat (2013)	✓			✓				✓			11	3
Medury and Madanat (2014)	✓			✓				✓			10-1,000	2
Zhou, Li et al. (2014)		✓		✓			✓				672	1
Chen, Henning et al. (2015)	✓	✓		✓			✓				699	1
Lee and Madanat (2015)	✓			✓						✓	2	2

In terms of scope of analysis, previous studies have implemented their formulations in a range of contexts that vary in terms of network size, time-horizon, and number of available maintenance actions. Each of these factors have a latent implication on the computational complexity and, therefore, appropriateness of methodology. The top-down methodology is particularly attractive from a computation standpoint given that it reduces a large pavement network to a few aggregate groups with similar characteristics. The drawbacks of such an approach, however, is two-fold. First, further subroutines are required for determining how to allocate across segments within a grouping. Second, the models implicitly assume that facilities within a grouping are homogenous, which is incorrect and can lead to sub-optimal allocation policies (Durango-Cohen 2007; Durango-Cohen and Sarutipand 2007). These two flaws, coupled with increasing computation power of mathematical software programs, have largely contributed to authors developing facility-specific models. Although many of the earlier models were developed for small pavement networks, more recent research has evaluated alternative heuristics that can scale for networks composed of hundreds of pavement segments (Kuhn 2010; Sathaye and Madanat 2012; Yeo, Yoon et al. 2013; Medury and Madanat 2014).

The analysis period across the majority of studies typically falls into the category of short-term (1-10 years) and medium-term (11-20 years), with the exception of a few papers (Ouyang and Madanat 2004; Ouyang 2007; Kuhn 2010; Zhang, Keoleian et al. 2013). This is interesting given that project-level models, such as life-cycle cost analysis (LCCA), tend to assume a much longer time-horizon, illustrating the disconnect between the two approaches (Walls and Smith 1998). As for available actions, studies have only considered a small subset (≤ 6) of the possible actions at the disposal of a state agency. Furthermore, rehabilitation alternative types are fairly generic except for the cases of Chan, Fwa et al. (1994) and Zhang, Keoleian et al. (2013). Alternatively, some studies only consider the predominant type of rehabilitation action, overlays, utilized by DOTs, allowing thickness to be a continuous function (Ouyang and Madanat 2004; Sathaye and Madanat 2011; Sathaye and Madanat 2012). An important gap that emerges from this discussion is the inability and/or ignorance of the current research to account for the benefits of a larger set of maintenance and preservation alternatives. Of course, as will be discussed in detail in the next section, part of the decision to do so is tied to the inability of the existing methodologies to capture the benefit of having a broader range of options available in an uncertain future.

Contextualization of previous research: methodology, uncertainty, and deterioration

The following section compares and contrasts the existing work from a methodological standpoint. Table 2-2 summarizes the key trends and differences as they relate to (a) optimization methods (b) sources of variation and (c) pavement degradation models.

Concerning optimization methods, existing studies have employed linear, integer, and dynamic programming, as well as genetic algorithms to determine an allocation policy over a planning horizon. With that said, the majority of Markov top-down models exploit the structure of the problem such that linear programming can easily be implemented in a computationally efficient manner (Golabi, Kulkarni et al. 1982; Chen, Hudson et al. 1996; Liu and Wang 1996; Wang and Liu 1997; Smilowitz and Madanat 2000; Kuhn and Madanat 2005; Wu and Flintsch 2009). The implementation of integer linear programming for facility-level decisions, however, is computationally costly, making the utilization of genetic algorithms, dynamic programming, and heuristics attractive alternatives. Heuristic-based approaches include Ouyang and Madanat (2004), who implement a greedy algorithm to make locally best decisions throughout the analysis period, and Kuhn (2010), who uses adaptive (also referred to as approximate) dynamic programming (ADP).

In general, facility-specific models apply a two-stage bottom-up approach for allocation choices. In the first stage, an algorithmic approach is used to determine the best set of policies for each facility. Subsequently, a network-level model selects the facilities to receive treatment via a knapsack approach, where the best projects are selected until there are no remaining funds in a given year (Yeo, Yoon et al. 2013; Zhang, Keoleian et al. 2013). As eluded to earlier, researchers prefer the cost minimization problem because it easily lends itself to dynamic programming for the two-stage bottom-up technique. Specifically, the first stage searches for the optimal maintenance action, a, that minimizes the total cost for the n^{th} pavement segment. The total cost of an action is a function

Table 2-2. Optimization methods, sources of variation, and deterioration assumptions of existing models.

	Study	Optimization Method					Deterioration Model			Other Sources of Variation
		LP/ILP	NLP	GA	DP	Others/Notes	Homo Markov	Hetero Markov	Continuous	
Top-Down Studies	Golabi, Kulkarni et al. (1982)	✓					✓			
	Carnahan, Davis et al. (1987)				✓		✓			
	Chen, Hudson et al. (1996)	✓					✓			
	Liu and Wang (1996)	✓					✓			
	Wang and Liu (1997)	✓					-	-	-	
	Fwa, Chan et al. (1998)			✓			✓			
	Pilson, Hudson et al. (1999)			✓					✓	
	Abaza, Ashur et al. (2001)		✓				✓			
	Smilowitz and Madanat (2000)	✓								Condition
	Abaza, Ashur et al. (2004)		✓				✓			
	Kuhn and Madanat (2005)	✓				Robust LP	✓			
	Abaza (2007)		✓				✓			
	Wang, Nguyen et al. (2007)			✓			✓			
	Wu and Flintsch (2009)	✓					✓			Budget
	Gao, Xie et al. (2012)		✓				✓			
	Gao and Zhang (2013)	✓					✓			
Facility-specific models	Chan, Fwa et al. (1994)			✓					✓	
	Mbwana and Turnquist (1996)	✓					✓			
	Li, Huot et al. (1997)	✓						✓		
	Ferreira, Antunes et al. (2002)	✓		✓			✓			
	Wang, Zhang et al. (2003)	✓					✓			
	Ouyang and Madanat (2004)	✓				Greedy Heuristic			✓	
	Chootinan, Chen et al. (2006)			✓					✓	Traffic
	Durango-Cohen and Sarutipand (2007)				✓				✓	
	Ouyang (2007)				✓				✓	
	Kuhn (2010)				✓	Approximate DP			✓*	Benefit
	Sathaye and Madanat (2011)		✓			Lagrangian dual			✓	
	Gao and Zhang (2012)	✓					-	-	-	
	Sathaye and Madanat (2012)		✓			Lagrangian dual			✓	
	Gao and Zhang (2013)	✓					✓			
	Yeo, Yoon et al. (2013)				✓		✓			
	Zhang, Keoleian et al. (2013)				✓				✓	
	Medury and Madanat (2013)					Approximate DP	✓			
	Medury and Madanat (2014)	✓					✓			
	Zhou, Li et al. (2014)	✓					-	-	-	
	Chen, Henning et al. (2015)	✓							✓	
	Lee and Madanat (2015)			✓	✓				✓	

of its immediate cost, C_t, and discounted cost-to-go, E[V_{t+1}], to the agency and user assuming in all future years the DOT continues to maintain the segment optimally. The optimal policy for each segment, V_t, is implicitly a function of the current state of the pavement segment, S_t. Based upon the above description, a simple dynamic program can be scripted that solves recursively for the optimal policy for each pavement segment per:

$$V_t(S_t) = \min_{a \in A} C_t(a_t) + \mathrm{E}\left[V_{t+1}(S_{t+1}(S_t, a_t))\right]$$

The framing of the problem in a cost-minimization (to the agency and user) framework leads to a non-trivial optimal maintenance policy despite the exclusion of the budget constraint at the facility-level. For example, when a segment is in poor condition, it is likely that it is worthwhile for the agency to apply a maintenance action, as its cost is less than the cost that the users of the facility are accruing at that moment in time. Conversely, if a facility is already in excellent condition, it is of little benefit for the agency to rehabilitate the segment, as the cost of any action is higher than current user costs. Subsequently, the optimal policy for the facility, in spite of the exclusion of a budget constraint, will involve maintenance actions in only some years across the planning horizon. However, if one were to implement a performance-based optimization approach using the same paradigm, the optimal policy will be to apply a maintenance action in all years across all segments, unrealistic in a resource-constrained world. As a result, the cost-minimization paradigm is the preferred approach among the recent academic literature, while few algorithmic techniques exist for the facility- specific performance maximization problem. Of course, from a practitioner standpoint, the user cost framework is of little interest given that the structural condition of the existing pavements is the overwhelming priority of planning agencies (Rangaraju, Amirkhanian et al. 2008). Clearly, heuristics are needed that can help planning agencies implement a bottom-up framework with performance as the objective function.

A secondary drawback of the current bottom-up approach (particularly in the dynamic programming framework) is that it ignores that a facility will likely be unable to follow its optimal policy due to future budgetary constraints on the network. Medury and Madanat (2014) implemented a methodology to overcome this issue by integrating the facility-specific dynamic programming approach with the typical top-down formulation. The authors of this study developed a mixed-integer linear program where decisions for the *facilities* in the current year have an impact on the *portion* of pavements in a given condition in future years. More simply put, one makes facility-level decisions today but the future is treated using the Markov top-down approach. The issue remains, however, that similar to traditional top-down approaches, the model assumes that segments are homogenous going forward.

Amongst both top-down and bottom-up studies, the literature generally consider uncertainty only as it relates to pavement deterioration. For these studies, Markov chains are used, where the probabilistic deterioration in the next period is only a function of the current state (e.g., pavement condition) of a segment. Uncertainty in pavement deteriorates is, therefore, purely aleatory, as deterioration is random and not due to any causal factors. Li, Huot et al. (1997) and Li, Haas et al. (1998) are the only two Markov decision process studies that attempt to address this issue by creating transition probability matrices that are a function of the structural design of the pavement and external factors such as traffic and climate. Madanat, Park et al. (2006) developed age-dependent transition probabilities, although they only implement their methodology in a project-level model.

On the other hand, studies that take into account the heterogeneous nature of pavements utilize deterministic, continuous functions that describe the process as a function of structural and environmental factors (Chan, Fwa et al. 1994; Pilson, Hudson et al. 1999; Chootinan, Chen et al. 2006). As noted by Durango-Cohen and Sarutipand (2007), a balance between the two extremes should be found in network-level research by using the insights from the pavement deterioration community (Aguiar-Moya, Prozzi et al. 2011; Khattaka, Landrya et al. 2013; Hong and Prozzi 2015).

Beyond pavement deterioration, however, few studies have accounted for other sources of uncertainty in the decision-making process. Smilowitz and Madanat (2000) extend the latent Markov decision process (LMDP) methodology developed by Madanat and Ben-Akiva (1994) for the integration of uncertainty in the measurement of pavement condition. Kuhn (2010) considers uncertainty in the benefit of a given treatment. Wu and Flintsch (2009) transform the stochastic uncertainty in future budget levels into a deterministic constraint, while Chootinan, Chen et al. (2006) utilize the same approach but this time for uncertainty in future traffic volumes for pavement segments. The latter two studies, although being the first two papers that consider sources of uncertainty outside of the pavement engineer's control, do so using a static approach. Consequently, the optimization paradigm outputs a highly conservative, risk-averse policy that might perform much lower, in terms of expectation, compared to a policy that sequentially makes decisions as information becomes available over time.

Pavement management summary and limitations

Pavement management is a mature field that has evolved since the introduction of the earliest systems almost a half century ago. Whereas the previous sections have shed some light on the state-of-the-art for pavement management, the remainder of Part I summarizes the work discussed and sets forth the specific gap that this thesis aims to address.

Existing pavement management research has primarily focused upon developing optimization-based techniques for either performance maximization of roadway segments and/or minimizing total costs subject to, most commonly, a financial constraint; defining performance is difficult to do as its definition is multifarious. An issue with the cost minimization approach is that although it provides an attractive mathematical framework for optimization, practitioners are far more interested in roadway conditions than user costs (Rangaraju, Amirkhanian et al. 2008). Additionally, the cost-based paradigms require strong assumptions regarding the relationship between pavement condition and user costs, something that is quite difficult to estimate despite several empirical endeavors (Vadakpat, Stoffels et al. 2000).

Regardless, an important trend that emerged from the previous discussion is that the dimensionality of problems has increased gradually over time, starting with earlier top-down approaches that allocate resources to groups of segments and gradually moving towards facility-specific models. Drawbacks of the top-down approach include the need for further sub-processes and the treatment of heterogeneous segments as homogenous, and so facility-specific models are just beginning to emerge for roadway networks composed of many pavement segments. With that said, although recent paradigms are able to accommodate a larger number of segments, the assumption of homogeneity across facilities and the reality that only a few possible maintenance actions are captured in such frameworks are shortcomings of existing work.

Another important methodological deficiency of previous research is the general exclusion of uncertainty other than as it relates to pavement degradation. The decision to do so, in many ways, is contradictory to the project-level models that DOTs are beginning to use that do account for other sources of variation in the decision-making process (Swei, Gregory et al. 2016). Furthermore, the few studies that have considered other sources of variation have done so through a static, highly conservative approach that significantly reduces expected performance over time. Table 2-3 synthesizes the main gaps that have been discussed up until now.

Table 2-3. List of gaps within existing pavement management systems.

Issue	Gaps
Objective Functions	❖ Objective functions amongst academic work do not necessarily correspond to the concerns of decision-makers
Dimensionality	❖ Models generally assume a homogenous, rather than heterogeneous, system ❖ Number of rehabilitation activities are not representative of the available options available to a DOT ❖ Time-horizon is designed for the short-term rather than long-term
Sources of Uncertainty	❖ Uncertainty only incorporated as it relates to deterioration
Optimization Method	❖ Approaches for optimization of large networks are designed for cost-minimization and not performance maximization ❖ Frameworks that account for a broader range of sources of uncertainty are static rather than dynamic
Deterioration Model	❖ Deterioration models either assume all variation is aleatory and assume segments are homogenous or account for heterogeneity but assume deterioration is deterministic

Dissertation focus and overview

The previous discussion illustrates that there are many opportunities to augment current pavement management systems. Having said that, this dissertation centers around the inclusion of uncertainty in pavement management and its implication on the decision-making process. Studies to date have generally excluded exogenous sources of uncertainty, such as sudden changes in budgetary levels or the cost of maintenance actions over time, in determining an optimal allocation policy. The decision to do so stems from the prevailing view that planners and designers have little control over such random shocks over time. Contrary to popular perception, however, this thesis postulates that there are opportunities in which designers can embed flexibility in the maintenance of pavement management system to proactively deal with such instances and improve expected system performance. One possible way to do so is by incorporating a broader and more diverse group of pavement maintenance alternatives in the decision-making process.

On the surface, it may seem that the hypothesis set forth in this dissertation overlaps with the concept of diversification within modern portfolio theory. Namely, that holding a group of financial instruments not perfectly correlated with one another reduces one's exposure to downside risk by shifting the outcome probabilities (Markowitz 1952). While these benefits may in fact be real, this thesis does not explore this source of benefit explicitly. Rather, this dissertation views that that the incorporation of a broader range of material and design maintenance activities by a planning agency should be viewed more so as a real option. Decision-makers have the right, though not the obligation, to change maintenance strategies as information becomes available, similar to the underlying concept of a real option (Cardin, de Neufville et al. 2008; Eckert, de Weck et al. 2009; Cardin 2011). By having a larger range of materials and designs at their disposal, planning agencies are better able to adapt to the trajectory of their network should drastic shocks occur to the status-quo. There are numerous examples across the academic literature, from the positioning of military equipment to the management of electric power grids, where the ability to alter decisions over time as information becomes available can enhance expected performance (Powell 2007).

Of course, the incorporation of flexibility via real options requires an overhaul of the current method used in pavement management systems. Rather than following a static approach, as was the case in Wu and Flintsch (2009), ROA builds upon the principals of stochastic control theory where decisions are changed as real-time information becomes available to the system manager. Most frequently, researchers develop stochastic simulation models to quantify the value of flexibility (de Neufville and Scholtes 2011). It is important to note that such stochastic simulation models are not only restricted to engineering systems; in fact, the same frameworks have been applied to traditional financial options (Longstaff and Schwartz 2001). Figure 2-1 presents a schematic of the real options approach through a typical simulation model.

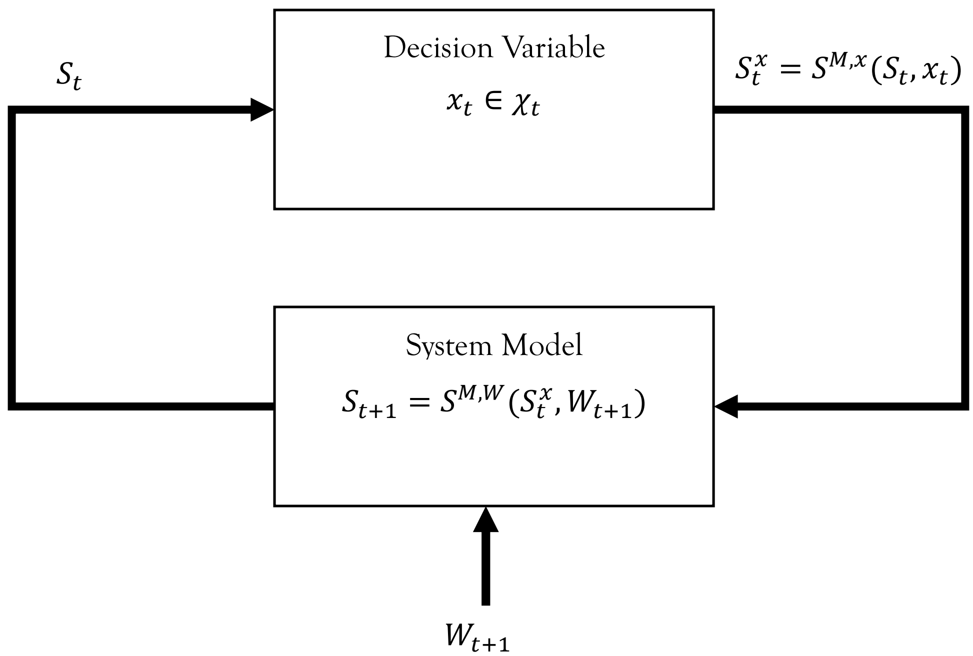


Figure 2-1. Schematic of sequential decision-making under uncertainty

As in stochastic control theory, there are six important components for the modeling framework:

- The ***state variable***, S_t, captures all information about the current state of our system
- The ***decision variable***, x_t, is the set of actions that the decision-makers applies to manage their system, which is a subset of the total available actions (χ_t). The decisions selected are based upon the underlying ***objective function*** of the model and subject to a ***set of constraints***.
- The ***exogenous information***, W_{t+1}, is that which becomes available between the time of the decision and the following year
- Lastly, the ***system model***, $S^{M,W}(S_t^x, W_{t+1})$, maps how the system evolves between time periods. This is, inherently, not only a function of the system state, but also the decision variable and exogenous information.

From the above schematic, it is paramount that the stochastic simulation model is composed of (a) a "sound" system model (b) reasonable estimates of the exogenous information and (b) a near-optimal allocation policy. The following two sections address these two core elements. Part II presents the methodology and parametric estimates for the former two elements that enter the stochastic model, while Part III details the allocation policy and tests its overall fidelity. Part IV utilizes both of these components in the complete stochastic simulation model to evaluate the ability of incorporating a larger range of materials and designs to improve performance across a pavement network. As mentioned earlier, this thesis postulates that the inclusion of concrete-based alternatives within a pavement management program can act as a put option. As a result, one would expect that the benefit of incorporating concrete-based designs arises from its ability to mitigate poor performance in the case of an unfavorable future.

II. SYSTEM MODEL AND EXOGENOUS INFORMATION

SYNTHESIS

The purpose of Part II is to develop novel approaches to estimate exogenous information that underlies the decision-making process for pavement management systems as well as an appropriate system model. Chapter 3 postulates a new pavement deterioration model for pavement management systems. Current deterioration models for network analyses use either homogenous Markov chains that do not capture the differences across pavement segments or continuous deterministic functions that do not reflect the uncertainty in the pavement degradation process. Furthermore, the more sophisticated deterioration models integrated into project-level tools are computationally expensive for network-level models, require data not available in planning agency databases, and incorrectly specify the pavement degradation process by assuming that stochastic shocks are transitory. As such, a simple, correctly specified probabilistic pavement deterioration model is proposed that accounts for the heterogeneity across roadway segments with factors that are available in planning agency databases. Chapter 4 subsequently presents a parametric approach to estimate the cost of alternative maintenance actions available to a planning agency. Results from this chapter demonstrate that the proposed approach frequently leads to consistent parametric estimates that address the structure bias and heteroscedasticity that plague current cost-estimation procedures. Lastly, Chapter 5 presents a novel approach to forecast the probabilistic cost of future maintenance actions. The chapter focuses on forecasting future paving material prices given that they are the dominant cost driver of pavement maintenance actions. A hybrid forecasting approach is introduced that combines traditional forecasts for underlying constituent prices and a long-run price equilibrium between those constituents and pavement materials.

CHAPTER 3: PAVEMENT DETERIORATION

Introduction to deterioration models

Pavement management systems, which are used by planners to determine an allocation policy across a network of pavement facilities (e.g., segments), require computationally resource-efficient pavement deterioration models that also accurately represent the degradation process (Durango and Madanat 2002). Interestingly, the current deterioration models integrated into such systems take contradictory views towards the pavement degradation process and its evolution over time. In particular, there is discrepancy amongst researchers regarding the degree to which variation is aleatory or epistemic and, furthermore, whether sudden stochastic shifts are transitory or permanent. As a result, the purpose of this chapter is to shed some light on the proper approach to specify its progression over time, something of utmost importance to ensure the allocation policies embedded within pavement management systems are optimal.

A simple, parsimonious deterioration model is proposed that assumes the pavement degradation process follows a random walk with drift. The drift term, which affects the directionality of deterioration over time, is a function of a non-linear interaction between pavement age, design, and traffic volume. An empirical model is subsequently developed for pavement roughness, a common deterioration mechanism that planning agencies seek to minimize across a roadway network. Results from the analysis indicate that such a model may appropriately specify the pavement deterioration process, implying that some, but not all, of the variability is epistemic and, furthermore, stochastic shifts have long-term effects on roadway roughness in the future.

Current modeling approaches

This section provides a brief overview of the existing Markov and regression-based pavement degradation models integrated within existing pavement management systems before comparing and contrasting their underlying assumptions.

Markov Chains

The most common modeling paradigm amongst current pavement management research is to assume that pavement allocation choices follow a Markov decision process (MDP) (Abaza, Ashur et al. 2004; Gao and Zhang 2013; Yeo, Yoon et al. 2013). The affinity of researchers to model the decision-making process as an MDP stems from the attractive mathematical properties that allow for an efficient solution to a complex problem via dynamic programming (Bellman 1957). Pavement management MDPs typically utilize a single transition probability matrix for all roadway segments, where the deterioration state of a pavement in year $t+1$, S_{t+1}, is only a function of its condition in year t, S_t. The condition of each pavement segment, which in reality follows a continuous function, is discretized into n states. For computational reasons, the number of discretized states is usually no more than 5-8 (Smilowitz and Madanat 2000). Given the condition, i, of a pavement segment in year t, the only states that a pavement can transition to with non-zero probability in year $t+1$ is its current condition, i, and $i+1$, where a lower condition index is associated with a better pavement. A more succinct representation of the above description is shown here:

$$\mathrm{P}(S_{t+1}|S_t) = \begin{bmatrix} \mathrm{P}_{11} & \mathrm{P}_{12} & 0 & 0 \\ 0 & \mathrm{P}_{i,i} & \mathrm{P}_{i,i+1} & \\ & & \ddots & \mathrm{P}_{n-1,n} \\ & 0 & & \mathrm{P}_{n,n} \end{bmatrix} \tag{3.1}$$

Despite being mathematically attractive, an important consequence of modeling the pavement degradation process with a homogenous Markov transition probability matrix is that such an approach does not capture the heterogeneity across pavement facilities (Durango-Cohen and Sarutipand 2007). In other words, all of the variation in pavement deterioration across roadway segments is assumed aleatory even though several explanatory factors related to the design of a facility as well as environmental conditions (e.g., traffic, climate) affect its evolution over time (Aguiar-Moya, Prozzi et al. 2011). Furthermore, the assumption of homogenous pavement deterioration across roadway segments influences the framing of the network-level problem, as design-specific considerations cannot be captured by the decision-variables within the model. The latter point is potentially of great significance given that the optimal policy to maintain a pavement segment is closely tied to context-specific information (Chan, Fwa et al. 1994). Consequently, although the assumption of homogeneity further simplifies the network-level problem, a sufficient amount of pavement-specific information is removed from the analysis such that the model is susceptible to selecting a sub-optimal maintenance policy (Embacher and Snyder 2001). As a result, a smaller body of network-level research integrates continuous, regression-based deterioration models to account for heterogeneity across pavement segments (Chan, Fwa et al. 1994; Ouyang and Madanat 2004; Chootinan, Chen et al. 2006).

Regression-based models

The majority of regression-based models are of the general form:

$$D_{t_f} = D_{t_0} + f(X_1, X_2, \dots, X_n) \tag{3.2}$$

where the distress, *D*, of a pavement segment at any future time period, t_f, is a function of its distress level in the present, t_0, and n explanatory variables, X_n. Covariates incorporated in such studies are usually limited to pavement age, material, and thickness as well as roadway traffic, which are all viewed as the most influential factors in the pavement degradation process (Chan, Fwa et al. 1994; Ouyang and Madanat 2004; Chootinan, Chen et al. 2006). In many ways, these distress models are simplified versions of some of the more advanced analytical models that have been developed at the project-level (Prozzi and Madanat 2004; Aguiar-Moya, Prozzi et al. 2011; Hong and Prozzi 2015). The most sophisticated of such models is the recently introduced pavement mechanistic empirical design (Pavement-ME), which makes use of data collected by the Federal Highway Administration (FHWA) as part of their long-term pavement performance (LTPP) program (Wang, Zhang et al. 2011). Such deterioration models, despite their computational cost, have been introduced in a modified form in FHWA's Pavement Health Track (PHT) to provide an estimate of the remaining service life (e.g., expected time to failure if no future maintenance events were to occur) of all pavement segments across a roadway network (FHWA 2013).

The discrepancies between the Markov-based and regression-based models

The Markov-based and regression-based deterioration models take, as is quite evident, divergent stances towards modeling the pavement degradation process. MDPs assume that no explanatory variables can account for variation in the pavement degradation process and, perhaps more importantly, that stochastic changes in the system state have a permanent effect on future outcomes. Put another way, a sudden change in the state of a pavement in an MDP affects pavement condition, if untreated, in all future years. Regression-based models, on the other hand, assume that variation is either partly epistemic, as is the case at the project-level, or completely epistemic at the network-level. The latter point is evident in Equation 3.2, where no error term is present within the model specification. Furthermore, even when uncertainty is incorporated at the project-level, the existing deterioration models are specified such that stochastic shocks are assumed to dissipate over time (Lee, Mohseni et al. 1993; Aguiar-Moya, Prozzi et al. 2011; Mandapaka, Basheer et al. 2012).

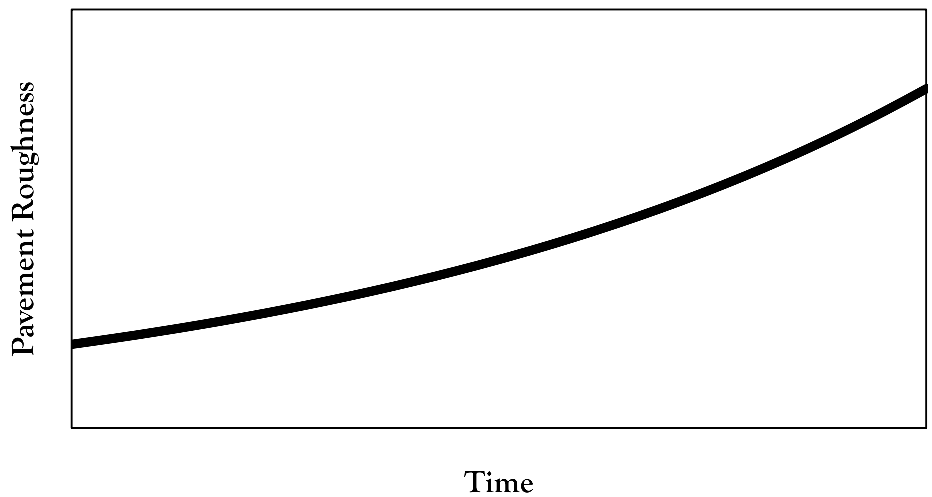


Figure 3-1. Typically assumed evolution of pavement roughness over the life of a segment (Ouyang and Madanat 2006).

To make this point clear, suppose that the deterioration of a pavement follows Figure 3-1, where the absolute rate of deterioration increases over time (Ouyang and Madanat 2006). For the purpose of simplification, suppose that pavement degradation, D_t, increases at some compound rate, r. Let it be also be assumed that innovations (i.e., shocks) in the time-series, ε_t, are structurally unbiased such that there is no need to model them as an autoregressive moving average (ARMA) process. Two alternative specifications of pavement deterioration could therefore be:

$$\text{Specification 1: } D_t = D_0 e^{rt} \varepsilon_t \tag{3.3a}$$

$$\text{Specification 2: } D_t = D_{t-1} e^{r} \varepsilon_t \tag{3.3b}$$

Although the two specifications may seem equivalent, they in fact make two completely different assumptions about the pavement degradation process. Taking the logarithm of the two proposed specifications in Equation 3.3, one finds that in Specification 1 stochastic shocks are assumed to be *transitory*, while in Specification 2 innovations have a *permanent* effect on future outcomes.

$$\text{Specification 1: } \ln(D_t) = \ln(D_0) + rt + \ln(\varepsilon_t) \tag{3.4a}$$

$$\text{Specification 2: } \ln(D_t) = \ln(D_0) + rt + \textstyle\sum_{i=1}^{t} \ln(\varepsilon_t) \tag{3.4b}$$

Specification 1 can be referred to as a trend-stationary process, where if the time-series is detrended, the residuals form their own stationary process (e.g., constant statistical properties). The assumption that pavement deterioration is a trend-stationary process underlies the previously cited regression-based models at the project and network-level. Such an assumption supposes that sudden shocks in the deterioration of a pavement dissipate by the next period. As a result, the variance of pavement degradation over time is expected to remain constant in terms of its levels. Conversely, Specification 2 assumes that the sudden propagation of rutting or cracking along a roadway segment does not suddenly vanish. Rather, these sudden shocks influence the deterioration level of a pavement in all future years. Such a proposition is closely aligned with the Markovian assumption that underlies the prevalent network-level models. Because the variance increases over time, making the process non-stationary, Specification 2 can be reformulated into a stationary process by estimating it in terms of its difference (hence, Specification 2 is coined a difference-stationary process):

$$\text{Reformulated Specification 2: } \frac{D_t}{D_{t-1}} = e^r \varepsilon_t \tag{3.5a}$$

$$\text{Reformulated Specification 2: } \Delta\ln(D_t) = r + \ln(\varepsilon_t) \tag{3.5b}$$

Gap Analysis and Chapter Objectives

The previous discussion illustrates the ambiguity regarding the proper specification for pavement deterioration amongst the current literature. Typical regression-based models assume that sudden changes in deterioration are transitory over time. MDPs, on the other hand, assume that all variation across segments is aleatory and, furthermore, that stochastic shocks have a permanent effect on all future periods. Furthermore, the decision on how to specify the pavement degradation process not only has far-reaching implications on allocation support tools at the network-level, but also the project-level. In particular, given that planners traditionally construct new roadway segments so that the probability of failure is less than a critical value over a prescribed design life, it is imperative that pavement engineers are provided accurate estimates of the evolution of degradation and its uncertainty (Mandapaka, Basheer et al. 2012); the specification of pavement degradation implicitly influences that estimate.

