Improving pavement networks through performance-based planning with optimal treatment strategies and management policies

by

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Abstract

Performance-based planning (PBP) is an efficient way to improve pavement networks. It is the practice of using data from pavement management systems (PMSs) to support analyses on the predicted network performance based on available budgets, treatment strategies and management policies. PBP involves the collection and analyses of PMS data, pavement deterioration prediction, budget allocation, the selection of treatment strategies, and the promotion of appropriate pavement management policies.

This dissertation provides a comprehensive framework for PBP. First, it focuses on the development of a pavement deterioration prediction model and a budget allocation model. A weighted-output neural network model is proposed, which can predict multiple pavement condition metrics simultaneously and incorporate their correlations into the prediction process. During model training, each condition metric is assigned a weight to reflect its relative importance. When the weights equal to those in the formula for a multi-condition metric pavement condition index (PCI), the prediction performance for PCI is optimal (13% lower mean squared error than optimal, single-output models). In terms of the budget allocation model, a probabilistic treatment path dependence (PTPD) model has been proposed. This model incorporates uncertainties of both treatment cost and pavement deterioration, and evaluates a treatment by considering benefits of both the evaluated treatment and its following actions. Compared to a conventional benefit cost ratio model, PTPD can deliver equivalent pavement network performance with an annual budget that is 10% less.

Most existing research on PBP focuses on improving allocation decisions through changes in the allocation algorithm without considering the consequences of how optimization analyses are framed. In this thesis, both the environmental and economic performance of a pavement network are evaluated for different framings of the problem. Specifically, framings in the form of different treatment strategies that consist of treatment materials, treatment types, and evaluation period are considered. Results show that the proposed strategy that uses multiple materials (both concrete and asphalt), an increased number of treatment types, and a long evaluation period could both reduce greenhouse gas emissions and improve pavement network performance. Finally, this thesis explores the potential impact of different federal or state policies regarding PBP. Three pavement management policies are proposed, including flexible decision-making, long-term planning, and market diversification. Model results suggest that incorporating these policies for the whole U.S. pavement network (compared to a business-as-usual scenario), could reduce total excess vehicle fuel expenditures from 2017 to 2050 due to poor road conditions by 28% or about 62 billion dollars. All states can benefit from the proposed management policies.

These research findings can help transportation agencies improve their performance-based planning for pavement networks within a limited budget. In addition, this thesis also provides insights for federal or state agencies regarding the value of key policies to improve pavement networks and to reduce greenhouse gas emissions due to poor road conditions.

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In memory of Grandpa Enfu Li.

&

In honor of Grandma Derong Li.

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Acronyms

AADTT/TRUCKS	average annual daily truck traffic
AC	asphalt concrete
ACRACK	alligator crack
ADT/AADT	average annual daily traffic
AGECON	construction age
AGERES	resurface age
AOC	asphalt overlay composite
ASCE	American Society of Civil Engineers
BASTHK	base thickness
BASTYP	base type
BAU	business as usual
B/C	benefit cost ratio
CAPDAT	crack & patch collected by vender test year
CART	classification and regression tree
CCI	combined condition index
COC	concrete overlay composite
CONYR	year of construction or reconstruction
DG	diamond grinding
DP	dynamic programming
ESAL	equivalent single axle load
EV	electrical vehicle
FHWA	Federal Highway Administration
FREEZE	freeze index
GHG	greenhouse gas emission
ICEV	internal combustion engines vehicle
IRI	international roughness index
IRIDAT	IRI test year
LAYR	layer year

LCA	life-cycle assessment
LCC	life-cycle cost
LCCA	life-cycle cost analysis
LCRACK	longitudinal cracking
LTPP	long-term pavement performance
LWCRACK	longitudinal wheelpath crack
MARS	multivariate adaptive regression splines
MEPDG	Mechanistic-Empirical Pavement Design Guide
MF	mil & fill
MRRNUM	number of treatment actions
MSE	mean squared error
NCHRP	National Cooperative Highway Research Program
NN	neural network
OLS	ordinary least squares
ORIGKEY	original smart key
PAVTYP	pavement type
PBP	performance-based planning
PCC	Portland cement concrete
PCCTHK	sublayer concrete thickness
PCI	pavement condition index
PMS	pavement management system
PMISYR	pavement management year
POR	preservation, overlay, and reconstruction
PRECIP	precipitation
PSR	pavement surface rating
PTPD	probabilistic treatment path dependence
PVI	pavement vehicle interaction
RESYR	year of last resurfacing
RMVTHK	removal thickness

RMVTYP	removal type
RNN	recurrent neural network
SN	structural number
SO	simulation-optimization
SUBTHK	subbase thickness
SUBTYP	subbase type
SURTHK	surface thickness
SURTYP	surface type
TCRACK	transverse cracking
TEMP	temperature
TOTTHK	total thickness
TSBU	two-stage bottom-up
TWIRI	traffic-length weighted IRI

CHAPTER 1 INTRODUCTION

1.1 Background

Inadequate funding to improve infrastructure system is a pervasive problem in the U.S. Since 1998, the American Society of Civil Engineers (ASCE) has published *The Report Card for America's Infrastructure* every four years, which grades each type of infrastructure from A through F (A is the highest score), and also provides the overall grade for all infrastructures in the U.S. The overall condition grade stayed as a D from 1998 to 2017 [1]. The Report Card for 2021 shows that the overall grade has been improved to a C- [2]. Poor road conditions lead to the increase of travel time and travel safety problems. An aging electricity grid and inadequate water distribution make utilities unreliable. All these problems induced by infrastructure in bad condition have a huge economic influence on the whole society. According to the report *Failure to act: Economic impacts of status quo investment across infrastructure systems* by ASCE, if there were no action, the U.S. is forecasted to lose $10.3 trillion in GDP, $2.4 trillion in exports, and 3 million jobs from 2020-2039 [1].

Even though a small improvement occurred in 2021 for the overall infrastructure condition, the grade for the road system has remained a D since 1998. Over 40% of the system is in poor or mediocre condition. However, transportation agencies are always underfunded to repair existing roads. The backlog in repairing existing roads has increased from $420 billion in 2017 [3] to $435 billion in 2021 [2]. To address current backlogs, a 29% growth of annual budget should be provided. However, the Highway Trust Fund, which provides the federal investment in roads, has been on the edge of insolvency due to limited funding.

To improve the pavement network condition, the enactment of the Moving Ahead for Progress in the 21st Century (MAP-21) Act compels transportation agencies to develop efficient pavement management systems (PMS) to improve the national highway system. PMSs are broadly concerned with the evaluation of current conditions, the prediction of future conditions, and the planning of various treatments, including preservation, overlay, and reconstruction (POR) for a segment or a pavement network [4] . Performance-based planning (PBP) is the practice of using data from PMSs to support analyses on the predicted network performance based on available budgets, treatment strategies, and management policies [5].

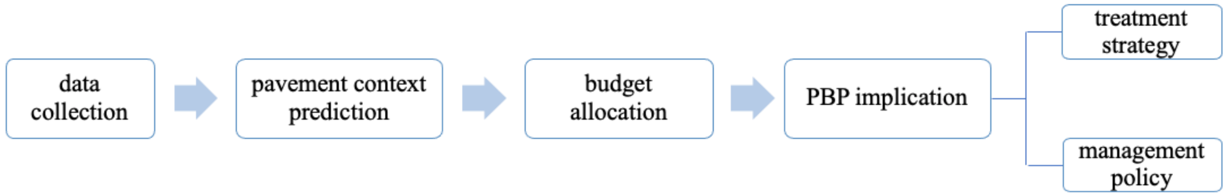


Figure 1-1. Flowchart of performance-based planning

PBP usually consists of three key components: data collection, pavement context prediction, budget allocation, and implication, as shown in Figure 1-1. Required data for PBP usually includes PMS data and pavement treatment cost data. PMS data includes pavement performance condition, traffic volume, pavement structure, maintenance history, and weather information. Two widely used national-level PMS data are the American Association of State Highway Officials (AASHO) road test [6] and Long-Term Pavement Performance (LTPP) program by the Federal Highway Administration [7]. LTPP covers more than over 2,500 segments in North America. Some states also collect their own PMS data, such as Nevada [8], Connecticut [9], Kansas [10], Florida [11], Minnesota [12], [13], Ohio [14], and Texas [15]. Even though there exist many data sources, not all of them are accessible, especially the state PMS data. In addition, the amount of available data is also very limited due to the high cost for data collection. To overcome these gaps, researchers have started to collect telematics data and use them to analyze road conditions, which can significantly cut off collection cost and speed up the collection process [16]–[19]. For example, the Carbin app developed by CSHub researchers at MIT can effectively detect road roughness condition and evaluate the environmental influence induced by roads in bad condition [17], [18]. The pavement treatment cost is usually obtained from the Oman systems [20], which provides the details for each pay item including material usage, cost and bid items.

The collected PMS data can be used to project future pavement conditions. As discussed in [21], deterioration modelling can be divided into two categories, Markov chains and regression models. For models based on Markov chains, pavement conditions are discretized into several states, and models mainly focus on the probability prediction from one state to another state. Different from Markov chains, regression models build relationships between independent variables (or features) and dependent variable (or target). The output of a regression model can be road condition, such as roughness, cracks, rutting, and faulting. Hence, there is no need to discretize pavement performance conditions. Common regression models include linear regression models [14], [22], non-linear models which are described by the sum of several nonlinear variables or by the exponential form [15], [23]–[25], neural network models [9]–[11], [26]–[32], tree-based models [11], [33], and fuzzy regression [34].

The projected future pavement condition can be applied to evaluate different pavement segments (or projects) and make pavement treatment schedules for a pavement network. Life-cycle cost analysis (LCCA) [35]–[38] and life cycle assessment (LCA) [39]–[42] are two common approaches to evaluate different pavement alternatives from the economic and environmental effects, respectively. The life-cycle phases usually include material extraction and production, construction, use, maintenance and end-of-life. By calculating the total life-cycle cost or greenhouse gas emissions (GHGs), it can help us decide which pavement design should be applied for a new pavement segment. Given a pavement network, a budget allocation model is usually applied to make treatment schedules for each pavement segment in the network [25], [43]–[46]. Essentially, a budget allocation model is an optimization algorithm, which maximizes pavement network condition with the budget constraint or minimizes the total budget with the constraint of performance threshold or even incorporates multi objectives. The budget allocation process for pavement network is a large-scale optimization problem. Suppose there are I segments and N available treatments, and the planning horizon is T years. The number of total possible treatment schedules is $(N+1)^{I*T}$ (number 1 represents that there is no treatment.). For a small pavement network with 100 segments, if the number of available treatments is 2, and the analysis period is 5 years, the total number of possible schedules can be as large as $3^{500} \approx 3 \times 10^{238}$. To overcome this large-scale issue, two approaches have been proposed, including top-down and bottom-up frameworks. The top-down approach divides the whole network into several groups and assume the pavement segments in the same group will use the same treatments [4], [43], [47]–[49]. This approach has a faster processing speed with the sacrifice of ignoring the heterogeneity of different segments. By contrast, the bottom-up approach incorporates the heterogeneity of different segments [50]–[55]. It finds optimal treatment alternative(s) for each segment and then decides which segments receive the treatment with the consideration of different constraints. Its processing speed is slower than the top-down approach. However, with the increasing of computational capacity, the bottom-up framework has become the focus of current research.

In addition to the data collection, modeling of pavement deterioration prediction, and budget allocation algorithms discussed above, how the budget allocation process is implemented is also very important, which involves treatment strategies and management policies. A treatment action is a specific technology (e.g., diamond grinding, asphalt overlay), and a treatment strategy is the use of a portfolio of treatment actions (e.g., preservation treatments, asphalt treatments). The determination of treatment strategies can be based on past experiences, and sometimes may be influenced by many other factors, such as policy, budget, and material availability, etc. From the perspective of optimization, the treatment strategy influences the solution space. An appropriate treatment strategy can contribute to the improvement of pavement network condition. The management policies are mainly concerned with potential approaches that should be taken by transportation agencies to improve pavement network condition from a long-term perspective. For example, the promotion of market diversification can lead to the decrease of unit prices for both materials.

To summarize, the current bad road condition in the U.S urgently requires transportation agencies and stakeholders to take effective PBP to make pavement treatment schedules. On one hand, it is necessary to improve data collection, increase projection performance for pavement condition, and optimize budget allocation models. On the other hand, different treatment strategies should be evaluated and compared before putting into real-world applications. Transportation agencies should also develop appropriate management policies that can improve pavement networks.

