Pavement Management Systems: Opportunities to Improve the Current Frameworks

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ABSTRACT

Pavement management systems have emerged as an effective tool for allocating resources for the maintenance and rehabilitation of pavement networks. The goal of this paper is to benchmark the existing literature in order to facilitate a better understanding of the opportunities to augment the current frameworks while remaining consistent with the aims of the Moving Ahead for Progress in the 21^{st} Century (MAP-21) Act. Key themes that emerge include the need to (a) consider sources of uncertainty beyond pavement deterioration (b) preserve and utilize multi-attribute condition information in a more efficient manner and (c) reach a consensus on the objective functions of relevance. Addressing these three areas, in the opinion of the authors, will place the pavement management community in a better position to maintain existing assets in the face of limited resources and an uncertain future.

The authors demonstrate the need to incorporate uncertainty for a larger range of inputs than currently implemented by developing a case study that evaluates the implications of uncertainty in future costs. Two methodologies are used; the first transforms stochastic uncertainty into a deterministic constraint, while the second is a locally optimal algorithm that makes the best decision at each time step as uncertainty evolves. Results suggest that (a) cost uncertainty has implications on the optimal maintenance strategy and (b) allowing decisions to evolve over time can lead to improved performance compared to finding the globally optimal decision at once.

INTRODUCTION

Federal and state transportation agencies currently stand at a crossroad. Decreasing transportation funds, increasing maintenance and construction 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 (*1, 2*). Such concerns, which have haunted transportation agencies for decades, have pushed several departments of transportation (DOT) towards adopting asset management, the use of quantitatively-based support tools in the planning and prioritization of infrastructure facilities (*3-5*). Pavement management systems, which apply these principals to pavement networks, have witnessed staggering developments, largely due to enhancements in modern computing. Starting with the earlier tools in the late 1960's and early 1970's which primarily served as a way to process and store data, optimization-based techniques have gradually been introduced in order to determine how to best allocate resources across a network of pavements; the first known pavement management system was developed for the state of Arizona in the early 1980's (*3, 6*).

Since the first seminal paper in pavement management in 1982, several alternative formulations to this particular resource allocation problem have been proposed (*6*). The overarching theme across these studies is searching for the optimal allocation solution while balancing between complexity and computational cost (*7*). Despite this commonality, the approaches, scopes, and objectives of some of the influential work in the field diverges in many directions. An important step to continue improving the existing tools is to be able to benchmark the status-quo and identify gaps for future researchers. This paper accomplishes that by synthesizing the development of pavement management systems over the last 30 years only as it relates to academic research and not those used in the field. The goal is to facilitate a better understanding of the strengths and weaknesses of previous research and motivate future work to address gaps, particularly those pertinent to the Moving Ahead for Progress in the 21st Century (MAP-21) Act. This includes understanding the role of uncertainty given that MAP-21 legislation requires state DOTs to develop *risk-based* management plans for the effective maintenance of the national highway system (*8*).

This study first broadly focuses on understanding the key methodological and case study differences in the literature. With respect to the latter, differences regarding (a) objective functions (b) network constraints and (c) dimensionality are examined in order to characterize trends in the scope and application of previous studies. As for methodological differences, an emphasis is placed on understanding (a) the incorporation of uncertainty (b) the types of pavement deterioration models utilized and (c) the ability of the models to cope with the computational complexity of modeling a large network of pavements. Once these are established, a set of recommendations is set forth in order to improve the existing methodologies. One of those proposals includes the incorporations of stochastic variation for a larger range of inputs; a case study is presented demonstrating the importance of one of those commonly ignored parameters.

PAVEMENT MANAGEMENT LITERATURE

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 paper) or network using quantitative information (*9*). 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 (*10*).

In many instances pavement management systems follow a top-down approach that establishes funding levels to meet long-term performance goals but requires further steps to prioritize specific segments (*11*). Increasingly, however, researchers have recognized the limitations of such an approach in its ability to consider the heterogenic nature of pavement segments, and, as such, have moved towards facility-specific (e.g., at the segment level) models (*12-14*).