As a result, this chapter evaluates the appropriate specification of the pavement deterioration process through the development and testing of a parsimonious degradation model. The analysis augments previous empirical findings that, although not explicitly stated, provide some elementary insight as to the correct model specification for pavement deterioration. These studies include Chu and Durango-Cohen (2008) and Ahmeda, Abu-Lebdeha et al. (2006), who assume that pavement deterioration follows a first-order autoregressive process with a set of explanatory covariates. From the previously mentioned studies, the estimation of the autoregressive component offers preliminary evidence regarding the appropriate specification of pavement degradation.

To illustrate this point, let it be assumed that the exogenous components of the models described can be embedded within r that, as defined previously, affects the directionality of the stochastic process over time. The models developed by Chu and Durango-Cohen (2008) and Ahmeda, Abu-Lebdeha et al. (2006) can subsequently be represented as:

$$D_t = r + \rho_1 D_{t-1} + \varepsilon_t \tag{3.6a}$$

$$(1 - \rho_1 L^1) D_t = r + \varepsilon_t \tag{3.6b}$$

where ρ_1 is the coefficient estimate for the one lag deterioration value. Equation 3.6b is the same as Equation 3.6a but in lag polynomial notation, where L^i is the i^{th} lag operator. The characterization equation and its roots, which can be used to determine whether the stochastic process is stationary, is then simply:

$$1 - \rho_1 z^1 = 0 \tag{3.7a}$$

$$z^* = {}^1/_{\rho_1} \tag{3.7b}$$

where z is the variable of the characteristic equation and z^* is the single characteristic root for the stochastic process. In order for a stochastic process to be dynamically stable (i.e., stationary), the characteristic root must lie outside of the unit-root circle, meaning that $|\rho_1| < 1$. Interestingly, first-order autoregressive coefficient estimates for Chu and Durango-Cohen (2008) are 0.98 and 0.995

for two alternative estimations while Ahmeda, Abu-Lebdeha et al. (2006) estimate coefficients that range from 1.06 to 1.37 depending upon the paving material, suggesting that the prevalent trend-stationary specification of regression-based models may be incorrect. The goal of this chapter, therefore, is to develop of a novel estimation procedure that can confirm the appropriate specification of pavement degradation for any mechanism of interest to a pavement engineer or planner.

Methodology

This section describes the data collected as part of this study, the proposed specification of pavement roughness, and the technique used to evaluate its appropriateness.

Description of Data

This chapter utilizes historical pavement distress, design, and environmental data collected as part of FHWA's LTPP project (FHWA 2016). Because pavement management systems make decisions annually over a defined time-horizon and, furthermore, the pavement degradation process is potentially autoregressive, only consecutive annual measurements (plus or minus a month) are preserved from the original dataset. This filtering procedure reduces the sample size available for statistical analysis such that only two lagged periods are considered. A benefit of evaluating evenly-spaced pavement distress data over time is that there are no concerns regarding the implication of seasonality on the degradation process (Prozzi and Madanat 2004). Furthermore, the authors remove sample outliers that arise due to measurement error.

Although the deterioration of a pavement facility encompasses multiple mechanisms, existing network-level research typically utilizes either a weighted composite index or a single mechanism to characterize the overall condition and/or ride quality of a roadway segment (Chen, Hudson et al. 1996; Liu and Wang 1996; Zhang, Keoleian et al. 2013). Research has demonstrated that pavement roughness, which is also strongly correlated with other distress mechanisms, provides a reasonable metric to estimate the ride quality and general condition of a roadway (Garg, Horowitz et al. 1988). As a result, this study only focuses on developing pavement degradation models as it relates to roughness, measured in terms of the international roughness index (IRI), of LTPP sections.

Model Specification

The development of a pavement degradation model that fits within existing network-level pavement management systems requires the omission of several factors that influence the deterioration process. The decision to eliminate such factors is not only for computational resource considerations, but also because many explanatory variables that underlie deterioration models such as Pavement-ME are not stored within existing pavement management databases (Lea and Harvey 2004). Therefore, this research implements a pavement roughness model that is only a function of the age, average annual daily truck traffic (AADTT), and structural number (SN)/thickness of a pavement. Previous findings suggest that these factors are some of, if not the most, influential factors in the pavement degradation process (Lee, Mohseni et al. 1993). The structural form of the model proposed overlaps conceptually with that of Lee, Mohseni et al. (1993) and is as follows:

$$\Delta D_{t,i} = \alpha Age_{t-1,i} AADTT_{t-1,i}^{\beta_1} SN_{t-1,i}^{\beta_2} + \varepsilon_{t,i} \tag{3.8}$$

Equation 3.8 is specified under the null hypothesis that pavement degradation follows a random walk with drift. ΔD_t is the first difference of pavement degradation at time t, ε_t are the innovations for each i^{th} sample, and α, β_1, β_2, β_3 are parametric estimates that capture the relationship between changes in pavement degradation and the non-linear interaction between pavement age, AADTT, and SN/thickness in the previous time period. Note that the model makes the assumption that the drift term increases linearly as the pavement ages, which will lead to the traditional degradation curve shown in Figure 3-1. Three separate models are estimated for hot mix asphalt (HMA), jointed plain concrete (JPCP), and composite pavements. Pavement deterioration is estimated in terms of its absolute rather than logarithmic differences (and hence, pavement age is incorporated as a covariate for the regression model) to allow the model to capture the cumulative impact of environmental conditions following a maintenance action. In other words, if there was no age term in the deterioration model, a network allocation tool would assume that maintenance actions reset a pavement to its initial condition in terms of both levels and deterioration rate. In reality, a maintenance action shifts the immediate state of a pavement but structural damage from previous years will influence the rate of degradation moving forward.

Testing of Model Specification

The null hypothesis in this research is that pavement deterioration is a difference-stationary process, contrary to the typical assumption of regression-based models. A novel method is proposed in this study that pavement engineers and researchers can begin to utilize to determine the appropriate structural form for pavement deterioration models. The method set forth extends the concept of variance ratio tests that the finance and economics community utilize to test for unit-roots and the persistence of shocks in a stochastic process (Lo and MacKinlay 1988).

Suppose that pavement degradation over time were to follow the random walk with drift model discussed previously. The model assumes that the random error of the process is Gaussian distributed with a constant variance, σ^2, over time (e.g., homoscedastic):

$$\Delta D_t = \alpha Age_{t-1} AADTT_{t-1}^{\beta_1} SN_{t-1}^{\beta_2} + \varepsilon_t \sim N(0, \sigma^2) \tag{3.9}$$

The variance of the differenced process, $\sigma_{\Delta D_t}^2$, if unbiased can be estimated as:

$$\sigma_{\Delta D_t}^2 = \frac{1}{n-1} \sum_{i=1}^{n} (\Delta D_{t,i} - \left(Age_{t-1,i} AADTT_{t-1,i}^{\beta_1} SN_{t-1,i}^{\beta_2} \right))^2 \tag{3.10}$$

where n is the available sample size for parameter estimation. For a difference-stationary process, the change in levels over Q periods is simply the summation of the stochastic shifts made along each point in time:

$$\Delta D_t(Q) = \sum_{q=1}^{Q} \Delta D_{t-q+1} \tag{3.11}$$

Consequently, the variance over Q periods, $\sigma_{\Delta D_t(Q)}^2$, is directly related to the covariance matrix for the Q differences in Equation 3.11. As mentioned previously, the LTPP dataset has a limited amount of data that is spread out evenly and consecutively over time. As a result, one can only look at the change in deterioration spread out over at most two time periods consecutively (e.g., $Q = 2$). Based upon Equation 3.11, the variance of the change in levels over two periods, $\Delta D_t(Q=2)$, is:

$$\sigma_{\Delta D_t(Q=2)}^2 = \sigma_{\Delta D_t}^2 + \sigma_{\Delta D_{t-1}}^2 + 2COV(\Delta D_t, \Delta D_{t-1}) \tag{3.12}$$

where COV stands for the covariance between the differenced pavement degradation in year t and one lagged period, t-1. Should the variance be homoscedastic, then Equation 3.12 simplifies to:

$$\sigma^2_{\Delta D_t(Q=2)} = 2\sigma^2_{\Delta D_t}(1 + \rho_{\Delta D_t, \Delta D_{t-1}}) \tag{3.13}$$

where $\rho_{\Delta D_t, \Delta D_{t-1}}$ is the correlation coefficient between ΔD_t and ΔD_{t-1} with the drift term removed. The correlation coefficient from Equation 3.13 offers tremendous insight regarding the appropriate specification for pavement deterioration. For example, a correlation coefficient estimate close to zero would suggest that deterioration follows a random walk with drift, the null hypothesis of this research. Conversely, a correlation coefficient less than zero provides evidence that pavement degradation is actually trend-stationary over time, as stochastic shocks slowly dissipate as the process reverts to its long-run levels trend. To test the null hypothesis that pavement degradation follows a random walk with drift, a two-sided p-value can be approximated per Fisher's z-transformation. The accuracy of such an approximation, as well as the simplification made to Equation 3.13, requires that the variance is both Gaussian distributed and consistent for ΔD_t and ΔD_{t-1}. A simple F-test for the assumption of constant variance across ΔD_t and ΔD_{t-1} is conducted as a part of this research, and the residuals are inspected to ensure that they exhibit normality.

Data analysis and results

Model Specification

Table 3-1 presents parameter estimates from the original non-linear regression. Directionally, one would expect a positive exponent term for β_1 and a negative estimate for β_2. In other words, an increase in traffic should be associated with a larger drift term, while an increase in the structural capacity of a pavement should lead to a lower rate of deterioration. For the most part, parameter estimates correspond well to initial expectations except for β_1 for the JPCP models. Having said that, this parameter estimate has a t-statistic much less than two, making it difficult to accept the null hypothesis that the estimate is different from zero.

As a result, the JPCP model is reformulated as:

$$\Delta D_{t,i} = \alpha Age_{t-1,i} \frac{AADTT_{t-1,i}^{\beta_1} - 1}{\beta_1} SN_{t-1,i}^{\beta_2} + \varepsilon_{t,i} \tag{3.14a}$$

Table 3-1. Parameter estimates for the random walk with drift specification.

Estimate/Statistic	HMA	Composite	JPCP
α	$1.59 * 10^{-3}$	0.0100	4.97
β_1	0.293	0.525	-0.19
β_2	-0.86	-1.03	-1.10
n	336	241	530
R^2	0.12	0.20	0.06

Specified model: $\Delta D_{t,i} = \alpha Age_{t-1,i} AADTT_{t-1,i}^{\beta_1} SN_{t-1,i}^{\beta_2} + \varepsilon_{t,i}$

where β_2 is equal to its estimate in Table 3-1. Specifying the deterioration model as such has practical advantages given that:

$$\lim_{z \to 0} \frac{x^z - 1}{z} = \log x \tag{3.15}$$

The parameter estimate for β_1 for JPCP segments still approaches zero, and so that covariates is logarithmically transformed in the parameter estimation. Table 3-2 synthesizes the final model specification for each of the three types of pavements classified within the LTPP dataset. All parameter estimates are moved towards a more traditional type of data transformation, as although the majority of the t-statistics reject the null hypothesis of coefficient estimates equaling zero, standard errors are large enough that such a decision is not unreasonable. T-statistics for α, as is noted parenthetically in Table 3-2, are significant and positive for all materials, as expected. It is also important to mention that the sample variance, s^2, is quite high across all three estimates. This result, in part, reflects not only the unexplained variation in the pavement degradation process, but also the uncertainty underlying the measurement of the physical condition of a roadway at a given point in time. Specifically, in many instances the measured IRI of a pavement segment in year t is higher than that same facility in year $t+1$. This outcome reinforces the findings of Madanat (1993) that the measurement of the condition for an infrastructure facility is not error-free.

Table 3-2. Final specification of pavement IRI degradation models. T-statistics for drift terms are noted in parenthesis.

Estimate/Statistic	Asphalt	Composite	JPCP
A	.00429 (7.59)	$1.83*10^{-5}$ (7.56)	0.355 (6.63)
β_2	0.33	0.5	*LN(AADTT)*
β_3	-1	-1	-1
s^2	0.34	0.31	0.34

Specified model: $\Delta D_{t,i} = \alpha Age_{t-1,i} AADTT_{t-1,i}^{\beta_1} SN_{t-1,i}^{\beta_2} + \varepsilon_{t,i}$

Testing of Model Specification

Table 3-3 presents estimates of the correlation coefficient between ΔD_t and ΔD_{t-1} (with the drift terms removed) to test the null hypothesis (H_0) that pavement deterioration follows a random walk with drift (e.g., $\rho_{\Delta D_t, \Delta D_{t-1}} = 0$). Residuals of the regression model conform well to normality, while an F-test on the variances for ΔD_t and ΔD_{t-1} is unable to reject the null hypothesis of constant variance between the two samples. The tests used in this analysis are biased towards rejection of the null hypothesis, as a negative correlation coefficient might arise due to measurement errors between year *t* and *t+1*. The HMA sections do not exhibit any noticeable mean-reversion, with a test statistics that cannot reject the null hypothesis of a random walk with drift at the 1%, 5%, or 10% levels. On the other hand, the composite and JPCP sections exhibit weak mean-reversion, though not strong enough to reject the null hypothesis of a random walk with drift These results, as a result, provide reasonable evidence that pavement degradation should be parameterized as a difference-stationary stochastic process over time, contrary to the popular trend-stationary models that exist amongst the academic literature.

Table 3-3. Test statistics for the null hypothesis that pavement degradation follows a random walk with drift.

Estimate/Statistic	Asphalt	Composite	JPCP
$\rho_{\Delta D_t, \Delta D_{t-1}}$	.028	-0.094	-0.117
P-value H_0: $\rho_{\Delta D_t, \Delta D_{t-1}} = 0$	0.98	0.41	0.14
Sample size (n)	89	79	162

Conclusions

Pavement degradation models are an important component of pavement management systems, both at the network and project-level. Interestingly, the existing tools developed for planners make different and, in many ways, contrasting assumptions regarding the evolution of deterioration over time. In particular, there is ambiguity as to whether pavement deterioration tends to exhibit trend-stationary or difference-stationary characteristics over time. A ramification of specifying the pavement degradation process incorrectly is that it leads to incorrect estimates of future expected deterioration and associated unexplained variation.

This chapter develops a statistical approach to determine the appropriate specification of pavement degradation over time. The analysis focuses upon characterizing the long-run evolution of pavement roughness only for LTPP sections collected by FHWA. Results from the study indicate that roughness has historically followed a random walk with drift, implying that stochastic shocks have a permanent effect on future deterioration levels. This result suggests that the MDP approach that previous authors have utilized is reasonable except that it does not account for the heterogeneity across segments. In order to account for this heterogeneity, a series of regression models have been estimated where the drift terms are a function of a non-linear interaction between pavement age, thickness, and traffic volume. Outcomes of the analysis demonstrate that such an approach helps explain some, but not all, of the variation across pavement segments. Furthermore, the models require low computational resources and make use of data generally available in pavement management databases, both of which are important considerations to integrate deterioration models within network-level allocation tools.

Several opportunities exist to extend the findings of this chapter. Future research, for example, should evaluate whether the findings presented hold true for a larger range of distress mechanisms. Moreover, given the pervasive measurement error for LTPP sections, future work should integrate methods that can decompose uncertainty between condition assessment and actual deterioration. Lastly, future studies should quantify the repercussions of a misspecification of the pavement degradation process at a network-level.

CHAPTER 4: INITIAL-COST OF MAINTENANCE ACTIONS

Background of existing initial-cost estimation methods

The prevalence of inaccurate and oftentimes biased early-cost estimates is a well-documented phenomenon within the construction community (Eliasson and Fosgerau 2013). Flyvberg, Holm et al. (2002), perhaps the most widely cited paper on this topic, note that roadway projects cost 20% more on average than initial estimates. Consequently, Flyvberg, Holm et al. (2002) postulate that the bias towards cost overruns in transportation projects is a result of strategic misrepresentation by planners to make projects seem more attractive than they are in reality. An alternative hypothesis that could potentially explain the tendency towards cost overruns in construction, however, is the poor fidelity of the existing tools used by planners. As an example, Lowe, Emsley et al. (2006) developed a series of regression models that, as the authors noted, systematically underestimated construction costs for large-scale building projects. Furthermore, the aforementioned study by Flyvberg, Holm et al. (2002) indicated that the coefficient of variation (COV) of the difference between estimated and actual costs was greater than one. These papers are just a couple of examples that shed light on the fact that the existing tools and methods used by practitioners are both imprecise and inaccurate.

Table 4-1 presents a larger set of cost estimation research for buildings and bridges, the two most common forms of infrastructure that researchers have studied in-depth. Existing research uses both cross-sectional and panel data to develop parametric and non-parametric models to predict project-level costs. Predictor variables across the multi-variate studies listed include general site conditions, location, and the geometric layout of a structure. Parametric approaches make use of multiple linear regression combined with dimensionality reduction techniques such as stepwise (both forward and backward) regression, factor analysis, and principal component analysis to elicit the important parameters that influence construction costs.

Alternatively, neural networks are a popular non-parametric approach for cost estimation that learns through iteration the response of a system given a set of external inputs (Garza and Rouhana 1995;

Hegazy and Ayed 1998). Although researchers have demonstrated the accuracy of neural networks for cost estimation, such models have inherent drawbacks that parametric methods can address (Emsley, Lowe et al. 2002). In particular, the ability of the parametric approach to (a) be transparent (b) explicitly account for uncertainty and (c) integrate with analytical tools such as probabilistic LCCA provides practical and theoretical advantages over non-parametric methods such as neural networks. Of course, the main advantage of an approach like a neural network is its ability to account for non-intuitive and non-linear relationships between response and predictor variables. As a result, an important component for measuring the fidelity of regression models is to ensure that the estimates are unbiased and the residuals are homoscedastic, two basic assumptions for ordinary least squares (OLS) regression. Doing so guarantees that parametric estimates that would enter a model like LCCA properly reflect the data at hand and the construction activity it represents.

Table 4-1. Statistical methods to estimate construction costs for buildings and bridges.

Study	Approach	Performance Metrics
McCaffer, McCaffrey et al. (1984)	Linear regression (OLS and alternative approaches)	COV of ratio of predicted over actual
Emsley, Lowe et al. (2002)	Neural networks and linear regression	Coefficient of determination (R^2) and mean absolute percent error (MAPE)
Trost and Oberlender (2003)	Factor analysis and multiple linear regression (MLR)	Not applicable
Chan and Park (2005)	Principal component analysis and MLR	R^2, MAPE, tests for heteroscedasticity and serial correlation of the residuals
Lowe, Emsley et al. (2006)	Stepwise MLR	R^2, MAPE, qualitatively assess bias and heteroscedasticity of the residuals
Ji, Park et al. (2010)	Stepwise MLR	Adjusted R^2, MAPE
Kim and Hong (2012)	Case-based reasoning and MLR	MAPE and standard deviation of MAPE

Of the studies listed in Table 4-1, the majority of them measure model fidelity via conventional metrics such as the sample coefficient of determination (R^2) and the mean absolute percent error (MAPE) of the model (Trost and Oberlender 2003; Ji, Park et al. 2010; Kim and Hong 2012). Chan and Park (2005), one exception to this trend, test for the presence of heteroscedasticity and serial correlation in their regression models for building construction in Singapore. Based upon those tests, both the null hypotheses of uncorrelated residuals and homoscedasticity are rejected based upon Engle's test for autoregressive conditional heteroscedasticity (ARCH) and White's test for heteroscedasticity without interaction terms. Notably, however, these test results were not viewed as sufficient reasons to abandon the OLS model of Chan and Park (2005). Lowe, Emsley et al. (2006) qualitatively evaluate whether or not the residuals of a building cost regression model are homoscedastic or biased for untransformed and logarithmically transformed data. The authors mention that the models are structurally biased such that they "overestimate the cost of cheaper projects and underestimate the cost of more expensive projects." Furthermore, the residuals are not always homoscedastic over the covariates, potentially leading to mischaracterized parametric estimates of expected construction costs and uncertainty. As the authors note, this may be due to "poor representation" of nonlinear relationships between the dependent and independent variables (Lowe, Emsley et al. 2006).

A smaller body of literature has focused on early cost estimation methods for pavements. Since traditional cost estimation tools for roadways tend to follow a bottom-up approach, where the cost of each individual item is aggregated to estimate total costs, these papers have focused more so on cost as it relates to individual pay items rather than the entire cost of a roadway (Chua and Li 2000; Hiyassat 2001; Williams 2003; Carr 2005). Sanders, Maxwell et al. (1992) is the first major work to have evaluated potential methods to characterize the variation that underlies bid unit-price data. The authors developed a series of linear regression models for nine different bid items in the state of Alabama as a function of quantity. An increase in the size of a project tended to decrease the winning bid unit-price (e.g., economies of scale) for all nine bid prices. The authors measured the fidelity of the estimated regression models using the sample R^2. Shrestha, Pradhananga et al. (2014) augmented the preceding research by conducting a linear regression analysis of winning bid unit-price versus quantity for twelve different bid items in the state of Nevada, but this time considering alternative traditional data transformations to achieve linearity. The data transformation that led to the highest sample R^2 was selected for each bid item. As expected, all bid items evaluated showed a statistically significant and negative correlation between bid unit-price and quantity. Although the aforementioned transformations improved the overall fit of the models, the authors did not report information on how they impacted bias and/or homoscedasticity.

The development of accurate and unbiased early cost estimates is an important component of comparing alternative transportation and infrastructure investments. In its current form, however, the current models are susceptible to both systematic bias and heteroscedasticity, both of which lead to incorrect assumptions about expected construction cost and uncertainty. As a result, this chapter presents a new approach for initial-cost estimation that more frequently leads to unbiased estimates and homoscedasticity across the covariates. The approach merges an optimization solver for data transformations and a dimensionality reduction technique for variable selection amongst multiple covariates. The approach can also scale to high-dimensional problems with many input factors to explain a larger portion of the variation than the bivariate models of Sanders, Maxwell et al. (1992) and Shrestha, Pradhananga et al. (2014).

Methodological approach

This chapter considers three possible parametric approaches to model the unit-price of bid items used in roadway construction. The baseline approach follows that of Shrestha, Pradhananga et al. (2014), where bid unit-prices (P_i) are regressed against bid quantity ($X_{i,q}$) with an ordinary least squares (OLS) estimator. The data is transformed in one of three ways based upon the coefficient of determination (R^2). The second approach is similar to the baseline except that the analysis searches for an optimal data transformation (denoted as λ). The third and final approach incorporates the optimal data transformation solution while also including variation across districts within a state ($X_{i,d}$) and the number of bidders for a project ($X_{i,b}$). The decision to incorporate number of bidders is due to the results of Shrestha and Pradhananga (2010), which evaluated the deviation between bid cost and early cost estimates as a function of the number of bids for a project. The authors found a strong negative correlation between the two, meaning that for low bid projects, total costs were significantly higher than expected. This same finding has been corroborated in the buildings community by the research of Carr (2005). Furthermore, since pay items typically convolve material and non-material costs, such as transportation of materials from the plant to the site, costs are likely to differ within a given state. Although this dissertation only considers these explanatory factors, the methodology to follow can easily accommodate a larger range of factors. Table 4-2 synthesizes the three modeling approaches discussed.

An important contribution of this dissertation is the evaluation as to whether or not the three proposed approaches adequately meet the assumptions of unbiased and homoscedastic residuals that underlie OLS regression. As such, the goodness-of-fit of the models described is not just measured using the coefficient of determination, but also the Breusch-Pagan test for heteroscedasticity and an F-test on the residuals that evaluates the presence of bias. Additionally, the second approach discussed requires a method to select an optimal data transformation, while the third approach necessitates a variable selection/dimensionality reduction technique. For this research, least angle regression (LAR), which is related to the least absolute shrinkage and selection operator (LASSO) algorithm, is conducted for dimensionality reduction. A Box-Cox transformation based off of a maximum likelihood (ML) estimator is used to find the optimal data transformation.

Table 4-2. Summary table of the structural form for the three approaches to model variation in unit-price data. The structural form selected in Approach 1 is determined by the transformation that leads to the highest R^2.

Approach	Model Type	Functional Form
1	Log	$P_i = \beta_0 + \beta_q LN(X_{i,q}) + u_i$
	Reciprocal	$\frac{1}{P_i} = \beta_0 + \beta_q X_{i,q} + u_i$
	Power	$LN(P_i) = \beta_0 + \beta_q LN(X_{i,q}) + u_i$
2	Box-Cox transformation (λ)	$P_i^{(\lambda_1)} = \beta_0 + \beta_q X_{i,q}^{(\lambda_2)} + u_i$
3	Box-Cox transformation (λ), district variation (d) , and number of bidders (b)	$P_i^{(\lambda_1)} = \beta_0 + \beta_q X_{i,q}^{(\lambda_2)} + \sum_{l=1}^{L} \beta_{d_l} X_{i,d_l} + \beta_b X_{i,b} + u_i$

Notes:
P_i – Bid unit-price for i^{th} sample
$X_{i,q}$ – Bid quantity
X_{i,d_l} – Dummy variable for l^{th} district within a state
$X_{i,q}$ – Number of bidders for a project
λ_1, λ_2 – Optimal data transformations for bid unit-price and quantity

A test for heteroscedasticity

Perhaps the most simple (yet highly effective) strategy to test for heteroscedasticity is the Breusch-Pagan test, which evaluates the null hypothesis that the residuals of an OLS regression meet the assumption of homoscedasticity (Breusch and Pagan 1979). In a typical multiple linear regression of the form:

$$Y_i = \beta_0 + \beta_1 X_{i,1} + \cdots \beta_p X_{i,p} + u_i \tag{4.1}$$

where for each individual sample, i, the predictor variable, Y_i, is a function of p covariates, $X_{i,p}$, and their associated effects, β_p, one would expect that the variance of the residuals, u_i, is constant across all covariates. Therefore, an auxiliary regression of the squared residuals as a function of those same covariates (with effects now denoted as γ_p) can be run to test whether or not the residuals meet the underlying assumption of homoscedasticity:

$$\hat{u}_i^2 = \gamma_0 + \gamma_1 X_{i,1} + \cdots \gamma_p X_{i,p} + v_i \tag{4.2}$$

The null hypothesis that the parameter estimates for the covariates are equal to zero (e.g., homoscedasticity) can subsequently be tested by use of a Lagrangian multiplier (LM). Furthermore, a t-test on the covariates for the above auxiliary regression can provide insight as to which covariate should be transformed such that the assumption of homoscedasticity is met. Given that bid quantity, $X_{i,q}$, is the only covariate that is continuous across all three approaches, it is likely that if the null hypothesis of the Breusch-Pagan test is rejected, then bid quantity will have a high t-statistic for the above auxiliary regression. With that said, such t-statistics are very valuable should future research consider a larger range of factors.

The concept of the Breusch-Pagan test is extended in this chapter to test for bias in the residuals over bid quantity per:

$$\hat{u}_i = \delta_0 + \delta_1 X_{i,q} + \delta_2 X_{i,q}^2 + \varepsilon_i \tag{4.3}$$

Although bias in the residuals could take other forms, this specific type of bias is particularly pervasive in regression models. The F-statistic for this regression is computed to evaluate the null hypothesis that the residuals are non-biased (e.g., $\delta_1 = \delta_2 = 0$) as a function of bid quantity.

Data transformation and dimensionality reduction

Logarithmic and reciprocal models are examples of simple data transformation techniques frequently used by statisticians to transform predictor variables and covariates such that homoscedastic and unbiased estimates are met in regression. A more broad and flexible class of models exist that are known as Box-Cox transformations, which are of the following form (Box and Cox 1964):

$$z^{(\lambda)} = \frac{z^{\lambda} - 1}{\lambda} \tag{4.4}$$

$$Y_i^{(\lambda_1)} = \beta_0 + \beta_n X_{i,n}^{(\lambda_2)} \tag{4.5}$$

In Equation 4.5, λ_1 and λ_2 represent the data transformation of the dependent variable, Y, and n^{th} covariate, X, for each sample, i, per the transformation for z shown in Equation 4.4. Table 4-3 presents the values of λ that correspond with the more traditional transformations used in statistical and econometric analyses. Given that the residuals of OLS regression are assumed to be Gaussian distributed, a fairly simple ML estimator can be constructed to find the 'optimal' values of λ_1 and λ_2. The determination as to which covariate(s) need to be transformed can be inferred from the t-test in the previously mentioned auxiliary regression of the residuals.

Table 4-3. Estimates of λ from Box-Cox MLE and associated 'traditional' transformation.

λ Value	Corresponding Transformation
0.75 to 1.50	z^1
0.42 to 0.75	$z^{0.5}$
0.17 to 0.42	$z^{0.33}$
-0.17 to 0.17	$Ln\ (z)$
-0.42 to -0.17	$z^{-0.33}$
-0.75 to -0.42	$z^{-0.5}$
-0.75 to -1.50	z^{-1}

As for dimensionality reduction, LAR is a recently developed method that has grown in popularly since it can be used as an efficient solution to the LASSO algorithm and address some of the concerns with forward stepwise regression (Efron, Hastie et al. 2004). Similar to forward stepwise regression, LAR functions as any greedy algorithm where a locally optimal choice is made without looking ahead to future steps. Initially, all parameter estimates are set to zero while values for the covariates are normalized. Subsequently, the covariate most correlated with the residuals is selected, and the parameter estimate is moved from zero towards its least-square coefficient until a second variable has just as much correlation with the residuals as the first covariate. This process of moving covariates until another variable is just as correlated with the residuals continues until the active set of parameters to select from is exhausted. For each new covariate added to the model, Mallow's C_p (one best-fit measure) is estimated; the step that minimizes its value is treated as the cut-off point for the number of variables to select in model estimation. The benefit of the LAR approach compared to other greedy approaches (such as stepwise regression) is that it does not add a predictor fully to the model at once. Rather, it does so gradually, causing it to be more robust than other greedy approaches.

Results of case study analyses

This dissertation evaluates the fidelity of the initial-cost approach proposed through bid data for asphalt and concrete pay items collected by Oman Systems, Inc. for the states of Missouri, Colorado, Indiana, Louisiana, and Kentucky between late 2011 and early 2014 (Oman Systems Inc., 2016). The selection of bid data rather than actual cost information is due to the general availability of the former in public databases. Approach 3, the multi-variate instance, incorporates both district variation within a given state and the implication of number of bidders (one metric for competition in a project) on bid unit-prices. To address district variation, bid data is divided (through dummy variables as noted in Table 4-2) into regions according to the current districts established for each respective DOT. Table 4-4 summarizes the bid datasets and number of districts within each state for this analysis.

Table 4-4. Summary table of datasets for analysis (Oman Systems Inc., 2016).

State	Number of Districts	Bid Datasets
Missouri	7	Concrete Pavements HMA Mixture BP-1 HMA PG64-22
Indiana	6	PCCP HMA Type A Surface HMA Type B Surface HMA Type A Inter.
Colorado	5	Concrete Pavement HMA PG64-22
Louisiana	9	PCCP Pavement HMA Superpave Level 1
Kentucky	12	JPC Pavement HMA CL2 0.38D PG64-22 HMA CL3 0.38D PG64-22 HMA CL2 1.00D PG62-22

To evaluate the performance of the traditional method (Approach 1) for cost estimation, the Breusch-Pagan heteroscedasticity test and the modified F-test for biased residuals are estimated for the baseline model. For all 15 bid datasets, a power model (where the independent and dependent variables are logarithmically transformed) is the best fitting model of the three choices available per the sample coefficient of determination. Table 4-5 presents bid quantity coefficient estimates and t-statistics, Breusch-Pagan test results (both LM and t-statistic for bid quantity) and biased F-test values for the baseline model as well as optimal Box-Cox transformations per the ML estimator.

Table 4-5. Summary statistics for Approach 1 (baseline). Values denoted with a '*' reject the null hypothesis of homoscedastic (Breusch-Pagan LM test) or unbiased (residual F-test) residuals. Optimal Box-Cox transformations per an ML estimator are listed below.