1.2 Literature Review and Gap Analysis

This section reviews existing research about performance-based planning. Even though the data collection process is a very important component in PBP, it is currently not the focus of my dissertation. Hence, the literature review about data collection is ignored in this section. The main topics for the literature review include pavement deterioration models, budget allocation models, treatment strategies, and management policies.

Pavement deterioration models

Pavement deterioration models predict future pavement condition without any treatment. Given the complex physical and chemical processes involved in the deterioration, most existing deterioration models are data-driven using statistical methods including linear regression [14], [22], non-linear models which are described by the sum of several nonlinear variables or by the exponential form [15], [23]–[25], neural network [9]–[11], [26]–[32], and decision trees [11], [33]. Common condition metrics used for PBP include pavement roughness (e.g., the international roughness index, IRI), rutting, faulting, and various forms of cracking [7], [24], [56]. Existing models mainly focus on the prediction of a single condition metric – a single overall metric like pavement condition index (PCI), or a specific metric like IRI. This type of single-output models lacks the consideration of correlations among different condition metrics, and potentially increase the computational cost compared to a multi-output model when generating multi specific metrics.

Common predictor (input) variables include traffic volumes/loads, pavement structure (e.g., pavement type, thickness), pavement age, pavement conditions and environmental factors (e.g., temperature, precipitation). Existing models are inherently limited to the variables described in available data, limiting their ability to incorporate the influence of maintenance history on pavement deterioration. For example, many models use total pavement thickness as an input variable. However, two pavement segments with the same total thickness are very likely to have different deterioration rates: one asphalt segment has an original 12-inch (304.8 mm) thickness and does not have an overlay, the other one has an original 8-inch (203.2 mm) thickness and also has a 4-inch (101.6 mm) asphalt overlay.

Before building a data-driven deterioration model, the PMS data should be "cleaned" first. One common problem for existing PMS data is the data quality, i.e., many outliers exist in the dataset. For example, when there are no treatment actions, the pavement condition should get worse due to the traffic and environmental factors. However, in much real-world PMS data, like LTPP, overall pavement condition is sometimes recorded as getting better from one measurement to the next. Some potential reasons include measurement error or missing treatment records. Given the same raw dataset, with different cleaning criteria, different training datasets are obtained. When datasets differ, even the same training method can generate different models with different evaluation performance. This makes it challenging to compare different methods when cleaning methods are not reproducible. Most existing papers in the deterioration modeling have an obscure description of the data cleaning process.

To summarize, there are several gaps for existing pavement deterioration models described in the literature. The first gap is about the correlations among condition metrics. Current models are single-output ones that focus on either an overall or a specific condition metric. They lack the consideration of correlations among different condition metrics. The second gap is about input variable selection. Variables in most existing models may not reflect the maintenance history of a pavement segment. The last gap is the unclear description about the data cleaning process, leading to the difficulty of comparing different models.

Budget allocation model

Optimal pavement POR actions for a pavement network can be selected by past practice or expert opinion [25], but here I focus on the use of budget allocation models to support that selection. Yeo et al. grouped such models into two methodological categories: top-down and bottom-up [57]. The bottom-up approach can incorporate the heterogeneities of each segment in the pavement network. With the increase of computational capacity, it has become the focus of current research. In current implementations, bottom-up allocation models most commonly comprise two key elements: a method to identify the best treatment for each segment (segment-optimal decision) and a method to select the best set of treatments for the network (network-optimal decision or system-optimal decision). In a so-called two-stage bottom-up (TSBU) model, first, one or several optimal treatment alternatives are chosen for each segment through a range of methods, such as decision trees [50], [58], agency cost [59], and benefit-cost analysis [51]–[53], [60]–[63] – including multi-objective definitions of benefit [64], utility analysis [65], or total cost (agency plus user) evaluated over some planning horizon [37], [54], [57], [66]–[68]. These segment-optimal decisions are then evaluated at the network level. The final treatment selection for each segment is generally determined by optimization methods. For this, some studies apply formal mathematical optimization methods such as linear programming [43], [69], non-linear programming [70], integer programming [71]–[73]. Another group of studies apply near-optimal heuristics such as genetic algorithms to allocate budget at the network level [57], [59], [66], [68], [74].

A key methodological challenge for budget allocation models is the explicit consideration of uncertainty – a pervasive issue in many aspects of real world allocation problems [75]. The most common aspects of uncertainty that have been considered to date are uncertain rates of deterioration [44], [57], [60], [66], [76]–[78], measurement error [8], [12], [79], [80], and budget [60], [76]. When deterioration or budget is uncertain, optimal treatment timing becomes uncertain. However, the uncertainty of treatment cost is often ignored in literature [81]. For example, if the price of material A rises faster than material B, rational decision-makers will switch away from some plans to use A and instead use B. This dependence of the optimal decision on the prevailing future context (i.e., future path) is called treatment path dependence. It is worth noting that cost uncertainty can have a different impact than budget uncertainty alone for a TSBU framework. When the budget is more constraining, it may force the use of more suboptimal treatments, but does not change the rank preference for treatments at the segment level. In contrast, when costs are uncertain, there is a chance that for any given segment the preferred future treatment actions are different than any plan based on today's costs.

Among the evaluation methods that have been proposed in the literature, dynamic programming (DP)-based models [57], [66], [77], [78] and simulation-based genetic algorithms [76] can incorporate the influence of treatment path dependence. Existing DP-based models allow for uncertain pavement performance but do not consider uncertainty of future treatment cost. Generally, the computational resources required by dynamic programming tend to grow rapidly with problem scale [82]. To overcome the limitations of a Markov decision process, Durango-Cohen and co-workers have developed a quadratic programming formulation to address infrastructure management problems by using continuous decision variables [83]–[86].

Finally, it is important to recognize an issue pointed out by Sinha et al. (2013). The introduction of uncertainty to an optimization immediately creates a multi-objective problem where tradeoffs must be made between the expected value of the solution and its uncertainty (or risk). To the best of the author's knowledge, most papers in the current literature evaluate this tradeoff through some a priori statement of risk preference [46]. For example, several models include explicit risk analysis on the network level by using chance constraints [47], [72], [87]. DP considers uncertainty by a state transition probability matrix, but the evaluation criterion is generally based on expected values without risk analysis. It would be valuable to evaluate treatment actions for different risk levels at both the segment and network levels.

To summarize, there are three key gaps: consideration of future cost uncertainty and therefore consideration of possible future treatment paths that differ in both timing and type of treatment and explicit risk evaluation for different treatment strategies – rather than considering only expected values – at both the segment and network levels.

Treatment strategies

Performance-based planning (PBP) is the practice of using data from PMSs to support POR decisions. As discussed in the previous section, a significant body of research has emerged on mathematical budget allocation algorithms. By focusing on the algorithm, these studies do not explore the influence of how the budget allocation problem is framed on those same metrics of performance. In particular, analyses are usually constrained to a single treatment strategy, which consists of a limited, fixed portfolio of treatment actions. For example, a set of available treatment actions that only use asphalt materials might be called an asphalt-only strategy. Framing the analysis around a single treatment strategy limits the possible solution space and may preclude the discovery of optimal treatment plans. There are few studies that explore the influence of including different treatment strategies within the problem framing on pavement network condition and / or cost of maintaining the network.

Additionally, existing research reported in the literature focuses on the economic aspects of pavement treatment decisions. To date, analyses that consider the associated environmental impacts (specifically GHG emissions), have not accounted for the growing influence of EVs or deflection-induced excess GHG emissions. Also, PBP models described in the literature are usually based on a single condition metric, such as the international roughness index (IRI), pavement condition index (PCI), pavement surface rating (PSR), or combined condition index (CCI), to evaluate network performance. However, real-world decisions are made based on the consideration of several condition metrics, such as IRI, various cracks, rutting, or faulting. Hence, treatment decision-making should incorporate multiple metrics.

To summarize, the main gaps include: (1) lacking the exploration of the influence of problem framing, especially on the scope of available solution space. (2) Most pavement network analyses focus on economic effects, and for analyses involving environmental effects, they have not incorporated the growing influence of EVs or deflection-induced excess GHG emissions. (3) Pavement treatment decisions are usually based on a single condition metric.

Management policies

The research gap analyses above mainly focus on the budget allocation process – the allocation algorithm plus the framework of the allocation problem. However, only an efficient budget allocation process is inadequate to improve the current road system considering the lack of funding. It is also necessary to apply the budget allocation process under the right policies. As suggested in *The Report Card for America's Infrastructure 2021* [2], both the state and local transportation asset management plans should consider the long-term planning and incorporate life-cycle cost analysis, which implicitly refers to two potential management policies, the long-term planning and decision-making flexibility. Essentially, the first policy focuses on a treatment's long-term benefit when it is evaluated. The second policy aims to relax the constraint for treatment selection, such as asphalt pavements can only be maintained by asphalt overlays. Under the policy of decision-making flexibility, the selection of treatments is based on the life cycle cost analysis and the treatment alternatives include both asphalt and concrete materials.

The next potential policy is to increase the market diversification, which can reduce the unit prices for both asphalt and concrete materials [88]. For most states in the U.S., asphalt is dominant in the paving material. Hence, by proactively increasing the concrete market share, i.e., the market diversification, the unit prices for both materials are expected to decrease, and more pavements are expected to be maintained.

Hence, the main gap is that the influence of potential management policies under which the budget allocation process happens is seldomly evaluated, including decision-making flexibility, long-term planning and market diversification.

1.3 Research Objectives

This thesis attempts to solve the gaps in the literature review and ultimately provide insights to improve current performance-based planning for pavement networks. The objective of this research is to develop an advanced analysis framework for PBP, including an accurate pavement deterioration model, a robust budget allocation model, and the approaches to evaluate different treatment strategies and management policies. In addition, the proposed analysis framework should be efficient and scalable for the analysis of a large pavement network, such as U.S pavement networks.

Based on the proposed PBP framework, research findings from this thesis are expected to help transportation agencies from different levels of pavement networks to improve pavement networks.

1.4 Research Questions

To achieve research objectives discussed above, several research questions concerning performance-based planning are framed as follows:

Pavement deterioration model

- There exist correlations among different pavement condition metrics. Do these correlations have an impact on the prediction performance of pavement conditions?
- Multi-output deterioration models can predict several condition metrics simultaneously. During the training process for a multi-output model, each output can be assigned a weight. How will these weights influence the model prediction performance and how to choose these weights?

Budget allocation model

- What's the influence of uncertainties and treatment path dependence on the treatment selection for a pavement segment?

- What's the benefit of incorporating uncertainties and treatment path dependence on the pavement networks?
- What's the influence of decision-maker's risk preference on treatment selections and pavement network conditions?

Pavement treatment strategies

- Asphalt materials are dominant for pavement projects in the U.S. due to their cheap cost and quick time from paving to using. Is this asphalt-only strategy always appropriate for the maintenance of existing pavement networks?
- For non-interstate pavement networks, perseveration (e.g., cracking sealing and diamond grinding) is widely used due to its cheap cost. However, the effectiveness of preservation is very short and cannot last long. Long-term treatments like overlays and reconstructions can last long but more expensive. Will the increase of long-term treatments improve current pavement networks?
- The benefit of a treatment is usually evaluated over an analysis period. How does the length of evaluation period influence the treatment selection and pavement network conditions?
- Existing research work concerning the budget allocation usually only focuses on the algorithm. What is the influence of the framework for the budget allocation problem?

Pavement management policies

- An efficient budget allocation process is not enough to improve current pavement networks. What are the potential management policies that can be beneficial to improve pavement networks?
- How much excess vehicle fuel cost can be saved by applying appropriate pavement management policies?

1.5 Research Methodology

To answer these research questions and achieve research objectives, models concerning performance-based planning are proposed, and different treatment strategies and management policies are evaluated:

- A weighted multi-output neural network model is proposed to predict pavement deterioration processes. This model is able to incorporate the correlations among different condition metrics during the training process. By modifying the weights for each output, the influence of weights can be discovered, and it provides insights about how to choose them appropriately.
- A probabilistic treatment path dependence (PTPD) model is proposed based on the TSBU framework. On the segment level, different treatments are evaluated based on their distributions of total cost given an analysis period. The total cost is determined based on an optimal treatment path by minimizing the total cost. On the network level, an integer programing is applied to determine which segments should be maintained with the consideration of budget constraint and decision-maker's risk preference.
- By using the multi-output deterioration model and the PTPD model, the environmental and economic influences of different treatment strategies are evaluated based on the Iowa U.S route network. Explored strategies are concerned with treatment materials, treatment types and treatment evaluation period.
- Three management policies are explored, including decision-making flexibility, the long-term planning and the promotion of market diversification for paving materials. These policies are evaluated for all states in the U.S. excluding Hawaii and Alaska.