The following sections compare 35 pavement management studies, both top-down and facility-specific, spanning the last 30-plus years in order to understand the state of current research and opportunities for augmenting the existing methodologies. Although not inclusive of every research effort, the authors believe the following provides a representative sample of pavement management since their early beginnings.

Objectives, Constraints, and Dimensionality of Existing Studies

TABLE 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, are excluded for the purposes of this paper (*15, 16*).

Objective Function(s)

The majority of research has focused on maximizing pavement performance and/or minimizing costs. Although TABLE 1 differentiates between the two metrics, they are oftentimes convolved in both single-objective and multi-objective frameworks. The first approach typically correlates pavement condition with user cost and integrates that into the objective function (*12, 14, 17-22*). The second method, as discussed in Ng et al. (*23*), Wu and Flintsch (*24*), and Gao et al. (*25*), applies weights to agency cost and network performance. The authors then search for the optimal weighting scheme that minimizes the Euclidian distance for the performance indicators. Exceptions to these objectives include work by Fwa et al. (*26*), which maximizes construction output, and Gao and Zhang (*27*), which introduces a budget constraint into the objective function via a Lagrangian relaxation.

It is important to realize that performance is an ill-defined term that carries numerous connotations. Examples include travel time to users, average pavement service rating (PSR), traffic-weighted average PSR, environmental impact, safety, and portion of segments in poor and/or excellent condition (*4, 23-25, 28-30*). The importance of these discrepancies is magnified due to MAP-21 legislation that requires the development of performance-oriented models that address safety, environmental, congestion, and infrastructure condition concerns (*8*).

TABLE 1 The following synthesizes the objectives, constraints, analysis periods (∞ indicates infinite), network size, and number of rehabilitation actions in the existing literature for 'top-down' and 'facility-specific' research chronologically

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 et al. (*6*)	✓				✓		✓				*Pavement Segments are Aggregated in Top-Down Studies*	
Carnahan et al. (*31*)	✓				✓			✓				
Chen et al. (*32*)	✓	✓		✓	✓			✓				
Liu and Wang (*33*)		✓		✓	✓		✓					
Wang and Liu (*34*)		✓		✓	✓		✓					
Fwa et al. (*26*)	✓	✓	✓				✓					
Abaza and Ashur (*35*)		✓		✓			✓					
Pilson et al. (*36*)		✓		✓					✓			
Abaza et al. (*37*)		✓		✓								
Smilowitz and Madanat (*38*)	✓			✓	✓			✓		✓		
Abaza et al. (*29*)	✓	✓		✓			✓					
Kuhn and Madanat (*20*)	✓			✓			✓					
Abaza (*39*)		✓		✓								
Wang et al. (*40*)	✓	✓		✓	✓		✓					
Wu and Flintsch (*24*)	✓	✓		✓			✓					
Gao et al. (*25*)	✓	✓		✓	✓							
Chan et al. (*41*)	✓	✓		✓	✓			✓			45	3
Mbwana and Turnquist (*42*)	✓			✓	✓		✓				60	4
Li et al. (*43*)		✓		✓			✓				18	5
Li et al. (*28*)		✓		✓			✓				5	3
Melachrinoudis and Kozanidis (*30*)		✓		✓							3	
Ferreira et al. (*7*)		✓		✓		✓	✓				9-254	6
Wang et al. (*44*)	✓	✓		✓	✓		✓				10	4
Ouyang and Madanat (*17*)	✓			✓			✓	✓	✓		3	Continuous
Chootinan et al. (*45*)	✓	✓		✓			✓				53	4
Durango-Cohen and Sarutipand (*22*)	✓			✓			✓				2-5	Continuous
Ouyang (*46*)	✓			✓					✓		2	Continuous
Kuhn (*21*)	✓			✓					✓		3-300	6
Sathaye and Madanat (*18*)	✓			✓						✓	3	Continuous
Gao and Zhang (*27*)	✓		✓				✓				5-1,000	1
Sathaye and Madanat (*13*)	✓			✓						✓	1,000	Continuous
Gao and Zhang (*47*)		✓		✓			✓				39,018	3
Yeo et al. (*12*)	✓			✓				✓				2
Zhang et al. (*4*)	✓			✓					✓		29	8
Medury and Madanat (*48*)	✓			✓				✓			11	3
Medury and Madanat (*14*)	✓			✓				✓			10-1,000	2