State	Dataset	Coefficient Estimate		Breusch-Pagan Test LM	Biased residual F-statistic	Box-Cox Transformation	
		Estimate	t-statistic			Price λ^{opt}	Quantity λ^{opt}
Missouri	Concrete Pavements	-0.14	-17.0	25.6*	3.1*	-0.96	-.02
	HMA Mixture BP-1	-0.19	-24.2	172.1*	23.9*	-1.04	-0.04
	HMA PG64-22	-0.05	-7.0	35.8*	8.6*	-0.92	-0.47
Indiana	PCCP	-0.17	-9.1	15.2*	0.3	-0.38	-.07
	HMA Type A Surface	-0.17	-17.7	126.3*	10.2*	-0.43	-0.11
	HMA Type B Surface	-0.18	-18.3	230.5*	9.1*	-0.46	-0.09
	HMA Type A Inter.	-0.19	-18.3	42.3*	6.1*	-0.37	-0.06
Colorado	Concrete Pavement	-0.14	-14.1	16.1*	1.1	-0.58	0.19
	HMA PG64-22	-0.14	-9.6	8.2*	4.4*	-0.51	-0.17
Louisiana	PCCP Pavement	-0.13	-11.9	29.7*	0.7	-0.75	0.20
	HMA Superpave Level 1	-0.18	-40.2	19.2*	36.9*	-0.35	-0.09
Kentucky	JPC Pavement	-0.12	-12.0	17.1*	1.1	0.22	0.11
	HMA CL2 0.38D PG64-22	-0.14	-42.8	706.5*	261.0*	-0.39	-0.33
	HMA CL3 0.38D PG64-22	-0.12	-10.5	73.7*	49.6*	-0.46	-0.53
	HMA CL2 1.00D PG62-22	-0.13	-19.1	115.3*	19.0*	-0.72	-0.11

Note:
Approach 1 (Power Model): $LN(P_i) = \beta_0 + \beta_q LN(X_{i,q}) + u_i$

As can be noted, across all 15 bid items there is a strong correlation between bid unit-price and quantity. On the other hand, the null hypothesis of homoscedasticity is rejected for all datasets, while the null hypothesis of unbiased residuals is rejected in 11 instances. Furthermore, t-statistics for bid quantity in the auxiliary regression of the squared residuals are significant and negative except for one instance. This result suggests two important aspects regarding the datasets at hand. First, the variance of the residuals decreases across bid quantity and, therefore, the OLS estimation overestimates the variance for large-scale projects while underestimates it for smaller construction activities. Second, the residuals are structurally biased such that the regression models underestimate prices for large projects, similar to what Lowe, Emsley et al. (2006) noted. These findings suggest that both the bias and heteroscedasticity in the baseline approach could potentially lead to a poor characterization of expected unit-prices and variance for roadway bid items, something that the Box-Cox transformations as presented at the end of Table 4-5 may address.

Table 4-6 presents results of the dimensionality reduction analysis via the LAR algorithm. Both bid unit-price and quantity are transformed in this section by rounding the optimal Box-Cox transformations listed in Table 4-5 to their closest traditional transformation per Table 4-3. In addition to economies-of-scale, as noted in Table 4-2, district variation is important and significant, while the number of bidders for a given project is only significant at the 5% level for half of the datasets.

Table 4-6. Summary of model for Approach 3 (Box-Cox transformations with district variation and number of bidders covariates). The positive and negative signs indicate the existence and direction of a statistically significant relationship.

State	Dataset	Price λ	Quantity λ	Quantity Estimate	Bids Estimate	Number of remaining dummy districts
Missouri	Concrete Pavements	-1	LN	-	-	4
	HMA Mixture BP-1	-1	LN	-	+	2
	HMA PG64-22	-1	-0.5	-	-	2
Indiana	PCCP	-0.33	LN	-	-	3
	HMA Type A Surface	-0.5	LN	-		5
	HMA Type B Surface	-0.5	LN	-		1
	HMA Type A Inter.	-0.33	LN	-		3
Colorado	Concrete Pavement	-0.5	0.33	-	-	3
	HMA PG64-22	-0.5	LN	-	-	3
Louisiana	PCCP Pavement	-1	0.33	-	-	4
	HMA Superpave Level 1	-0.33	LN	-		5
Kentucky	JPC Pavement	0.33	LN	-		4
	HMA CL2 0.38D PG64-22	-0.33	-0.33	-	-	9
	HMA CL3 0.38D PG64-22	-0.5	-0.5	-	-	7
	HMA CL2 1.00D PG62-22	-0.5	LN	-		4

Note:
Approach 3: $P_i^{(\lambda_1)} = \beta_0 + \beta_q X_{i,q}^{(\lambda_2)} + \sum_{l=1}^{L} \beta_{d_l} X_{i,d_l} + \beta_b X_{i,b} + u_i$

Table 4-7 compares the Breusch-Pagan LM critical values, biased F-statistic estimates, and coefficient of determination (R^2) of the baseline model (Approach 1), the Box-Cox transformation model (approach 2), and the multi-variate Box-Cox model (Approach 3). Although some of the models still exhibit biased residuals (6 of 15) and heteroscedasticity (8 of 15) in Approach 3, it still significantly improves both aspects relative to the current benchmark. Furthermore, the improvement of the coefficient of determination (R^2) between Approach 2 and Approach 3 signifies the ability of additional covariates to reduce unexplained variation in the data, with the Kentucky HMA CL3

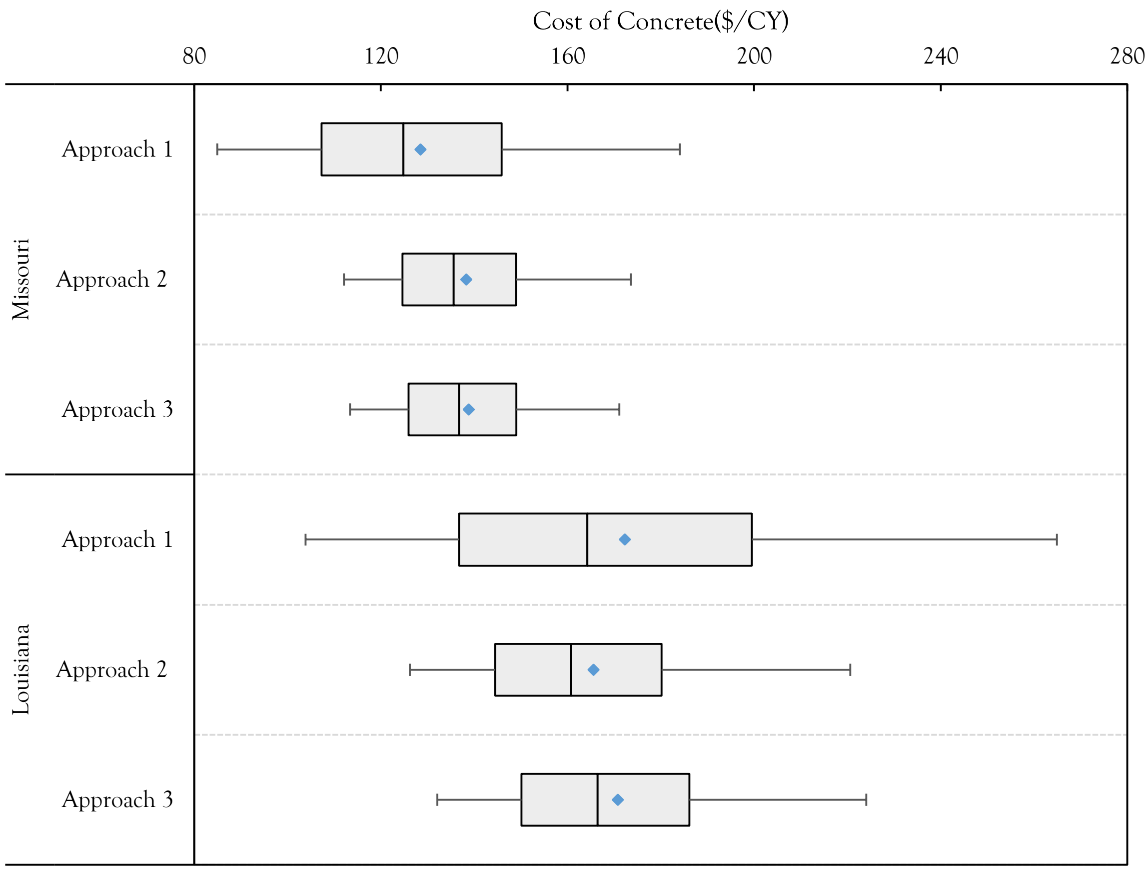
0.38D PG64-22 pay item the most extreme example. These findings are particularly promising and provide strong evidence that the modeling approach proposed in this chapter can aid the development of initial-cost estimates that better reflect the structural form of the actual data.

Table 4-7. Biased F-test, Breusch Pagan heteroscedasticity test, and R^2 values for Approach 1, 2, and 3. Values denoted with a '*' reject the null hypothesis of homoscedastic (Breusch-Pagan LM test) or unbiased (residual F-test) residuals.

State	Dataset	Biased F-stat			Breusch-Pagan LM			R^2		
		1	2	3	1	2	3	1	2	3
Missouri	Concrete Pavements	3.1*	0.1	0.0	25.6*	0.2	0.8	0.66	0.68	0.74
	HMA Mixture BP-1	23.9*	1.6	1.8	172*	30.2*	29.0*	0.64	0.69	0.72
	HMA PG64-22	8.6*	0.5	4.4*	35.8*	7.3*	6.8*	0.12	0.14	0.18
Indiana	PCCP	0.3	0.0	0.4	15.2*	2.6	0.2	0.26	0.26	0.34
	HMA Type A Surface	10.2*	0.5	1.4	126*	7.4*	5.9*	0.42	0.42	0.48
	HMA Type B Surface	9.1*	1.3	3.5*	231*	69.6*	25.9*	0.45	0.44	0.47
	HMA Type A Inter.	6.1*	0.8	0.5	42.3*	0.5	0.2	0.50	0.49	0.54
Colorado	Concrete Pavement	1.1	3.5*	4.4*	16.1*	4.9*	1.0	0.50	0.52	0.59
	HMA PG64-22	4.4*	0.7	0.0	8.2*	1.3	2.1	0.35	0.34	0.56
Louisiana	PCCP Pavement	0.7	0.4	0.1	29.7*	0.2	0.9	0.49	0.56	0.64
	HMA Superpave Level 1	36.9*	14.6*	23.0*	19.2*	0.8	2.1	0.74	0.74	0.78
Kentucky	JPC Pavement	1.1	0.2	0.5	17.1*	42.8*	4.3*	0.37	0.37	0.44
	HMA CL2 0.38D PG64-22	261*	0.9	5.2*	707*	101*	145*	0.47	0.52	0.69
	HMA CL3 0.38D PG64-22	49.6*	0.3	0.4	73.7*	7.3*	16.0*	0.22	0.27	0.63
	HMA CL2 1.00D PG62-22	19.0*	7.1*	14.8*	115*	27.9*	26.8*	0.50	0.52	0.58

Note:
Approach 1 (Power Model): $LN(P_i) = \beta_0 + \beta_q LN(X_{i,q}) + u_i$
Approach 2: $P_i^{(\lambda_1)} = \beta_0 + \beta_n X_{i,n}^{(\lambda_2)} + u_i$
Approach 3: $P_i^{(\lambda_1)} = \beta_0 + \beta_q X_{i,q}^{(\lambda_2)} + \sum_{l=1}^{L} \beta_{d_l} X_{i,d_l} + \beta_b X_{i,b} + u_i$

To illustrate the potential impact of the proposed method on early-cost estimates, the unit-price of each bid item is estimated using the three approaches discussed for 15,000 cubic yards of concrete and 15,000 tons of asphalt, representative of the amount of material that goes into large construction projects. The number of bidders that are input for each regression in Approach 3 is the sample average for that individual dataset. Figure 4-1 and Figure 4-2 present box-and-whisker plots of the estimated bid unit prices of concrete and asphalt and the associated uncertainty for four of the datasets: Missouri and Louisiana concrete pavements and Missouri BP-1 and Indiana Type B Surface asphalt mixtures. As can be seen, the first three bid items are excellent examples of how optimized data transformations and the expansion of the number of explanatory variables both shifts the distribution mean/median and, for large projects, reduces the expected variance. The Indiana Type B Surface asphalt mixture is one example where the proposed approach has a smaller impact on the estimated cost. This finding does not render the preceding results useless, but rather demonstrates the value of the models and approaches discussed are largely a function of the structure of the data at hand.



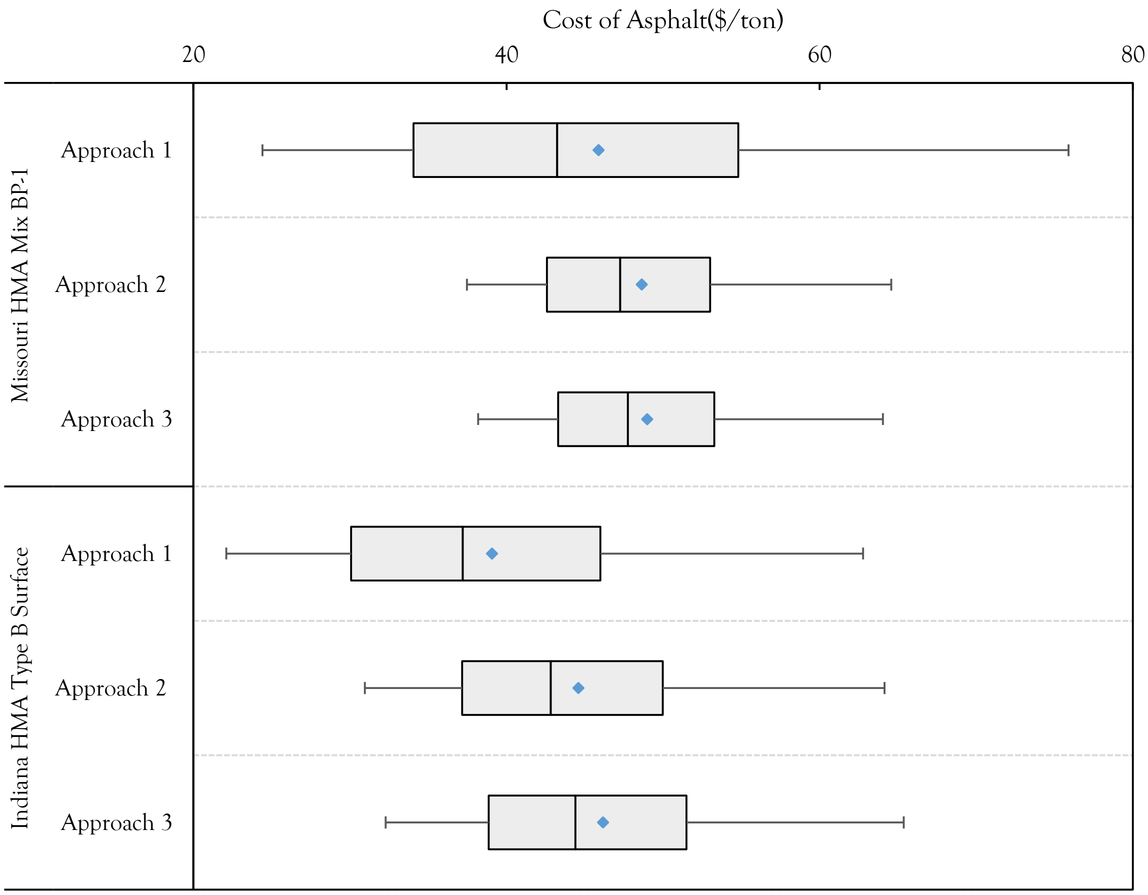
Note:
Approach 1 (Power Model): $LN(P_i) = \beta_0 + \beta_q LN(X_{i,q}) + u_i$
Approach 2: $P_i^{(\lambda_1)} = \beta_0 + \beta_n X_{i,n}^{(\lambda_2)} + u_i$
Approach 3: $P_i^{(\lambda_1)} = \beta_0 + \beta_q X_{i,q}^{(\lambda_2)} + \sum_{l=1}^{L} \beta_{d_l} X_{i,d_l} + \beta_b X_{i,b} + u_i$

Figure 4-1. Box-whisker plot of bid unit-price expectation (represented by the dots) and its uncertainty for the three approaches for 15,000 cubic yards of concrete. Whiskers represent the 5th and 95th percentiles of the theoretical distribution.

Another important point is that due to the selected data transformations, the distribution of bid unit-prices is implicitly asymmetric, which leads to expected unit-prices (blue dots) that are greater than the medians (central line) for all cases analyzed, as shown in Figure 4-1 and Figure 4-2. The simplest example to demonstrate this effect is to consider the model form associated with Approach 1, which assumes that natural logarithmic unit-prices are Gaussian distributed. Based upon the properties of a log-normal distribution, expected bid unit-prices, P, given a quantity, Q, in Approach 1 would be:

$$E[P|Q] = e^{\beta_0 + \beta_q LN(Q) + \frac{s^2}{2}} \tag{4.6}$$

where s^2 is the unbiased estimator of the variance, σ^2. This discussion suggests that practitioners are not only prone to underestimate expected construction costs because they fit their data to a structurally biased regression model, but also because they do not account for the error term when transforming data back to its original form. Changes in practice that address these possible pitfalls could potentially reduce the bias in construction cost estimates as discussed by Flyvberg et al. (2002).



Note:
Approach 1 (Power Model): $LN(P_i) = \beta_0 + \beta_q LN(X_{i,q}) + u_i$
Approach 2: $P_i^{(\lambda_1)} = \beta_0 + \beta_n X_{i,n}^{(\lambda_2)} + u_i$
Approach 3: $P_i^{(\lambda_1)} = \beta_0 + \beta_q X_{i,q}^{(\lambda_2)} + \sum_{l=1}^{L} \beta_{d_l} X_{i,d_l} + \beta_b X_{i,b} + u_i$

Figure 4-2. Box-whisker plot of bid unit-price expectation (represented by the dots) and its uncertainty for the three approaches for 15,000 tons of asphalt. Whiskers represent the 5th and 95th percentiles of the theoretical distribution.

Conclusions

Representative parametric estimates of maintenance action costs are important components that affect the allocation decisions of pavement management systems. Unfortunately, however, the existing cost estimation models presented in the literature can lead to biased estimates and the presence of heteroscedasticity, potentially causing planners to select less economically efficient design alternatives for a given roadway project.

This chapter presents one alternative approach for initial cost estimates via the integration of a maximum likelihood (ML) estimator to search for an optimal data transformation combined with least angle regression (LAR) for variable selection/reduction. The proposed approach leads to unbiased and homoscedastic residuals more frequently than current practice and simultaneously reduces the unexplained variation via the introduction of new explanatory variables (district variation, for example) for the pavement community. The results and contribution of the work presented are particularly important for large projects which could dominate total network expenditures in a given year, as the traditional approach tends to lead to (a) overestimation of variance and (b) biased estimates that underestimate expected costs.

Despite the promising results from the case study, opportunities exist to further augment the approach proposed in this dissertation. Future research, for example, could explore the fidelity of alternative dimensionality reduction techniques (e.g., factor analysis, LASSO, principal component analysis) and non-linear frameworks (e.g., regression trees) to predict bid unit-prices. Furthermore, a similar study could be conducted but now using actual construction costs rather than bid prices. Lastly, a comparison of the deviation between estimated and actual prices could be conducted to test if the analytical approaches proposed by the authors corrects for the biased towards cost overruns as discussed by Flyvberg, Holm et al. (2002).

CHAPTER 5: FORECAST FUTURE PAVING MATERIAL PRICES

Motivation for chapter

As alluded to in previous chapters, planning agencies utilize pavement management systems to determine an allocation policy across a network of pavements facilities. For the most part, these frameworks only consider uncertainty as it relates to pavement deterioration, a topic that this dissertation has discussed in detail in Chapter 2 and Chapter 3. Of course, several other exogenous inputs affect the decision-making process and are, also, subject to uncertainty; one such input is the future price of maintenance actions.

The academic literature for pavement management, as a whole, is void of studies that consider how the price structure (and the associated uncertainty) of different maintenance and rehabilitation alternatives may evolve over time (Guo, Liu et al. 2012; Swei, Gregory et al. 2016). This common theme to disregard forecasting future construction prices in the academic literature is also found in practice, where state departments of transportation (DOT), such as Alabama, Colorado, and South Dakota, assume that the future real price of all inputs will remain constant over time (Demos 2006; Mctigure 2013; Qin, Wang et al. 2014; Musselman 2015). Of course, it is both likely that the cost of different construction actions will evolve separately from general inflation and, furthermore, from one another. Therefore, planning agencies are ill-prepared to deal with an uncertain economic future that will likely unfold differently from expectations. Material diversification, the focus of this dissertation, is an example of something that might be more common amongst DOTs if pavement management tools explicitly accounted for the potential differential cost growth of alternative actions.

The decision to ignore this important input is likely driven by two key facts. First, little research to date has evaluated the fidelity of projection models to estimate expected price and price volatility over a multi-decade period for construction commodities. Second, quite frequently there is a lack of significant empirical data to inform reasonable price projections using traditional econometric techniques. These reasons, surely, are no excuse to forego accounting for this source of variation in the decision-making process. However, these intricacies pose a challenge regarding the development of representative volatility estimates that would integrate within a pavement management system.

Therefore, the goal and contribution of this chapter is the demonstration that long-term probabilistic price projection models can be developed that perform well and provide insight into future price uncertainty in spite of limited historical data. Previous research suggests that material costs are the dominant contributor to the total cost of roadway construction activities (Herbsman 1983). As a result, the focus of this chapter is on forecasting future material prices, namely asphalt and concrete, within the construction sector.

To do so, a hybrid probabilistic forecasting approach is implemented for asphalt and concrete, two dominant materials in roadway construction that have significantly less available historical data than other material inputs in construction, such as aggregate and cement. The probabilistic component of the projection model, in particular, can significantly augment the existing pavement management paradigms as it allows for a better understanding of future volatilities in construction inputs.

Background on forecasting within the construction community

Although cost forecasting is not an element of existing pavement management systems, the construction community has made significant progress over the last few decades towards developing methods to project construction costs and indices. The methods used in this construction-cost projection research falls into two broad categories. The first, and more common approach, is to employ univariate time-series models based upon the very general autoregressive integrated moving average (ARIMA) model to project future costs (Hwang 2009). These types of models have the benefit of being easy to implement while also performing quite well for forecasting over short time periods. Hwang (2011) projected a future construction cost index (CCI), a composite measure of labor, materials, and equipment, over two years utilizing the aforementioned ARIMA model and compared performance using the mean absolute error (MAE). Ashuri and Lu (2010) used an ARIMA model that accounted for seasonality to project future values for the Engineering News Record (ENR) CCI over a 12-month span. Forecasting accuracy was evaluated using the MAE, mean square error (MSE), and mean absolute percent error (MAPE). Ng, Cheung et al. (2000) developed a similar model to forecast the future index value of the Hong Kong construction industry in the following quarter. Performance of the model was measured as the frequency the projection correctly predicted an upward or downward trend in the next quarter.

The alternative approach for forecasting is to derive a relationship between construction costs and various endogenous and exogenous factors (Wilmot and Cheng 2003). As an example, Wilmot (1994) used neural networks and regression analysis to predict ENR's CCI over 1-month and 6-month periods. Factors incorporated were quite complex, such as the number of housing starts in the construction sector and the prime lending rates charged by banks. Interestingly, the findings suggested that linear regression performed similarly to exponential smoothing (one type of ARIMA model) while neural networks, despite being more complex, actually lagged behind both approaches in terms of predictability (which was measured by estimating the sum of square errors). As another example, Xu and Moon (2013) characterized the link between general inflation and a CCI via cointegration (which will be expanded upon in the methodology section). The relationship established was subsequently used to inform a projection of future construction costs over a 54-month span with projection accuracy measured with metrics such as the MSE and MAE.

Despite the prevalence of forecasting in the construction management community, the current pavement management frameworks still do not consider future price trends and their uncertainty. This tendency is likely because studies to date are geared towards forecasting in the short-term (less than 5 years) and only measure the fidelity of their models with deterministic metrics such as the MAE, MSE, and MAPE. On the other hand, pavement management systems evaluate multi-decade investments which are subject to a higher level uncertainty given the time horizon. Therefore, there is a need to understand and measure if probabilistic price projections can be developed for the timeframes used in pavement management systems to inform better investment decisions. The performance of these models need to be measured not just with some of the deterministic metrics alluded to, but also some measure that provides inference on the value of recognizing uncertainty.

Therefore, the contribution of this chapter is the demonstration that probabilistic price projection models can be developed that perform well in terms of expectation and, perhaps more importantly, provide excellent estimates of future volatility in material prices (even when data availability is limited). The remaining sections test this assertion by implementing a probabilistic hybrid approach for the price projection of asphalt and concrete and comparing it to the no real price change assumption of current pavement management practice. It is worth mentioning that such a baseline model in the forecasting literature has been used in other sectors, including energy (Alquist and Kilian 2010). The tools used in this analysis are available in multiple statistical software packages (the analysis is conducted in Stata and EViews), and the data utilized is available in accessible public databases, making this research tangible and implementable for practitioners and academics.

Methodology

Herbsman (1983) suggests that material costs make up the majority of the total cost for roadway projects on average. Unfortunately, historical data for some of these commodities, particularly as it relates to concrete and asphalt, tends to be limited. On the other hand, significant empirical data that precedes the early 1900s exists for many of the key constituents for these materials. Therefore, a hybrid approach is implemented where constituent materials are projected using the univariate time-series techniques described and a long-run price trend between paving materials and constituents is established to make use of those forecasts. This approach involves four high-level steps that are described briefly here and elaborated upon afterwards.

Step 1: Establish a long-run price trend between paving materials and their constituents –

A series of methods are utilized to establish a long-run price equilibrium between paving materials and constituents. It is important to note, as will be expanded upon later, that the robustness of the tests used in this section are sensitive to sample size. For this reason, the long-run price equilibrium will be established using monthly rather than annual data.

Step 2: Project the future price of relevant constituents – The first step defines which inputs have a statistically significant relationship with the price of concrete and asphalt. The second step requires developing some simple univariate time-series models for the constituents that do have a statistically significant relationship.

Step 3: Project the future price of paving materials – The constituent projections are integrated into the long-run price equilibrium so that future prices of paving materials can be projected. Monte Carlo simulations are utilized to estimate the uncertainty in the forecasts.

Step 4: Validate relative performance of model to current practice. The fidelity of the price projection model is compared to the current assumption via out-of-sample forecasts. In this step, price projections are made prior to the present and are compared to what actually occurred.

Step 1: Establish a long-run price trend between paving materials and their constituents

Determining the order of integration for a stochastic process

As discussed in Chapter 3, it is important in time-series analysis to understand if the data at hand exhibits stationary or non-stationary characteristics. As a reminder to the reader of this dissertation, a stationary time-series is a stochastic process whose statistical properties, such as mean or variance, remain constant over time. If a time-series is non-stationary, however, it can frequently be transformed into a stationary process by differencing the dataset (referred to as a differenced stationary process); the number of times it takes to difference the process until it becomes stationary is referred to as the order of integration. Two of the more common tests that can be used for quantifying the order of integration of a process is the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests (Leybourne and Newbold 1999). For this particular chapter, the ADF test is used to evaluate if the relevant datasets are stationary or not (and to what order of integration).

The value of testing for stationarity is that it informs the types of models that should be used for understanding if a long-run price equilibrium exists between commodities. For example, in the case that two stochastic processes are stationary over time, a simple ordinary least squares (OLS) regression is effective and unbiased for testing the relationship between commodities. Frequently, however, time-series will be non-stationary over time, making the OLS approach susceptible to spurious regression (Franses and Dijk 2010).

An alternative approach that has gained traction over the last two decades for modeling the relationship between different factors that are non-stationary is to test for cointegration. Two non-stationary stochastic processes are said to be cointegrated if a stationary linear combination exists between them such that the residuals are a non-differenced stationary process. In other words, only in the case that two non-stationary processes are cointegrated can spurious regression be avoided via the typical OLS regression approach. Several empirical studies have made use of cointegration to understand the price-link between commodities such as primary and secondary scrap metals and crude oil, natural gas, and other refined products (Gjoldberg and Johansen 1999; Ewing, Malik et al. 2002; Lanza, Manera et al. 2005; Xiarchos 2006; Ramberg and Parsons 2012). For the purposes of this chapter, if all relevant time-series are non-stationary and integrated to the same order then conventional cointegration is implemented. If that is not the case, however, this research formulates an autoregressive distributed lag (ARDL) approach for cointegration that is consistent with the oft-cited work of Pesaran, Shin et al. (2001).

The basis of the ADF test is an ARIMA (*p, d, q*) model, where *p* is the number of autoregressive terms, *d* is the number of non-seasonal differences, and *q* is the number of moving average terms. More generally, a time-series, *P,* is defined by:

$$P_t\left(1-\sum_{i=1}^{p}\alpha_i L^i\right)(1-L)^d = \varepsilon_t\left(1-\sum_{i=1}^{q}\beta_i L^i\right)+C \tag{5.1}$$

where P_t and ε_t are the price and error terms in year *t*, α and β represent the coefficients of the autoregressive and moving average terms, C is a constant drift term, and *L* is the lag operator, meaning:

$$P_t L^i = P_{t-i} \tag{5.2a}$$

$$\varepsilon_t L^i = \varepsilon_{t-i} \tag{5.2b}$$

The ADF tests the null hypothesis of a non-stationary, autoregressive process with a trend against a stationary, autoregressive model that is constant over time. In other words, an ARIMA (*p, 1,* 0) is the null-hypothesis, and is compared to an ARIMA (*p+1,* 0*,* 0) process (Cheung and Lai 1995). The regression equation of the ADF test, which is a result of Equation 5.1, is as follows:

$$\Delta P_t = C + \lambda t + \gamma P_{t-1} + \sum_{i=1}^{p-1} \theta_i \Delta P_{t-p} + \varepsilon_t \tag{5.3}$$

where ΔP_t is the first difference operator, C, λ, θ, and γ are parameter estimates, and ε represents unexplained noise. For the given regression equation, there are three types of ADF tests that may be conducted where λ and/or C are set equal to zero. For simplification, let it be assumed that there is no serial correlation amongst the residuals such that Equation 5.3 simplifies to:

$$\Delta P_t = \gamma P_{t-1} + \lambda t + C + \varepsilon_t \tag{5.4}$$

The purpose of the test is to understand the negativity of γ. If γ is equal to zero, the process is non-stationary as the time-series growth is independent upon its price level in year *t-1*. Hence, it will grow at some rate (αt + C) with some error term to account for the uncertainty. More formally, this is referred to as a unit-root being present. On the other hand, if γ is less than zero, future growth is dependent upon the current position of the process. This outcome implies that if the position in year *t* is high, it is likely growth in year *t+1* will turn downward, consistent with what one would expect if a process exhibits mean-reversion (i.e., stationarity).

The ADF test will evaluate the null-hypothesis of γ being equal to zero (i.e., a unit-root existing). If one cannot reject the null hypothesis of γ equaling zero then the process is assumed to be non-stationary and, therefore, one should difference the time-series until it is stationary.

The ADF test can be run under three cases:

1) Unit-root test with no constants: $\Delta P_t = \gamma P_{t-1} + \varepsilon_t$

2) Unit-root test with drift: $\Delta P_t = \gamma P_{t-1} + C + \varepsilon_t$

3) Unit-root test with drift and a deterministic time trend: $\Delta P_t = \gamma P_{t-1} + \lambda t + C + \varepsilon_t$

Selecting which test to conduct is not necessarily intuitive and can have implications on test results, leading many authors to propose approaches to increase the likelihood of the correct classification of a process. For this chapter, the approach suggested by Elder and Kennedy (2001) is followed, where data is visualized and a simple regression of the price as a function of time is conducted to understand the growth of the stochastic process. If it seems as though the stochastic process has grown over time, then an ADF test is conducted using Case 2. If the growth over time has remained steady, however, Case 1 is implemented.

It should be emphasized that the above description only includes one autoregressive term. The number of autoregressive terms that should actually be included will typically be selected by using some form of a best-fit metric such as the Akaike information criterion (AIC) or Bayesian information criterion (BIC), as one lag may not adequately address serial correlation in the process (Liew 2004).