1.6 Intellectual Contribution of the Dissertation

This thesis fills in the gaps in the literature of performance-based planning for pavement engineering. It has the following contributions:

- A weighted multi-output neural network model is proposed for pavement deterioration prediction.
- The incorporation of correlations among different condition metrics can improve the prediction performance for a single condition metric.
- This multi-output model provides the convenience to make treatment decisions based on multiple condition metrics.
- A probabilistic treatment path dependence model is proposed to select treatments with the consideration of uncertainties and treatment path dependence.

- A simulation-optimization approach is proposed to evaluate different treatments given one segment based on Monte Carlo simulation. Given one future scenario, a backtrack algorithm is proposed to find the optimal treatment path with the smallest total cost given an analysis period.
- Different treatment strategies are evaluated and compared from both economic and environmental perspectives. When the budget level is moderate, it is suggested to apply both asphalt and concrete materials, both short-term and long-term treatments, and a long evaluation period.
- Three management policies are provided and evaluated, including decision-making flexibility, long-term planning and market diversification. Compared to the business-as-usual scenario, after incorporating these policies, the pavement network conditions can be improved significantly.

1.7 Outline of Dissertation

There are 6 chapters in this thesis. The first chapter starts with the background information for current pavement network condition in the U.S and the historical development of performance-based planning. Then current research gaps are presented after the literature review. The objective of this thesis work is to fill in research gaps, improve current analysis framework for performance-based planning, and provide treatment insights for transportation agencies. Next, research questions are proposed, and corresponding methodologies are introduced.

Chapter 2 presents a novel weighted multi-output neural network to predict pavement deterioration for the rigid pavements. This model simultaneously predicts IRI, faulting (FAULT), longitudinal cracking (LCRACK) and transverse cracking (TCRACK) for concrete pavements, providing convenience for pavement management systems whose treatment decisions are based on composite, multi-condition metrics such as the pavement condition index (PCI). First, the process of data collection and cleaning are described in detail. Next, the weighted multi-output neural network model is introduced, including the selection and generation of input parameters, the normalization of training data, and the selection of hyperparameters in the neural network model based on the cross validation. Then the results about the comparison among single-output models and multi-output models with different weights are discussed. Results show that the multi-output model can improve prediction performance in cases where correlation exists. Furthermore, variable weighting is important to achieve the optimal balance of prediction performance among the various metrics.

Chapter 3 introduces a budget allocation model called probabilistic treatment path dependence (PTPD) model. This model is based on the two-stage bottom-up framework. On the segment level, both deterioration and treatment cost uncertainties are considered. Different treatment actions are evaluated based on their distributions of total cost. The total cost is based on the optimal future treatment path by minimizing total cost given an analysis period. This optimization problem is solved by a backtrack algorithm. This model evaluates treatments based on both its own immediate benefit and also the expected benefits of its possible subsequent treatments. On the network level, the goal is to minimize the total cost for all segments within the budget constraint. An integer programming is proposed to formulate the optimization problem. In addition, explicit risk trade-offs are incorporated during the optimization process for both segment and network analyses. Compared to conventional benefit cost ratio approach, PTPD model improves network condition significantly. To achieve a similar performance level, the conventional model requires a 10.4% higher annual budget for the given case study.

Chapter 4 evaluates different treatment strategies that consist of treatment materials, treatment types, and evaluation period for treatments. It aims to explore how optimization analyses are framed in budget allocation models impacts on the pavement network condition and greenhouse gas (GHG) emissions. Both environmental and economic comparisons of different treatment strategies are presented based on the Iowa U.S. route network. Considering the rapid market growth of electrical vehicles (EVs), their environmental effect is also incorporated in the analyses. Results show that the proposed strategy that uses both concrete and asphalt, different treatment types, and a moderate evaluation period could improve the pavement network condition. Compared to the 5-year asphalt-only strategy, the proposed strategy can save about 32% of the annual budget and reduces associated GHG emissions by 21%.

Chapter 5 explores the benefits of three management policies that can help improve pavement networks, including decision-making flexibility, long-term planning and market diversification. The evaluation of these three policies is based on the U.S pavement networks, including interstate, arterial, collector and local road systems. The evaluation metric is the cost of excess vehicle fuels due to pavement vehicle interaction. Considering the rapid market growth of electrical vehicles (EVs), their electricity cost is also incorporated in the analyses. Comparing the business-as-usual scenario, after incorporating all three management policies, the total vehicle fuel cost can be saved by 28%, about 62 billion dollars for the whole U.S. pavement networks from 2017 to 2050. All states can benefit from the proposed management policies. States in the wet freeze climate zone, California, and Washington have larger benefits than other states.

Chapter 6 summarizes the findings about how to improve current models concerning performance-based planning and insights about treatment strategies and management policies. It also provides suggestions for future work at the end.

CHAPTER 2 A WEIGHTED MULTI-OUTPUT NEURAL NETWORK MODEL FOR THE PREDICTION OF RIGID PAVEMENT DETERIORATION

This chapter introduces a novel weighted multi-output neural network (NN) model for the prediction of rigid pavement deterioration based on Iowa Pavement Management System data. This first-of-a-kind model simultaneously predicts four pavement condition metrics concerning rigid pavements, including IRI, faulting, longitudinal crack and transverse crack. Compared to traditional single-output NN models, this multi-output model is capable of incorporating correlations among different condition metrics. The proposed model can also be applied for flexible pavements.

2.1 Introduction

Performance-based planning (PBP) is an important tool to mitigate the pervasive problem of inadequate budget faced by transportation agencies [5]. A key element for implementing PBP is efficient prediction of future pavement conditions. This depends on a robust deterioration prediction model. Over the last decades, many deterioration models have been described in the literature. Given the complex physical and chemical processes involved in pavement deterioration, most existing deterioration models are data-driven using many statistical methods including Markov chains [89], [90], linear/nonlinear regression [22], [91], neural network [92], [93], and decision trees [11].

In practice, PBP-based decisions are based on multiple metrics of pavement condition. These can include metrics of pavement roughness (e.g., the international roughness index (IRI)), rutting, faulting, and various forms of cracking [7], [24], [56]. To date, deterioration models described in the literature predict single metrics (there are papers that describe multiple models for multiple metrics, but each metric is projected using a distinct single model). As will be shown in this chapter, by examining panel data from the Iowa Pavement Management System (PMS) (which will be discussed in Section 2.3), it has been observed that several of these metrics evolve in a coordinated manner. Failure to account for this correlation may lead to misestimation of future pavement condition, particularly in a stochastic context.

In making PBP-based decisions, transportation agencies may also use an overall condition metric – that is a weighted composite metric – to evaluate pavement performance. For example, the state of Iowa uses the pavement condition index (PCI), which is a weighted function of IRI, faulting, longitudinal and transverse cracking for rigid pavements [56]. The nature of this weighting should be considered in the development of a correlation-aware prediction model.

In this chapter, a new weighted multi-output neural network model for rigid pavements is proposed and evaluated using empirical data from the Iowa Pavement Management System. Considering the importance of data cleaning for the training of a data-driven model, a detailed description for the data cleaning process is presented. This model simultaneously predicts four individual metrics of pavement condition and a composite PCI. Different from multiple single-output models, this multi-output model can and does incorporate correlations among different condition metrics. Results show that after incorporating correlations among different condition metrics based on the weighed multi-output model, the prediction performance of the overall condition metric has been improved. In addition, the prediction performances of individual condition metrics are equal to or better than the performance of single-output models. Finally, by adding weights for each condition metric during the model training process, their importance levels can be tailored to the specific decision-making context.

2.2 Literature Review

For data-driven models, the first methodological consideration is selection of the model form and the method to estimate model parameters in the deterioration model. As suggested in [21], deterioration modeling methods can be divided into two categories, Markov chains and regression models. Models based on Markov chains focus on the probability that pavement condition evolves from one condition state to another [89], [90], [94], [95]. This type of models usually assumes the variation of pavement deterioration to be aleatory. Since the Markov property assumes that future deterioration rates only depend on the current pavement condition (i.e., pavement state), historical dependence is ignored during the prediction process.

There are several types of regression models, among which the most commonly applied in the deterioration literature is linear regression (including both explicitly linear forms [22] and linear forms by transformation[a] [21], [91], [96]). These models can be readily solved by ordinary least squares (OLS). In order to consider the heterogeneity of individual pavements in the same pavement group, Zhang et al. proposed a clusterwise linear regression model [97], while Yu et al. proposed linear mixed effects models [14]. When the prediction is concerned with classification or the probability of performance failure occurrence, logistic regression can be applied. Heidari et al. applied a logistic regression to predict the subclasses of pothole, rutting and protrusion for forest roads [98]. Chen et al. evaluated the failure probability of asphalt preventive treatments by both logistic and Bayesian logistic models [99].

The second type of regression models are non-linear models which are described by the sum of several nonlinear variables or by the exponential form. AASHTO models are examples of this type that were once widely applied and cited. These models were estimated from the AASHO road test data and updated for several versions [6], [23]. Based on the first version of the AASHTO model, Ben-Akiva et al. developed a latent model for pavement deterioration, which assumed that the pavement performance condition is a latent variable [8]. Abaza et al. proposed a deterministic prediction model based on the AASHTO serviceability concept and an incremental solution of the AASHTO basic design equation [100]. Following the AASHTO model form, Hong et al. developed a nonlinear model that incorporated heterogeneity using Bayesian analysis [13], [101]. The Mechanistic-Empirical Pavement Design Guide (MEPDG) is a collection of models that were developed as an update to AASHTO through the National Cooperative Highway Research Program (NCHRP) Project 1-37A [24]. Considering the fact that the input parameters in the MEPDG model could be estimated by separate models and thus cause bias, Aguiar-Moya et al. introduced instrumental variables to update the MEPDG model [102]. Other nonlinear models include the exponential form [15], [25] and multivariate adaptive regression splines [103].

Another class of regression models that have been applied to predict pavement performance are neural networks. A neural network model is an example of machine learning where a prediction

a Models like $f\left(\mathbf{x}\right)=\prod_{i} a_i x_i^{b_i}$ can be transformed into explicitly linear models by log-transformation: $\log f\left(\mathbf{x}\right)=\sum_{i}\left(\log a_i + b_i \cdot \log x_i\right)$.

algorithm is developed through iterations among a training set of values. The ultimate prediction algorithm combines both linear and non-linear elements weighted to produce a best prediction. Recent years have witnessed rapid expansion in the application of neural network models due to their efficiency to describe nonlinear relationships in many phenomena including pavements' deterioration [9]–[11], [26]–[31]. Neural network models usually consist of input layer, hidden layer and output layer. With the increase in model complexity, such as the increase of hidden layers and the increase of the neurons in each hidden layer, the neural network could fit the training data perfectly but may lack the capacity to predict the future deterioration at the same time. This phenomenon is called 'overfitting'. There are several ways to detect and prevent it, such as out-of-sample prediction, cross-validation, regularization, and early-stopping, etc. However, some exiting models may lack the analysis to check if the neural network model is overfitting or not [9], [10], [30], [31]. These models focus more on the fitting process. Attoh-Okine [31] and Roberts and Attoh-Okine [10] mainly use the training error as the evaluation criteria for model performance, Owusu-Ababio [9] and Mazari and Rodriguez [30] just use 1-fold validation instead of multi folds (i.e. cross validation).

There are also some other types of regression models. Inkoom et al. proposed a classification and regression tree (CART) model to predict crack condition [11]. Pan et al. used fuzzy regression to predict present serviceability index by considering visual inspection data as fuzzy data [34]. Bianchini et al. proposed a neuro-fuzzy model with the consideration of IF-THEN fuzzy rules [104].

Existing models mainly focus on the prediction of a single condition metric – a single overall metric like PCI, or a specific metric like IRI. This type of single-output models lacks the consideration of correlations among different condition metrics. They could also potentially increase the computational cost when generating multi specific metrics to obtain an overall metric, and lead to some inconvenience for a pavement management system whose treatment decisions are based on multi metrics.