Constraint(s)

The prevailing constraint across most formulations is financially related, where the goal is to optimize the objective function subject to an annual available budget. Slight nuances to this formulation have been proposed that allow for a decision-maker to carry over funds to the following year (*19*). The next most common constraint is related to pavement condition; namely, only a portion of pavements are allowed to be in a 'poor' state in a given year. Beyond this, studies have incorporated serviceability and physical resource constraints, albeit sparingly. Ferreira et al. (*7*), for example, allows no more than one major rehabilitation for each segment over the analysis period in order to reduce disturbances for users. Fwa et al. (*49*) incorporates constraints related to material, equipment, and manpower availability in a given timeframe. In short, although availability of financial resources and pavement condition are the primary constraints considered, other intricate constraints have been introduced previously

Dimensionality

Researchers have implemented their formulations in a range of contexts that vary in terms of network size, time-horizon, and number of maintenance actions available. These factors have a latent implication on the computational complexity, and therefore, appropriateness of methodology. The top-down methodology is particularly attractive as it reduces a large pavement network to a few aggregate groups with similar characteristics (*6, 20, 24, 29, 31, 32, 34, 37-40*). 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 have large implications (*22, 50*). 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 been demonstrated to scale efficiently for larger networks on the order of hundreds (and even thousands) of pavement segments (*12-14, 21*).

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 (*4, 17, 21, 46*). This is particularly interesting given that project-level models, which are typically used once a network-level model has determined projects to fund, tend to be utilized for longer periods, illustrating the disconnect between the two approaches (*51*). As for rehabilitation alternatives, generally studies only consider a small subset (≤ 6) of the possible actions at the disposal of a state agency. Furthermore, rehabilitation alternative types are fairly generic except for Chan et al. (*41*) and Zhang et al. (*4*), the latter considering very specific actions for both asphalt and concrete pavements. Alternatively, some studies only consider the predominant type of rehabilitation action, overlays, allowing thickness to be a continuous function (*13, 17, 18*). As researchers continue to move towards larger networks while preserving segment-specific information, being able to consider a large number of realistic rehabilitation types presents an opportunity to continue to progress the existing pavement management tools.

Methodology, Uncertainty, and Pavement Deterioration

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

Optimization Method

Different modeling techniques employed in studies include linear, integer, and dynamic programming, as well as genetic algorithms. 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 (*6, 20, 24, 32-34, 38*). The implementation of integer linear programming for facility-level decisions, however, is computationally costly, making the utilization of genetic algorithms, dynamic programming, and heuristic-based offshoots attractive alternatives. Heuristic-based approaches include Ouyang and Madanat (*17*), who creates a greedy algorithm to make locally best decisions throughout the analysis period, and Kuhn (*21*), who uses approximate dynamic programming.

Generally speaking, however, facility-specific models apply a two-stage bottom-down approach, where dynamic programming is first used to determine the best set of policies for each facility (Bellman's principal of optimality) and then a network-level model selects the facilities to receive treatment in the current year based on the available budget (*4, 12*). The drawback of such an approach is that it ignores the fact a facility will, potentially, be unable to follow the optimal path due to future budgetary constraints on the network. As a result, a very limited body of research has emerged that accounts for future possible constraints. Medury and Madanat (*14*) developed a methodology that integrates the facility-specific dynamic programming approach within the typical top-down formulation. Alternatively, the same authors evaluated Approximate Dynamic Programming (ADP) as an alternative method to account for future network-level constraints (*48*).