Traditional cointegration in the case that all time-series are non-stationary and integrated to the same order

The most popular cointegration test is the Johansen test, which tests the restrictions imposed by cointegration on an unrestricted vector autoregression (VAR) model (Xiarchos 2006). A VAR model captures the interdependencies between multiple time-series and is described by the following equation:

$$Y_t = C + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \varepsilon_t \tag{5.5}$$

where C is a k x 1 vector of constants (k is the amount of annual or monthly price data used), Y_t is a k x 1 vector of the considered variables, A is a k x k matrix that describes the price transmission between the variables considered, and p represents the number of lag terms in the VAR model. Given data prior to t-1, the model can project the price for different commodities in year t. One important consideration when constructing a VAR model is to select the appropriate number of lags, p. Unfortunately, the selection of the correct lag order is not necessarily intuitive. This issue in the VAR literature has been considered, and to date, a large body of empirical research has explored the topic (Kilian 2001). Potential goodness-of-fit metrics which can be used are the Akaike information criterion (AIC), Hannan-Quinn information criterion (HQIC), and Schwarz Bayesian information criterion (SBIC). One empirical study found that for finite samples with 160 data points (this study will use around 350) the HQIC tended to perform better than other common metrics (Kilian 2001). That same study found that the accuracy (via simulation) of estimating the true lag order of a model using a sample size of only 80 ranged from 2%-56% across different metrics whereas a sample size of 160 approached an accuracy as high as 89%. For that reason, this research will use monthly rather than annual data for this step.

As mentioned, the Johansen cointegration test is used to test the restrictions imposed by cointegration on the above, unrestricted VAR model (Xiarchos 2006). This is accomplished by transforming the VAR into the following vector error correction model (VECM):

$$\Delta P_t = \Pi P_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta P_i + \varepsilon_t \tag{5.6a}$$

$$\Pi = \sum_{i=1}^{p} A_i - I_i \;\; and \;\; \Gamma_i = \sum_{j=i+1}^{p} A_j \tag{5.6b}$$

where *I* is the identity matrix, P_t and $P_{t\text{-}1}$ represent the price in year *t* and *t-1*, and all other terms remain the same as in Equation 5. If the coefficient matrix, Π, reduces in rank order, *r*, then it can be said that there are *r* cointegration relationships amongst the variables of interest and the stationary linear combination between them is the long-run price equilibrium.

An alternative approach to cointegration should the stochastic processes not be integrated to the same order

The motivation for traditional cointegration stemmed from the prevalence of integrated time-series in the econometric literature. Unfortunately, the approach described breaks down when testing for a relationship between a dependent variable (which is differenced stationary) and relevant covariates that are not all differenced stationary. More recently, Pesaran and Shin (1999) and Pesaran, Shin et al. (2001) developed an approach that overcomes this shortcoming by formulating an unrestricted error correction model (ECM) from an autoregressive distributed lag (ARDL) framework. The very general ARDL (p, q_1,.., q_k) model has the form of:

$$Y_t = c + \sum_{p=1}^{p} \alpha_{t-p} Y_{t-p} + \sum_{j=1}^{k} \sum_{i=0}^{q_j} \beta_{j,t-i} X_{j,t-i} + \varepsilon_t \tag{5.7}$$

where p is the number of autoregressive terms of the dependent variable Y, q_k is the number of autoregressive terms of the k^{th} covariate, α and β are coefficient estimates and ε_t is unexplained variation. In other words, the price of the relevant time-series is not only a function of the lagged values of itself (as was noted in the ARIMA case) but also the independent variables as they are distributed over time. This important aspect lends itself in understanding the short-term and long-term interactions amongst commodities. Specifically, via manipulating Equation 7, one can extract the long-run price equilibrium between covariate k and the dependent variable as:

$$\theta_j = \frac{\sum_{i=0}^{q_j} \beta_{j,t-i}}{1 - \sum_{p=1}^{p} \alpha_{t-p}} \tag{5.8}$$

Similar to Johansen, Pesaran and Shin (1999) develop a cointegration equation but this time by transforming the ARDL (p, q_1,.., q_k) model in Equation 7 into an unconstrained error correction model (ECM). This is done so by differencing the ARDL model and integrating the long-run price equilibrium equations. As an example, if the model is *ARDL (1,1)* then the unconstrained ECM simplifies to:

$$\Delta Y_t = c + \gamma_{1,t-1}\Delta X_{1,t-1} + \delta_0 Y_{t-1} + \delta_1 X_{t-1} + \varepsilon_t \tag{5.9}$$

Based upon the above ECM, a Bounds test is conducted that evaluates the null hypothesis of the level terms (in this case δ_0 and δ_1) being equal to zero (Pesaran, Shin et al. 2001). The Bounds test involves computing the F-statistic and comparing it to the lower and upper bound critical values computed by Pesaran, Shin et al. (2001) In the case the null hypothesis is rejected (which is when the F-statistic is greater than the critical values), one can say the time-series of interest are cointegrated with one another.

Step 2: Project the future price of relevant commodities

The next step in this analysis is to develop price projections for each constituent that has a statistically significant price relationship with asphalt and concrete. Similar to the previous discussion, it is important to understand the price behavior of each constituent to inform a reasonable forecasting model. What was not discussed previously, however, is that the ADF test is sensitive, similar to cointegration, to sample size (Pindyck 1999). Since the constituent forecasts will use data that is annual rather than monthly, the sample-size to analyze will be limited. Unit-root test can have difficulty distinguishing if $\gamma = 0$ or if γ is slightly less than zero, implying the time-series exhibits slowly mean-reverting characteristics, and so this study implements the ADF test discussed and an alternative procedure. This procedure is to estimate the parameters of a stationary, first-order auto-regressive process ARIMA (*1*,*0*,*0*), where:

$$P_t = \rho P_{t-1} + \mu + \varepsilon \tag{5.10}$$

Since a stationary process is, by definition, mean-reverting, it is equivalent to an Ornstein-Uhlenbeck process which reverts to a constant mean:

$$dP_t = K(\mu - P_t)dt + \sigma dtW_t \tag{5.11}$$

where K is the speed of mean-reversion, μ is the mean value the process tends to revert to, σ represents the volatility, and W_t is Brownian motion (unexplained variation). The discretized form of this (ignoring the second term) is:

$$P_t - P_{t-1} = K(\mu - P_{t-1}) \tag{5.12a}$$

$$P_t = (1 - K)P_{t-1} + K\mu \tag{5.12b}$$

Therefore, if one estimates the parameters of an ARIMA (*1*,*0*, *0*) process, the rate of mean-reversion is simply $1\text{-}\rho$. This means that if ρ is nearly one, the time-series exhibits nearly no reversion to a mean. Previous research has shown the rate of reversion for certain commodities can take up to a decade or more, and so if $\rho \leq 0.9$ year^{-1}, this paper considers the process as stationary (Pindyck 1999). A nice aspect of the latter approach is that it is quite intuitive.

Constituent Projection Model

Depending upon the characterization of historical data for the time-series of interest, multiple modeling techniques are available. For this research, if a time-series exhibits stationary characteristics then it is assumed to follow an *ARIMA (1, 0, 0)* process. Although this analysis could further study the number of lags to include through a best-fit measure, only one lag is incorporated as this is both simpler and the implication is minimal given that the proposed application for this work is for projecting prices decades, not years, into the future.

In the case, however, that a process has historically behaved in a non-stationary manner (i.e., differenced stationary), a geometric Brownian motion (GBM) model estimated of the following form:

$$P_t = P_{t-1}e^{\mu-\frac{1}{2}\sigma^2+\sigma W_t} \tag{5.13}$$

where P_t is the price in year t, μ and σ represent the logarithmic growth rate and standard deviation (volatility measure), and W_t is standard Brownian motion. Parameters can be estimated by transforming the dataset into logarithmic form and calculating the sample's differenced average and standard deviation.

Oil Projection Model

As shown in Figure 5-1, the detrended historical price for oil over the last century has exhibited two characteristics, as discussed by Pindyck (1999). First, the real price of oil has tended to exhibit mean reversion to a continually shifting mean, which represents the continually shifting marginal cost of oil production. This reversion has taken the form of a quadratic function, which intuitively makes sense: initial oil production became cheaper as technology improved, but as demand and cost to extract have increased over time, so too has the marginal cost. Second, the time it takes for the price of oil to revert back to its marginal cost can take up to a decade. Due to its monopolistic nature, the price of oil has experienced short-run prices that are extremely volatile and do not match expected competitive prices. Fortunately, given that the purpose of this research is to project the long-term cost of concrete and asphalt, the implication of these short-term price swings should be mitigated.

Based upon these qualitative characteristics, one possible model is the Ornstein-Uhlenbeck mean-reverting process, as described previously, but this time to a quadratic function (Pindyck 1999):

$$dP_t = KCdt + \varepsilon_t \tag{5.14a}$$

$$C = \alpha t^2 + \beta t + \mu - P_t \tag{5.14b}$$

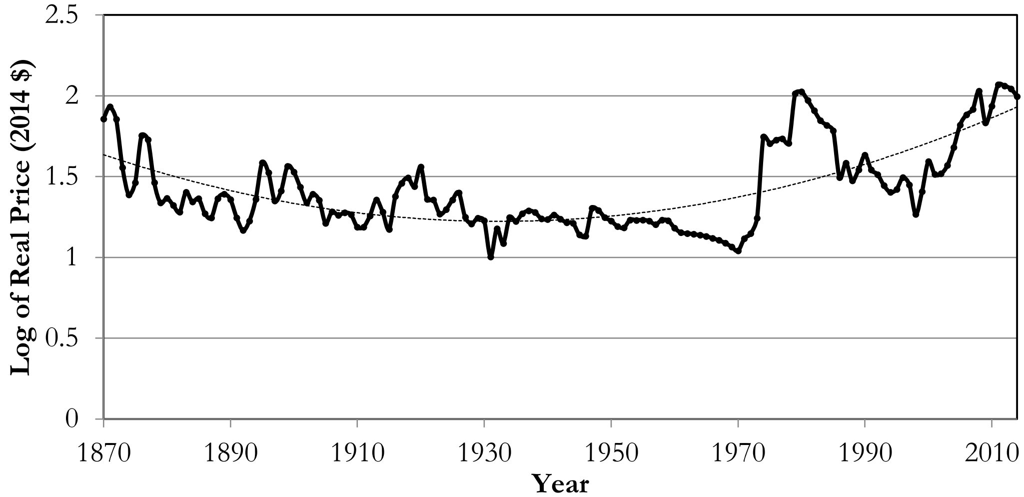


Figure 5-1. Detrended real-price of crude oil over time (BP 2014).

K is the speed of mean-reversion, C is the quadratically shifting mean-value the process tends to revert to, P_t is the price in year t, ε_t represents the unexplained noise of the process, and α, β, and μ are constants. Pindyck (1999) builds upon this general model by considering a multivariate case that allows for fluctuations in both level and slope. Hence, Equation 11 now becomes:

$$dP_t = (KC + \lambda_1 Y + \lambda_2 Zt)dt + \varepsilon_t \tag{5.15}$$

where in addition to the previous terms, Y and Z are themselves their own Ornstein-Uhlenbeck process, and λ_1 and λ_2 are constants such that:

$$dY = \delta_1 Y dt + \varepsilon_t \tag{5.16a}$$

$$dZ = \delta_2 Z dt + \varepsilon_t \tag{5.16b}$$

where, similarly, δ_1 and δ_2 are constants. Combining all terms in the discretized case leads to the following solution (where C_1 thru C_6 are constant terms and $\theta_{1,t}$ and $\theta_{2,t}$ are unobservable state variables):

$$P_t = C_1 + C_2 t + C_3 t^2 + C_4 P_{t-1} + \theta_{1,t} + t\theta_{2,t} + \varepsilon_{1t} \tag{5.17a}$$

$$\theta_{1,t} = C_5\theta_{1,t-1} + \varepsilon_{2t} \tag{5.17b}$$

$$\theta_{2,t} = C_6\theta_{2,t-1} + \varepsilon_{3t} \tag{5.17c}$$

It is important to note that many other oil price forecasting models exist and could potentially be used as a substitute for the approach developed by Pindyck (1999). In fact, future research could potentially explore the results of the asphalt and concrete forecasting model using alternative approaches available (EIA 2015).

Step 3: Project the future price of paving materials

Once price projections have been derived for each constituent material, the next step is to integrate them within the paving material price forecast. This step is accomplished by inputting each constituent price projection into the derived long-run price equilibrium in Step 1 (and their respective uncertainty terms). An unfortunate consequence of using monthly data via the bureau of labor statistics (BLS) for estimating a long-run price equilibrium while employing annual data from the U.S. Geological Survey (USGS) for the constituent price projections is that the two data sources have closely, but not perfectly, aligned over time. For that reason, constituent forecasts are generated using the trends established via USGS but shifting the initial starting points to BLS values. For each forecast, a Monte Carlo simulation is conducted for developing a large sample of 40-year forecasts in order to estimate the underlying uncertainty of the forecasting model.

Step 4: Validate Performance of Model Relative to Current Practice

An important step to quantify the performance of the proposed approach is to benchmark its performance relative to current practice. One common method to measure the fidelity of a model is out-of-sample forecasting. This technique is grounded in the concept that one should construct a forecasting model using data up until a certain moment in time, project the future, and compare the error in the prediction relative to what actually occurred. For the purposes of this chapter, out-of-sample forecasts are constructed between 1985-2000 to generate a sample of predictions using the proposed approach. It is important to recognize that the constituent price forecasts only use data up until the time of the forecast (as opposed to all data that is privy to the researchers) for model selection and parameter estimation so that possible bias is eliminated.

Ideally, one should compare the performance of the proposed model relative to the current baseline. Unfortunately, since the latter assumes future prices are static over time, one can only compare the two alternatives utilizing a deterministic measure. Therefore, the sample errors of the expected future prices using both approaches are utilized to estimate the MAPE of both models:

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{Actual - Predicted}{Actual}\right| \tag{5.18}$$

With that said, it is important to elicit how well the probabilistic approach captures the true uncertainty in price forecasting. Therefore, this research also tracks for each out-of-sample forecast whether or not future prices fell within the projected 75th and 90th percentile prediction intervals (PI). A one sample binomial test is subsequently conducted in each year to understand if the actual frequency future prices fell within the projected PI is significantly different from the expected frequency. No research, as far as this dissertation is aware of, have evaluated the probabilistic performance of a forecasting model using the proposed technique.

Data Analysis and Results

This section outlines data and results following the four steps outlined previously: implementation of cointegration, projection of commodities and paving materials, and validation of model performance via out-of-sample forecasting.

Step 1: Establish a long-run price trend between paving materials and their constituents

This analysis uses monthly data from the Bureau of Labor Statistics (BLS) for the ready-mix concrete, asphalt paving, crushed stone, and cement datasets dating back to January of 1985 and Brent spot oil prices made first available starting in May of 1987 (BLS 2015a-d; EIA 2015). Again, the reasoning for using monthly data rather than annual data is due to the minimum sample size needed for cointegration to run effectively. All time-series are deflated with the consumer price index (CPI) and normalized such that the average value for each index in 2013 is 100 (BLS 2015e). Figure 5-2 presents the price indexes analyzed in this section.

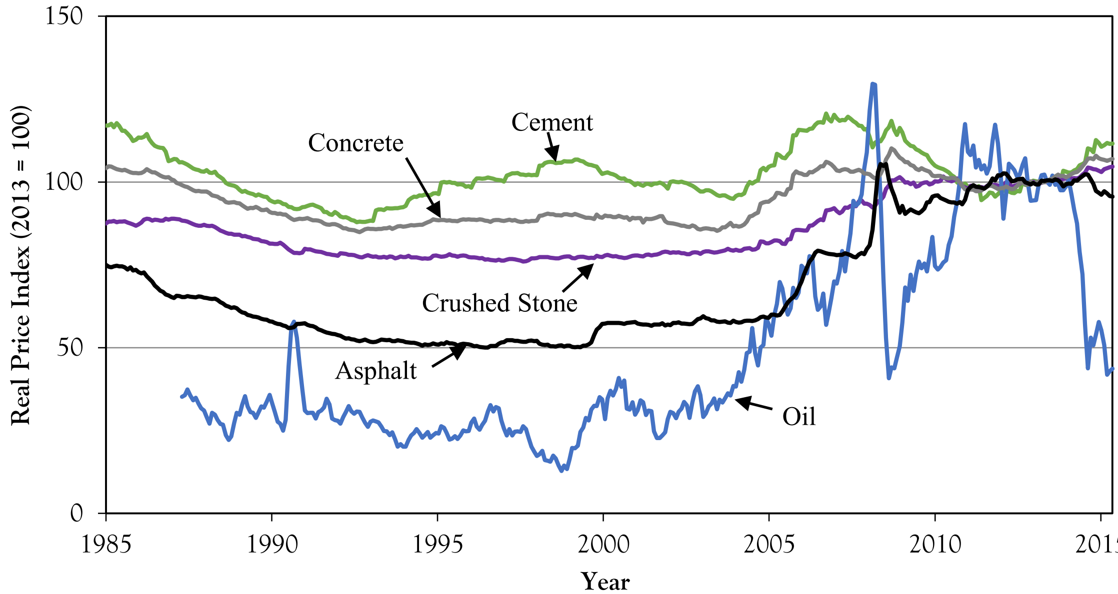


Figure 5-2. Historical real-price of concrete and its constituents (BLS 2015a-e; EIA 2015).

An ADF test is conducted for all five time-series for lag orders selected by the AIC. Results from the ADF test are presented in Table **5-1**, where a test statistic greater than the critical value suggests that a unit-root exists. The reason that the BIC is ignored in this section is that further inspection of the residuals of the ADF regression suggest that serial correlation exists when using the BIC. This is because the BIC tends to select a lower lag order, leading to the exclusion of seasonality in the data. The presence of seasonality can be noted by both plotting the partial autocorrelation function and observing that many of the lag orders selected by the AIC hover around 12.

Table 5-1. ADF test results for lag orders selected by AIC, where a test statistic greater than the critical value suggests that a unit-root exists. Starred values are less than 5% critical values.

No Difference and ADF Case 2 where $\Delta Y_t = \gamma Y_{t-1} + \beta + \varepsilon_t$				
Commodity	Number of lags	Test statistic	1% Critical Value	5% Critical Value
Concrete	12	-1.693*	-2.337	-1.649
Asphalt	10	-0.041	-2.337	-1.649
Cement	12	-3.157*	-2.337	-1.649
Crushed Stone	13	0.039	-2.337	-1.649
Oil	13	-1.408	-2.337	-1.649
First Difference and ADF Case 1 where $\Delta Y_t = \gamma Y_{t-1} + \varepsilon_t$				
Asphalt	16	-4.117*	-2.580	-1.950
Crushed Stone	12	-2.726*	-2.580	-1.950
Oil	12	-6.072*	-2.580	-1.950

Regressing all of the indexes over time indicates that growth has been positive and significant for each time-series and so Case 2 of the ADF test is employed for all datasets. The test statistic is greater than the 5% critical values for asphalt, crushed stone, and oil, suggesting that they all exhibit non-stationarity. When these three time-series are differenced, however, and Case 1 (the most restrictive case) is applied, the test statistic is less than the 5% critical values for all commodities. This suggests that the null hypothesis of a unit-root existing can be rejected, and therefore, these three time-series are likely integrated to the same (first) order. The asphalt model, therefore, can be analyzed via traditional cointegration where a VAR model is computed to test for a long-term equilibrium amongst relevant inputs.

On the other hand, since the concrete and cement time-series are both stationary, a simple OLS regression could be conducted to establish whether a long-run price equilibrium exists between just the two commodities. However, since concrete and crushed stone are integrated to different orders, an ARDL cointegration model must be constructed first to test if crushed stone and concrete have shifted stochastically over time together – if that is the case, it is reasonable to implement an OLS model for concrete as a function of crushed stone and cement.

Establishing a long-run equilibrium for asphalt

A VAR model of three lags (based upon the HQIC) is constructed to explore the long-run price relationship between asphalt, crushed stone, and oil. In order to characterize the number of cointegration relations that exist, this research uses the trace statistic, where the first rank order, r, that is less than the critical value represents the number of cointegration relationships. From Table 5-2, the asphalt model is clearly cointegrated with both of these constituents over time.

Table 5-2. Johansen test results for the asphalt model. The first value that is less than the 5% critical value is starred.

Asphalt VAR model with crushed stone and oil		
Rank	trace statistic	5% critical value
0	67.42	29.68
1	21.97	15.41
2	0.00*	3.76

From the cointegration analysis, a stationary linear combination is derived from the VECM for asphalt, representing the long-run price equilibrium between constituents and paving material prices:

$$P_{Asphalt,t} = 1.41P_{Crushed\ Stone,t} + 0.20P_{Oil,t} - 61.6 + N(0,3.5) \quad (5.19)$$

where $P_{x,t}$ is the price of commodity x in year t and the last term is a Gaussian distributed random error. The price models work extraordinarily well, with an R^2 of 0.96, as can be noted in Figure 5-3:

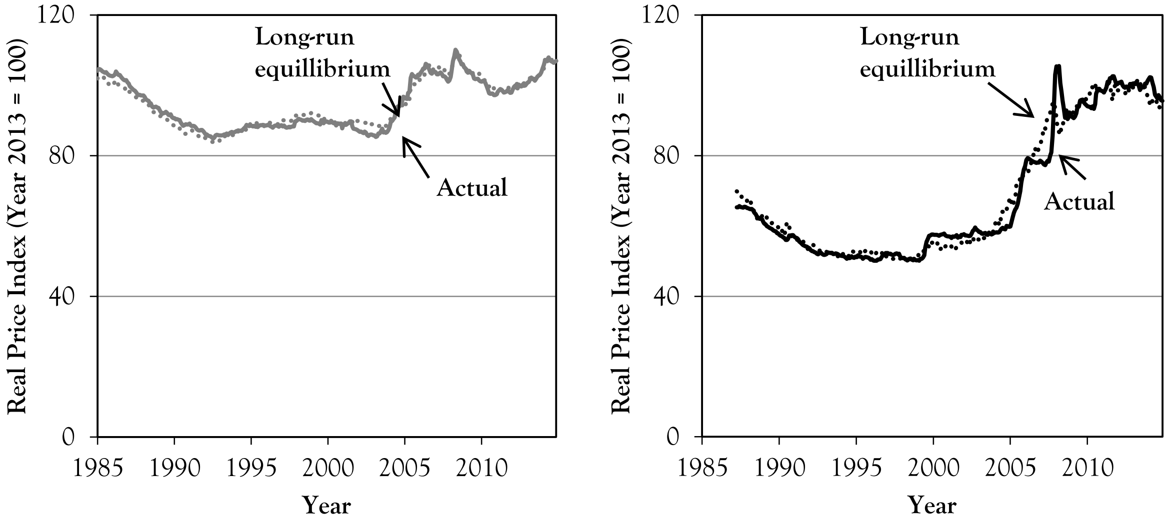


Figure 5-3. Predicted price using long-run price equilibrium (dashed) versus what actually occurred (solid) for concrete (left side) and asphalt (right side).

Establishing a long-run equilibrium for concrete

An unrestricted ECM is developed to test for the existence of cointegration between crushed stone and concrete. Since the dependent variable in this framework must be a first difference process, crushed stone is modeled as a function of concrete. Estimation of the parameters for the ECM is of the following form (with lag order selected by the BIC):

$$\Delta P_{crushed\ Stone,t} = -1.27 + 0.21\Delta P_{Concrete,,t-1} - 0.01P_{Crushed\ stone,t-1} + 2.17P_{Concrete,t} \quad (5.20)$$

A Bounds test is subsequently conducted to evaluate the null hypothesis of the level terms being equal to zero (i.e., cointegration does not exist). The F-statistic for this particular model is 10.346, which is greater than the upper bound 1% critical value of 7.84 as established per Pesaran (2001). Therefore, the null hypothesis can be rejected and it is reasonable to model concrete as a function of crushed stone and cement in terms of its levels via OLS regression. The long-run price equilibrium is estimated as follows:

$$P_{Concrete,t} = 0.51P_{Crushed\ Stone,t} + 0.44P_{cement,t} + 5.3 + N(0,1.6) \tag{5.21}$$

with an R^2 of 0.95 and p-values significantly less than 0.01. A comparison of actual concrete prices over time relative to the long-run equilibrium can be noted in Figure 5-3. Interestingly, the long-run coefficients for crushed stone and cement using an ARDL (p, $q_{crushed\ stone}$, q_{cement}) are 0.48 and 0.37, respectively, further suggesting the OLS model provides reasonable estimates of the long-run relationship.

Step 2: Project the future price of relevant commodities

Historical data is readily available dating back to the early 1900s via USGS for cement and crushed stone while British Petroleum has collected real price data for oil since 1870 (BP 2014; Kelly and Matos 2014a,b). Figure 5-4 superimposes the historical real-price of the three time-series. As noted earlier, the historical behaviors must first be characterized so that an appropriate model can be inferred. The only constituent this does not apply to is oil since a pre-determined model is specified based upon previous research.

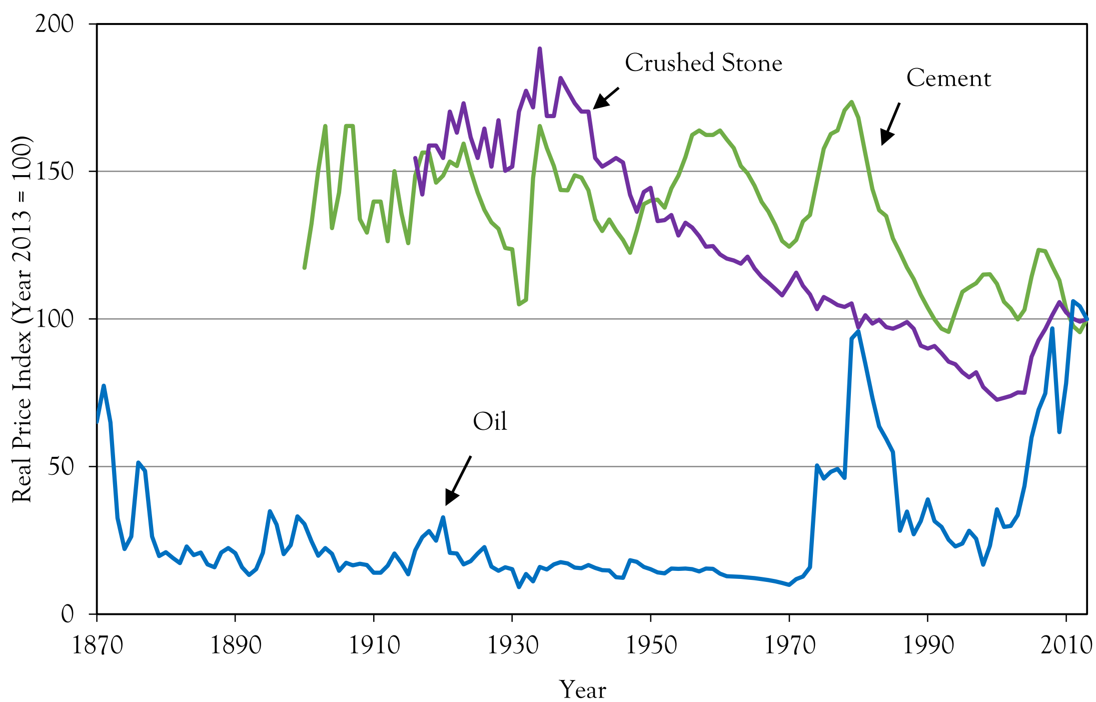


Figure 5-4. Historical real-price for cement, crushed stone, and oil with 2013 as the base year.

Constituent Projection Model

Similar to the previous section, an ADF test is conducted for Case 2, the most appropriate model for each time-series. Table 5-3 presents the results from the ADF test for cement and crushed stone, where again a test statistic greater than the critical value suggests that a unit-root exists.. Unlike the crushed stone time-series with a test statistically significantly greater than even the 10% critical value, the cement time-series can be classified as non-stationary using 11 lags while stationary with only 1 lag. In order to better understand if the cement time-series is non-stationary or slowly mean-reverting, parameters are estimated for an ARIMA *(1,0, 0)* process. The estimated autoregressive coefficient corresponds to a rate of reversion of 9.1 years^{-1} (ρ = 0.89), suggesting that a slow, yet present, mean-reversion is taking place.

Table 5-3. ADF test results for USGS data for lag orders selected by BIC and AIC criteria, where a test statistic greater than the critical value suggests that a unit-root exists. Starred values are less than 5% critical values.

No Difference and ADF Case 2 $\Delta Y_t = \gamma Y_{t-1} + \beta + \varepsilon_t$						
Commodity	Number of lags	Selecting Criteria	Test statistic	1% Critical Value	5% Critical Value	10% Critical Value
Cement	1	BIC	-2.881*	-2.361	-1.659	-1.289
Cement	11	AIC	-1.109	-2.369	-1.662	-1.291
Crushed Stone	4	BIC, AIC	-0.715	-2.367	-1.661	-1.291

Parameters for each constituent model are estimated with 2013 as the base year as was shown in Figure 5-4. Given the characteristics of the crushed stone time-series, a geometric Brownian motion (GBM) process is selected with the following parameter estimates:

$$\text{Crushed Stone: } P_t = P_{t-1}e^{(-0.0045+N(0,0.047))} \tag{5.22}$$

where P_t is the price in year t, P_{t-1} is the price in year t-1, and N (μ, σ) is a normal distribution with a mean of μ and a standard deviation of σ. As for cement, an ARIMA *(1, 0, 0)* is estimated as follows:

$$\text{Cement: } P_t = 0.89P_{t-1} + 14.3 + N\ (0,9.5) \tag{5.23}$$

Oil Projection Model

To estimate the parameters of equations 5.17a-c, a Kalman filter is used, which uses input data to estimate the 'optimal' system state. A Kalman filter operates recursively, estimating parameters using a maximum likelihood (ML) estimator. After running the model, it became quite clear that many of the p-values for the final values and/or the coefficients of the state space variables were quite large. As such, a simple quadratic mean-reverting process is estimated instead via OLS regression. It should be noted the state space model and OLS regression were compared and resulted in very similar price projection trends. The R^2 for this particular model is 0.84 with the following parameter estimates:

$$Log(P_t) = 65.1 - 0.067t + 1.75 * 10^{-5}t^2 + 0.82Log(P_{t-1}) + N\ (0,0.10) \qquad (5.24)$$

The above model leads to an expected increase in real oil prices twice their 2013 levels by 2025. In order to account for the model potentially overestimating future costs, a price cap of 2.4 times the 2013 real-price of oil is implemented, which is consistent with what the U.S. Energy Information Administration (EIA) considers as its "high" price scenario by 2040 (Conti 2015). It should be emphasized that because of the long-run price equilibrium estimated, where the coefficient in front of the price of oil is much less than one, some of the concerns with the oil projection model are muted.

Step 3: Project the future price of paving materials

In the previous section, a set of price projection models have been developed for the constituents that have a long-run price trend with asphalt and concrete. The last step is to integrate those constituent models within the long-term price equilibrium for asphalt and concrete. Equations 5.25a-e summarizes the five key equations listed throughout the balance of this paper:

$$P_{Concrete,t} = 1.41P_{Crushed\ Stone,t} + 0.20P_{Oil,t} - 61.6 + N(0,3.5) \qquad (5.25a)$$

$$P_{Asphalt,t} = 0.51P_{Crushed\ Stone,t} + 0.44P_{cement,t} + 5.3 + N(0,1.6) \qquad (5.25b)$$

$$P_{Crushed\ Stone,t} = P_t = P_{t-1}e^{(-0.0045+N(0,0.047))} \qquad (5.25c)$$

$$P_{cement,t} = P_t = 0.89P_{t-1} + 14.3 + N\ (0, 9.5) \qquad (5.25d)$$

$$Log(P_t) = 65.1 - 0.067t + 1.75 * 10^{-5}t^2 + 0.82Log(P_{t-1}) + N\ (0,0.10) \qquad (5.25e)$$

Future prices of asphalt and concrete are subsequently simulated thousands of times over the next 40 years to estimate the mean, 5th percentile, and 95th percentile projected price in each year, as shown in Figure 5-5. Interestingly, although future expected prices do not differ greatly between the two models, expected volatilities stepping into the future are significantly different.