The second methodological consideration is the selection of predictor (input) variables for deterioration models, which is strongly related with the available parameters in the PMS dataset available to the model developer. Common input variables include traffic volumes/loads, pavement structure (pavement type, thickness), pavement age, pavement conditions, and maintenance history. Environmental factors can also have a significant influence on the pavement deterioration, such as ambient temperature, precipitation, freeze-thaw cycles, and freeze index. Incorporating all parameters in regression models, on one hand could increase the model complexity and lead to overfitting, on the other hand it prevents us from understanding the role of each parameter. Several studies have conducted sensitivity analysis to explore the significance of input variables [92], [93], [105]–[107].

Models are inherently limited to the variables described in available data. Unfortunately, several current PMS datasets do not fully describe the maintenance history of a pavement segment, limiting the ability to model this effect. For example, many models use total pavement thickness as an input variable. However, two pavement segments with the same total thickness are very probable to have different deterioration rates: one asphalt segment has an original 12-inch (304.8 mm) thickness and does not have an overlay, the other one has an original 8-inch (203.2 mm) thickness and also has a 4-inch (101.6 mm) asphalt overlay.

Another important methodological consideration is the data "cleaning" process, which usually takes data scientists about 60% of the total time for a project [108]. One common problem is the identification and processing of outliers in the dataset. For example, when there are no treatment actions, the pavement condition should get worse due to the traffic and environmental influence. However, in much real-world PMS data, like LTPP, overall pavement condition is sometimes recorded as getting better from one measurement to the next. There are several reasons for the existence of outliers, such as measurement error or missing treatment records. Given the same raw dataset, with different cleaning criteria, different training datasets are obtained. When datasets differ, even the same training method can generate different models with different evaluation performance. This makes it challenging to compare different methods when cleaning methods are not reproducible. Most existing papers in the deterioration modeling literature have an obscure description about the data cleaning process.

To summarize, there are several gaps for existing pavement deterioration models described in the literature. The first gap is about the correlations among condition metrics. Current models are single-output ones that focus on either an overall or a specific condition metric. They lack the consideration of correlations among different condition metrics. The second gap is about input variable selection. Variables in most existing models may not reflect the maintenance history of a pavement segment. The last gap is the unclear description about the data cleaning process, leading to the difficulty of comparing different models.

To bridge current gaps in pavement deterioration models, an innovative weighted multi-output neural network model is proposed. Most existing models only focus on flexible pavements. According to the FHWA road statistics [109], rigid pavements account for over 25% in terms of interstate system. This chapter uses rigid pavements as an example to illustrate this new multi-output neural network model. A detailed description of data cleaning process is presented. This new model incorporates correlations among different condition metrics during the model training process. Considering the fact that different metrics may have different importance levels for transportation agencies, each output condition metric is assigned a weight number instead of being uniformly weighted during the training process. Model evaluation results show that after incorporating correlations among different condition metrics, the prediction of the overall condition metric could be improved. In addition, the prediction performance of a single condition metric is better or equal to the performance of single-output models.

2.3 Data Preparation

The proposed deterioration model is trained on data from the Iowa PMS database and climate data from LTPP. In the following section, a detailed description is presented for the data preparation, which is concerned with data extraction, transformation and cleaning in terms of input and output variables. At the end of this section, the selection of input variables is discussed based on a correlation analysis.

Iowa PMS data

The Iowa PMS database contains detailed records for around 4,000 pavement segments on 26 years of pavement condition for the years 1992 to 2017. It covers three systems: 1,566 miles (2,520 km) for interstate system, 4,626 miles (7,445 km) for U.S route system, and 4,891 miles (7,871 km) for Iowa route system. Approximately, 15.6% of total miles are asphalt pavements, 32.9% are concrete pavements, and 51.5% are composite pavements.

This data can be divided into three groups based on the units used and the presence of crack information as shown in Table 2-1. Because the early period of data (Group 1) contains different information about the state of cracking, it is not considered in this analysis. In the dataset, there are two variables called 'IRIDAT' and 'CAPDAT' which record the dates of measurement for the IRI and crack information, respectively. For each segment in the network, the performance data is collected biennially. For the dataset of year 2013, 'CAPDAT' is missing, and for the dataset of year 2016 and 2017, 'IRIDAT' is missing. Therefore, the PMS data that is used for training the deterioration model is based on year 2000-2012, year 2014 and 2015.

Table 2-1. Iowa PMS data groups

Group	**Period**	**Units**	**Crack info**
1	1992-1999	1992-1995: English, 1996-1999: Metric	DCRACK, HCRACK, LCRACK, TCRACK
2	2000-2012	Metric	ACRACK, LCRACK, LWCRACK, TCRACK
3	2013-2017	English	ACRACK, LCRACK, LWCRACK, TCRACK

Note: ACRACK=alligator crack, DCRACK=durability crack, HCRACK=half-crack, LCRACK=longitudinal crack, LWCRACK=longitudinal wheel-path crack, TCRACK=transverse crack

The detailed information for parameters in the selected PMS data can be found in [110]. Based on suggestions from engineering experts, four types of parameters have been selected in this analysis as listed in Table 2-2. Parameters in the *Basic Info* group include the segment name (ORIGKEY), the year for the database (PMISYR), system type (SYSTEM, including interstate, U.S. route, and Iowa route), the construction year (CONSYR) and the year for last resurfacing (RESYR). Group *Traffic* includes two types of traffic statistics, ADT and TRUCKS. Different kinds of condition metrics and corresponding measurement dates are in group *Distress*. The last group *Maintenance History* records treatment information for each layer.

Table 2-2. Description of selected parameters.

Data type	Name	Description
Basic Info	ORIGKEY	Original smart key
	PMISYR	Pavement management year
	SYSTEM	Roadway system
	PAVTYP	Pavement type
	CONYR	Year of construction or reconstruction
	RESYR	Year of last resurfacing
Traffic	ADT	Average annual daily traffic
	TRUCKS	Average annual daily truck traffic
Distress	IRI	International roughness index
	RUT	Rut depth
	FAULT	Average faulting only on faulted joints in a segment
	ACARCKH, ACRACKM, ACRACKL	High/moderate/low severity alligator cracks
	LCARCKH, LCRACKM, LCRACKL	High/moderate/low severity longitudinal cracks
	LWCARCKH, LWCRACKM, LWCRACKL	High/moderate/low severity longitudinal wheel-path cracks
	TCARCKH, TCRACKM, TCRACKL	High/moderate/low severity transverse cracks
	IRIDAT	IRI test year
	CAPDAT	Crack & patch collected by vender test year
Maintenance History	TREATMENT	Surface treatment type
	LAYR (1-8)	Layer year # (1-8)
	SURTYP (1-8)	Surface type # (1-8)
	SURTHK (1-8)	Surface thickness # (1-8)
	BASTYP (1-8)	Base type # (1-8)
	BASTHK (1-8)	Base thickness # (1-8)
	SUBTYP (1-8)	Subbase type # (1-8)
	SUBTHK (1-8)	Subbase thickness # (1-8)
	RMVTYP (1-8)	Removal type # (1-8)
	RMVTHK (1-8)	Removal thickness # (1-8)

As for *Basic Info* parameters, based on 'PMISYR', 'CONYR' and 'RESYR', two new variables 'AGECON' and 'AGERES' were generated by equation (2.1) and (2.2). These two variables were used to describe the period since construction/reconstruction and last resurfacing, respectively.

$$\text{AGECON=PMIYR-CONYR} \tag{2.1}$$

$$\text{AGERES} = \text{PMIYR} - \text{RESYR} \tag{2.2}$$

Distress parameters in year 2014 and 2015 were transformed into metric units. Each type of crack distress is described by three sub-categories, which can be converted to a single crack distress metric by equation (2.3) [56]. Using this, four new variables can be obtained, namely: 'ACRACK', 'LCRACK', 'LWCRACK' and 'TCRACK'.

$$\text{CRACK} = \text{CRACKL} + 1.5\text{CRACKM} + 2\text{CRACKH} \tag{2.3}$$

According to the Iowa Department of Transportation, overall pavement condition is not evaluated directly from condition metric (e.g., IRI). Instead, condition metrics are transformed into indexes including the cracking index, riding index (IRI), and faulting index [56]. Table 2-3 lists the threshold values for the calculation of indexes for rigid pavements. Each metric has two threshold values. When the metric ζ is less than or equal to the small threshold value ζ_*, the index equals 100; When the metric is larger than or equal to the large threshold value ζ^*, then the index equals 0. Other index values can be obtained by linear interpolation. Following this, for any metric ζ, the corresponding index, I^ζ, is defined formally as:

$$I^\zeta = \begin{cases} 100 & \zeta \le \zeta_* \\ \dfrac{\zeta - \zeta^*}{\zeta_* - \zeta^*} \cdot 100 & \zeta_* < \zeta < \zeta^* \\ 0 & \zeta^* \le \zeta \end{cases} \tag{2.4}$$

An integrated cracking index was obtained as a weighted sum of indexes of LCRACK and TCRACK with the corresponding weights listed in Table 2-4.

Table 2-3. Thresholds for condition metrics

	IRI (m/km)	FAULT (mm)	LCRACK (m/km)	TCRACK (count/km)
threshold	0.5&4	0&12	0&250	0&150

Table 2-4. Cracking sub-index weights

sub-index	LCRACK	TCRACK
weights	0.4	0.6

Based on these indexes, an overall condition metric called PCI was obtained by equation (2.5) for rigid pavements. PCI ranges from 0 to 100, and 100 represents that pavement is in perfect condition. In this expression, each of the condition indexes have different coefficients which may represent the significance of that index in the eyes of the Iowa transportation agency.

$$PCI = 0.4I^{Crack} + 0.4I^{Ride} + 0.2I^{Fault} \tag{2.5}$$

The last group of parameters describe the maintenance history for each segment, from which historical structure information could be generated, including construction year, resurface year, thickness and pavement type. Table 2-5 presents an example for the maintenance history for a rigid pavement segment. Its ORIGKEY is "08012183 67192 8279". This segment was constructed in 1964 and maintained with an overlay of Portland cement concrete (PCC) in 1984. Based on Table 2-5, structure information could be obtained as shown in Table 2-6. From year 1964 to year 1983, the segment structure stayed the same, AGECON (equation (2.1)) changes each year and AGERES remained 0. After year 1984, due to the overlay action, the segment structure was changed. The new surface thickness SURTHK is 102mm, and previous surface PCC thickness become PCCTHK. TOTTHK is the total thickness, which is equal to the sum of SURTHK and PCCTHK (RMVTHK should be considered when it exists). MRRNUM is the number of treatment actions. In this case, MRRNUM became 1 since 1984. Instead of a single total thickness value as shown in the original PMS dataset, the introduction of SURTHK, PCCTHCK and MRRNUM could reflect the maintenance history of a pavement segment. (If the pavement type is asphalt or composite pavements, a variable called 'HMATHK' is introduced similar to PCCTHK.)

Table 2-5. Maintenance history for a rigid pavement segment

LAYR	SURTYP	SURTHK	BASTYP	BASTHK
1964	PCC	254	GSB	102
1984	PCC	102	-	-

Note: LAYR=layer year, SURTYP=surface type, BASTYP=base type, BASTHK=base thickness, PCC=Portland cement concrete, GSB=granular subbase

Table 2-6. Structure information for a rigid pavement segment

PMISYR	CONYR	RESYR	PAVTYP	TOTTHK	SURTHK	PCCTHK	MRRNUM
1964~1983	1964	-	PCC	254	254	0	0
>=1984	1964	1984	PCC	356	102	254	1

Note: PMISYR=pavement management year, CONYR=Year of construction or reconstruction, PAVTYP=pavement type, TOTTHK=total thickness, SURTHK=surface thickness, PCCTHK=sublayer concrete thickness, MRRNUM= number of treatment actions, PCC=Portland cement concrete.

After generating parameters for model training, the total dataset is filtered based on ‘PAVTYP’ to obtain the data for rigid pavements. Next, input and output variables are determined with the consideration of time series analysis and treatment actions. In terms of the time series analysis, time lag = 1 is suggested in [21], [111], which means that the condition prediction at year t+1 is only related with the information at year t. Since the condition metrics are collected every two years in Iowa, time lag is selected as 2 years here. For example, the information at year 2000 can be considered as inputs and the condition metrics at year 2002 are outputs.

During the process of paring input and output variables, attention should be paid to pavement treatments. If there is a treatment action at year 2000, then it is not appropriate to use year 2000 as input and 2002 as output. This kind of pairing data should be excluded from the training dataset. In the dataset, the improvement of pavement condition may be postponed after a treatment. For example, there is a treatment at year 2002, but the condition improvement is reflected at year 2004. Therefore, during the pairing process, when there exists a treatment action, its adjacent years are checked to decide which year should be considered as the treatment year.