Incorporation of Uncertainty and Pavement Deterioration

A discussion around uncertainty must focus its attention on pavement deterioration as it oftentimes the only source of variation considered in a study. Typically, Markov chains are used, where the probabilistic deterioration in the next period is only a function of the current state. Uncertainty in pavement deteriorates is, therefore, purely aleatory, as deterioration is random and not due to any heterogeneous/external factors. Li et al. (*43*) and Li et al. (*28*) try to account for this by developing heterogeneous Markov Chains, where transition probabilities are a function of the structural design of the pavement and external factors such as traffic and climate. Madanat et al. (*5*) developed age-dependent transition probabilities, although they are only implemented 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 (*36, 41, 45*). As noted by Durango-Cohen and Sarutipand (*22*), a balance between the two extremes should be found in network-level research by using the insights from the pavement deterioration community (*52-53*).

TABLE 2 Optimization methods (LP/ILP = linear programming, NLP = non-linear programming, GA = genetic algorithms, DP= dynamic programming), sources of variation, and deterioration models (Homo = homogenous, Hetero = heterogeneous, Cont. = continuous) of previous work are listed below. Performance metrics are PCI (pavement condition index), RO (roughness), CR (cracking) and RU (rutting)

Category	Study	Optimization Method: LP/ILP	NLP	GA	DP	Others/Notes	Variation besides PC deterioration	PC Deterioration Model: Homo Markov	Hetero Markov	Cont.	Metric
Top-Down Studies	Golabi et al. (*6*)	✓						✓			RO, CR
	Carnahan et al. (*31*)				✓			✓			PCI
	Chen et al. (*32*)	✓						✓			PCI
	Liu and Wang (*33*)	✓						✓			PCI
	Wang and Liu (*34*)	✓						-	-	-	-
	Fwa et al. (*26*)			✓				✓			PCI
	Abaza and Ashur (*35*)		✓					✓			PCI
	Pilson et al. (*36*)			✓						✓	PCI
	Abaza et al. (*37*)		✓					✓			PCI
	Smilowitz and Madanat (*38*)	✓					Condition				PCI
	Abaza et al. (*29*)		✓					✓			PCI
	Kuhn and Madanat (*20*)	✓				Robust LP		✓			PCI
	Abaza (*39*)		✓					✓			PCI
	Wang et al. (*40*)			✓				✓			PCI
	Wu and Flintsch (*24*)	✓					Budget	✓			PCI
	Gao et al. (*25*)		✓					✓			PCI
Facility-specific models	Chan et al. (*41*)			✓						✓	RO, CR, RU
	Mbwana and Turnquist (*42*)	✓						✓			PCI
	Li et al. (*43*)	✓							✓		PCI
	Li et al. (*28*)	✓							✓		PCI
	Melachrinoudis and Kozanidis (*30*)	✓						-	-	-	-
	Ferreira et al. (*7*)	✓		✓				✓			PCI
	Wang et al. (*44*)	✓						✓			PCI
	Ouyang and Madanat (*17*)	✓				Greedy Heuristic				✓	RO
	Chootinan et al. (*45*)			✓			Traffic			✓	PCI
	Durango-Cohen and Sarutipand (*22*)				✓					✓	PCI
	Ouyang (*46*)				✓					✓	RO
	Kuhn (*21*)				✓	Approximate DP	Rehab effectiveness			✓*	PCI
	Sathaye and Madanat (*18*)		✓			Lagrangian dual				✓	RO
	Gao and Zhang (*27*)	✓						-	-	-	PCI
	Sathaye and Madanat (*13*)		✓			Lagrangian dual				✓	RO
	Gao and Zhang (*47*)	✓						✓			PCI
	Yeo et al. (*12*)				✓			✓			PCI
	Zhang et al. (*4*)				✓					✓	PCI
	Medury and Madanat (*48*)					Approximate DP		✓			PCI
	Medury and Madanat (*14*)	✓						✓			PCI

Additionally, there is little consideration in the mentioned research of incorporating uncertainty while preserving multi-attribute condition data for pavements. The majority of studies use a composite pavement condition index that estimates overall pavement condition via best-judgement or weighting different pavement serviceability measurements (e.g., roughness, cracking, faulting). Of course, the appropriateness of a maintenance alternative is largely driven by the failure mechanism of a segment. Chan et al. (*41*), for example, tries to account for this by decoupling three failure mechanisms (roughness, cracking, and rutting); for each failure mechanism in the model, there is an appropriate rehabilitation type.