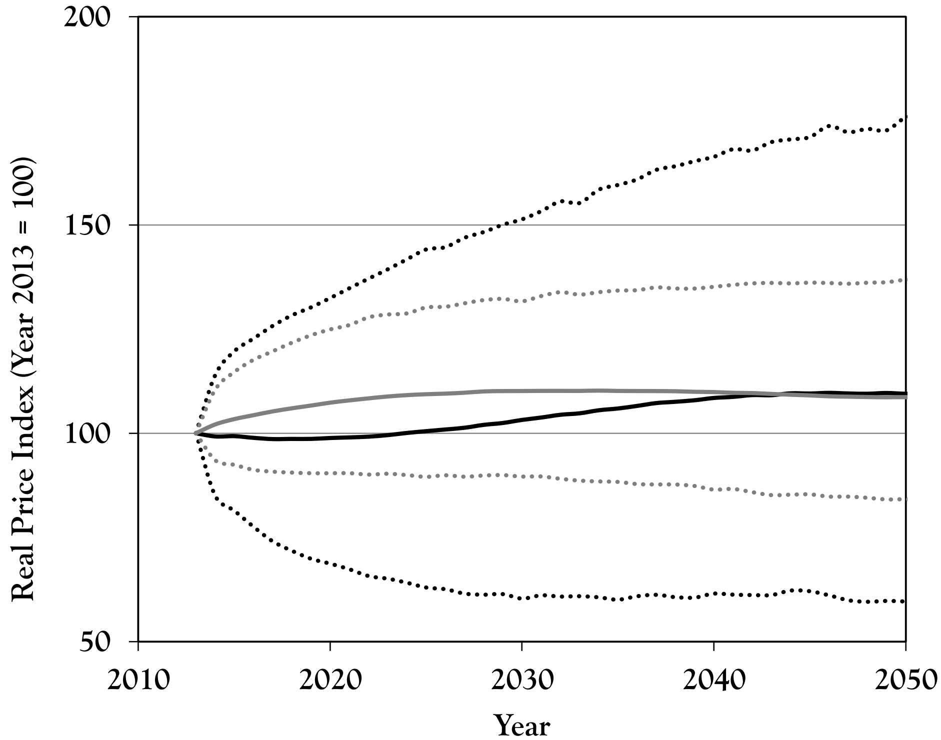


Figure 5-5. Probabilistic real-price projection for concrete (gray) and asphalt (black). Dashed lines represent the 5th/95th percentile of the forecasts and solid lines represent the mean expected price.

Step 4: Validate Performance of Model Relative to Current Practice

Due to the recognized uncertainty in deriving an effective price model, especially in the case of oil, it is pertinent to characterize how well the selected concrete and asphalt model would have historically performed. Out-of-sample price forecasts are conducted between 1985 and 2000 using the established approach in this paper. Model fidelity is measured using a traditional deterministic metric, the MAPE, and a probabilistic metric that tracks the frequency future forecasts fall within the forecasted prediction index (PI). Since current practice (future real prices are constant) ignores uncertainty, the former metric can only be used to benchmark the relative performance of the proposed hybrid approach. It is important to clarify that data made available for constituents after the year of the out-of-sample forecasts are excluded in the model selection and parameter estimation process. Therefore, data used for parameter estimation could be viewed as the 'training' set while data available after the year of the out-of-sample forecast can be seen as the 'validation' set.

Figure 5-6 presents the MAPE of the established approach relative to current practice. The hybrid projection approach performs no worse and generally better than current practice for asphalt. As for concrete, the proposed model only performs better after a decade. Evaluating the results in terms of the MAPE, however, undermines the true contribution of this work. Figure 5-7 presents the frequency that actual asphalt and concrete prices fell within the hypothesized 75th and 90th prediction intervals (PI). Values that fall outside of the dashed lines reject the null hypothesis via a one sample binomial test (at a 5% level of significance) that the measured frequency is the same as the theoretical PI. For a PI of 75%, both the asphalt and concrete models generally fall within the lower and upper limits, suggesting the model provides a good description of uncertainty when excluding the tails of the distribution. For a PI of 90%, the concrete model generally captures all actual realizations of the future; results for the asphalt model, however, indicate that the tails of the distribution do not capture the full volatility in asphalt prices.

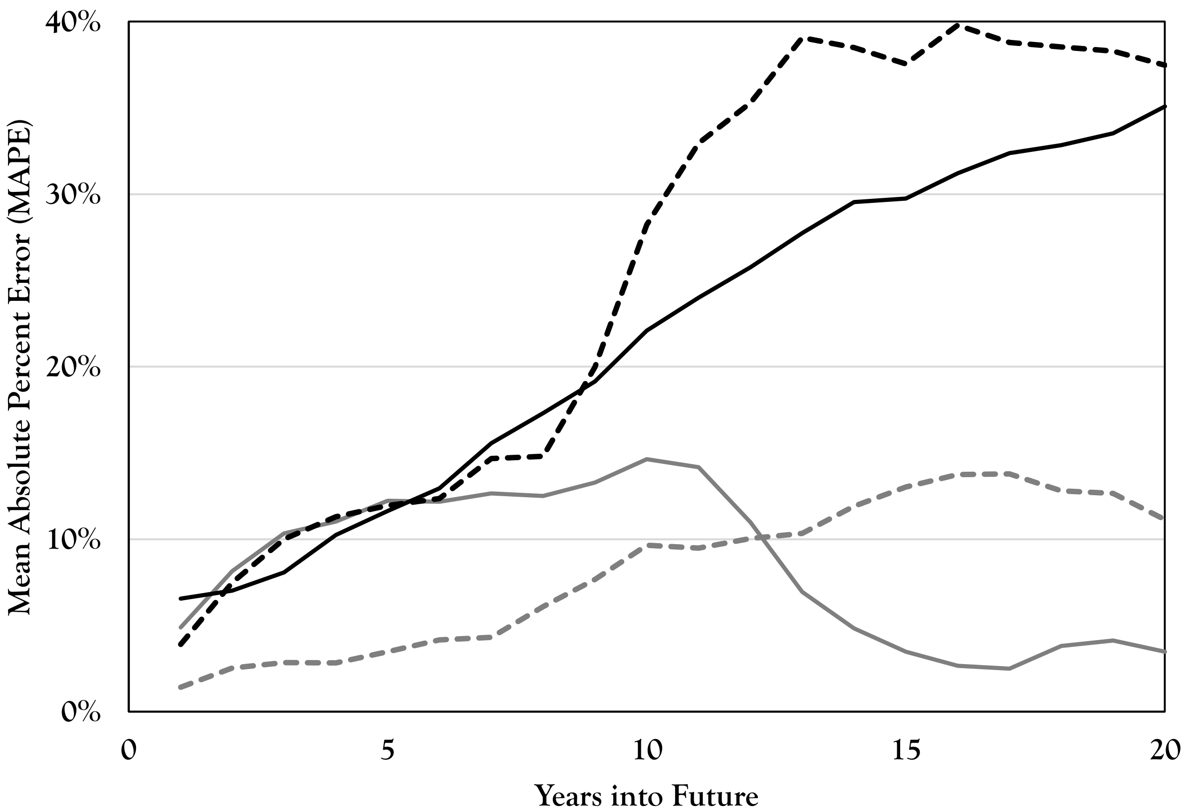


Figure 5-6. MAPE of the asphalt (black) and concrete (grey) time-series using a) the established price model in this thesis (solid color) and b) a model where real prices remain constant (dashed).

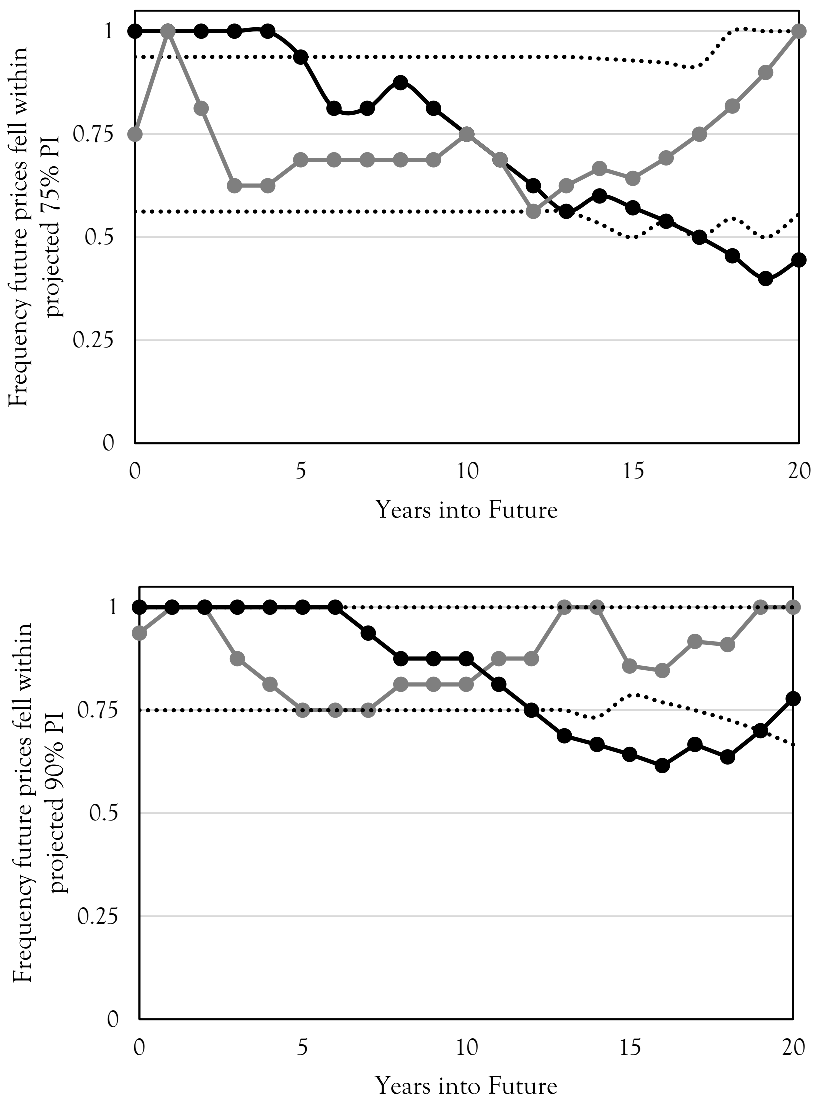


Figure 5-7. Frequency that the out-of-sample forecasts for asphalt (black) and concrete (grey) fall within the 75th (top) and 90th (bottom) percentile prediction intervals. Dashed lines represent the upper and lower bounds of the null hypothesis that the sample frequency is the same as the prediction interval per a one sample binomial test at a 5% significance.

Conclusions

Over the last decade, pavement management systems have grown in sophistication and can now take into account a range of sources of variation that exist in the decision-making process. Unfortunately, these frameworks do not account for possible differential future changes in the cost of construction inputs. In part, this is because studies to date have neither evaluated the performance of forecasting models over multiple decades nor compared performance using a probabilistic metric.

This chapter presents a first of its kind case study that evaluates the fidelity of probabilistic price projections within a context of limited data availability and over extended time-horizons. The results from the case study demonstrate that, in general, the proposed model performs similar to current practice in a deterministic sense. However, the real contribution of the proposed approach is that it does an excellent job of representing and predicting the volatility of these commodities. As such, the models described here not only outperform current practice on average in the long-run, but also easily support a probabilistic, risk-based paradigm within pavement management systems that will be presented in full in Chapter 7.

III. ALLOCATION POLICY

SYNTHESIS

Part III is composed of a single chapter that details the allocation algorithm for the stochastic simulation model in Part IV. A simple greedy heuristic algorithm is proposed that can scale computationally for realistic problems sizes of interest for the pavement management community. It can also make decisions sequentially over time, an important aspect for estimating the value of real options in such systems. Although simple and intuitive, it is important to understand the properties of this particular technique for pavement management problems. Unfortunately, deriving the fidelity of such algorithms can be quite difficult, and so this section estimates it by comparing its solution to that of a recursive divide and conquer algorithm for a range of small, deterministic problems. The latter technique will search across the decision space until it finds the globally optimal solution for the problem at hand.

Across the case studies, the greedy technique proposed falls within 2% of the globally optimal solution 96% the time. These results strongly indicate that the greedy heuristic for the particular set of constraints, objectives, and system model set forth in this research provides a high fidelity solution with low computational complexity. Therefore, this dissertation foregoes alternative algorithmic approaches for sequential decision-making under uncertainty that are discussed earlier in the chapter. Such methods could be important, however, should future research implement a system model or set of constraints that caused the greedy heuristic to drift far from the global optimum.

CHAPTER 6: NETWORK-LEVEL ALLOCATION POLICY

Sequential decision-making under uncertainty

As planning agencies continue to search for ways to maintain roadway networks with limited financial resources, it is important that pavement management systems embed near-optimal allocation policies when prioritizing alternative investments. Because the decision-making process is subject to uncertainty, the optimal maintenance policy will evolve as uncertainty unfolds over time. As a result, a critical element of these allocation policies is their ability to adapt with future conditions.

Amongst the existing literature, as discussed in Chapter 2, a significant portion of academic research assume a deterministic future. These papers, consequently, search for a globally optimal allocation plan for all years across the analysis period at once. This static approach to pavement management, with of course small nuances, can also be found across many of the recent probabilistic approaches of today (Chootinan, Chen et al. 2006; Wu and Flintsch 2009). In the case of Wu and Flintsch (2009), for example, a highly conservative maintenance plan is proposed to reduce the risk of exceeding an uncertain future budget. A consequence, however, is that although the fixed maintenance policy has a low risk of cost overruns over the prescribed analysis period, the proposed solution cannot adapt should the future available budget not follow a pessimistic path. Thus, it is likely that the risk-averse solution has a lower expected performance than an allocation policy that made decisions sequentially, even if not optimally, over time.

Having said the above, several studies do correctly assume that the optimal maintenance policy of pavement networks should be structured as a sequential decision problem (Kuhn 2012; Yeo, Yoon et al. 2013; Zhang, Keoleian et al. 2013). These papers, although not explicitly considering uncertainty for exogenous information beyond pavement deterioration, utilize Bellman's principal of optimality to structure a recursive dynamic program (DP) to find a near-optimal allocation policy for roadway systems (Yeo, Yoon et al. 2013). The models generally follow a two-stage bottom-up approach to minimize total cost to the agency and users, where in the first stage the best action is found for each pavement segment via a recursive DP and in the second stage a knapsack technique is used to apply allocation funds to the most promising projects. Mathematically, the first stage of the two-stage bottom-up solution is of the general form:

$$V_{n,t}(a^*_{n,t}) = \min_{a_{n,t} \in A_{n,t}} C_{n,t}(a^*_{n,t}) + \alpha \mathrm{E}\left[V_{n,t+1}\left(S_{n,t+1}\left(S_{n,t}, a^*_{n,t}\right)\right)\right] \tag{6.1a}$$

$$V_{n,t}(a_{n,t} = 0) = \alpha \mathrm{E}\left[V_{n,t+1}\left(S_{n,t+1}\left(S_{n,t}, a_{n,t} = 0\right)\right)\right] \tag{6.1b}$$

$V_{n,t}$ is the total expected cost of an action, $a_{n,t}$, on the n^{th} segment in year t. The cost of an action is a function of its immediate agency cost, $C_{n,t}$, and expected cost-to-go to the agency and user, $V_{i,t+1}$, assuming that in all future years the agency follows an optimal policy for each segment. The optimal action is a function of the current condition/state of a pavement segment, $S_{n,t}$, and it is assumed that future costs should be discounted at some rate, α. For the most part, current approaches only store the total expected cost of two decisions from the subset of all actions available, $A_{n,t}$: the cost of the optimal action, $a^*_{n,t}$, and the cost to do nothing, $a_{n,t} = 0$ (Yeo, Yoon et al. 2013). The implication of ignoring the alternative available actions is small should the pavement network be sufficiently large.

The cost minimization problem, as elaborated upon in Chapter 2, is preferred because it leads to a non-trivial maintenance solution in the first stage of the allocation algorithm. More specifically, in a performance maximization framework where there is no resource constraint at the facility-level, the optimal policy for any segment is to apply a maintenance action in all years irrespective of the condition of the roadway. On the other hand, for the cost minimization approach, maintenance actions will only be applied at times where the user cost savings from such treatments would outweigh the cost to the agency. Of course, two problems with framing the problem in the manner is (a) the difficulty in mapping pavement condition to user cost and (b) that planning agencies are more interested in the structural condition and ride quality of pavement assets (Rangaraju, Amirkhanian et al. 2008).

Nevertheless, the second stage of the two-stage bottom-up algorithm follows a knapsack approach. Resources are allocated to the set of actions that minimize total expected costs (TEC_t) moving forward subject to an available budget for the given year (B_t):

$$\min TEC_t = \sum_{n=1}^{N} V_{n,t}(a_{n,t}) \tag{6.2}$$

subject to

$$a_{n,t} \in A_{n,t} = \{a^*_{n,t}, a_{n,t} = 0\} \tag{6.3}$$

$$\sum_{i=1}^{N} C_{n,t}(a_{n,t}) \leq B_t \tag{6.4}$$

The authors of the previously mentioned studies have found that the discussed approach leads to a high fidelity solution for network-level allocation problem (Zhang, Keoleian et al. 2013). Although these research efforts do not explicitly account for the uncertainty beyond pavement deterioration underlying the decision-making process, the concept of sequential decisions made over time is an important element for the real options approach. An important methodological gap that previous research has not fully addressed, however, is the determination of an allocation policy (referred to interchangeably as "decision-rule") that leads to a near-optimal solution for the performance maximization objective.

As a result, the purpose of this chapter is the development of a simple heuristic that provides high-fidelity allocation choices for the performance maximization problem. Such a technique is necessary for realistic network-size problems, deterministic or probabilistic, given the computational complexity of solving high-dimensional problems. A greedy heuristic algorithm for sequential decision-making is proposed in this chapter that overlaps with a similar technique developed by Ouyang and Madanat (2004) but for the cost-minimization problem. The fidelity of the algorithm is measured by comparing its solution for the deterministic maintenance problem to that of a mixed-integer non-linear program (MINLP) solved with a branch and bound (B&B) solver that searches for the global optimum.

Methodology

The methodology section for Chapter 6 is comprised of two sections. First, a MINLP is presented that can be solved via a B&B (e.g., divide and conquer) algorithm. The B&B solver, although computationally expensive, will eventually find the globally optimal allocation policy across a network of pavement facilities for the deterministic problem. As a result, the MINLP acts as the benchmark to characterize the fidelity of the heuristic approach for decision-making. Subsequently, the greedy algorithm is detailed in this chapter, which again overlaps with the work of Ouyang and Madanat (2004) for cost minimization problems. The objective function, which is the same as that discussed in Chapter 4 and Chapter 7, is to minimize traffic-weighted roughness (IRI) of all pavement segments across a roadway network. The two algorithms are, subsequently, implemented in a series of case studies to measure the fidelity of the latter approach.

Mixed-integer non-linear program (MINLP)

Equations 6.5-11 summarize the mixed-integer non-linear program (MINLP) optimization problem for minimizing traffic-weighted IRI across a roadway network. Equation 6.5 states the objective function: minimize total IRI (weighted by traffic volume) of the network over T years and N facilities.

Equations 6.6-8 are the system model, which maps the evolution of the system between year t and $t+1$. Details on the principles of a system model can be found in Chapter 2. Equation 6.6 asserts that the roughness of a pavement segment immediately following a maintenance action is equal to that of a brand new pavement. However, that does not mean that the deterioration rate will be equivalent to a new pavement, as the rate of degradation is not only a function of AADTT and pavement thickness/structural number, but also the age of a pavement, as noted in Equation 6.7. The deterioration models that are integrated into the MINLP and greedy heuristic can be found in Chapter 4. Equation 6.8, the last part of the system model, declares that the degradation level of a pavement at the start of the next year is equal to its immediate post-decision state (Equation 6.6) and rate of deterioration between years (Equation 6.7).

Equations 6.9-11 are the major constraints of the model. Equation 6.9 conditions that no more than one rehabilitation action can be applied to any segment in a given year. Furthermore, Equation 6.10 declares that the decision to apply a maintenance action is a binary choice. Lastly, Equation 6.11 stipulates that expected costs at each year must be less than the budget made available in that year. Definitions for all terms and variables that are part of the MINLP can be found in Table 6-1.

$$\min \sum_{t=0}^{T} \sum_{n=1}^{N} AADT_{n,t} IRI_{n,t} \tag{6.5}$$

subject to

$$IRI_{n,t}^{x} = IRI_{n,t} - \sum_{a=1}^{A} X_{a,n,t}\left(IRI_{n,t} - IRI_{min}\right) \; \forall\, n = 1,2, \dots N \,, \forall\, t = 0,1, \dots T-1 \tag{6.6}$$

$$D(t)_{n,t} = f(SN_{n,t}^{x}, AADT_{n,t}, Age_{n,t}^{x}) \tag{6.7}$$

$$IRI_{n,t+1} = IRI_{n,t}^{x} + D(t)_{n,t} \tag{6.8}$$

$$\sum_{a=1}^{A} X_{a,n,t} \leq 1 \qquad \forall\, n = 1,2, \dots N \,, \forall\, t = 0,1, \dots T-1 \tag{6.9}$$

$$X_{a,n,t} \in \{0,1\} \tag{6.10}$$

$$\sum_{n=1}^{N} C_{n,t}(X_{n,t}) \leq B_t \qquad \forall\, t = 0,1, \dots T-1 \tag{6.11}$$

Table 6-1. Definition of all variables that are part of the MINLP.

Variable	Meaning
n	Index of n^{th} pavement segment across a roadway network
t	Discretized time interval
a	Index of maintenance action applied to n^{th} segment in year t
$AADT_{n,t}$	Average annual daily traffic (AADT) for the n^{th} segment in year t
$IRI_{n,t}$	International roughness index (IRI) value for the n^{th} segment prior to a decision in year t
$IRI_{n,t}^{x}$	The immediate post-decision IRI of the n^{th} segment in year t
IRI_{min}	The minimum IRI for a new or rehabilitated segment
$IRI_{n,t+1}$	International roughness index (IRI) value for the n^{th} segment at the start of year $t+1$
$X_{a,n,t}$	Decision variable to apply rehabilitation action a to segment n in year t
$D(t)_{n,t}$	Degradation rate of n^{th} pavement segment between year t and $t+1$
$SN_{n,t}^{x}$	The immediate post-decision thickness/SN of the n^{th} segment in year t
$AADTT_{n,t}$	Average annual daily truck traffic (AADTT) for the n^{th} segment in year t
$Age_{n,t}^{x}$	The immediate post-decision age of the n^{th} segment in year t
$C_{n,t}(X_{n,t})$	Function that maps the agency cost of the decisions made for segment n in year t
B_t	Available annual budget for network in year t

As mentioned previously, the MINLP can be solved using a divide and conquer optimization algorithm to search for the global optimum of the deterministic problem. Because there is no guarantee regarding how long it will take the solver to find the globally optimal solution, however, the tolerance of the algorithm is relaxed such that it stops searching when it is within at least 2% of the best solution.

Greedy heuristic

This dissertation proposes a heuristic approach for sequential decision-making that overlaps with an earlier algorithm developed by Ouyang and Madanat (2004) but now for the performance maximization problem. The algorithm assumes that the two-stage bottom-up technique for pavement management can also lead to a near-optimal policy in performance maximization problems with some amendments. In the first stage, rather than solving a trivial dynamic program for each pavement facility, an alternative calculation is proposed to measure the efficacy of a given rehabilitation action. Specifically, at the start of each year, the first stage of the algorithm calculates the expected difference in pavement degradation between the present year, t^*, and the end of the analysis period, T, should (a) only the k^{th} maintenance action be applied at year t^* and (b) no maintenance action, k=0, be applied between t^* and T. Figure 6-1 depicts the previous description, with accompanying definitions of terms provided in Table 6-3.

Table **6-2** offers a more detailed description of the algorithm proposed for the first stage of the performance maximization problem. A potential drawback of the below formulation is that the algorithm does not consider the path dependence of allocation choices over time. One alternative formulation that this dissertation considered, as a result, was combining the first and second stages of the algorithm as an adaptive dynamic program (ADP). Such an approach could account for the path dependence of decisions and simultaneously cope with the "curse of dimensionality" (Powell 2007). However, the ADP technique is unnecessary should the below formulation lead to a near-optimal solution.

Table 6-2. First stage of two-stage bottom-up algorithm for the network-level performance maximization problem.

For n = 1 to N

  Calculate the integral of E[$D_t(a_{t^*}^{k=0})$] between year t^* and T

    For k = 1 to A

      Calculate the integral of E[$D_t(a_{t^*}^{k})$] between year t^* and T

      Compute $\Delta D(a_{t^*}^{k})$ per Figure 6-1

      Store estimate of $\Delta D(a_{t^*}^{k})$ and pass on to second stage of the algorithm

    Next k

Next n

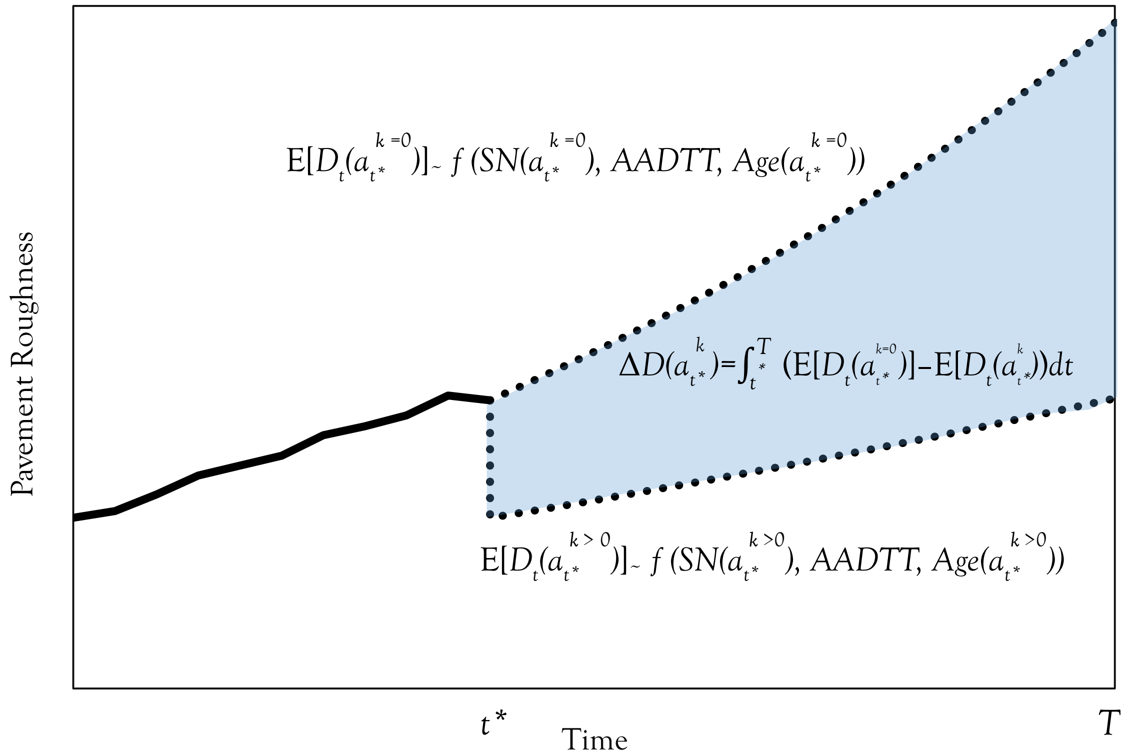


Figure 6-1. Schematic of greedy algorithm proposed for first stage of the performance maximization algorithm.

Table 6-3. Definition of parameters for greedy heuristic for n^{th} pavement segment.

Variable	Meaning
t	Discretized time interval
t^*	Specific time interval when allocation decision is made
T	End of analysis period
$a_{t^*}^{k}$	Counter of k^{th} possible action that can be applied to segment n at t^*. k=0 refers to the decision to "do nothing"
$E[D_t]$	The expected roughness level of a pavement in all future years under the assumption that the k^{th} activity is applied at t^*.
$SN(a_{t^*}^{k})$	Thickness/(SN) of the n^{th} segment following action k in year t^*. Structural number is assumed to be constant between year t^* and T following the application of the k^{th} decision
$AADTT$	Average annual daily truck traffic (AADTT) for the n^{th}
$Age(a_{t^*}^{k})$	Age of the n^{th} segment between t^* and T if only the k^{th} action occurs at t^*
$\Delta D(a_{t^*}^{k})$	Calculated benefit per Table 6-2 and Figure 6-1 for the k^{th} action for segment n

The outputs of the first stage of the algorithm are passed on to the second stage, which follows a traditional knapsack approach. Because the goal of this thesis is to search for an allocation decision in year t^* that causes the system to minimize traffic-weighted IRI over the analysis period, the objective function is set to maximize the summation of the product of roadway volume and the expected performance benefit of an action per the first stage of the algorithm (Equation 6.12). Constraints are similar to that of the MINLP, where only one maintenance event, $X_{k,n}$, can be applied to a segment at a given time period (Equation 6.13), the decision to apply an action is binary (Equation 6.14), and the total cost of the final actions selected, X_n, for all segments, $C_n(X_n)$, cannot exceed the available budget (Equation 6.15). The one obvious difference, however, is that constraints must only be satisfied in the present year, t^*, rather than across all years, T, in the MINLP.

$$\max \sum_{n=1}^{N}\sum_{k=1}^{A} AADT_n\, \Delta D_n(a_{t^*}^{k}) X_{k,n} \tag{6.12}$$

subject to

$$\sum_{k=1}^{A} X_{k,n} \leq 1 \qquad \forall\, n = 1,2, \ldots N \tag{6.13}$$

$$X_{k,n} \in \{0,1\} \tag{6.14}$$

$$\sum_{n=1}^{N} C_n(X_n) \leq B_{t^*} \tag{6.15}$$

Case study analyses and findings

Table 6-4 provides an overview of the context(s) that the MINLP and two-stage bottom-up algorithm are implemented in, with the goal of measuring the fidelity of the solution for the latter. The state of Virginia's DOT currently maintains 3,000 pavement segments that traverse more than 4,000 lane-miles. For this particular chapter, both algorithms search for an optimal/near-optimal allocation policy to maintain six randomly selected segments from the available population over a 25-year analysis period. For each randomly generated scenario, the problem is solved for a budget constraint of \$300k/year, enough for two minor maintenance actions or a single major maintenance in a given year, and \$600k/year, which can accommodate a single reconstruction at any point in time. This research solves the described problem 200 separate iterations with the two algorithms.

Table 6-4. Summary of case study inputs

Input	Value
Number of Segments (n)	6
Analysis Period (T)	25
Budget (B_t)	\$300k-\$600k
$SN_{n,t=0}$	3.2-13.8
$AADT_{n,t=0}$	7,400-213,400
$AADTT_{n,t=0}$	210-15,270
$Age_{n,t=0}$	0-60
$IRI_{n,t=0}$	40-321

To generate a sufficient sample to comment on the overall fidelity of the two-stage bottom-up algorithm, the optimization problem only considers three alternative maintenance actions: a 2" mill and fill, a 4" thick overlay, and an 8" pavement reconstruction. Expected costs for each of these maintenance actions for a 1-mile long, 2-lane wide pavement, are based upon cost data collected by the state DOT. Table 6-5 summarizes the total cost of each action and immediate impact of each action (a^k) on the age ($Age^x_{n,t}$) and thickness ($Thick^x_{n,t}$) of a pavement segment. As mentioned in previous sections, the option to do nothing is referenced as $a^{k=0}$.

Table 6-5. Summary of decision-variables for case study optimization.