After this step, input variables include: 1). Basic info: AGECON, AGERES; 2). Traffic: ADT and TRUCKS; 3). Distress: IRI_t , FAULT_t , LCRACK_t , TCRACK_t ; 4). Maintenance history: TOTTHK, SURTHK, PCCTHK, MRRNUM. Output variables include IRI_{t+2} , FAULT_{t+2} ,

LCRACK_{t+2}, TCRACK_{t+2}. The subscription *t* and *t*+2 represent measurement years of condition metrics.

Iowa PMS data cleaning

After generating the initial input and output variables, the next step is to deal with data outliers. For this case, outliers are defined as values or pairs of values that indicate physically unreasonable pavement condition values. In terms of the overall pavement condition (i.e. PCI in this analysis), it should decrease when there is no treatment action due to running traffic and environmental effects [24]. But for other single performance metrics (IRI, faulting and cracks), their performances may improve due to some negative correlations. Differences for all performance metrics between input and output are calculated,

$$\Delta\text{PCI} = \text{PCI}_{t+2} - \text{PCI}_{t} \tag{2.6}$$

$$\text{IRI\_diff} = \text{IRI}_{t+2} - \text{IRI}_{t} \tag{2.7}$$

$$\text{FAULT\_diff} = \text{FAULT}_{t+2} - \text{FAULT}_{t} \tag{2.8}$$

$$\text{LCRACK\_diff} = \text{LCRACK}_{t+2} - \text{LCRACK}_{t} \tag{2.9}$$

$$\text{TCRACK\_diff} = \text{TCRACK}_{t+2} - \text{TCRACK}_{t} \tag{2.10}$$

When ΔPCI is larger than 0, the data point is considered as an outlier and is deleted from the training dataset. In terms of other single performance metrics, interquartile range (IRQ) is applied, which can be calculated by equation (2.11),

$$IQR = Q_3 - Q_1 \tag{2.11}$$

Where Q_1 and Q_3 represent values of 25th and 75th percentiles, respectively. Usually, if a data point is below $Q_1 - 1.5 \cdot IQR$ or above $Q_3 + 1.5 \cdot IQR$, it is considered as an outlier [112]. In this case, all lower quartile boundaries are negative values, indicating unexplained performance improvement. These lower bounds have been used to identify outliers. There is less theoretical support to suggest that pavements could not deteriorate rapidly. Therefore, an upper bound of one half of the threshold values has been adopted for use in Table 2-3, namely 2 for IRI. Table 2-7 shows the outlier threshold for condition metrics based on IQR and the half of index approach. Values outside the lower and upper bound were eliminated from the training dataset.

Table 2-7. Outlier threshold for condition metrics

	IRI_diff	FAULT_diff	LCRACK_diff	TCRACK_diff
$Q_1 - 1.5 \cdot IQR$	-0.3	-4.9	-23.0	-13.5
$Q_3 + 1.5 \cdot IQR$	0.4	6.0	34.4	18.5
Half of index threshold	2.0	6.0	125.0	75.0

Climate Data

Climate data was primarily extracted from LTPP, including annual average temperature (TEMP), precipitation (PRECIP), and freeze index (FREEZE). For a given year, there are several records for each climate variable. Annual averages of these were used. Climate data was matched to the other training data by condition metric measurement year, IRIDAT and CAPDAT.

2.4 Weighted Multi-Output Neural Network Model

2.4.1 Selection of input parameters

Based on the previous analysis, a candidate set of input variables were generated. However, some variables may not contribute to the pavement deterioration process to an extent that is observable in the current data. To select the most relevant input parameters, a correlation analysis was conducted. This approach is similar to the linear regression analysis described by [107].

Figure 2-1 shows the heatmap for the correlations among input and output variables. The output variables are the variations of condition metrics, including IRI_diff, FAULT_diff, LCRACK_diff, and TCRACK_diff (equations (2.7)-(2.10)). All other listed variables are candidate inputs. In this analysis, an input variable would be excluded if either the absolute value of the correlation coefficient is less than 0.05 for all four outputs or if it is less than 0.05 for three outputs and less than 0.1 for the fourth. Using these criteria for this dataset, AGERES, PCCTHK, MRRNUM and TEMP were excluded. One main reason that output response is not correlated with AGERES, PCCTHK, MRRNUM is that for most rigid pavements in Iowa the historical overlay number is zero across the dataset. When overlay number is zero, AGERES, PCCTHK, MRRNUM are all equal to zero, and TOTTHK is equal to SURTHK for most rigid pavements. To simply the problem, AGERES, PCCTHK, and MRRNUM are deleted from the set of input variables. But to be noted that, for asphalt and composite pavements, MRRNUM is usually larger than 0, these variables should be considered. ADT is insignificant for both variations of IRI (IRI_diff) and longitudinal crack (LCRACK_diff). In addition, it is also strongly correlated with TRUCKS. Hence, ADT is also deleted.

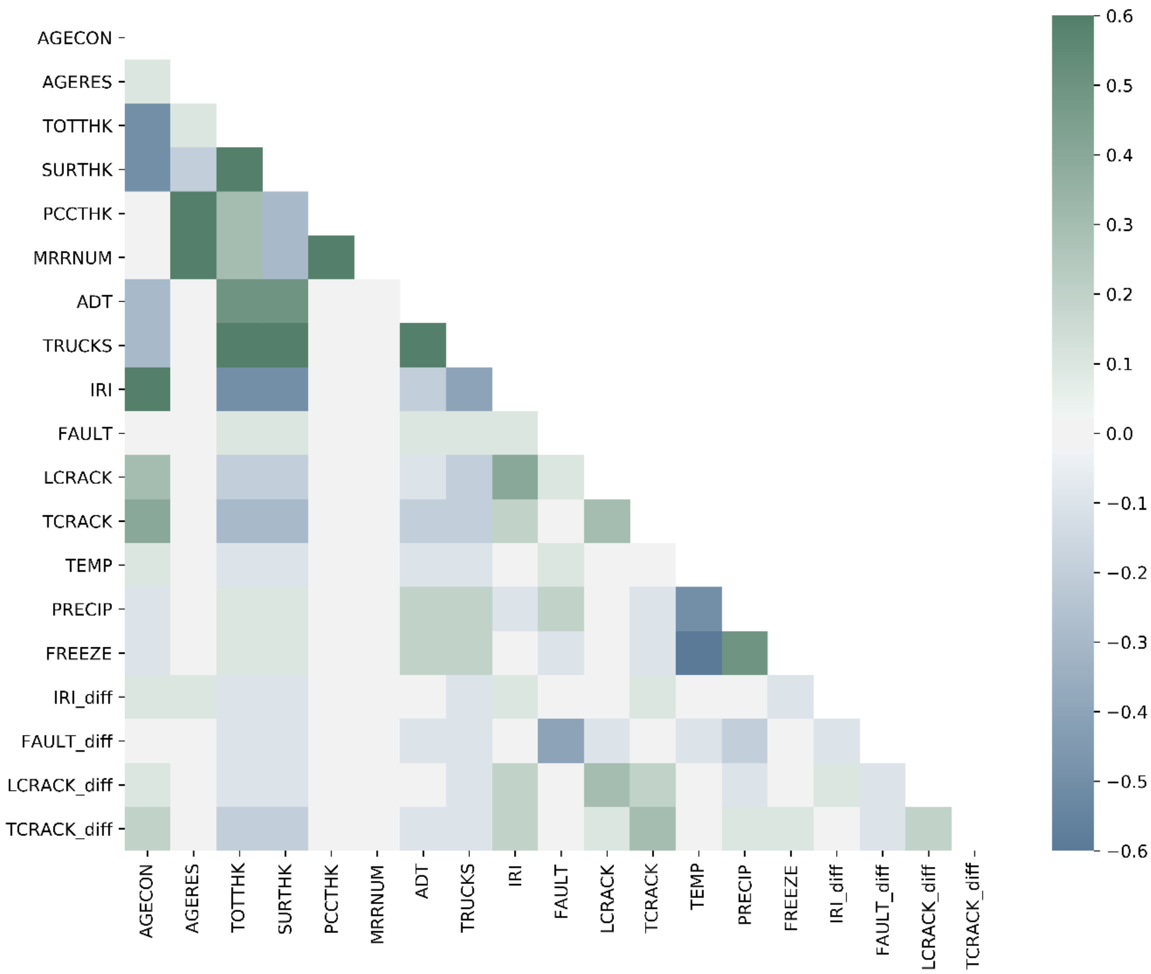


Figure 2-1. Heatmap for variables' correlations (green color represents positive correlation, blue represents negative correlation, and grey color represents weak correlation)

Among the four outputs, several interesting correlation trends can be observed. First, the variation of IRI (IRI_diff) is positively correlated with both the level of IRI (collection coefficient, ρ = 0.13) and the level of transverse cracking (TCRACK, ρ = 0.08). For this modeling, a positive correlation suggests that IRI increases more rapidly when values for IRI or TCRACK are higher. Additionally, it has been noticed that the variation of FAULT (FAULT_diff) is strongly negatively corelated with the level of faulting (FAULT, ρ = -0.36) and longitudinal cracking (LCRACK, ρ = -0.12). This suggests that faulting grows more slowly when faulting or longitudinal cracking is more severe. The variation of LCRACK (LCRACK_diff) and TCRACK (TCRACK_diff) are both strongly positively correlated with IRI, LCRACK and TCRACK. From this correlation analysis, it can be concluded that the deterioration of each single condition metric is statistically dependent on at least some of the other condition metrics. This observation implies that it's better to incorporate the state of all condition metrics during the prediction of single condition metric.

Table 2-8 summarizes the distribution of input variables for the neural network model. As for four condition metrics, when their standard deviation and mean values are compared, IRI has the smallest ratio between standard deviation and mean value, representing the IRI distribution is more centralized. TCRACK has the largest ratio, and its distribution is the sparsest, which might be caused by the measurement quality.

Table 2-8. Statistical summary for input variables

	AGECON	TOTTHK	TRUCKS	IRI	FAULT	LCRACK	TCRACK	PRECIP	FREEZE
mean	22.2	248.8	1660	2.2	4.6	19.6	13.4	820.8	286.8
std	14.9	32.5	2559.7	0.8	2.6	37.8	26.8	112.2	156.6
min	0	150	1	0.7	0	0	0	650.5	317.8
max	71	559	14293	5	12	350	240.5	1077.2	840.8

Note: std=standard deviation

2.4.2 Normalization of training data

As listed in Table 2-8, each variable has a different magnitude. To avoid fitting problems due to this, all input and output variables are normalized. Considering that both input and output variables have condition metrics but for different years, all condition metrics are normalized together. Suppose **X** is the input matrix with the dimension is $d_x \times n$, d_x is the number of input variables, and n is the number of data points. $\mathbf{Y}$ is the output matrix. Its dimension is $d_y \times n$, and d_y is the number of output variables. The normalization process is shown as follows:

$$x_{j,i} = \frac{X_{j,i} - \overline{X}_{j,}}{\sigma_{X_{j,}}} \quad \left(j \notin \left\{ \text{IRI}, \text{FAULT}, \text{LCRACK}, \text{TCRACK} \right\} \right) \tag{2.12}$$

$$x_{j,i} = \frac{X_{j,i} - \overline{Y}_{j,}}{\sigma_{Y_{j,}}} \quad \left(j \in \left\{ \text{IRI}, \text{FAULT}, \text{LCRACK}, \text{TCRACK} \right\} \right) \tag{2.13}$$

$$y_{k,i} = \frac{Y_{k,i} - \overline{Y}_{k,}}{\sigma_{Y_{k,}}} \quad \left(k \in \left\{ \text{IRI}, \text{FAULT}, \text{LCRACK}, \text{TCRACK} \right\} \right) \tag{2.14}$$

Where $x_{j,i}$ and $y_{k,i}$ are normalized input and output values, where *i* represents the index of data point, *j* is the input variable index and *k* is the output variable index. $\overline{X}_{j,}$ and $\overline{Y}_{k,}$ are mean values for j_{th} input and k_{th} output. $\sigma_{X_{j,}}$ and $\sigma_{Y_{k,}}$ are standard deviations for j_{th} input and k_{th} output.