It is worth noting that uncertainty beyond pavement deterioration is limited. Smilowitz and Madanat (*38*) extend the latent Markov decision process (LMDP) methodology developed by Madanat and Ben-Akiva (*54*) for the integration of uncertainty in the measurement of pavement condition. Kuhn (*21*) considers uncertainty in the benefit of a given treatment. Wu and Flintsch (*24*) transform the stochastic uncertainty in future budget levels into a deterministic constraint, finding that ignoring future budget uncertainty and not accounting for the aversion of decision-makers to go over budget leads to overly-optimistic maintenance plans. Chootinan et al. (*45*) utilizes the same approach, but this time transforms uncertainty in future traffic volumes into a deterministic constraint. What is particularly striking is that although only a few types of uncertainty are considered in network level models, several other sources of variation have been incorporated in project-level models (*55*).

SUMMARY AND RECOMMENDATIONS FOR PAVEMENT MANAGEMENT SYSTEMS

Pavement management is a mature field that has continued to evolve since the earliest systems were introduced for resource allocation more than 30 years ago. The purpose of this paper has not been to minimize the significance of previous work, but rather to shed some light on the important research questions facing the pavement management community moving forward. The focus has not only been on understanding the methodological gaps but also on increasing cognizance of the types of contexts in which these models have been implemented historically. Addressing the latter makes this article particularly timely as public agencies grapple with integrating asset management as part of MAP-21 legislation. The proceeding section summarizes the key takeaways from the previous discussion and develops a set of recommendations for future work.

Summary of Gaps

The existing research primarily focuses on developing optimization-based techniques for either maximizing performance of roadway segments and/or minimizing total costs subject to, generally speaking, a financial and minimum pavement condition constraint; defining performance is difficult to do as its definition is multifarious. An important trend that emerges is that the dimensionality of the context 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 includes the need for further sub-processes and the treatment of heterogeneous segments as homogenous, while the facility-specific model for large systems, generally, is unable to estimate a facility-specific cost-to-go function (a fundamental part any dynamic program) that considers the impact of future system-level constraints. Additionally, although the size of the network has continued to grow, the rehabilitation types are still fairly ambiguous and the time-horizon continues to leans towards the short/medium-term.

In terms of methodological shortcomings, uncertainty is primarily limited to pavement deterioration even though uncertainty for future economic and environmental conditions has been established as important at the project-level. Likewise, the drawback of modeling pavement deterioration using Markov chains with homogenous transitional probabilities for a pavement condition index is three-fold. Differently designed pavement segments subject to diverse conditions are assumed similar, uncertainty is overestimated by treating explainable variation as unexplainable noise, and multi-attribute information, which provides insight on the appropriate rehabilitation action to apply, is removed.

Recommendations Moving Forward

TABLE 3 summarizes a list of recommendations that will better align future research with current needs. First, academics must work with regional and national agencies in developing paradigms that match with the goals of federal legislation. This will lead to a set of consistent metrics that will facilitate a more direct comparison between alternative methodologies. Second, although the benefit of facility-specific models has been discussed, approaches are still needed that can model system performance over longer time-horizons, incorporate maintenance and rehabilitation activities representative of the types an agency might consider, and be able to consider the implication of network-level constraints on future facility-specific decisions. Third, the pavement management community should begin incorporating the sources of variation that have been demonstrated as being significant at the project-level; this includes both economic and environmental parameters. Lastly, multi-attribute condition models should be integrated that consider uncertainty yet incorporates covariates that explain variation due to heterogeneity.