	Maintenance Action (a^k)			
Input	**k=0**	**k=1**	**k=2**	**k=3**
Cost of action (\$), $C_{n,t}(X_{n,t})$	0	\$132k	\$209k	\$529k
Post-decision Age (yrs.), $Age^x_{n,t}$	$Age_{n,t}$	$Age_{n,t}$	$Age_{n,t}$	0
Post-decision (x) Thickness (in.), $Thick^x_{n,t}$	$Thick_{n,t}$	$Thick_{n,t}$	$Thick_{n,t}+4$	8

Figure 6-2 summarizes the performance of the greedy heuristic relative to the MINLP across all permutations. The results presented in Figure 6-2 speak highly to the fidelity of the algorithm proposed in this dissertation. Approximately 96% of the solutions from the simple heuristic fall within 2% of the global optimum. Interestingly, across many of the simulations the heuristic's locally optimal solution actually outperforms the global optimum. Of course, such a result is a byproduct of the 2% tolerance placed upon the latter algorithm.

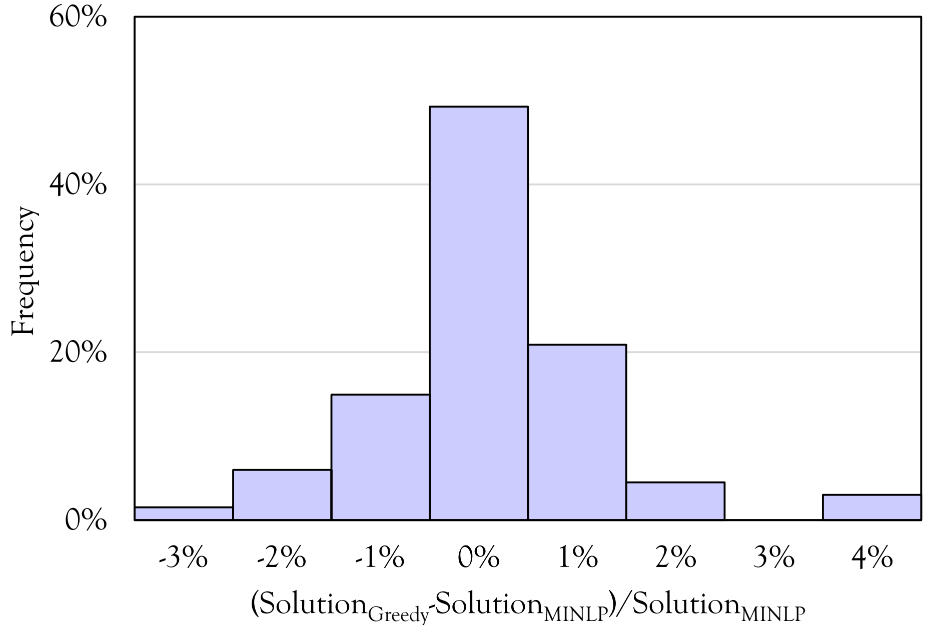


Figure 6-2. Relative difference between MINLP and two-stage bottom-up greedy heuristic across the iterations.

Figure 6-3 illustrates the reduction in computational complexity for the greedy heuristic relative to the MINLP. The two-stage bottom-up algorithm proposed in this dissertation arrives to its solution in less than 1 second, on average, for the 6 pavement, 25-year analysis period. On the other hand, the MINLP takes anywhere from 2-30 minutes to solve the exact same allocation problem. Such a result is important to comment on the feasibility of the proposed heuristic to scale to realistic size network-level problems.

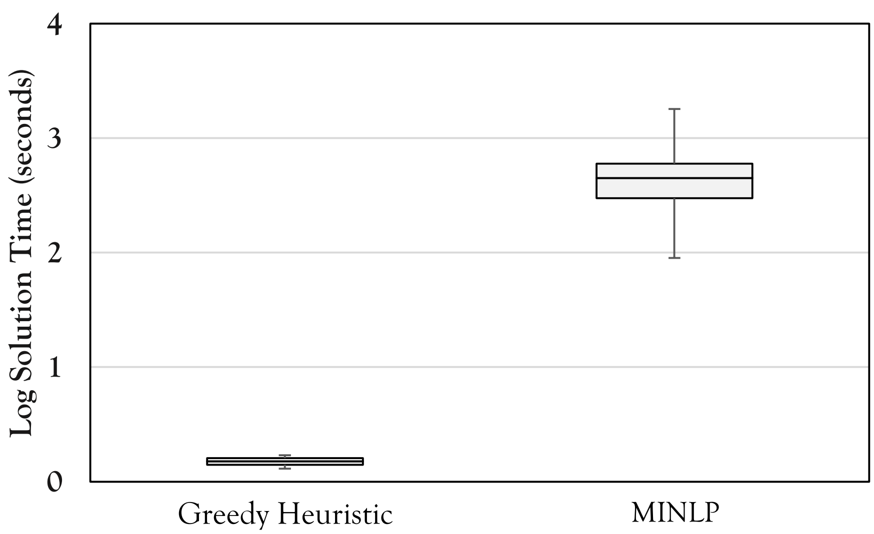


Figure 6-3. Computational time to solve the 6 pavement, 25-year analysis period problem per the MINLP and two-stage bottom-up greedy heuristic across the iterations.

Conclusions

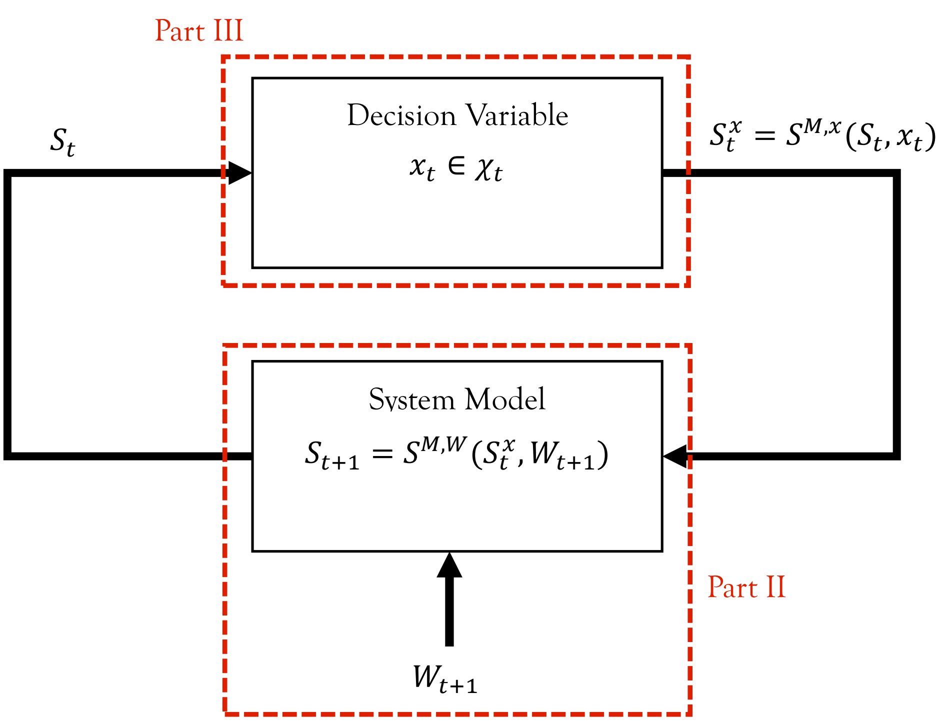
The preceding analysis provides a measure of the fidelity of the two-stage bottom-up greedy heuristic algorithm proposed in this research. Across the small deterministic case studies, the greedy algorithm solution is within 2% of the global optimum for 96% of the iterations. This result demonstrates that the greedy algorithm is an effective mechanism for decision-making with the additional benefit of being able to allow decisions to change in the probabilistic context. The greedy algorithm also solves the small, deterministic problem in less than 1 second across all iterations. This outcome, consequently, suggests that the algorithm presented has reduced computational complexity as compared to alternative techniques, allowing the approach to solve large-scale pavement management problems (such as the one to be presented in Chapter 7). The findings of this chapter, hence, provide robust evidence that the algorithmic approach proposed in this dissertation offers a high-fidelity solution for the particular network-level performance maximization problem of interest.

With that said, the greedy algorithm described is potentially susceptible to sub-optimal allocation decisions should it be applied for a problem under a different set of constraints or with a starkly different system model. After all, even though the algorithm can be viewed as an *augmented* greedy technique due to its ability to *partially* account for the future, the algorithm is nevertheless shortsighted, as the implication of future decisions cannot be captured. Should such a scenario cause the greedy algorithm to drift away from the optimal allocation policy, researchers should evaluate alternative methods to improve the fidelity of the proposed algorithm.

IV. STOCHASTIC MODEL

SYNTHESIS

Part IV integrates the results of Part II and Part III within a stochastic simulation model to estimate the value of incorporating concrete-based technologies for the maintenance of pavement networks. The complete model is applied to the Commonwealth of Virginia's interstate system, whose DOT currently preserve their roadway network with asphalt-based treatments only. Results from the analysis demonstrate that VDOT is able to achieve its desired performance goals, on average, at a cost reduction of 10% by incorporating multiple paving materials as part of their pavement management strategy. The expected difference stems from the availability of concrete-based designs to act as an insurance policy at moments of elevated asphalt prices and stable/suppressed concrete maintenance costs. The results for the case study analysis hold true even in the iso-performance case, where the degradation models for both materials are equivalent.



7. CHAPTER 7: THE INCORPORATION OF CONCRETE-TECHNOLOGIES TO MITIGATE DOWNSIDE RISK

Background on the Virginia interstate system

Charged with the task of maintaining an extensive roadway system that spans nearly 60,000 miles, the Virginia Department of Transportation (VDOT) continues to search for new techniques to preserve the Commonwealth's aging roadway network (VDOT 2016). With an annual fiscal budget that exceeds $6 billion, the long-term performance of Virginia's roadway system is not only a concern for transportation officials but also the policy-makers who appropriate available tax funds to the agency amongst competing public needs (VDOT 2016). In fact, only spending on education and healthcare has exceeded transportation expenditures over the last decade within the Commonwealth (U.S. Census 2013). As a result, the purpose of this chapter is to assess the implication of the status-quo policy for highway maintenance by VDOT and quantify the potential value of incorporating concrete-based maintenance alternatives as part of their pavement management strategy.

This chapter estimates the long-term performance of VDOT's interstate system, which constitutes an important 2% of the total miles that VDOT maintains and preserves. Figure 7-1 and Figure 7-2 summarize the current state of the interstate system within the Commonwealth with respect to (a) traffic volume and (b) roadway condition, measured in terms of the international roughness index (IRI). As was mentioned previously, DOTs generally prioritize available resources, either implicitly or explicitly, towards roadways subject to higher traffic volumes. As can be noted in the figures below, within Virginia, pavement segments that are in a "good" state of repair are generally located around populous city centers (i.e., Washington, D.C., Arlington, and Richmond) as well as major thruways (i.e., Interstate-95). These figures support the notion that the minimization of IRI, weighted by traffic volume, across the network over a designated analysis period (AP) is an objective function that corresponds well to the current decision-making process for VDOT.

The following sections proceed by first providing an overview of the techniques typically used by researchers to assess the value of a real option. Subsequently, this chapter discusses a nuanced valuation approach for the performance maximization problem prior to presenting case study results.

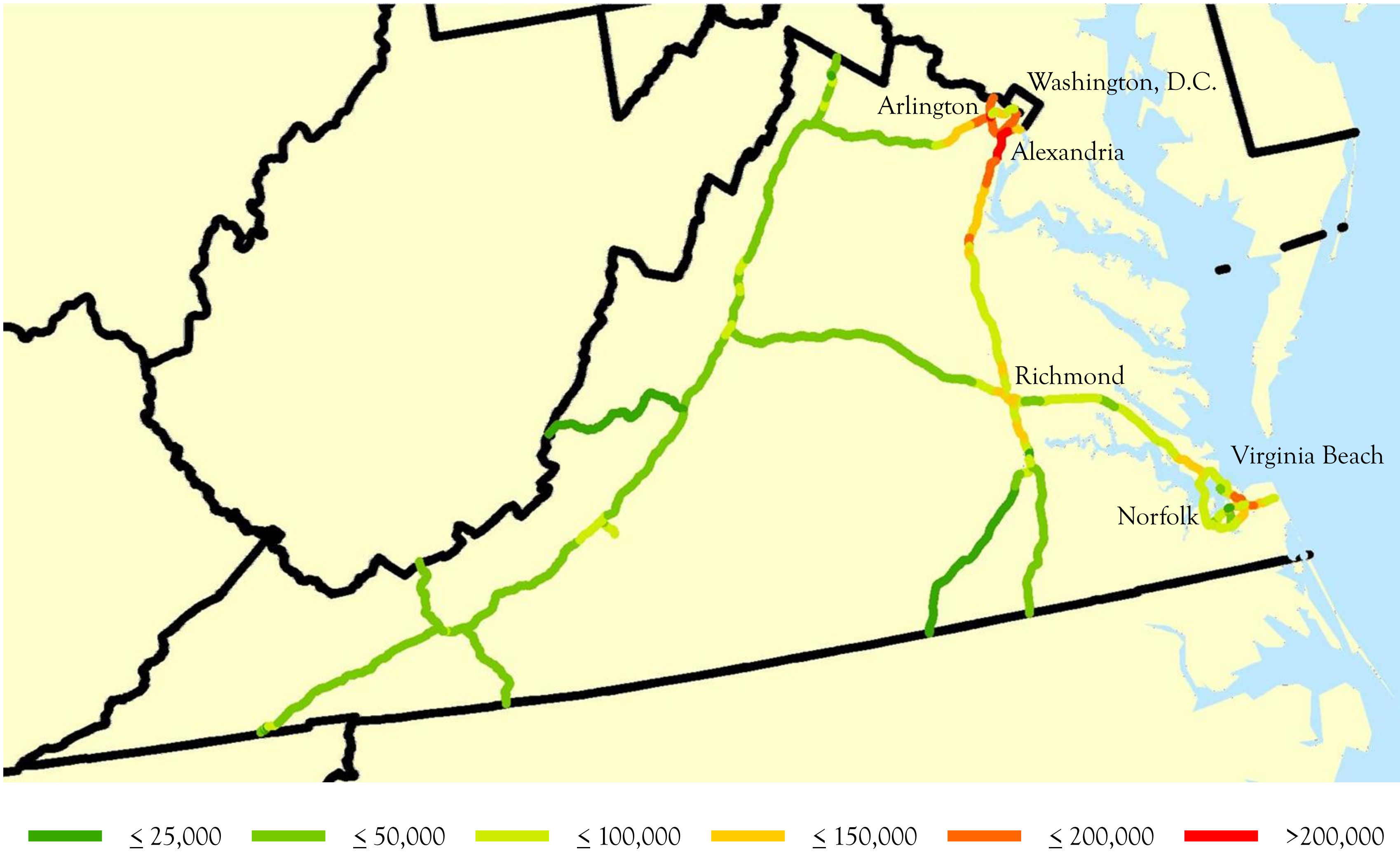


Figure 7-1. Average annual daily two-way traffic (AADT) of roadway segments within the Commonwealth of Virginia as of 2014.

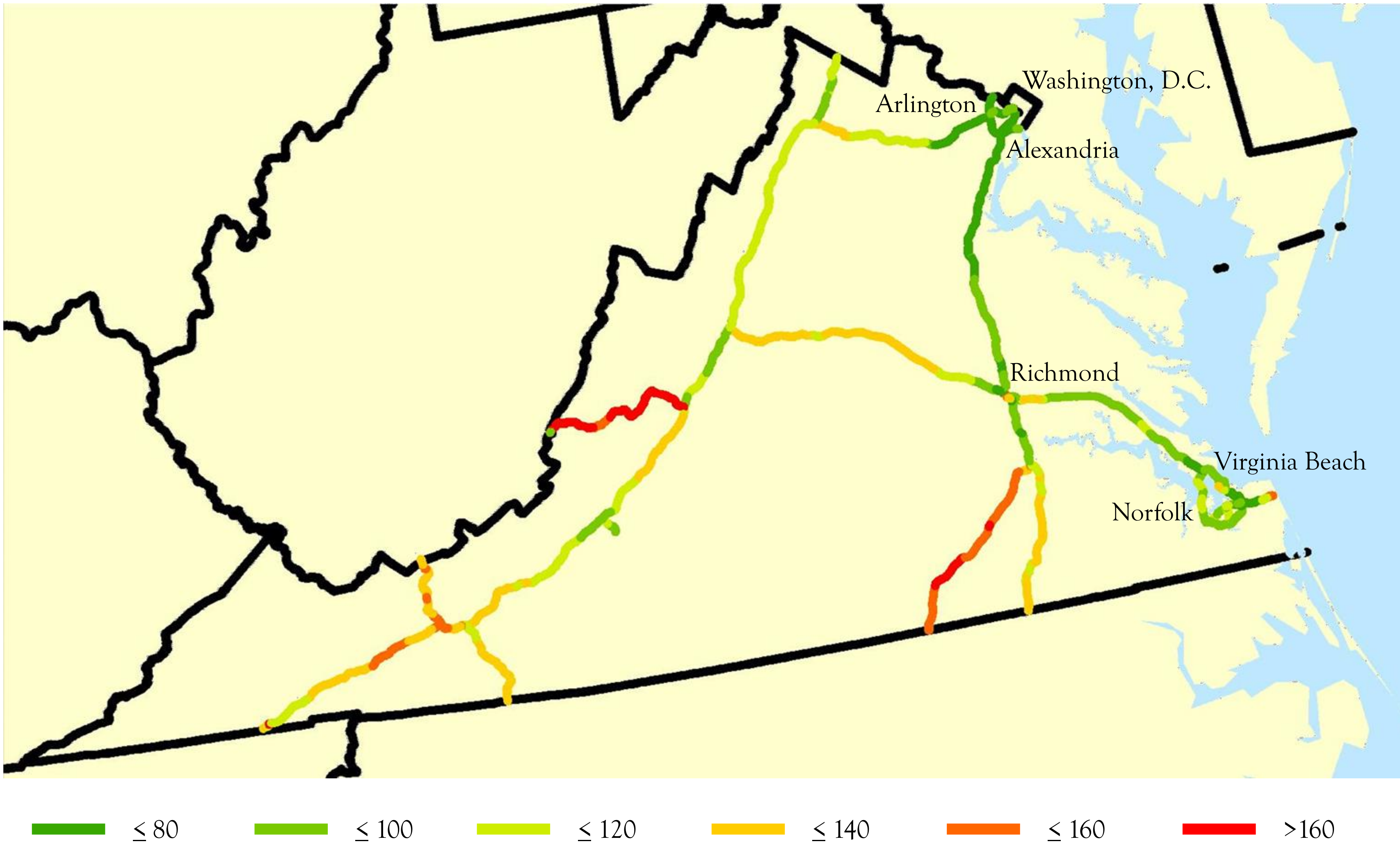


Figure 7-2. Average two-way IRI (inches/mile) of roadway segments within the Commonwealth of Virginia as of 2014.

Valuation of financial and real options

In the field of financial derivatives, an option is the right, though not the obligation, to buy (referred to as a "call") or sell (referred to as a "put") an asset for a pre-determined "strike" price at any point prior to its expiration (Wang 2005). The concept of real options, which was pioneered by Stewart Myers over 40 years ago, extends these principles for the strategic planning of large-scale projects (Lin, de Weck et al. 2013; Myers 1984). More specifically, real options are sources of flexibility embedded within complex engineering systems that managers have the right to call upon at a future date in time. These sources of flexibility oftentimes come at some specified initial-cost, similar to financial options, and may also require a "maintenance" cost to ensure that the right exists to call upon them in the future (de Neufville and Scholtes 2011). Unlike financial derivatives, however, a real option may not (and frequently will not) expire.

The types of real options available to a decision-maker can be broadly classified into three types: the ability to change the size of a system, the ability to change its function, and the ability to protect against potential failures (de Neufville and Scholtes 2011). Such real options may be designed "on" the system, typically in the form of managerial decisions (e.g., the decision to abandon a project), or "in" the system through a technological knowledge of the system at hand (Yang 2009). The decision to incorporate concrete-based technologies by VDOT would represent one possible real option "in" the system available to the planning agency.

For the most part, researchers typically construct stochastic simulation models, such as the one developed in this dissertation, to estimate the value of embedding real options within a project/system (Cardin 2011; de Neufville and Scholtes 2011). Such a valuation approach is simple with today's available computing resources, which can easily accommodate thousands of uncertain parameters that underly the decision-making process. Furthermore, such a method does not require restrictions regarding distribution type that one finds in financial option valuation techniques such as the Black Scholes option pricing model (Black and Scholes 1973).

Once a stochastic simulation has been developed, such as the pavement management model per Figure 2-1, Monte Carlo simulations are typically conducted to estimate the distribution of system performance (a) using the conventional, static approach for design and (b) after embedding flexibility into the system. Because decision-makers are usually interested in the present value for a given investment, managers make use of three metrics from the Monte Carlo simulations: expectated net present value (ENPV), the Value at Risk (VaR), and the Value at Gain (VaG) (de Neufville and Scholtes 2011). ENPV represents the sample average of the outcomes for the system over the set of Monte Carlo iterations. Such a metric is particularly useful should the decision-maker be risk-neutral, meaning that one is indifferent between multiple investment choices with the same expected payoff but with different levels of risk. Should a decision-maker exhibit these characteristics, then it would be expected that they would embed the flexible option in their system so long as:

$$ENPV_{with\ flexibility} - ENPV_{without\ flexibility} > 0 \tag{7.1}$$

The above calculation is similar, in many ways, to the traditional approach to estimate the "value of information" in decision analysis (de Neufville 1990). Of course, two issues with ENPV is that (a) it provides no insight regarding the degree to which the option is mitigating downside risk and/or capitalizing on a positive future and (b) decision-makers frequently have a non-linear preference towards more certain investments, even if the expected payoffs are lower (e.g., risk-aversion) (de Neufville 1990). As a result, decision-makers will frequently benefit from plotting the cumulative distribution of outcomes (e.g., "target curve") to have a concise graphical representation of the effect of the real option on system performance. Two particular values researchers are interested in from the target curve are the VaR(α), where there is only α probability that net present value (NPV) will fall below a certain threshold, and VaG(α), the NPV estimate in which there is only α probability that NPV may exceed its value (Brealey et al. 2006). More generally, the VaR and VaG of an investment are two quantile functions of the random variable NPV, x_{NPV}, that can be represented as:

$$\text{Value at Risk}(\alpha) = \inf\{x_{NPV(\alpha)} \in \mathbb{R} : \alpha \leq F_{X_{NPV}}(x_{NPV})\} \tag{7.2}$$

$$\text{Value at Gain}(\alpha) = \inf\{x_{NPV(1-\alpha)} \in \mathbb{R} : 1 - \alpha \leq F_{X_{NPV}}(x_{NPV})\} \tag{7.3}$$

where F_x is the cumulative distribution function for a random variable. Figure 7-3 illustrates an academic example where a decision-maker has two available strategies to carry through with an investment. Alternative 1 should be viewed as the static design choice for the decision-maker, while Alternative 2 embeds flexibility into the system by spending an upfront cost to have the contractual right to abandon the project should the future follow a pessimistic path. As can be noted in Figure 7-3, although the ENPV of the two alternative investement strategies is the same, the VaR and VaG of those same alternatives are quite different. Consequently, should a decision-maker exhibit a non-linear preference towards "safer" investments choices, one would expect that Alternative 2 would be the prefered decision, illustrating that ENPV offers an incomplete picture of the value of flexibility in engineering design.

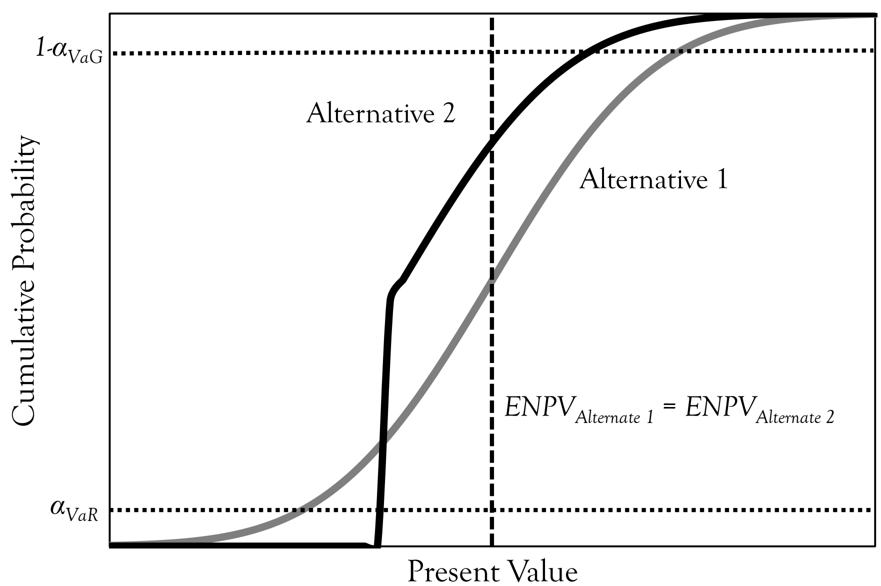


Figure 7-3. Illustrative example of ENPV, VaR, and VaG of two investments

Valuation methodology of this thesis

Estimating the value of incorporating a broader range of pavement materials and designs within VDOT's pavement preservation strategy presents difficulties given that the objective function is to maximize the pavement condition of roadways within the Commonwealth. One potential strategy to overcome this problem would be to transform the condition of roadway segments into a cost to the users of those facilities, as discussed in Chapter 2 and Chapter 6. Of course, there are two issues with framing the outputs of the analysis in terms of an equivalent user cost. First, it is immensely difficult to estimate a reasonable function that maps the condition of pavement segments to user costs. Second, such an output is potentially of little use to a planning agency given that the structural condition/ride quality of pavement facilities is their primary concern (Rangaraju, Amirkhanian et al. 2008). As a result, this dissertation proposes an alternative method to estimate the economic value of this particular source of flexibility within a DOT's pavement management plan.

Suppose that policy-makers within the Commonwealth of Virginia are interested in the following question: what is the minimum annual budget that must be allocated to the interstate system such that, on average, VDOT is able to reach its long-term performance goal(s)? Posing the problem as such makes two important assumptions; namely, that policy-makers are risk-neutral towards their infrastructure investments and that the planning agency will utilize appropriated financial resources in an optimal/near-optimal fashion. Should both assumptions be fulfilled, a simple iterative search algorithm can be constructed that solves for the annual budget (in real dollars), B_t, that is needed by VDOT to, on average, reach its long-term objective(s) both with and without concrete-based technologies made available. The difference in the annual budgets can be viewed as the expected value of the real option proposed in this dissertation. Of course, this calculation does not account for the cost to the agency to attain this source of flexibility, an important consideration should the expected value be small.

Table **7-1** summarizes the search algorithm procedure for this dissertation, which finds the budget level in which the expected traffic-weighted IRI across the network over a fixed analysis period (AP), $\bar{S}_{AP}$, is equal to the long-term goal of the agency, $\bar{S}_0$. To initiate the algorithm, an annual budget, B_t^0, is purposely selected such that $\bar{S}_{AP}$ will be greater than $\bar{S}_0$. To estimate the expected performance of the system for the defined AP and budget level, the model conducts J Monte Carlo simulations using the system model, exogenous information, and allocation policy of Part II and Part II of this thesis. Subsequently, the annual available budget is increased in increments of Δ until the absolute expected difference between current and future system performance, δ, no longer monotonically decreases.

One major drawback of the above valuation method is that it provides no mechanism to characterize whether a change in expected value is a result of the concrete-based technologies allowing the planning agency to mitigate downside risk and/or capitalize on a prosperous future. Therefore, this research generates target curves of average network-level performance both with and without this particular type of real option for the budget-level selected in the status-quo maintenance policy scenario.

Table 7-1. Search algorithm to estimate the value of the real option to incorporate concrete-based technologies in a pavement preservation plan.

Average system performance over AP for j^{th} iteration, $\bar{S}_{AP}^{j} = \sum_{t=0}^{T} \sum_{n=1}^{N} \frac{AADT_{n,t} IRI_{n,t}}{AADT_{n,t}}$

Average system performance over j iterations, $\bar{S}_{AP} = \sum_{j=1}^{J} \bar{S}_{AP}^{j}$

Average system performance goal, $\bar{S}_0$

Initialization:

Set B_t^0 such that $\bar{S}_{AP} < \bar{S}_0$

For i =1 to B

  $B_t^i = B_t^0 + \Delta i$

  For j = 1 to J

    For t = 0 to T

      Per Figure 2-1:

        Allocate resources across network, $x_t \in \chi_t$

        Determine post-decision state of network, $S_t^x = S^{M,x}(S_t, x_t)$

        Generate one sample path (ω_{t+1}^j) of how the system evolves between t and $t+1$

        Determine state of system in year $t+1$, $S_{t+1} = S^{M,W}(S_t^x, W_{t+1})$

      Next t

    Store $\bar{S}_{AP}^{j}$

  Next j

  Calculate $\bar{S}_{AP}$ for B_t^i

  Calculate $\bar{S}_{AP} - \bar{S}_0 = \delta^i$

  If $|\delta^i| > |\delta^{i-1}|$

    Report B_t^{i-1}

    Output Monte Carlo simulations for B_t^{i-1}

    Exit For loop

  Else End If statement

Next n

Summary of case studies

The purpose of this chapter is to quantify the value to a planning agency of deploying concrete-based rehabilitation actions as part of their pavement management strategy. The status-quo approach for many planning agencies, including VDOT, is to utilize only asphalt-based technologies and, furthermore, estimate expected future system-wide performance using a deterministic model. A potential consequence of the static nature of current practice, however, is that it makes VDOT unable to appreciate the value of being able to adapt to an uncertain future. Specifically, the future price of construction commodities, particularly as it relates to asphalt, are highly volatile. Thus, the hypothesis of this dissertation is that concrete-based maintenance alternatives can act as an insurance policy that protects planners at moments in time of spiraling asphalt prices and suppressed concrete construction costs.

One issue in testing this hypothesis is that the pavement deterioration models in Chapter 3 make very different assumptions regarding the pavement degradation process for alternative paving materials. Potentially, the benefit of incorporating concrete-based technologies for preserving a pavement network is not due to the flexibility it offers the decision-maker, but rather a result of the lower rate of degradation for concrete-based designs. As a result, this dissertation conducts the analyses (a) incorporating the pavement deterioration models in Chapter 3 and (b) assuming that concrete-based pavements have the same rate of degradation as asphalt pavements, referred to as the iso-performance instance (per Table 7-2).

Table 7-2. Scenarios analyzed to test hypothesis of dissertation.

Deterministic Approach		
(1)	Degradation Models per Chapter 3	(a) Asphalt (b) Asphalt and Concrete
(2)	Iso-performance pavement degradation	(a) Asphalt (b) Asphalt and Concrete
Stochastic Simulation Model		
(1)	Degradation Models per Chapter 3	(a) Asphalt (b) Asphalt and Concrete
(2)	Iso-performance pavement degradation	(a) Asphalt (b) Asphalt and Concrete

The objective of the case studies defined in Table 7-2 is to determine the budget-level where VDOT is able to maintain their interstate system over a 50-year analysis period such that, on average, traffic-weighted IRI across the network is equal to the current condition of the system (88 in./mi.). To accommodate the computational expense associated with the iterative search algorithm, this section uses large budget increments, Δ, of $5 million followed by $1 million, while the number of Monte

Carlo iterations is close to 100. A larger sample of Monte Carlo iterations is generated once the search algorithm converges to a particular budget level.

The maintenance actions available to the planning agency, as well as their expected costs, are listed in Table 7-3. These cost estimates are based off of an analysis of publically available bid data per the approach in Chapter 4 (Oman Systems Inc., 2016). It is important to note that although there is uncertainty related to the actual cost of construction for each facility at a given point in time, its importance is minimal for a reasonably large pavement network. For illustrative purposes, suppose that one applies the same action to a number of homogenous pavement facilities, n, at any point in time. If the cost of the individual maintenance action is Gaussian distributed and uncorrelated across the facilities, then the expected total cost of applying that action to the entire system scales by n while the standard deviation only increases by $n^{1/2}$. Therefore, if n is sufficiently large, then it is reasonable to assume that the implication of this source of variation is minimal. Hence, this dissertation only incorporates cost uncertainty as it relates to the *evolution* of the average cost of construction per the approach and estimates in Chapter 5.