2.4.3 Model framework

In recent years, feed-forward neural network (NN) models have been widely applied for pavement deterioration prediction due to their superior performance when dealing with strongly nonlinear relationships [11], [30], [93], [98], [105], [106]. A NN model usually consists of an input layer, one or several hidden layers, and an output layer. Each layer has several neurons. Hidden layers are usually used to describe the nonlinear relationships via activation functions (also known as transfer functions). The connection between two layers is usually through a linear mapping. A NN model can be mathematically described as equation (2.15)

$$\hat{\mathbf{Y}} = \sigma_{H+1}\left(\mathbf{W}^{H+1}\sigma_{H}\left(\mathbf{W}^{H}\sigma_{H-1}\left(\mathbf{W}^{H-1}...\sigma_{2}\left(\mathbf{W}^{2}\sigma_{1}\left(\mathbf{W}^{1}\mathbf{X}\right)\right)\right)\right)\right) \tag{2.15}$$

where $\hat{\mathbf{Y}}$ represents the prediction values. $\mathbf{W}^{h}\left(h = 1,\dots H+1\right)$ is the linear transformation matrix, and $\sigma_{h}\left(h = 1,\dots H+1\right)$ is the activation function. Common nonlinear activation functions include ReLU, sigmoid, and Tanh. Their ouptut sets are $\left[0,\infty\right]$, $\left(0,1\right)$ and $\left(-1,1\right)$. ReLU is often used for regression problems while the other two are more commonly applied for classification problems

[113]. In terms of the current regression problem, ReLU (equation (2.16)) is applied for the hidden layers and a linear function is applied for the output layer.

$$f(x)=\begin{cases} x & x>0 \\ 0 & \text{otherwise} \end{cases} \tag{2.16}$$

The goal of training a NN model is to determine an optimal structure that can minimize the loss funcion. A loss function is used to describe the relationship between the predicted value $\hat{\mathbf{Y}}$ and the true value $\mathbf{Y}$. In this regression analysis, mean squared error is chosen as the loss function (equation (2.17)), where λ_k^2 is the weight value for each output variable.

$$\min : L\left(\hat{\mathbf{Y}},\mathbf{Y}\right)=\frac{1}{2}\sum_{k=1}^{d_y}\lambda_k^2\left\|\hat{\mathbf{Y}}_k-\mathbf{Y}_k\right\|_2^2=\frac{1}{2}\sum_{k=1}^{d_y}\sum_{i=1}^{n}\lambda_k^2\left(\hat{Y}_{k,i}-Y_{k,i}\right)^2 \tag{2.17}$$

After normalization process introduced in the previous sub-section, the training problem for a NN model (equation (2.15) and (2.17)) can be reformulated as,

$$\hat{\mathbf{y}}=\sigma_{H+1}\left(\mathbf{W}^{H+1}\sigma_H\left(\mathbf{W}^H\sigma_{H-1}\left(\mathbf{W}^{H-1}...\sigma_2\left(\mathbf{W}^2\sigma_1\left(\mathbf{W}^1\mathbf{x}\right)\right)\right)\right)\right) \tag{2.18}$$

$$\min : L\left(\hat{\mathbf{y}},\mathbf{y}\right)=\frac{1}{2}\sum_{k=1}^{d_y}\lambda_k^2\left\|\hat{\mathbf{y}}_k-\mathbf{y}_k\right\|_2^2=\frac{1}{2}\sum_{k=1}^{d_y}\sum_{i=1}^{n}\lambda_k^2\left(\hat{y}_{k,i}-y_{k,i}\right)^2 \tag{2.19}$$

In this case, the prediction value is $\hat{\mathbf{y}}$, which is in the normalization space. Equation (2.20) is applied to obtain the prediction value with a real magnitude.

$$\hat{y}_{k,i}=\frac{\hat{Y}_{k,i}-\overline{Y}_{k,}}{\sigma_{Y_{k,}}}, \text{ and } \hat{Y}_{k,i}=\overline{Y}_{k,}+\hat{y}_{k,i}\cdot\sigma_{Y_{k,}} \tag{2.20}$$

When the dimension of the output variable d_y is equal to 1, the NN is a single-output model, which is very common in existing literatures. When d_y is larger than 1, and $\lambda_k=1$ for all output variables, then this is a uniformly weighted multi-output model. When d_y is larger than 1, and λ_k are different for all output variables, it is a weighted multi-output NN model, which is the focus of this analysis.

In order to incorporate weights for each output variable, insert equation (2.14) to equation (2.19), then,

$$
\begin{aligned}
\min : L(\hat{\mathbf{y}}, \mathbf{y}) &= \frac{1}{2}\sum_{k=1}^{d_y}\sum_{i=1}^{n}\lambda_k^2\left(\hat{y}_{k,i} - y_{k,i}\right)^2 = \frac{1}{2}\sum_{k=1}^{d_y}\sum_{i=1}^{n}\lambda_k^2\left(\frac{\hat{Y}_{k,i} - \overline{Y}_{k,}}{\sigma_{Y_{k,}}} - \frac{Y_{k,i} - \overline{Y}_{k,}}{\sigma_{Y_{k,}}}\right)^2 \\
&= \frac{1}{2}\sum_{k=1}^{d_y}\sum_{i=1}^{n}\left(\frac{\hat{Y}_{k,i} - \overline{Y}_{k,}}{\sigma_{Y_{k,}} / \lambda_k} - \frac{Y_{k,i} - \overline{Y}_{k,}}{\sigma_{Y_{k,}} / \lambda_k}\right)^2
\end{aligned}
\tag{2.21}
$$

By changing the standard deviaiton during the normalization process, weights in the loss function can be incorporated.

2.4.4 Weighted multi-output NN model for rigid pavements

In terms of the NN model structure for rigid pavement deterioration, the number of hidden layers can be determined first. As mentioned by Heaton [114], one hidden layer can approximate any function that contains a continuous mapping from one finite space to another. With the increase of hidden layers, the NN model could have an excellent fitting performance, but it may decrease the prediction capacity due to overfitting. Since the dataset applied in this work contains only around 2,500 training data points, one hidden layer should work well enough and minimize the risk of overfitting [113]. In this case, the training problem (equation (2.18)) can be rewritten as,

$$
\hat{\mathbf{y}} = \sigma_2\left(\mathbf{W}^2\sigma_1\left(\mathbf{W}^1\mathbf{x}\right)\right) \tag{2.22}
$$

Where, the activation function for the output layer σ_2 and hidden layer σ_1 is chosen as a linear function and ReLU, respectively.

The determination of weight matrixes is usually based on a back-propagation algorithm**.** In terms of equation (2.22), the partial derivative for the loss function L to $\mathbf{W}^1$ can be expressed as,

$$\frac{\partial L}{\partial \mathbf{W}^1} = \frac{\partial L}{\partial \hat{\mathbf{y}}} \frac{\partial \hat{\mathbf{y}}}{\partial f_2} \frac{\partial f_2}{\partial \mathbf{W}^2 f_1} \frac{\partial f_1}{\partial \mathbf{W}^1 \mathbf{x}} \frac{\partial \mathbf{W}^1 \mathbf{x}}{\partial \mathbf{W}^1} = \mathbf{W}^{2^T} \frac{\partial L}{\partial \hat{\mathbf{y}}} \frac{\partial f_1}{\partial \mathbf{W}^1 \mathbf{x}} \mathbf{x}^T \tag{2.23}$$

$$\frac{\partial L}{\partial W^1_{m,j}} = \mathbf{W}^2_{m,} \frac{\partial L}{\partial \hat{\mathbf{y}}} \frac{\partial f_1}{\partial \mathbf{W}^1 \mathbf{x}}\bigg|_{m,} \mathbf{x}_{j,} \text{, where } \frac{\partial L}{\partial \hat{y}_{k,i}} = \lambda_k^2 \left(\hat{y}_{k,i} - \hat{y}_{k,i} \right) \tag{2.24}$$

where $m \in M$ and M is the number of neurons in the hidden layer.

When $k = 1$, namely, the model has a single output, each value in the linear transition matrix $W^1_{m,j}$ is only influenced by the single output. However, when $k > 1$, $W^1_{m,j}$ are influenced by all outputs. Therefore, the correlations among different output variables could be incorporated during the training process.

2.4.5 Model training

In addition to the number of hidden layers, there are three other main parameters concerning the training of NN models: 1). The number of neurons M in the hidden layer; 2). The epoch number: one epoch represents one forward pass and one backward pass of all the training examples; 3). Batch size: the number of training examples in one forward/backward pass.

As suggested by [114], the number of hidden neurons should be 2/3 the size of the input layer, plus the size of the output layer, which equals to 10 in this analysis. But in reality, considering that each dataset has different characteristics, 6 neuron numbers are selected as candidates including 10, 16, 32, 48, 64 and 80. As for the epoch number, when it is small, the NN model may not be well trained. When it is large, the NN model has the potential to be over-trained. Here, three epoch numbers are considered, 50, 100, and 150. In addition, early-stopping is incorporated in order to avoid overfitting. Batch size determines the number of data points that can be trained for each time. When it is small, the NN model has the potential to be over-trained. Here, three batch sizes (8, 32 and 64) are considered.

The optimal combination of these three parameters is determined by grid search based on a 5-fold cross-validation. For each fold, all training data are randomly divided into three groups, including 70% training data, 20% validation data, and 10% test data. The training data and validation data are used to train the model and the test data is used to check the out-of-sample performance of the NN model. Theoretically, the dataset should be divided so that the three partitions – training, validation, and test – are large enough that we have a reasonable expectation that they are all representative of the same distribution. Practically, the ratio selection is mainly based on the data amount. For example, when the number of total data points is very large, 50% of the total data can be selected as the test data. When the number of data points is very small, there is only train and validation data, and no test data at all. Because, in this case, it is better to use as many training data as possible to fully train the model. As for Iowa dataset, the number of total data points for rigid pavements is around 2,500, so 10% of the test data is selected to make sure the model can be fully trained. By using the 5-fold cross-validation, the model can be tested by 5 different sets of test data.

The mean squared error (MSE) of the test data is chosen as the model performance metric, which is the same as the loss function (equation (2.19)) for the training process. After a 5-fold cross-validation, the average MSE is considered to compare NN models with different structure parameters. The model with the lowest average MSE was selected as the representative NN model.

2.5 Results and Discussions

In order to explore the influence of incorporating multi-output variables, and various weights for each output variable on the model prediction performance, four single-output models were trained for each variable (i.e., IRI, FAULT, LCRACK and TCRACK) along with ten multi-output models with different sets of weights. The first multi-output model (listed as NN0 in Table 2-9) uses a set of weights that are uniform, [1, 1, 1, 1]. The second model (NN1) uses a set of weights equal to those used in the Iowa DOT PCI equation (equation (2.5)), i.e., [10, 5, 4, 6]. The other eight weight sets (for the other eight models, NN2 – NN10) are shown in Table 2-9 and explore how disparity of weighing among the four variables impacts model results.

The training speed for single-output and multi-output models is related with the training parameters, including the number of neurons, and the epoch number and the batch number. When both types of models use the same parameters: Neuron=64, Epoch=50, Batch=32, the training time for single-output and multi-output models are 26.3s and 29.8s, respectively (the training time is based on 5-fold cross-validation). The difference between these two models in terms of training speed is not large.

Table 2-9 lists the optimal set of model parameters and the smallest MSEs found during the grid search for these 4 single-output and 10 multi-output models, respectively. For the multi-output models, the optimal NN structure is selected based on average MSE of PCI prediction across a 5-fold cross-validation. Three things are immediately notable from this table. First, the multi-output models have better prediction performances (smallest MSEs) for IRI, FAULT, and TCRACK (see values with an asterisk in Table 2-9) compared to the corresponding single variable models. Both types of models have similar prediction performance for LCRACK. The improvement in prediction performance is particularly notable for the prediction of FAULT (single variable model MSE = 1.069, model NN1 MSE for FAULT=0.778, a 27% reduction) and for the highly influential prediction of IRI (single variable model MSE = 0.044, NN1 MSE for IRI = 0.033, a 25% reduction).