TABLE 3 Recommendations for future pavement management research

Issue	Recommendations
Objective Functions	❖ Develop a set of consistent metrics that addresses the long-term goals of the national highway system and transportation agencies nationally
Constraints	❖ Continue incorporating financial and performance-level requirements in the existing models
Dimensionality	❖ Model performance of systems over the long-term ❖ Continue developing facility-specific models for heterogeneous systems ❖ Incorporate rehabilitation activities representative of the types available in practice
Optimization Method	❖ Develop facility-specific models that can account for future system-level constraints for large networks
Sources of Uncertainty	❖ Incorporate uncertainty for parameters besides pavement deterioration ❖ Examples include future cost of maintenance, traffic volumes, and available resources
Deterioration Model	❖ Decompose pavement condition indices and begin considering multi-attribute conditional data ❖ Integrate deterioration models that consider aleatory uncertainty while incorporating covariates that explain the heterogeneous nature of pavements

CASE EXAMPLE: INCORPORATING COST UNCERTAINTY IN PAVEMENT MANAGEMENT

In order to demonstrate the importance of one of the recommendations presented, a case study that integrates uncertainty in construction costs, one of the several stochastic inputs not treated as such in the current frameworks, is presented using two methodologies. It is important to note that cost variation can manifest in two forms: future costs within the analysis period and variation across pavement facilities at a given point in time. Although the latter tends to be quite important at the project-level, one would expect its implications to be mitigated for a network. Assume one applies the same action, a, to a number of homogenous facilities, n, at year t with an associated cost, $C_{a=1,nt}$. If $C_{a=1,nt}$ is Gaussian distributed and uncorrelated across facilities then the expected cost of applying that action across the network rather than a single pavement scales by n while the standard deviation only increases by $n^{1/2}$. Therefore, if n is sufficiently large, then its reasonable to assume that the implications of this source of variation would be minimal, and so only uncertainty in how average construction costs will evolve over time is modeled.

The case study developed is for ten fictional, yet realistic, interstate pavements in a wet-freeze climate as shown in TABLE 4. It is assumed that each pavement segment is one mile (1.61 km) long and 28 feet (8.5 m) wide. Pavement deterioration models, cost of alternative rehabilitation types and their associated benefits are taken from the previously cited Chootinan et al. (*45*) and can be seen in TABLE 5. The fundamental assumption of the deterioration model is that the annual change in PSR is deterministic and a function of climactic, traffic, structural, and age factors.

In order to account for future cost uncertainty, a construction cost index (CCI) is incorporated that projects the future cost of maintenance actions. It is presumed that any unit change in the CCI has a corresponding effect on the cost of all rehabilitation actions; in other words, if the CCI increases by 1%, so to do all treatments. This is perhaps extreme, but is more reasonable than assuming that the future cost of different actions is completely uncorrelated.

TABLE 4 Data for the ten fictional pavement segments in the case study. The structural number for composite and JPCP pavements is the pavement layer thickness

Segment	Material	Age (years)	Structural Number	PSR	AADT	AADTT
1	HMA	20	4.2	3.70	9,100	1,047
2	HMA	14	4.7	4.20	35,512	2,105
3	HMA	15	4.5	4.13	10,035	1,154
4	HMA	24	3.5	3.70	19,403	2,231
5	HMA	30	4.01	3.54	40,371	3,432
6	HMA	12	4.6	3.87	32,636	1,795
7	HMA	23	4.0	3.71	15,836	1,900
8	JPCP	11	10.5	3.61	61,368	3,375
9	Composite	9	11.5	3.66	29,488	1,769
10	Composite	37	11.5	3.66	30,784	1,847

TABLE 5 Cost and maximum change in PSR for the four possible actions per Chootinan et al. (*45*). Linear interpolation is used to estimate benefits for non-listed ages