Table 7-3. Available actions incorporated into simulation model.

Maintenance Type	Name of Action	Applicable Sections	Expected Cost ($/SQY)
Minor Rehabilitation	Diamond Grinding	Concrete top layer only	6.87
Minor Rehabilitation	2” Mill and Fill	Asphalt top layer only	8.03
Major Rehabilitation	4” Asphalt Overlay	Concrete/Asphalt top layer	12.18
Major Rehabilitation	4” Concrete Whitetopping	Concrete/Asphalt top layer	16.67
Reconstruction	New 8” Asphalt	Concrete/Asphalt top layer	26.10
Reconstruction	New 12” Asphalt	Concrete/Asphalt top layer	39.15
Reconstruction	New 8” JPCP	Concrete/Asphalt top layer	33.33
Reconstruction	New 12” JPCP	Concrete/Asphalt top layer	50.00

Results

Deterministic case studies

Table 7-4 synthesizes the findings for the deterministic case studies detailed previously. As can be noted in Table 7-4, the expected annual budget to maintain the network at its current level with the status-quo preservation policy for VDOT is $67 million. Should VDOT incorporate the concrete-based technologies detailed in Table 7-4, however, it is expected that the agency can achieve an equivalent level of performance with a reduced budget of $64 million annually. In other words, the deterministic approach suggests that VDOT would save $3 million annually by integrating concrete-based technologies for the maintenance of their interstate system. These savings in the deterministic case primarily stem from the lower rate of deterioration for concrete pavements per the degradation models of Chapter 3, as the expected savings in the iso-performance scenario is only $1 million per year.

Table 7-4. Results for deterministic case studies.

	Degradation Model Type	Materials Incorporated	Annual Budget (B_t)
(1)	Degradation Models per Chapter 3	(a) Asphalt	$67m/year
		(b) Asphalt and Concrete	$64m/year
		Expected Value of Concrete:	**$3m/year**
(2)	Iso-performance pavement degradation	(a) Asphalt	$67m/year
		(b) Asphalt and Concrete	$66m/year
		Expected Value of Concrete:	**$1m/year**

The previous deterministic analysis, although offering some initial insight for the system at hand, is unable to estimate the value of the flexibility to alter maintenance strategies through the integration of a broader set of materials and designs by VDOT. Specifically, embedding flexibility within engineering systems will typically generate asymmetric returns, as the real option is exercised only at moments in time where it is advantageous to do so (de Neufville and Scholtes 2011). The results for the probabilistic case, therefore, will offer better insight regarding the value of the added flexibility made available to VDOT by incorporating concrete-based pavement technologies for their pavement preservation strategy.

Probabilistic case studies

Table 7-5 summarizes the findings of the probabilistic case studies. Interestingly, the search algorithm converges to the same annual budget of $67 million for the asphalt-only maintenance policy as was found in the deterministic case. Figure 7-4 plots the target curve for this particular scenario, in addition to a policy with an equivalent annual budget where VDOT maintains their interstate system (a) only with concrete-based technologies and (b) utilizing both materials. As a reminder to the reader, a *lower* traffic-weighted IRI is associated with a *higher* performing network, and so a stochastically dominant maintenance strategy would be on the left-hand side of Figure 7-4.

Table 7-5. Results for probabilistic case studies.

	Degradation Model Type	Materials Incorporated	Annual Budget (B_t)
(1)	Degradation Models per Chapter 3	(a) Asphalt	\$67m/year
		(b) Asphalt and Concrete	\$60m/year
		Expected Value of Concrete:	**\$7m/year**
(2)	Iso-performance pavement degradation	(a) Asphalt	\$67m/year
		(b) Asphalt and Concrete	\$63m/year
		Expected Value of Concrete:	**\$4m/year**

As can be noted in Figure 7-4, the expected traffic-weighted IRI of a concrete-only maintenance policy is slightly lower (86 in./mi.) than an asphalt-only pavement preservation strategy (88 in./mi.). Furthermore, because asphalt prices are highly volatile, the traffic-weighted IRI for the asphalt-only preservation policy exhibits a greater amount of dispersion than the concrete-only maintenance alternative. Consequently, the maintenance policy that integrates both materials is able to limit downside risk at moments of spiraling asphalt prices while still being able to capitalize, for the most part, when prices are lower than expectations.

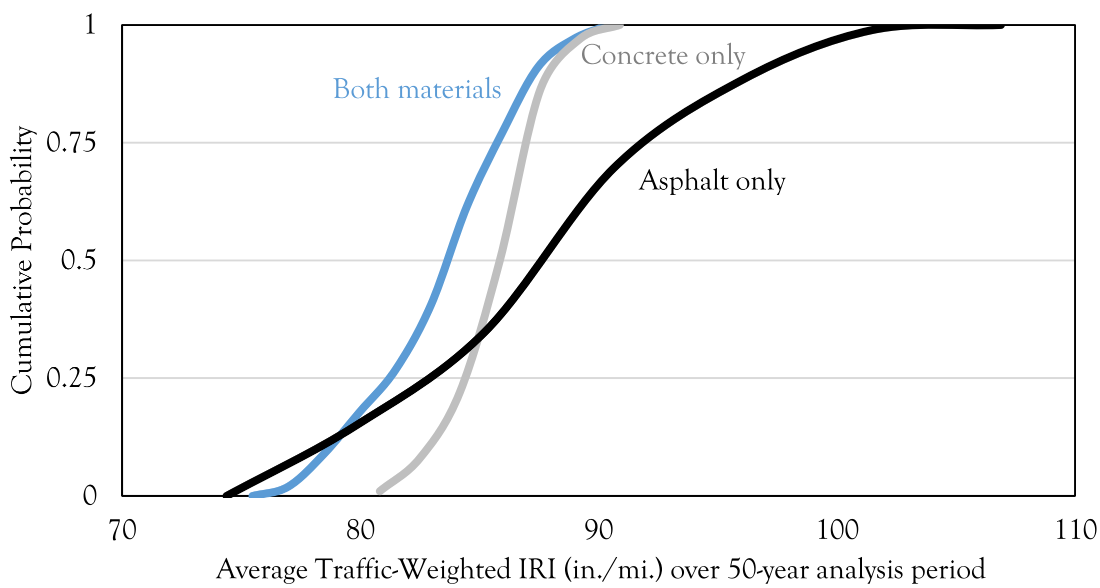


Figure 7-4. Traffic-weighted IRI of system over prescribed analysis period for \$67 million annual budget utilizing (a) only asphalt (b) only concrete and (c) both materials. Pavement deterioration follow the findings of Chapter 3.

To make this important insight clearer, Figure 7-5 plots the percent composition of the system that remains asphalt by the end of the analysis period for the \$67 million annual budget scenario using

(a) only asphalt (b) only concrete and (c) both materials. In the case that both materials are present in the system, there is high variability regarding how the network will evolve over time. Figure 7-7 subsequently plots the average traffic-weighted IRI of the system for each Monte Carlo simulation when multiple paving materials are used relative to the percent composition of the system that is asphalt by the end of the analysis period. There is a strong negative correlation (-0.79) between the two variables, indicating that the simulations in which the highest system-wide performance is achieved coincides with the iterations where asphalt is heavily used. Of course, the scenarios where the network remains primarily asphalt is a result of asphalt price volatility making it advantageous to continue maintaining the system following current practice. Conversely, the simulations where concrete becomes the dominant pavement type over the 50-year analysis period occur when the system performance is worst, as the concrete-based technologies act as an insurance policy to protect the agency when asphalt prices are elevated well above their current levels. Figure 7-6 illustrates the expected benefit of incorporating multiple paving materials by mapping the expected performance of segments across the network with a $67 million annual budget for that scenario. As is quite evident, the expected condition of the system is much higher than its current state per Figure 7-2.

It is worth mentioning that a downside of the proposed heuristic is its inability to account for the path dependence of decisions. As a result, the system in some simulations begins changing its composition earlier than optimal, as can be noted Figure 7-4, where the target curve with both materials present underperforms the asphalt-only scenario for low cumulative probabilities. Such an outcome motivates the evaluation of alternative allocation policies in future academic research.

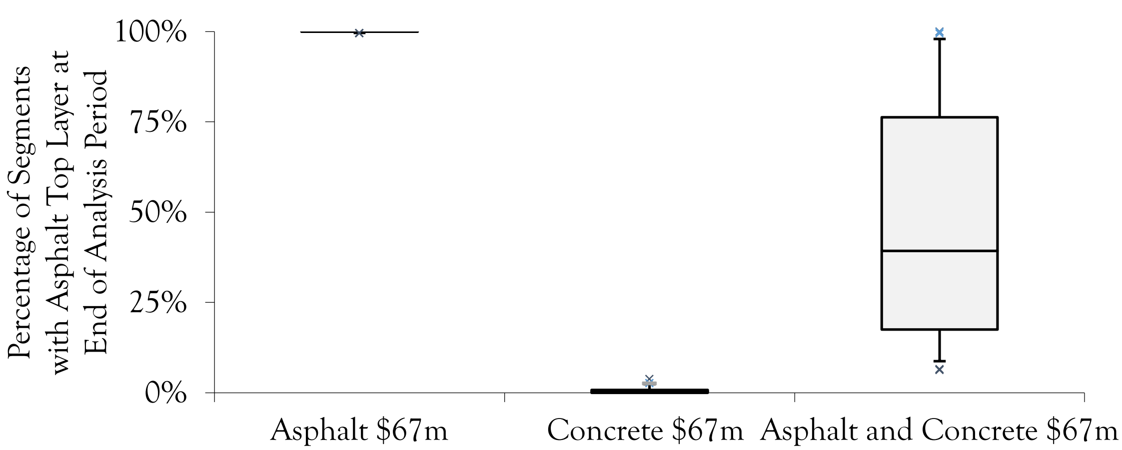


Figure 7-5. Percentage of pavement segments with asphalt as its top-layer at the end of the 50-year analysis period for the $67 million annual budget scenario using (a) only asphalt (b) only concrete and (c) both materials.

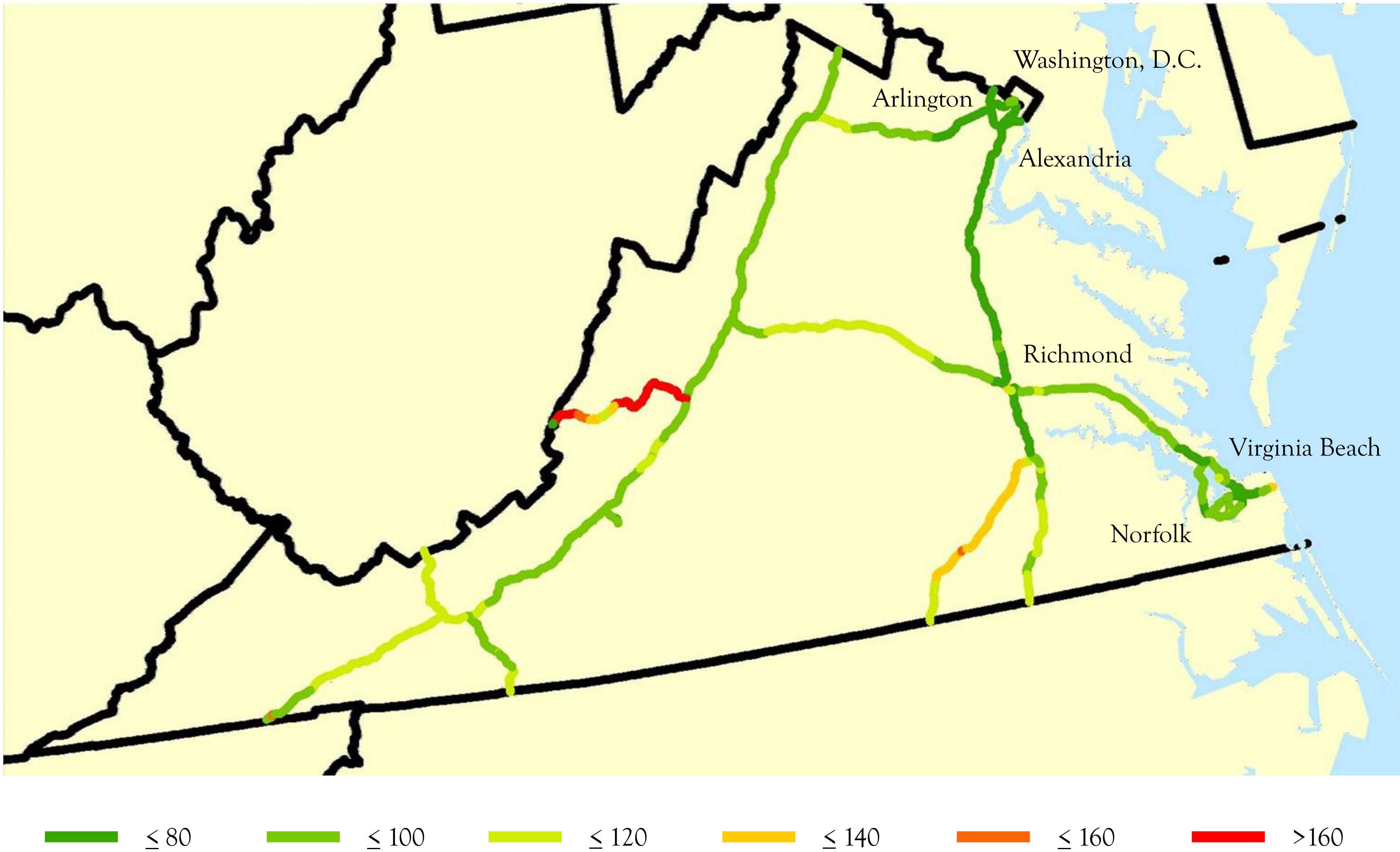


Figure 7-6. Average two-way IRI (inches/mile) of roadway segments within the Commonwealth of Virginia with a $67 million annual budget and both materials present over a 50-year analysis period.

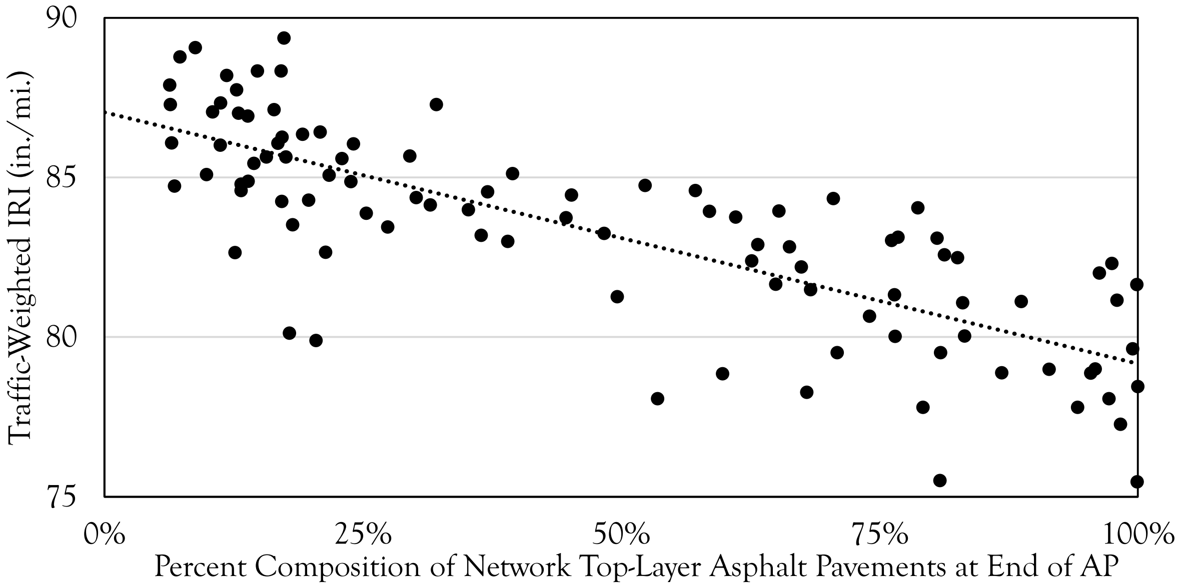


Figure 7-7. Average traffic-weighted IRI of network vs. percent of segments that are asphalt at the end of the analysis period for each Monte Carlo simulation for the $67 million annual budget scenario with both materials.

To demonstrate that the results presented in Figure 7-4 and Figure 7-6 are of statistical significance, Figure 7-8 plots the outcomes of a bootstrap (sampling with replacement) for the null hypothesis that the difference in the expected traffic-weighted IRI between the multiple-material and single-material maintenance policies is zero. Results of this statistical analysis indicate that one can reject the null hypothesis that the expected performance for the single-material preservation strategy, whether it be concrete or asphalt, is equal to that of the multiple-material scenario. Such a result demonstrates that the conclusions of this analysis are robust despite the small number of Monte Carlo simulations generated.

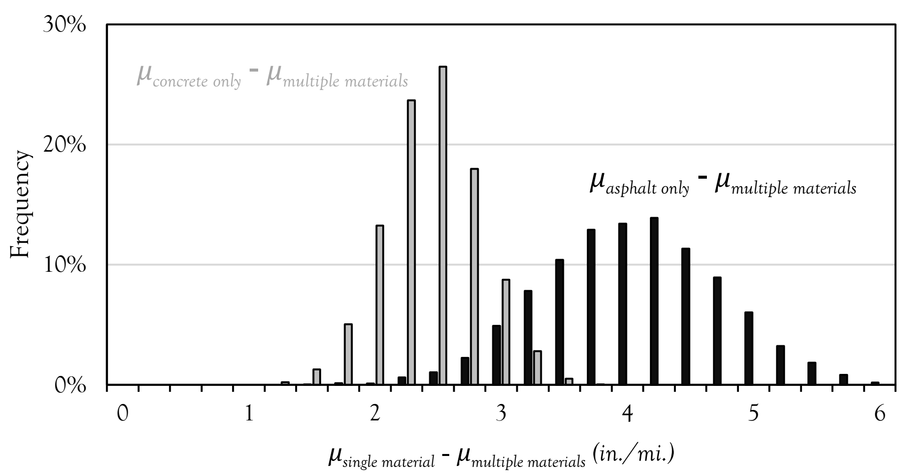


Figure 7-8. Bootstrap results for the null hypothesis that the difference between the expected traffic-weighted IRI when utilizing multiple paving materials, $\mu_{multiple\ materials}$, versus a single paving material, $\mu_{single\ material}$, is zero.

Figure 7-9 plots the target curve for the maintenance policy that utilizes both materials but with an annual budget of $60 million relative to the previously described asphalt-only policy. The expected traffic-weighted IRI of the network across the two instances is approximately equivalent (88 in./mi.), yet a decision-maker might prefer the former policy should they exhibit risk aversion. An important outcome for this section is that the benefit of concrete in the probabilistic case is $4 million per year higher than the result for the deterministic case, suggesting that the value generated from this source of flexibility is significant.

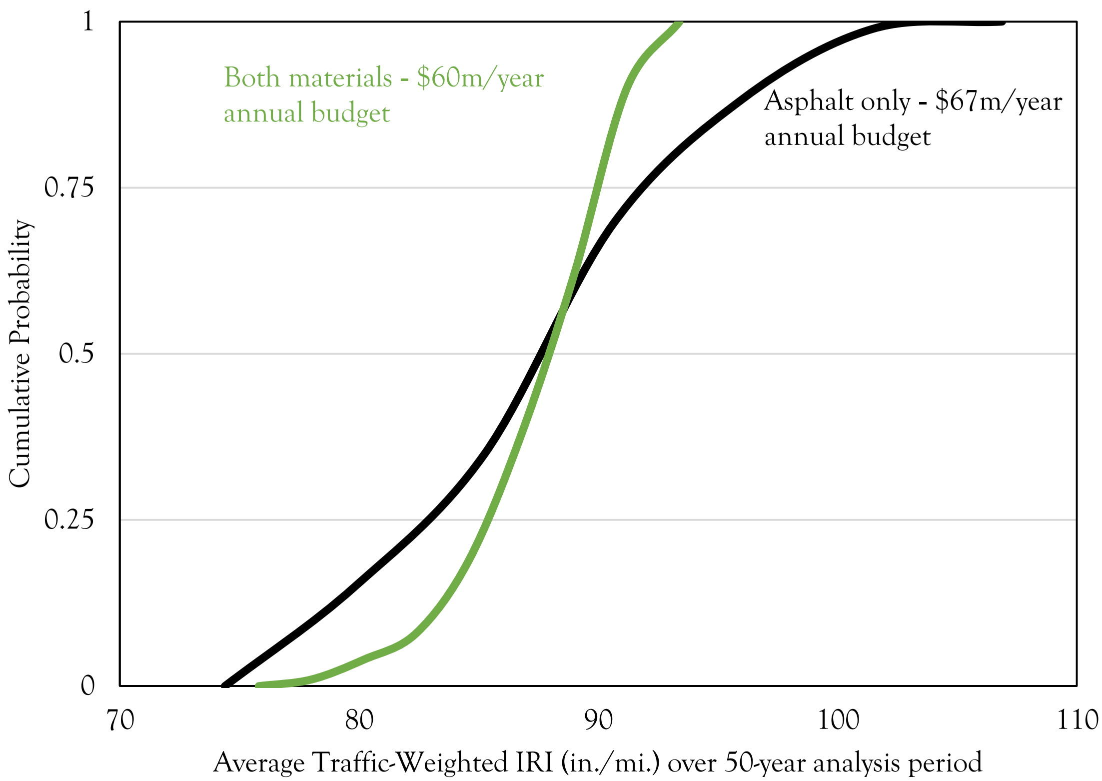


Figure 7-9. Traffic-weighted IRI of system over prescribed analysis period for (a) asphalt-only network with $67 million annual budget and (b) maintenance policy of both materials with an annual budget of $60 million. Pavement deterioration follow the findings of Chapter 3.

Figure 7-10 provides a similar result as Figure 7-9, except now for the iso-performance scenario. Again, the inclusion of concrete for the maintenance of the pavement network adds greater value in the probabilistic case ($4 million annually) than in the deterministic case ($1 million annually). Furthermore, the benefit of this form of flexibility could be considered larger by a decision-maker should they be particularly concerned with mitigating downside risk.

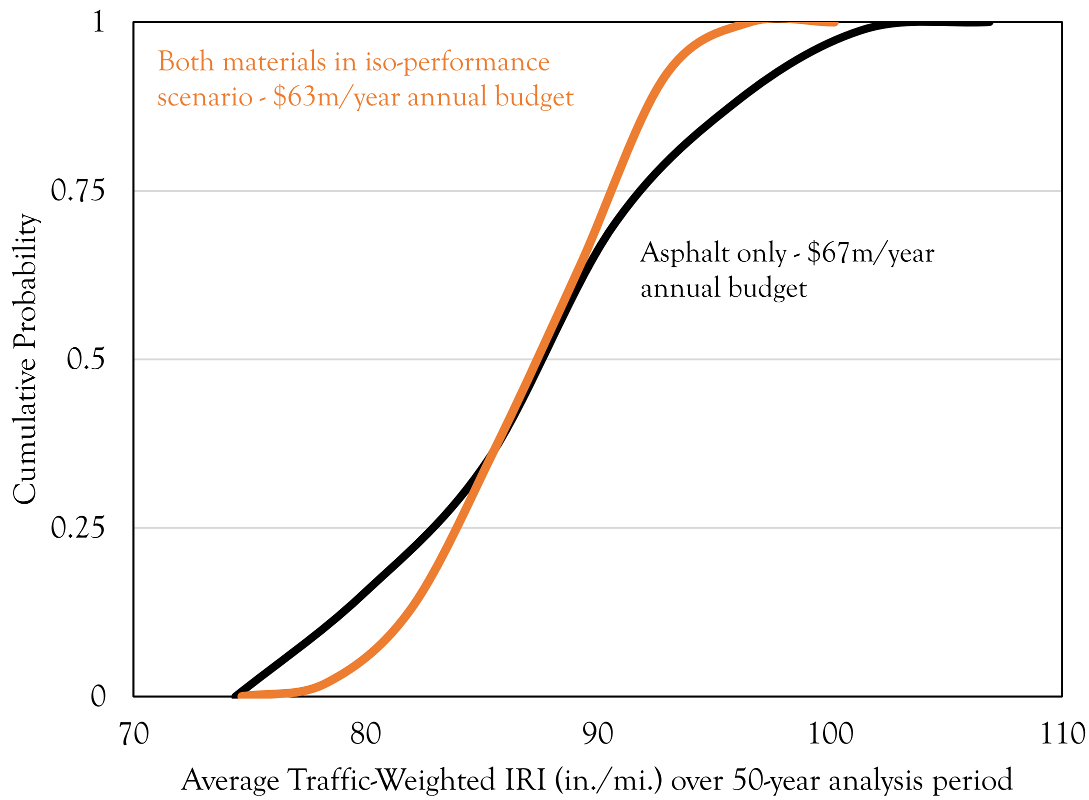


Figure 7-10. Traffic-weighted IRI of system over prescribed analysis period in iso-performance scenario for (a) asphalt-only network with $67 million annual budget and (b) maintenance policy of both materials with an annual budget of $63 million.

Conclusions

As planning agencies continue to search for cost-effective strategies to maintain an aging infrastructure network, the incorporation of real options to proactively deal with an uncertain future is one method that decision-makers can begin to use to improve system-wide performance. To do so, stochastic simulation models must begin to replace the current deterministic paradigms of today such that planning agencies can have a mechanism to capture the asymmetric benefits associated with flexibility. The previous section discussed and analyzed the impact of one type of flexibility, the incorporation of a broader range of pavement materials and designs, to increase the expected performance of a pavement network.

Results from this chapter suggest that planning agencies can achieve a performance level equivalent to the status-quo policy with a reduced budget of more than 10% by incorporating concrete-based technologies into their pavement management plan. This benefit is a convolution of (a) the value of flexibility and (b) the lower rate of deterioration, in general, for concrete pavements. Holding deterioration constant between the two materials to remove the latter phenomenon, the value due to flexibility is approximately 6% for this particular case study. Consequently, these results make a strong argument that allowing pavement maintenance strategies to be more flexible to proactively deal with an uncertain future is of significant value to a planning agency.

An important next step for future work is to determine, approximately, the cost to integrate the proposed source of flexibility in this dissertation within a planning agency. These costs include those associated with obtaining the technological knowledge (i.e., pavement engineers) of the proposed real option as well as, potentially, the cost to allocate resources towards concrete-based designs when it is disadvantageous to do so to ensure that the necessary market structure is in place to call upon the option at a future date.

V. DISCUSSION

SYNTHESIS

Part V summarizes the major insights, conclusions, and contributions of this dissertation. This discussion ties together the findings from the earlier chapters, which developed novel methods for the characterization of uncertainty for exogenous information, up until the previous section, which evaluated the hypothesis that concrete-based maintenance alternatives may act as an insurance policy to protect a planning agency from downside risk. Part V also discusses some of the opportunities to augment this dissertation from a methodological perspective.

CHAPTER 8: CONCLUDING REMARKS AND FUTURE WORK

Conclusions and contribution

As transportation agencies continue to grapple with limited funds and mounting maintenance needs, pavement management systems have emerged to allow planning agencies to implement more cost-effective resource allocation policies. In their current form, planning agencies generally model exogenous information that underlies the decision-making process with single-point estimates. Practitioners and academics appreciate the simplicity of the deterministic approach, as it only requires considering one set of conditions that may arise in the future. The deterministic approach leaves decision-makers, however, susceptible should the future unfold differently from their expectations. Without explicitly considering uncertainty, planning agencies can neither identify opportunities to embed sources of flexibility to proactively deal with an unknown future nor quantify their value. The optimal solution from deterministic tools, in other words, may very well be sub-optimal, unbeknownst to the planners who carry through with implementing their suggestions.

As a result, this dissertation has focused on understanding the performance roadway systems when uncertainty is explicitly considered. In particular, this thesis has centered on understanding the ability of one potential type of real option, the deployment of concrete-based maintenance and rehabilitation alternatives, to mitigate downside risk in the case of an unfavorable future. For the most part, planning agencies currently maintain their roadway networks only with asphalt-based technologies, leaving them vulnerable to the material price volatility for such maintenance actions. Consequently, concrete-based maintenance alternatives can act as an insurance policy/put option that protects planners at moments in time of elevated asphalt prices and suppressed concrete prices. To test the hypothesis set forth in this dissertation, a stochastic simulation model has been developed that incorporates uncertainty for exogenous information that underlies the decision-making process. The below sections discuss some of the novel findings for each component of the simulation model.

Part II: System Model and Exogenous Information

Over the course of this thesis, several novel methodological approaches have been proposed to characterize expectations and uncertainty for important inputs in pavement management systems. Chapter 3 offers a new pavement degradation model for network-level decisions that requires low computational resources and is specified according to empirical data. The results in this chapter potentially have far-reaching implications not only on network-level models but also on some of the current project-level tools used by DOTs and MPOs. Chapter 4 proposes the integration of a maximum likelihood (ML) estimator for data transformations combined with least angle regression (LAR) for variable selection/reduction to estimate expectations and uncertainty for initial construction costs. Such an approach offers a new way to address the systematic bias and heteroscedasticity that plagues existing cost-estimation methods. Lastly, Chapter 5 develops a new hybrid approach for probabilistically forecasting the long-run price of material commodities. Results from the chapter demonstrate that, unlike conventional opinion, forecasts can be constructed that provide excellent estimates of long-run price expectations and volatility.

Part III: Allocation Policy

Chapter 6 details a two-stage bottom-up greedy technique to determine the allocation of resources in the performance maximization problem. The algorithmic approach has low computational complexity and, for the set of case studies analyzed, leads to near-optimal allocation solutions. As a result, the algorithm provides a mechanism to solve realistic size problems without having to resort to the cost-minimization framework. Furthermore, the algorithm makes decisions sequentially over time, thus allowing the decision-making framework to integrate within the real option approach of this thesis.

Part IV: Stochastic Model

Chapter 7 tests the hypothesis that concrete-based maintenance alternatives act as an insurance policy to reduce downside risk for a planning agency by simulating the performance of Virginia's interstate system over a 50-year analysis period using the exogenous information and allocation policy models of Part II and Part III. The objective is to minimize traffic-weighted roughness, a common metric of system performance used by planning agencies, for a network only composed of asphalt moving forward and one that utilizes both asphalt and concrete. A comparison of the solutions indicates that a planning agency can achieve the performance of the status-quo maintenance policy with multiple materials at a reduced cost of 10%. This outcome stems from the availability to invest more in concrete-based maintenance actions at times of spiraling asphalt prices and stable concrete material costs for contractors. Although this research has not determined the actual cost for this particular type of real option, its value is large enough such that it is likely worth the cost to obtain it.

Limitations and future work

There are several opportunities for future research to both extend and improve the general framework set forth in this dissertation. Algorithmically, this research proposes a two-stage bottom-up greedy heuristic for allocation decisions. The major drawback of such an approach, however, is its general inability to account for the path dependence of allocation decisions over time. Future research should evaluate if alternative methodological paradigms, such as adaptive dynamic programming (ADP) discussed in Chapter 6, can lead to higher fidelity solutions.

Furthermore, the proposed algorithms of this dissertation seek to maximize expected network-level performance over time, implicitly assuming that planning agencies hold a risk-neutral perspective towards their infrastructure investments. However, it is likely that transportation agencies, similar to managers of many other engineering systems, are risk-averse. In other words, decision-makers frequently have a non-linear preference towards investments that have a low probability of poor performance (Hastings and McManus 2004). Consequently, the investment strategy that maximizes expected performance is not always preferred; rather, for risk-averse decision-makers, it can be of higher utility to sacrifice expected returns for the sake of reducing downside risk. Future research in pavement management should develop approaches that can account for the potential risk-averse nature of planners.