Table 2-9. Optimal single-output model structure and prediction performance (first four rows) and Optimal multi-output model structure and prediction performance (last 10 rows)

		NN structure			Mean Squared Error (MSE)				
Name		**Neuron**	**Epoch**	**Batch**	**PCI**	**IRI**	**FAULT**	**LCRACK**	**TCRACK**
IRI		32	150	32	11.78	0.044			
FAULT		80	150	8			1.069		
LCRACK		80	50	64				**468.9**	
TCRACK		32	50	8					137.9
Name	**Weights**	**Neuron**	**Epoch**	**Batch**	**PCI**	**IRI**	**FAULT**	**LCRACK**	**TCRACK**
NN0	[1, 1, 1, 1]	48	150	36	10.25*	0.034	0.764	482.3	133.1
NN1	[10, 5, 4, 6]	64	50	32	10.24* (0.035)	0.033* (2e-5)	0.778 (4e-4)	491.3 (0.3)	132.4* (0.04)
NN2	[10, 1, 1, 1]	80	100	8	10.37	**0.033***	0.800	489.2	141.4
NN3	[50, 1, 1, 1]	48	150	8	10.53	**0.033***	0.859	511.6	153.6
NN4	[1, 10, 1, 1]	80	50	8	11.09	0.038	**0.703**	501.0	140.1
NN5	[1, 50, 1, 1]	64	150	8	12.72	0.051	**0.690***	519.1	151.7
NN6	[1, 1, 10, 1]	48	100	8	11.03	0.038	0.827	**468.1***	136.4
NN7	[1, 1, 50, 1]	80	150	8	12.62	0.047	0.926	**470.2***	158.1
NN8	[1, 1, 1, 10]	48	50	8	10.68	0.039	0.835	500.8	**132.1***
NN9	[1, 1, 1, 50]	80	100	8	12.04	0.052	0.947	540.5	**132.3***

Note: Smallest observed MSE for that variable

Secondly, and more importantly, from Table 2-9 it is clear that the PCI prediction performance associated with either multi-output model NN0 or NN1 (MSE = 10.24) is better for than for the PCI prediction derived from the four optimal single output models (MSE = 11.78). As mentioned in Section 2.4.4, the training process for multi-output models incorporates the correlations among variables. This correlation could improve the prediction performance for a single variable and should improve the prediction of a multi-variable metric like PCI.

Finally, although the multi-output models can outperform single metric models in predicting PCI, because PCI is a composite performance metric, when it is optimal, it does not mean all other single performance metrics are optimal.

Due to the existence of uncertainty in a multi-fold validation, the values listed in Table 2-9 could change if the same model was regenerated. In order to compare different models statistically, a bootstrap analysis was conducted to estimate the standard deviation for the average MSE obtained by 5-fold cross-validation. Because this uncertainty in MSE derives solely from the random partitioning of training and validation data, all 10 multi-output models have the same source of uncertainty. Therefore, a bootstrap analysis was conducted only for the NN1 model. The bootstrap sample size was 100. The standard deviation in MSE for each variable is listed in Table 2-9 (i.e., values in parentheses). Using these standard deviation values, statistically significant differences among the lowest observed MSE values was tested using a two-sample t-test assuming equal variance and a confidence level of 95%. The MSE values highlighted in Table 2-9 (asterisk) for PCI, IRI, FAULT, LCRACK and TCRACK are the lowest values. When multiple values in a given column have an asterisk, they are not statistically different.

In terms of PCI prediction, normally, the NN1 model would be expected to have the best prediction performance since its weights resemble the PCI formula. However, both NN0 and NN1 models have the smallest MSE. This is because in the current PCI formula, the coefficients (weightings) for all four variables are similar in magnitude. Figure 2-2 shows the comparison between true PCI and predicted PCI based on out-of-sample data for NN1 model, which presents a good prediction performance.

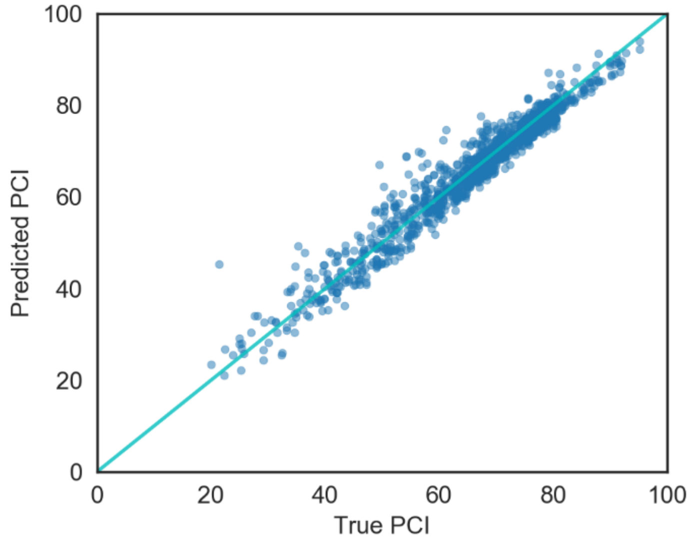
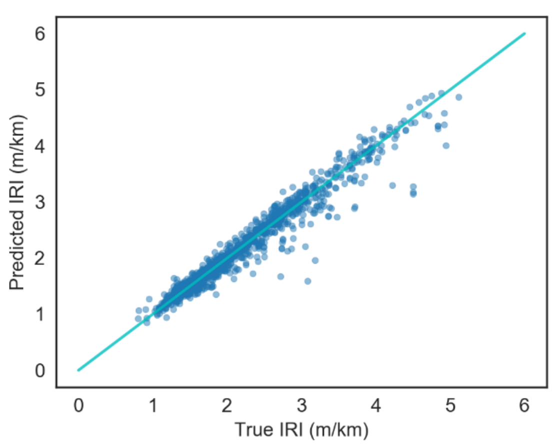


Figure 2-2. Comparison between true PCI and predicted PCI based on out-of-sample data when weights are [10, 5, 4, 6] (NN1 model).

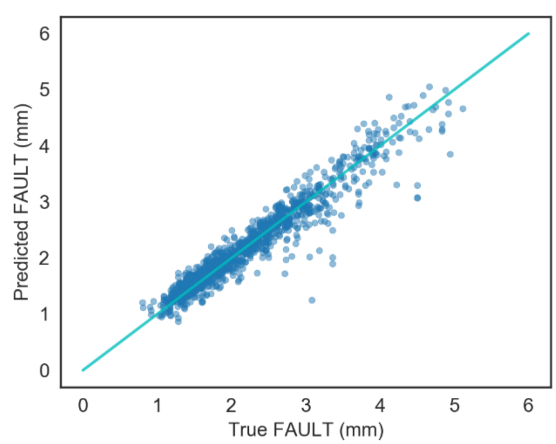
The models NN2 to NN9 have two larger weights (10x or 50x) for IRI, FAULT, LCRACK, TCRACK, respectively. For each of these models, the prediction performance of the variable with the largest weight (highlighted in bold) and the PCI prediction performance are emphasized. Generally, when an output is more heavily weighted, the training process emphasizes this output. As shown in equation (2.21), when the output Y_k is heavily weighted, the minimization process will concentrate more on improving the prediction performance on Y_k to minimize the total weighted loss value. When this occurs, prediction performance for that focal output would be expected to be higher than for an NN model with a smaller weight on that same output. It is important to note that models NN2 to NN9 are not expected to or intended to improve on the prediction of PCI compared to NN1. Instead, the role of these models is to see how the multi-output model algorithm behaves as weighting shifts. In this case, where correlation is present, these also serve to demonstrate both the ability of a multi-output model to outperform single-output models and the fact that as weights become more disparate there may be an important tradeoff between performance in predicting the composite metric (PCI) and the individual metrics.

As for IRI, when its weight is 2 times larger than other variables (NN1), its MSE value is already the smallest. With an increase of IRI weight (models NN2 and NN3), IRI prediction performance stays almost the same while MSE for PCI prediction increases very slightly. The behavior of

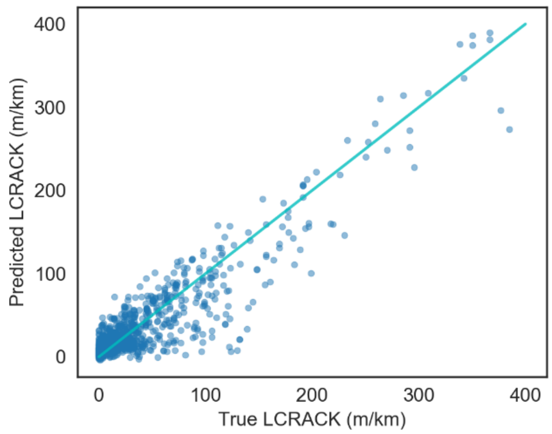
TCRACK prediction is similar to IRI. The NN1 model has a low MSE for TCRACK that is not statistically resolvable from models NN9 and NN10. However, TCRACK is influential in the prediction of PCI (only IRI is more influential). Therefore, as the TCRACK weight grows relative to the other variables (NN9 and NN10), PCI prediction performance deteriorates. For both FAULT and LCRACK, when they have larger weights (i.e., 10 and 50), their prediction performances are better than NN0 and NN1. Hence, with the increase of the weight for a single variable, its own prediction performance could be improved. However, other variables' prediction performances would decrease, as well as the PCI prediction performance. To this last point, it can be seen that the difference in model performance between a uniformly trained option and a weighted option increases as the heterogeneity of the weights grows. Figure 2-3 presents the comparison between true and predicted values for IRI, FAULT, LCRACK, and TCRACK. Generally, all four plots demonstrate good model performance without significant systematic deviations in correspondence between the predicted and actual values. Both LCRACK's and TCRACK's plots show a small number of low range values (~50 to 100 m/km LCRACK and ~50 to 100 count/km TCRACK) that are underestimated by the model. It is believed that this occurs for two reasons: (1). Data quality for these two variables is poor with standard deviations roughly two times the mean for the samples of both; (2). Some crack-related maintenance records may be missing. The record number of surface treatment (e.g., crack sealing) is extremely small. Hence, some input and output parings may not be appropriate when there exists a surface treatment but without a record. Underestimates at these low values should not cause significant problems at these are well below current treatment threshold triggers.



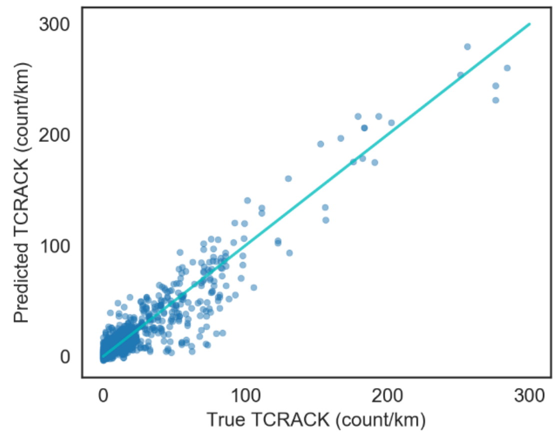
(a). IRI



(b). FAULT



(c). LCRACK



(d). TCRACK

Figure 2-3. Comparison between true and predicted values based on out-of-sample data for (a). IRI (NN3 model); (b). FAULT (NN5 model); (c). LCRACK (NN7 model); (d). TCRACK (NN9 model)

2.6 Conclusions and Future Work

A new weighted multi-output neutral network model for the deterioration of rigid pavements has been proposed based on the Iowa Pavement Management System database. This new model simultaneously predicts IRI, faulting (FAULT), longitudinal cracking (LCRACK) and transverse cracking (TCRACK) for pavements, providing convenience for pavement management systems whose treatment decisions are based on composite, multi-condition metrics such as the pavement condition index (PCI). Considering the fact that different condition metrics may have different importance levels, each metric to be predicted is given a weight during the model training process.

Compared to single-output models, an appropriately weighted, multi-output model (NN1) performs better at estimating PCI (13% lower MSE) than an estimate derived from four optimal, single-output models. Furthermore, the multi-output model generates better estimates than corresponding single-output models for three of the four individual metrics considered – IRI (25% lower MSE), FAULT (27% lower) and TCRACK (4% lower). For the fourth metric, LCRACK, the multi-output model has a 5% higher MSE than the single-output model. The observed improvements derive directly from incorporating correlation relationships among different variables within the multi-output model. The deterioration in LCRACK prediction performance demonstrates the tradeoff that is made when simultaneously estimating correlated metrics.

The results presented in this chapter make it clear, that multi-output models can improve prediction performance in cases where correlation exists. Furthermore, variable weighting is important to achieve the optimal balance of prediction performance among the various metrics. Analysis of extremely weighted models (NN2 to NN9) suggests that the relevance of understanding the nature of this tradeoff will grow as weights become more heterogeneous.