Treatment	Real Cost ($/SQY)	Increase in PSR for each action as a function of age							
		20	19	16	13	10	7	4	1
Routine Maintenance	0.2	0	0	0	0.23	0.23	0.45	0.45	0.45
Surface Treatment	0.74	0	0.45	0.68	1.13	1.58	1.58	1.58	1.58
Overlay	4.67	0	0.9	1.58	1.8	1.8	1.8	1.8	1.8
Rehabilitation	7.74	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5

Accounting for Cost Uncertainty: Two Alternative Formulations

The objective of this rather simple case study is to maximize the PSR rating of the pavement segments over a ten-year time-horizon subject to an available budget of $150,000 annually, enough to perform one major rehabilitation in each time-period. The CCI is assumed at any future year to be Gaussian distributed around current day construction costs with a COV equal to 0.1. Two possible methodologies are implemented; the former transforms the stochastic uncertainty in future construction cost into a deterministic constraint, similar to Wu and Flintsch (*24*), and the latter is a step by step greedy heuristic that maximizes performance as uncertainty evolves, as in Ouyang and Madanat (*17*).

Methodology 1: Transforming a stochastic parameter into a deterministic constraint

Equations 1-5 summarizes the mixed-integer non-linear program (MINLP) for maximizing average PSR while transforming cost variation into a deterministic constraint. A branch and bound algorithm is implemented via LINGO software in order to find the global solution. Equation 1a states the objective: maximize the total PSR of the network over T years and N facilities. Equation 1b defines that the PSR of facility n in year $t+1$, $PSR_{n,t+1}$, is a function of the PSR in the previous year of that facility, $PSR_{n,t}$, the deterioration rate at that particular year, $D(t)_{n,t}$, and the increase in PSR from an action in the previous year. That last component is composed of B_{ant}, the increase in PSR from action a, and X_{ant}, a binary decision variable defining whether or not action a is applied. Equation 2 asserts that the benefit of any rehabilitation action cannot exceed the maximum possible PSR (4.5) for a facility. Equation 3 and 4 condition that no more than one rehabilitation action is used for any segment in a given year and that the decision is binary. Lastly, Equation 5 stipulates that expected costs at each year, $X_{ant}*C_{ant}$, plus cost at a risk averse profile is less than the annual available budget, B. The second term is composed of $\Phi^{-1}(\delta_t)$, or the z-score of standard normal distribution at a risk-profile δ_t, and $\sigma_{CCI,t}$, or the standard deviation in the CCI index. Therefore, setting δ_t equal to 50% is the equivalent of the prevalent deterministic assumption.

$$\max PSR(T,N) = \sum_{t=0}^{T} \sum_{n=1}^{N} PSR_{n,t} \tag{1a}$$

$$PSR_{n,t+1} = PSR_{n,t} - D(t)_{n,t} + X_{ant}B_{ant} \tag{1b}$$

subject to

$$0 \le B_{ant} \le PSR_{max} - PSR_{n,t} \tag{2}$$

$$\sum_{a=1}^{A} X_{ant} \le 1 \qquad \forall\, n = 1,2 \ldots N\,, \forall\, t = 0,1, \ldots T-1 \tag{3}$$

$$X_{ant} \in \{0,1\} \tag{4}$$

$$\sum_{n=1}^{N} X_{ant}C_{ant} + \Phi^{-1}(\delta t)\sigma_{CCI,t}X_{ant}C_{ant} \leq B \qquad \forall\, t = 0,1, \dots T-1 \tag{5}$$

Methodology 2: Implementing a Greedy Algorithm

An alternative formulation is built off the work established by Ouyang and Madanat (*17*) that demonstrated that a greedy algorithm (i.e., the best decision is made at each time step) can lead to a solution very close to the global optimal. The fundamental assumptions are (a) uncertainty in cost at each year reveals itself and (b) a rehabilitation only changes a pavement's condition and not its rate of decay. Equation 6 states that at the start of each year, t^*, the objective is to maximize the change in PSR of the network. All other constraints remain the same as in the previous method except for the removal of the risk-aversion term in Equation 5. This is because, theoretically, there is no uncertainty in a single period decision. Since the problem is very tractable, a Monte Carlo simulation is integrated into the analysis. For each simulation, construction costs are randomly generated over the time-horizon and locally optimal decisions are made each year. The analysis is conducted for 1,000 simulations in order to estimate the uncertainty in how the model performs.