Additionally, the objective function of this research is to minimize traffic-weighted roughness across a pavement network. Having said that, planners are becoming interested in not only the general ride quality of pavements, but also their impact on the natural environment. Future studies should evaluate whether the findings of this study hold true for other objective functions of interest for transportation agencies. Lastly, and as mentioned earlier, this study has not quantified the economic cost to integrate concrete-based alternatives as part of a pavement preservation strategy. Future research should work with planning agencies to estimate the approximate cost to integrate the proposed source of flexibility.

REFERENCES

1. AASHTO (1990). "Guidelines for Pavement Management Systems." American Association of State Highway and Transportation Officials, Washington, D.C.

2. Abaza, K. A. (2007). "Expected Performance of Pavement Repair Works in a Global Network Optimization Model." *Journal of Infrastructure Systems*, 13(2): 124-134.

3. Abaza, K. A., Ashur, S.A. (1999). "Optimum Decision Policy for Management of Pavement Maintenance and Rehabilitation." *Transportation Research Record: Journal of the Transportation Research Board*,1655: 8-15.

4. Abaza, K. A., Ashur, S.A., Abu-Eisheh, S.A., Rabay, A. (2001). "Macroscopic Optimum For Management of Pavement Rehabilitation." *Journal of Transportation Engineering* **127**(6): 493-500.

5. Abaza, K. A., Ashur, S.A., Al-Khatib, I.A. (2004). "Integrated Pavement Management System with a Markovian Prediction Model." *Journal of Transportation Engineering*,130(1): 24-33.

6. Aguiar-Moya, J. P., Prozzi, J.A., de Fortier Smit, A. (2011). "Mechanistic-Empirical IRI Model Accounting for Potential Bias." *Journal of Transportation Engineering*, 137(5): 297-304.

7. Ahmeda, K., Abu-Lebdeha, Lylesa, R.W. (2006). "Prediction of pavement distress index with limited data on causal factors: an auto-regression approach." *International Journal of Pavement Engineering*, 7(1): 23-35.

8. Alquist, R., Kilian, L. (2010). "What do we learn from the price of crude oil futures?" *Journal of Applied Econometrics*, 25(4): 539-573.

9. Ashuri, B., Lu, J. (2010). "Forecasting ENR Construction Cost Index: A Time Series Analysis Approach." *Construction Research Congress 2010*, Alberta, Canada: 1345-1355.

10. Bellman, R. (1957). *Dynamic Programming*. Princeton, NJ: Princeton University Press.

11. Black, F., Scholes, M. (1973). "The Pricing of Options and Corporate Liabilities." *Journal of Political Economy*, 81(3): 637-654.

12. Box, G. E. P., Cox, D.R. (1964). "An Analysis of Transformations." *Journal of the Royal Statistical Society. Series B (Methodological)*, 26(2): 211-252.

13. Brealey, R.A., Myers, S.C., Allen, F. (2006). *Principles of Corporate Finance – 8th Edition*. New York, NY: McGraw-Hill/Irwin

14. Breusch, T. S., Pagan, A.R. (1979). "A Simple Test for Heteroscedasticity and Random Coefficient Variation." *Econometrica*, 47(5): 1287-1294.

15. British Petroleum. (2015). "Statistical Review of Energy Prices." <http://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html> (Access Date: Nov. 25, 2015).

16. Bureau of Labor Statistics. (2015a). "Asphalt Paving Mixture and Block Manufacturing: PCU324121324121." <http://www.bls.gov/cpi/home.html> (Access Date: Nov. 25, 2015).

17. Bureau of Labor Statistics (2015b). "Cement Manufacturing: PCU32731032731." <http://www.bls.gov/cpi/home.html> (Access Date: Nov. 25, 2015).

18. Bureau of Labor Statistics (2015c). "Ready-Mix Concrete: PCU327320327320." <http://www.bls.gov/cpi/home.html> (Access Date: Nov. 25, 2015).

19. Bureau of Labor Statistics (2015d). "Stone Mining and Quarrying: PCU21231-21231." <http://www.bls.gov/cpi/home.html> (Access Date: Nov. 25, 2015).

20. Bureau of Labor Statistics (2015e). "Consumer Price Index: CUUR0000SA0." <http://www.bls.gov/cpi/home.html> (Access Date: Nov. 25, 2015).

21. Bush, V. (1945). "Science: The Endless Frontier." United States Government Printing Office, Washington, D.C.

22. Cardin, M. A., de Neufville, R., Kazakidis, V. (2008). "A Process to Improve Expected Value in Mining Operations." *Mining Technology: IMM Transactions, Section A*,117(2): 65-70.

23. Cardin, M. A. (2011). "Quantitative Performance-based Evaluation of a Procedure for Flexible Design Concept Generation." Engineering Systems Division: Massachusetts Institute of Technology, Cambridge, MA, Doctoral Thesis.

24. Carnahan, J. V., Davis, J., Keane, P., Wu, M. (1987). "Optimal Maintenance Decisions for Pavement Management." *Journal of Transportation Engineering*, 113(5): 554-572.

25. Carr, P. G. (2005). "Investigation of Bid Price Competition Measured through Prebid Project Estimates, Actual Bid Prices, and Number of Bidders." *Journal of Construction Engineering and Management*, 131(11): 1165-1172.

26. Chan, S. L., Park, M. (2005). "Project Cost Estimating Using Principal Component Regression." *Construction Management and Economics*, 23(3): 295-304.

27. Chan, W. T., Fwa, T. F., Tan, C.Y. (1994). "Road-Maintenance Planning Using Genetic Algorithms I: Formulation." *Journal of Transportation Engineering*, 120(5): 693-709.

28. Chen, L., Henning, T. F. P., Raith, A., Shamseldin, A.Y. (2015). "Multiobjective Optimization for Maintenance Decision Making in Infrastructure Asset Management." *Journal of Management in Engineering*, 31(6): 04015015.

29. Chen, X., Hudson, S., Pajoh, M., Dickenson, W. (1996). "Development of New Network Optimization Model for Oklahoma Department of Transportation." *Transportation Research Record: Journal of the Transportation Research Board*, 1524: 103-108.

30. Cheung, Y.W., Lai, K.S. (1995). "Lag Order and Critical Values of the Augmented Dickey-Fuller Test." *Journal of Business and Economic Statistics*, 13(3): 277-280.

31. Chootinan, P., Chen, A., Horrocks, M., Bolling, D. (2006). "A multi-year pavement maintenance program using a stochastic simulation-based genetic algorithm approach." *Transportation Research Part A*, 40(9): 725-743

32. Chu, C.-Y., Durango-Cohen, P. L. (2008). "Estimation of dynamic performance models for transportation infrastructure using panel data." *Transportation Research Part B*, 42(1): 57-81.

33. Chua, D. K. H., Li, D. (2000). "Key Factors in Bid Reasoning Model." *Journal of Construction Engineering and Management*, 126(5): 349-357.

34. Conti, J. J. (2015). "Annual Energy Lookout 2015 with Projections to 2040", Energy Information Administration, Washington, D.C.

35. de la Garza, J. M., Rouhana, K. G. (1995). "Neural Networks Versus Parameter-Based Applications in Cost Estimating." *Cost Engineering*, 37(2): 14-18.

36. de Neufville, R. (1990). *Applied Systems Analysis: Engineering Planning and Technology Management*. New York, NY: McGraw-Hill Publishing Company.

37. de Neufville, R., Scholtes, S. (2011). *Flexibility in Engineering Design*. Cambridge, MA: MIT Press.

38. de Neufville, R., Mori, Y. (1970). "Optimal Highway Staging by Dynamic Programming." *Transportation Engineering Journal of ASCE*, 96(1): 11-24

39. de Weck, O., de Neufville, R. (2004). "Staged Deployment of Communications Satellite Constellations in Low Earth Orbit." *Journal of Aerospace Computing, Information, and Communication* 1(3): 119-136.

40. Demos, G. P. (2006). "Life Cycle Cost Analysis and Discount Rate on Pavements for the Colorado Department of Transportation." Colorado Department of Transportation, Denver, CO.

41. Dixit, A. K., Pindyck, R. S. (1994). *Investment under Uncertainty*. Princeton, NJ: Princeton University Press.

42. Durango-Cohen, P. L. (2007). "A time series analysis framework for transportation infrastructure management." *Transportation Research Part B*, 41(5): 493-505.

43. Durango-Cohen, P. L., Sarutipand, P. (2007). "Capturing Interdependencies and Heterogeneity in the Management of Multifacility Transportation Infrastructure Systems." *Journal of Infrastructure Systems*, 13(2): 115-123.

44. Durango, P. L., Madanat, S.M. (2002). "Optimal maintenance and repair policies in infrastructure management under uncertain facility deterioration rates: an adaptive control approach." *Transportation Research Part A*, 36(9): 763–778.

45. Eckert, C., Clarkson, J., de Weck, O., Keller, R. (2009). "Engineering Change: Drivers, Sources and Approaches in Industry." *Proceedings of the International Conference on Engineering Design*, Palo Alto, CA.

46. Efron, B., Hastie, T., Johnstone, I., Tibshirani, R. (2004). "Least Angle Regression." *Annals of Statistics*, 32(2): 407-499.

47. Energy Information Administration (2015). "Oil." <http://www.eia.gov/> (Access Date: Nov. 25, 2015).

48. Elder, J., Kennedy, P.E. (2001). "Testing for Unit Roots: What Should Students Be Taught?" *Journal of Economic Education*, 32(2): 137-146.

49. Embacher, R. A., Snyder, M.B. (2001). "Life-Cycle Cost Comparison of Asphalt and Concrete Pavements on Low-Volume Roads." *Transportation Research Record: Journal of the Transportation Research Board*, 1749: 28-37.

50. Emsley, M. W., Lowe, D. J., Duff, A. R., Harding, A., Hickson, A. (2002). "Data Modelling and the Application of a Neural Network Approach to the Prediction of Total Construction Costs." *Construction Management and Economics*, 20(6): 465-472.

51. Ewing, B. T., Malik, F., Ozfidan, O. (2002). "Volatility Transmission in the Oil and Natural Gas Markets." *Energy Economics*, 24(6): 525-538.

52. Ferreira, A., Antunes, A., Picado-Santos, L. (2002). "Probabilistic Segment-Linked Pavement Management Optimization Model." *Journal of Transportation Engineering* 126(6): 568-577.

53. FHWA (2006). "Pavement Management Systems: The Washington State Experience." U.S. Department of Transportation: Federal Highway Admministration, Washington, D.C.

54. FHWA (2013). "Enhancement of the Pavement Health Track (PHT) Analysis Tool: Final Report." U.S. Department of Transportation: Federal Highway Administration, Washington, D.C.

55. FHWA (2013). Transportation Statistics Annual Report. U.S. Department of Transportation: Federal Highway Admministration, Washington, D.C.

56. FHWA (2016). Long-Term Pavement Performance Data. U.S. Department of Transportation: Federal Highway Admministration, Washington, D.C.

57. Flyvberg, B., Holm, M. S., Buhl, S. (2002). "Underestimating Cost in Public Work Projects - Error or Lie?" *Journal of the American Planning Association* 68(3): 279-295.

58. Franses, P. H., Dijk, D. (2010). "Cointegration in a Historical Perspective." *Journal of Econometrics*, 158(1): 156-159.

59. Fwa, T. F., Chan, W. T., Hoque, K.Z. (1998). "Analysis of Pavement Management Activities Programming by Genetic Algorithms." *Transportation Research Record: Journal of the Transportation Research Board*, 1643: 1-6.

60. Fwa, T. F., Chan, W. T., Tan, C.Y. (1996). "Genetic-Algorithm Programming of Road Maintenance and Rehabilitation." *Journal of Transportation Engineering*, 122(3): 246-253.

61. Fwa, T. F., Cheu, R. L., Muntasir, A. (1998). "Scheduling of Pavement Maintenance To Minimize Traffic Delays." *Transportation Research Record: Journal of the Transportation Research Board*, 1650: 28-35.

62. Gao, H., Zhang, X. (2013). "A Markov-Based Road Maintenance Optimization Model Considering User Cost." *Computer-Aided Civil and Infrastructure Engineering*, 28(6): 451-464.

63. Gao, L., Xie, C., Zhang, Z., Waller, S.T. (2012). "Network-Level Road Pavement Maintenance and Rehabilitation Scheduling for Optimal Performance Improvement and Budget Utilization." *Computer-Aided Civil and Infrastructure Engineering*, 27(4): 278-287.

64. Gao, L., Zhang, Z. (2012). "Approximate Approach to Problem of Large-Scale Pavement Maintenance and Rehabilitation." *Transportation Research Record: Journal of the Transportation Research Board*, 2304: 112-118.

65. Gao, L., Zhang, Z. (2013). "Management of Pavement Maintenance, Rehabilitation, and Reconstruction Through Network Partition." *Transportation Research Record: Journal of the Transportation Research Board*, 2366: 59-63.

66. Garg, A., Horowitz, A., Ross, F. (1988). "Establishing relationships between pavement roughness and perceptions of acceptability." *Transportation Research Record: Journal of the Transportation Research Board*, 1196: 276-285.

67. Gjoldberg, O., Johansen, T. (1999). "Risk Management in the Oil Industry: Can Information on Long-run Equillibrium Prices be Utilized?" *Energy Economics*, 21(6): 517-527.

68. Golabi, K., Kulkarni, R.B., Way, G.B. (1982). "A Statewide Pavement Management System." *Interfaces*, 12(6): 5-21.

69. Goold, M., Luchs, K. (1993). "Why diversity? Four decades of management thinking." *Academy of Management Executive*, 7(3): 7-25.

70. Guignier, F., Madanat, S. (1999). "Optimization of Infrastructure Systems Maintenance and Improvement Policies." *Journal of Infrastructure Systems*, 5(4): 124-134.

71. Guo, T., Liu, T., Li, A. (2012). "Pavement Rehabilitation Strategy Selection for Steel Suspension Bridges Based on Probabilistic Life-Cycle Cost Analysis." *Journal of Performance of Constructed Facilities*, 26(1): 76-83.

72. Hastings, D., McManus, H. (2004). "A Framework for Understanding Uncertainty and its Mitigation and Exploitation in Complex Systems". *MIT Engineering Systems Symposium*, Cambridge, MA.

73. Hegazy, T., Ayed, A. (1998). "Neural Network Model for Parametric Cost Estimation of Highway Projects." *Journal of Construction Engineering and Management*, 124(3): 210-218.

74. Herbsman, Z. (1983). "Long-Range Forecasting Highway Costs." *Journal of Construction Engineering and Management*, 109(4): 423-434.

75. Hiyassat, M. A. S. (2001). "Construction Bid Price Evaluation." *Canadian Journal of Civil Engineering*, 28(2): 264-270.

76. Hong, F., Prozzi, J.A. (2015). "Pavement Deterioration Model Incorporating Unobserved Heterogeneity for Optimal Life-Cycle Rehabilitation Policy." *Journal of Infrastructure Systems*, 21(1): 04014027.

77. Hwang, S. (2009). "Dynamic Regression Models for Prediction of Construction Costs." *Journal of Construction Engineering and Management*, 135(5): 360-367.

78. Hwang, S. (2011). "Time Series Models for Forecasting Construction Costs Using Time Series Indexes." *Journal of Construction Engineering and Management*, 137(9): 656-662.

79. Ji, S.H., Park, M., Lee, H.S. (2010). "Data Preprocessing-Based Parametric Cost Model for Building Projects: Case Studies of Korean Construction Projects." *Journal of Construction Engineering and Management*, 136(8): 844-853.

80. Khattaka, M. J., Landrya, C., Veazey, J., Zhang, Z. (2013). "Rigid and composite pavement index-based performance models for network pavement management system in the state of Louisiana." *International Journal of Pavement Engineering*, 14(7): 612-628.

81. Kilian, L. (2001). "Impulse Response Analysis in Vector Autoregressions with Unknown Lag Order." *Journal of Forecasting*, 20(3): 161-179.

82. Kim, B.S., Hong, T. (2012). "Revised Case-Based Reasoning Model Development Based on Multiple Regression Analysis for Railroad Bridge Construction." *Journal of Construction Engineering and Management*, 138(1): 154-162.

83. Knight, F. H. (1921). *Risk, Uncertainty, and Profit*. Boston, MA: Hart, Schaffner & Marx; Houghton Mifflin Co.

84. Kuhn, K. (2012). "Pavement network maintenance optimization considering multidimensional condition data." *Journal of Infrastructure Systems*, 18(4): 270-277.

85. Kuhn, K. D. (2010). "Network-Level Infrastructure Management Using Approximate Dynamic Programming." *Journal of Infrastructure Systems*, 16(2): 103-111.

86. Kuhn, K. D., Madanat, S.M. (2005). "Model uncertainty and the management of a system of infrastructure facilities." *Transportation Research Part C*, 13(5-6): 391–404.

87. Lanza, A., Manera, M., Giovannini, M. (2005). "Modeling and Forecasting Cointegrated Relationships Among Heavy Oil and Product Prices." *Energy Economics*, 27(6): 831-848.

88. Lea, J., Harvey, J. (2004). "Data Mining of the Caltrans Pavement Management System (PMS) Database." Pavement Research Center: University of California at Berkeley, Richmond, CA.

89. Lee, J., Madanat, S. (2015). "A Joint Bottom-up Solution Methodology for System-Level Pavement Rehabilitation and Reconstruction." *Transportation Research Part B*, 78: 106-122.

90. Lee, Y. H., Mohseni, A., Darter, M.I. (1993). "Simplified pavement performance models." *Transportation Research Record: Journal of the Transportation Research Board*, 1397: 7-14.

91. Leybourne, S. J., Newbold, P. (1999). "The Behavious of Dickey-Fuller and Phillips-Perron Tests Under the Alternative Hypothesis." *Econometrics Journal*, 2(1): 92-106.

92. Li, N., Haas, R., Huot, M. (1998). "Integer Programming of Maintenance and Rehabilitation Treatments for Pavement Networks." *Transportation Research Record: Journal of the Transportation Research Board*, 1629: 242-248.

93. Li, N., Huot, M., Haas, R. (1997). "Cost-Effectiveness-Based Priority Programming of Standardized Pavement Maintenance." *Transportation Research Record: Journal of the Transportation Research Board*, 1592: 8-16.

94. Liew, V. K. S. (2004). "Which Lag Length Selection Criteria Should We Employ?" *Economic Bulletin*, 3(33): 1-9.

95. Lin, J., de Weck, O., de Neufville, R., Yue, H.K. (2013). "Enhancing the Value of Oilfield Developments with Flexible Subsea Tiebacks." *Journal of Petroleum Science and Engineering*, 102: 73-83.

96. Liu, F., Wang, K. C. P. (1996). "Pavement Performance–Oriented Network Optimization System." *Transportation Research Record: Journal of the Transportation Research Board*, 1524: 86-93.

97. Lo, A. W., MacKinlay, C. (1988). "Stock Market Prices do not Follow Random Walks: Evidence from a Sample Specification Test." *The Review of Financial Studies*, 1(1): 41-66.

98. Longstaff, F. A., Schwartz, E.S. (2001). "Valuing American Options by Simulation: A Simple Least-Squares Approach." *The Review of Financial Studies*, 14(1): 113-147.

99. Lowe, D. J., Emsley, M.W., Harding, A. (2006). "Predicting Construction Cost Using Multiple Regression Techniques." *Journal of Construction Engineering and Management*, 132(7): 750-758.

100. Ma, W., Cheu, R. L., Lee, D.H. (2004). "Scheduling of Lane Closures Using Genetic Algorithms with Traffic Assignments and Distributed Simulations." *Journal of Transportation Engineering*, 130(3): 322-329.

101. Madanat, S. (1993). "Optimal Infrastructure Management Decisions under Uncertainty." *Transportation Research Part C*, 1(1): 77-88.

102. Madanat, S., Ben-Akiva, M. (1994). "Optimal Inspection and Repair Policies for Infrastructure Facilities." *Transportation Science*, 28(1): 55-62.

103. Madanat, S., Park, S. Kuhn, K. (2006). "Adaptive Optimization and Systematic Probing of Infrastructure System Maintenance Policies under Model Uncertainty." *Journal of Infrastructure Systems*, 12(3): 192-198.

104. Mandapaka, V., Basheer, I., Sahasi, K., Ullidtz, P., Harvey, J., Sivaneswaran, N. (2012). "Mechanistic-Empirical and Life-Cycle Cost Analysis for Optimizing Flexible Pavement Maintenance and Rehabilitation." *Journal of Transportation Engineering*, 138(5): 625-633.

105. Markow, M. J. (1995). "Highway Management Systems: State of the Art." *Journal of Infrastructure Systems*, 1(3): 186-191.

106. Markowitz, H. (1952). "Portfolio Selection." *The Journal of Finance*, 7(1): 77-91.

107. Mbwana, J. (2001). "A Framework for Developing Stochastic Multi-Objective Pavement Management." *Technology Transfer in Road Transportation in Africa Conference Proceedings*, Dar es Salaam, Tanzania, 350-363.

108. Mbwana, J. R., Turnquist, M.A. (1996). "Optimization Modeling for Enhanced Network-Level Pavement Management System." *Transportation Research Record: Journal of the Transportation Research Board*, 1524: 76-85.

109. McCaffer, R., McCaffrey, M. J., Thorpe, A. (1984). "Predicting the Tender Price of Buildings During Early Design: Method and Validation." *The Journal of the Operations Research Society*, 35(5): 415-424.

110. Mctigure, J. R. (2013). "Federal-Aid Highways:: Improved Guidance Could Enhance States' Use of Life-Cycle Cost Analysis in Pavement Selection." United States Government Accountability Office, Washington, D.C.

111. Medury, A., Madanat, S. (2013). "Incorporating Network Considerations into Pavement Management Systems: A Case for Approximate Dynamic Programming." *Transportation Research Part C*, 33: 134-150.

112. Medury, A., Madanat, S. (2014). "Simultaneous Network Optimization Approach for Pavement Management Systems." *Journal of Infrastructure Systems*, 20(3): 967-974.

113. Melachrinoudis, E., Kozanidis, G. (2002). "A mixed integer knapsack model for allocating funds to highway safety improvements." *Transportation Research Part A*, 36(9): 789-803.

114. Musselman, M. (2015). "A Review of the Alabama Department of Transportation's Policies and Procedures for Life-Cycle Cost Analysis for Pavement Type Selection." Department of Civil Engineering: Auburn University, Auburn, AL, Master of Science Dissertation.

115. Myers, S. (1984). "Finance Theory and Financial Strategy." *Interfaces*, 14(1): 126-137.

116. Ng, M., Lin, D.Y., Wallter, S.T. (2009). "Optimal Long-Term Infrastructure Maintenance Planning Accounting for Traffic Dynamics." *Computer-Aided Civil and Infrastructure Engineering*, 24(7): 459-469.

117. Ng, S. T., Cheung, S. O., Skitmore, R.M., Lam, K.C., Wong, L.Y. (2000). "The Prediction of Tender Price Index Directional Changes." *Construction Management and Economics*, 18(7): 843-852.

118. Oman Systems, Inc. (2016). "Bid Tabs Data".Nashville, TN.

119. Ouyang, Y. (2007). "Pavement Resurfacing Planning for Highway Networks: Parametric Policy Iteration Approach." *Journal of Infrastructure Systems*, 13(1): 65-71.

120. Ouyang, Y., Madanat, S. (2004). "Optimal scheduling of rehabilitation activities for multiple pavement facilities: exact and approximate solutions." *Transportation Research Part A*, 38(5): 347-365.

121. Ouyang, Y., Madanat, S. (2006). "An analytical solution for the finite-horizon pavement resurfacing planning problem." *Transportation Research Part B*, 40(9): 767-778.

122. Pesaran, M. H., Shin, Y. (1999). "An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis." *The Ragnar Frisch Centennial Symposium,* Oslo, Norway: 371-413.

123. Pesaran, M. H., Shin, Y., Smith, R.J. (2001). "Bounds Testing Approaches to the Analysis of Level Relationships." *Journal of Applied Econometrics*, 16(3): 289-326.

124. Pilson, C., Hudson, W.R., Anderson, V. (1999). "Multiobjective Optimization in Pavement Management by Using Genetic Algorithms and Efficient Surfaces." *Transportation Research Record: Journal of the Transportation Research Board*, 1655: 42-48.

125. Pindyck, R. S. (1999). "The Long-Run Evolution of Energy Prices." *The Energy Journal*, 20(2): 1-27.

126. Powell, W. J. (2007). *Approximate Dynamic Programming: Solving the Curses of Dimensionality*. Hoboken, NJ: John, Wiley & Sons Inc.

127. Prozzi, J. A., Madanat, S.M. (2004). "Development of Pavement Performance Models by Combining Experimental and Field Data." *Journal of Infrastructure Systems*, 10(1): 9-22.

128. Qin, X., Wang, K., Wang, Z. (2014). "Selection of Interest and Inflation Rates for Infrastructure Investment Analyses." Mountain Plains Consortium, Fargo, ND.

129. Ramberg, D. J., Parsons, J.E. (2012). "The Weak Tie Between Natural Gas and Oil Prices." *The Energy Journal*, 33(2): 13-35.

130. Rangaraju, P., Amirkhanian, S., Guven, Z. (2008). "Life Cycle Cost Analysis for Pavement Type Selection." Department of Civil Engineering: Clemson University, Clemson, SC.

131. Sanders, S. R., Maxwell, R. R., Glagola, C.R. (1992). "Preliminary Estimating Models for Infrastructure Projects." *Cost Engineering*, 34(8): 7-13.

132. Santero, N. J., Masanet, E., Horvath, A. (2011). "Life-cycle assessment of pavements. Part I: Critical review." *Resources, Conservation, and Recycling*, 55(9-10): 801-809.

133. Sathaye, N., Madanat, S. (2011). "A bottom-up solution for the multi-facility optimal pavement resurfacing problem." *Transportation Research Part B*, 45(7): 1004-1017.

134. Sathaye, N., Madanat, S. (2012). "A bottom-up optimal pavement resurfacing solution approach for large-scale networks." *Transportation Research Part B*, 46(4): 520-528.

135. Shrestha, P. P., Pradhananga, N. (2010). "Correlating Bid Price with the Number of Bidders and Final Construction Cost of Public Street Projects." *Transportation Research Record: Journal of the Transportation Research Board*, 2151: 3-10.

136. Shrestha, P. P., Pradhananga, N., Mani, N. (2014). "Correlating the Quantity and Bid Cost of Unit Price Items for Public Road Projects." *KSCE Journal of Civil Engineering*, 18(6): 1590-1598.

137. Smilowitz, K., Madanat, S. (2000). "Optimal Inspection and Maintenance Policies for Infrastructure Networks." *Computer-Aided Civil and Infrastructure Engineering*, 15(1): 5-13.

138. Swei, O., Gregory, J., Kirchain, R. (2016). "A Probabilistic Approach for Long-run Price Projections: Case Study of Concrete and Asphalt." *Journal of Construction Engineering and Management*, DOI: 10.1061/(ASCE)CO.1943-7862.0001211.

139. Swei, O., Gregory, J., Kirchain, R. (2016). "Probabilistic Life-Cycle Cost Analysis of Pavements: Drivers of Variation and Implications of Context." *Transportation Research Record: Journal of the Transportation Research Board*, 2523: 47-55.

140. Torres-Machi, C., Pellicer, E., Chamorro, A. (2013). "Heuristic Optimization Model for Infrastructure Asset Management." *Advances in Artificial Intelligence*, 300-309.

141. Trost, S. M., Oberlender, G. D. (2003). "Predicting Accuracy of Early Cost Estimates Using Factor Analysis and Multivariate Regression." *Journal of Construction Engineering and Management*, 129(2): 198-204.

142. U.S. Congress (2012). "Moving Ahead for Progress in the 21st Century (MAP-21)." *112th Congress Public Law 141*, Washington, D.C.

143. U.S. Census Bureau (2013). "2013 Annual Survey of Government Finances." United States Census Bureau, Washington, D.C.

144. Vadakpat, G., Stoffels, S., Dixon, K. (2000). "Road User Cost Models for Network-Level Pavement Management." *Transportation Research Record: Journal of the Transportation Research Board*, 1699: 49-57.

145. VDOT (2016). "Fiscal Year 2016: VDOT Annual Budget." Virginia Department of Transportation, Richmond, VA.

146. Walls, J., Smith, M. (1998). "Life-Cycle Cost Analysis in Pavement Design - Interim Technical Bulletin." U.S. Department of Transportation: Federal Highway Administration, Washington, D.C.

147. Wang, T. (2005). "Real options 'in' projects and Systems Design – Identification of Options and Solution for Path dependency." Engineering Systems Division: Massachusetts Institute of Technology, Cambridge, MA, Doctoral Thesis.

148. Wang, F., Zhang, Z. Machemehl, R.B. (2003). "Decision-Making Problem for Managing Pavement Maintenance and Rehabilitation Projects." *Transportation Research Record: Journal of the Transportation Research Board*, 1853: 21-27.

149. Wang, K., Liu F. (1997). "Fuzzy Set-Based and Performance-Oriented Pavement Network Optimization System." *Journal of Infrastructure Systems*, 3(4): 154-159.

150. Wang, K., Nguyen, V., Zaniewski, J.P. (2007). "Genetic Algorithms Based Network Optimization System with Multiple Objectives." *Transportation Research Record: Journal of the Transportation Research Board*, 2016: 85-96.

151. Wang, L., Zhang, J., Liu, Z. (2011). Predicting Pavement Service Life Using M-EPDG with LTPP Climatic Database. *Geo-Frontiers 2011*, Dallas, TX, 4584-4593.

152. Williams, T. P. (2003). "Predicting final cost for competitively bid construction projects using regression models." *International Journal of Project Management*, 21(8): 593-599.

153. Wilmot, C. (1994). "Predicting Changes in Construction Cost Indexes Using Neural Networks." *Journal of Construction Engineering and Management*, 120(2): 306-320.

154. Wilmot, C., Cheng, G. (2003). "Estimating Future Highway Construction Costs." *Journal of Construction Engineering and Management*, 129(3): 272-279.

155. Wu, Z., Flintsch, G. W. (2009). "Pavement Preservation Optimization Considering Multiple Objectives and Budget Variability." *Journal of Transportation Engineering*, 135(5): 305-315.

156. Xiarchos, I. M. (2006). "Three Essays in Environmental Markets: Dynamic Behavior, Market Interactions, Policy Implications." Department of Natural Resource Economics: West Virginia University, Morgantown, West Virginia, Doctoral Dissertation.

157. Xu, J. W., Moon, S. (2013). "Stochastic Forecast of Construction Cost Index Using a Cointegrated Vector Autoregression Model." *Journal of Management in Engineering*, 29(1): 10-18

158. Yang, Y. (2009). "A Screening Model to Explore Planning Decisions in Automotive Manufacturing Systems under Demand Uncertainty." Engineering Systems Division: Massachusetts Institute of Technology, Cambridge, MA, Doctoral Thesis.

159. Yeo, H., Yoon, Y., Madanat, S. (2013). "Maintenance Optimization for Heterogeneous Infrastructure Systems: Evolutionary Algorithms for Bottom-Up Methods." *Sustainable and Resilient Critical Infrastructure Systems: Simulation, Modeling, and Intelligent Engineering*, 185-200.

160. Zhang, H., Keoleian, G.A., Lepech, M.D. (2013). "Network-Level Pavement Asset Management System Integrated with Life-Cycle Analysis and Life-Cycle Optimization." *Journal of Infrastructure Systems*, 19(1): 99-107.

161. Zhang, H., Keoleian, G.A., Lepech, M.D., Kendall, A. (2010). "Life-Cycle Optimization of Pavement Overlay Systems." *Journal of Infrastructure Systems*, 16(4): 320-332.

162. Zhou, B., Li, Z., Patel, H., Roshandeh, A.M., Wang, Y. (2014). "Risk-Based Two-Step Optimization Model for Highway Transportation Investment Decision-Making." *Journal of Transportation Engineering*, 140(5): 04014007.

163. Zimmerman, K. A. (1995). "Pavement Management Methodologies *to* Select Projects and Recommend Preservation Treatments." Washington, D.C.: National Academy Press.