$$\max \Delta PSR = \sum_{n=1}^{N} X_{ant^*}B_{ant^*} \tag{6}$$

$$\text{s.t.}$$

$$0 \leq B_{ant^*} \leq PSR_{max} - PSR_{n,t^*} \tag{7}$$

$$\sum_{a=1}^{A} X_{ant^*} \leq 1 \qquad \forall\, n = 1,2 \dots N \tag{8}$$

$$X_{ant^*} \in \{0,1\} \tag{9}$$

$$\sum_{n=1}^{N} X_{ant^*}C_{ant^*} \leq B \tag{10}$$

Results and Takeaways from Simplified Case Study

FIGURE 1 presents the average PSR of the pavement network for three cases: a deterministic globally optimal (DGO) model (Methodology 1, $\delta_t = 50\%$), a globally optimal risk-averse (GORA) approach (Methodology 1, $\delta_t = 90\%$), and a locally optimal stepwise (LOS) method (Methodology 2). The expected PSR of DGO is the highest, but, it is also the most susceptible to cost over-runs. On the other hand, GORA is less likely to exceed budget in a given year but at the expense of lower pavement condition. Interestingly, LOS outperforms both DGO and GORA when balancing between average PSR and susceptibility to cost over-runs as, on average, the PSR for LOS is similar to DGO and significantly higher than GORA without exceeding budget.

The results from this case study are not meant to suggest that these two methodologies are the only available to account for cost variation, but rather, makes two strong arguments. First, cost variation is one example of the type of uncertainty currently being ignored by the literature as a whole and can have implications on the optimal pavement management strategy. Second, methodologies that allow for decisions to evolve as information reveals itself represent a powerful way of increasing performance relative to a global solution that makes future decisions at once.

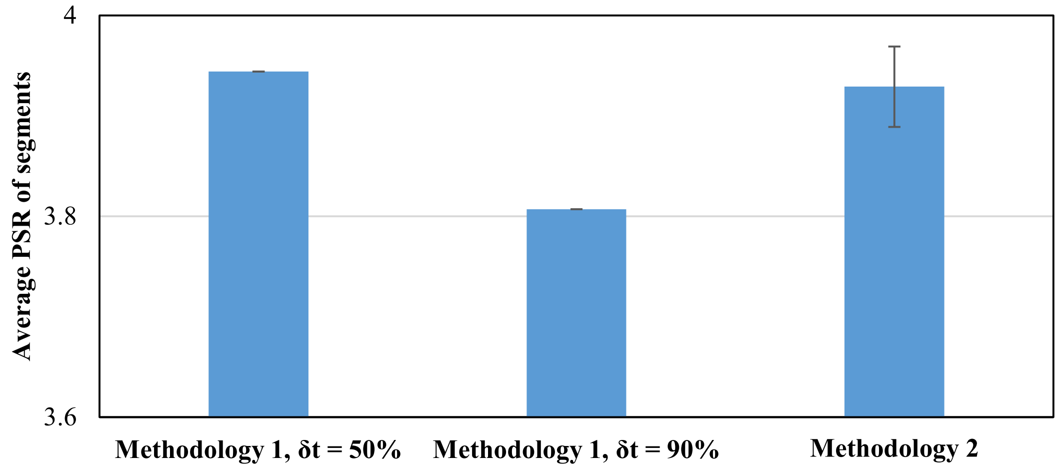

FIGURE 1 Average PSR of the pavement segments over a 10-year planning horizon for Methodology 1 (δ_t = 50%), Methodology 1 (δ_t = 90%) and (c) Methodology 2. Error bars in Methodology 2 capture the 10^{th}/90^{th} percentiles.

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