As for the future work to improve the prediction performance for pavement deterioration, one aspect is to improve data quality, which is a common problem for data-driven deterioration models. The Iowa PMS provides one of the best pavement databases that are available. However, there still exist some problems, such as large measurement errors, missing maintenance history, and data entry errors. On one hand, these problems increase the difficulty to generate the data for training the model, on the other hand, a large ratio of data points has to be removed. To improve the model performance, it is necessary to obtain data with a good quality. Another aspect is about the time series analysis. Currently, it is assumed that the time step is just two years due to limited data. With the increase of available records, it is necessary to test different time steps. As for the model structure, one potential drawback for neural network model is its 'black box' feature, which means that the relationship between input and output variables are not clear. In some research fields such as choice models in transportation, some attempts have been made to integrate theoretical model and data-driven models. In the future, this idea could also be applied in pavement deterioration analysis.

2.7 Other Related Works by the Author

In addition to this weighted multi-output neural network model, several other deterioration models are also proposed by the author. But in order to make this dissertation concise, corresponding descriptions are ignored here and they are submitted for journal publications.

Recurrent Neural Network (RNN) Model

RNN models are developed to explore the influence of overweight vehicles on pavement performance. Overweight vehicles are known to accelerate the pavement deterioration process. Many states in the U.S. implement permitting fees to be compensated for this additional damage. In this analysis, the influences of traffic weights on pavement performance have been evaluated for both asphalt and concrete pavements using data from the LTPP database. A qualitative evaluation is conducted through linear regression, which shows that roughness (measured as IRI), rutting, and alligator cracking are sensitive to traffic weights for asphalt pavements. By contrast, concrete pavement conditions appear to be insensitive to traffic weights. In order to predict the influence of traffic weights on pavement deterioration, three RNN models have been developed for asphalt pavement IRI, rutting, and alligator cracking. For a given pavement segment, when the overweight vehicle ratio doubles, results show that the pavement deterioration rates increase by 7%, 35%, and 18% for IRI, rutting, and alligator cracking, respectively. To explore the economic loss brought by the overweight vehicles, life-cycle cost analysis is conducted for pavement networks in states with wet-freeze climates under two types of traffic weight scenarios. When the overweight vehicle ratio doubles, the total annual average additional life-cycle cost can be $64.8M, and the unit cost is $0.006/(ESAL·mile). When the transported weights increase by 2%, the total annual average additional life-cycle cost can be $35M, and the unit cost is $0.002/(ESAL·mile). Results show that the growth of the overweight vehicle ratio is more problematic than the growth of transported weights. Results can provide policy-makers insights about the economic losses caused by overweight vehicles and aid in setting permitting fee level.

Performance Jump Model

Both weighted multi-output neural network and recurrent neural network models are applicable for the prediction of pavement condition without any treatment during the prediction period. In addition to deterioration models mentioned above, a model that describes the pavement condition improvement after a treatment action is also needed, which is usually called performance jump model. The reason why to use 'performance jump' is mainly related with the performance condition metrics. After a treatment action, the performance condition metrics will jump to a smaller value, i.e., the pavement condition is improved. Based on the LTPP database, three sets of performance jump models are proposed based on the linear regression. Corresponding treatment actions include preservation for asphalt and concrete pavements, and asphalt overlays. Different from existing performance jump models, the measurement interval is considered as a variable during the model training process. The proposed the performance jump models are applied for the national analysis in Chapter 5.

CHAPTER 3 INCORPORATING COST UNCERTAINTY AND PATH DEPENDENCE INTO TREATMENT SELECTION

This chapter introduces a budget allocation model called probabilistic treatment path dependence (PTPD) model. During the evaluation of treatment alternatives for a segment in a pavement network, this model considers benefits of both the evaluated treatment and its following actions. It also incorporates the influence of treatment cost and deterioration uncertainties. Treatments are selected for each segment in the pavement network using a risk-based optimization model. The results presented here suggest that elements of this model – notably consideration of uncertainty in deterioration and cost, treatment path dependency, and explicit risk trade-offs – could be incorporated into asset management tools to improve the cost-effectiveness of pavement network planning.

3.1 Introduction

Inadequate funding is a pervasive problem faced by departments of transportation in the U.S. According to the 2017 Infrastructure Report Card by ASCE, the backlog in repairing existing roads is about 420 billion dollars [3]. The backlog has increased to $435 billion in the 2021 Infrastructure Report Card [2]. To improve pavement network performance with insufficient funding, it is important to select and time preservation, overlay, and reconstruction (POR) actions effectively. As noted by [25], these selection decisions have often relied on past practice and expert opinion. To improve the effectiveness of these decisions, a significant body of research has emerged on mathematical budget allocation models that would support POR decision-making.

Most of these models assess the benefits, or more generally utility, and costs of various POR treatments for each segment in a network and then identify the set of segment actions that are expected to yield the best outcome (typically some balance of benefit and cost) for a given budget. Of the models described to date, the majority evaluate benefit and cost for an individual, current-year treatment or a fixed sequence of follow-on treatments. For example, when evaluating a new 12-inch asphalt pavement, most models assume that it will always be maintained by applying two mill & fill actions over its lifetime. Real-world experience likely differs. The real future is almost always different than what a model might predict. Sometimes an asphalt pavement is treated using an asphalt overlay and sometimes a concrete overlay. The actual treatment sequence, or path, is uncertain – dependent on the decisions made now and the evolution of uncertain factors such as the price of materials and the rate of pavement deterioration.

In several studies [45], [68], [77], [78], [115], Madanat et al. apply variations of dynamic programming-based (DP-based) models to explicitly consider uncertainty in future treatment path and its dependence on current decisions. Considering the computational limitations of traditional discrete DP models, Durango-Cohen et al propose a model based on quadratic programming [85], [86], [116]. Specifically, they address this challenge for cases where deterioration is uncertain. When deterioration is uncertain, optimal treatment timing becomes uncertain. In this chapter, the extension of this to cases where future costs are also uncertain is explored. This extension does not simply introduce another dimension to the state space. When cost is uncertain, both optimal treatment timing and type (that is the specific POR treatment strategy used) become uncertain. This makes the number of potential future treatment paths much larger.

To solve this problem, a combination of simulation is applied – to identify probable future treatment paths – and optimization – to identify the best combination of treatments. This approach preserves an estimate of the distribution of modeled outcomes and, therefore, allows decision-makers posteriori consideration of both expected future benefits as well as the risk associated with achieving those.

Based on applying this model in a small case study, this new approach identifies POR plans that lead to a better average network performance compared to the plans from a benefit-cost ratio approach. In fact, to achieve a similar performance level using the benefit-cost ratio approach would require an annual budget nearly 10% higher. After considering both future treatment paths and corresponding risks, the new approach chooses more overlays and reconstructions for the first few years and then shifts to preservations.

3.2 Literature Review

Optimal pavement POR actions for a pavement network can be selected by past practice or expert opinion [25], but here only the use of budget allocation models is discussed. Yeo et al. grouped such models into two methodological categories: top-down and bottom-up [57]. Top-down approaches usually divide the whole pavement network into several groups and pavements in the same group have the same characteristics. While computationally attractive, top-down approaches do not provide results at the segment level [4], [43], [47]–[49]. Bottom-up approaches consider each segment individually, can accommodate heterogeneity across the network, and provide segment (sometimes referred to as facility) level recommendations, so they have become the focus of current research.

In current implementations, bottom-up allocation models commonly comprise two key elements: a method to identify the best treatment for each segment (segment-optimal decision) and a method to select the best set of treatments for the network (network-optimal decision or system-optimal decision). In a so-called two-stage bottom-up (TSBU) model, first, one or several optimal treatment alternatives are chosen for each segment through a range of methods, such as decision trees [50], [58], agency cost [59], benefit-cost analysis [51]–[53], [60]–[63] – including multi-objective definitions of benefit [64], utility analysis [65], or total cost (agency plus user) evaluated over some planning horizon [37], [54], [57], [66]–[68]. These segment-optimal decisions are then evaluated at the network level. The final treatment selection for each segment is generally determined by optimization methods. For this, some studies apply formal mathematical optimization methods such as linear programming [43], [69], non-linear programming [70], integer programming [71]–[73]. Another group of studies apply near-optimal heuristics such as genetic algorithms to allocate budget at the network level [57], [59], [66], [68], [74].

There is a subset of the bottom-up modeling literature that presents models that simultaneously select both the optimal segment-level treatment and optimal allocation of budget across the network [35], [71], [73], [76]–[78], [117]. This simultaneous approach is attractive but can introduce added computational complexity. As the goal here involves significantly expanding the uncertain solution space, a TSBU framework is selected. Future work should explore the potential to also include simultaneous segment and network decision-making.

A key methodological challenge for budget allocation models is the explicit consideration of uncertainty – a pervasive issue in many aspects of real world allocation problems [75]. The most common aspects of uncertainty that have been considered to date are uncertain rates of deterioration [44], [57], [60], [66], [76]–[78], measurement error [8], [12], [79], [80], and budget

[60], [76]. When deterioration or budget is uncertain, optimal treatment timing becomes uncertain. In this chapter, the extension of this to cases where future costs are also uncertain is explored. If the price of material A rises faster than material B, rational decision-makers will switch away from some plans to use A and instead use B. This dependence of the optimal decision on the prevailing future context (i.e., future path) is referred as treatment path dependence. It is worth noting that cost uncertainty can have a different impact than budget uncertainty alone for a TSBU framework. When a budget is uncertain, it can be more or less constraining. When the budget is more constraining, it may force the use of more suboptimal treatments, but does not change the rank preference for treatments at the segment level. In contrast, when costs are uncertain, there is a chance that for any given segment the preferred future treatment actions are different than any plan based on today's costs.

Among the evaluation methods that have been proposed in the literature, DP-based models [57], [66], [77], [78], simulation-based genetic algorithms [76] and reinforcement learning [118], [119] can incorporate the influence of treatment path dependence. DP-based method is often associated with the Markov decision process. As an example, Yeo et al. applied a DP to an allocation problem involving 2000 segments for a case where deterioration was uncertain [57]. The DP identified the future treatment schedule with the smallest expected cost given an analysis period. This model allowed for uncertain pavement performance but did not consider uncertainty of future treatment cost. Generally, the computational resources required by dynamic programming tend to grow rapidly with problem scale [82]. To overcome the limitations of a Markov decision process, Durango-Cohen and co-workers have developed a quadratic programming formulation to address infrastructure management problems by using continuous decision variables [83]–[86]. Such formulations assume that the maintenance cost function is quadratic in form, but in doing so provide both computational efficiency and the ability to capture functional, stochastic, and economic interdependency across facilities within the network problem. Here the computational performances of different models are not tested, but instead a simulation-optimization (SO) framework is applied, which relies on a backtrack-search algorithm for optimization. This framework provides for maximum flexibility in the forms of the system performance function and cost function. In fact, a goal of this research is to eventually use this framework to explore the implications of cost and performance functions that do not follow a Markovian process. (For example, see [120]–[122] for non-Markovian models of future cost and [11], [26] for models of performance evolution.) For the problem considered here, the SO formulation proved sufficiently fast to explore the implication of cost uncertainty.

Finally, it is important to recognize an issue pointed out by Sinha et al. [75]. The introduction of uncertainty to an optimization immediately creates a multi-objective problem where tradeoffs must be made between the expected value of the solution and its uncertainty (or risk). To the best of the author's knowledge, most existing literature evaluate this tradeoff through some a priori statement of risk preference [46]. For example, several models include explicit risk analysis on the network level by using chance constraints [47], [72], [87]. For the segment level analysis, Deshpande et al. use parametric fragility curves to model pavement reliability [123]. DP considers uncertainty by a state transition probability matrix, but the evaluation criterion is generally based on expected values without risk analysis. It would be valuable to evaluate treatment actions for different risk levels at both the segment and network levels. In this chapter, a problem formulation is described and solution that allows for this with either a priori or posteriori evaluation of risk preference is presented.

From the previous review about the current state of budget allocation models, there are three key gaps: consideration of future cost uncertainty and therefore consideration of possible future treatment paths that differ in both timing and type of treatment and explicit risk evaluation for different treatment strategies – rather than considering only expected values – at both the segment and network levels.

3.3 Methodology

To fill in the current gaps, a new probabilistic treatment path dependence (PTPD) model is proposed. It is based on a TSBU approach. Ultimately, the PTPD model comprises four elements. The four elements are needed to: 1) project future pavement performance and context; 2) estimate the performance distribution for each initial treatment alternative for each segment; 3) select the optimal initial treatment for each segment; and 4) select the set of treatments applied across the network. The flow of information among these in the PTPD model is shown schematically in Figure 3-1. After obtaining input data, such as current pavement condition and treatment cost, the PTPD model first conducts analyses on the segment level. Monte Carlo simulations are used to generate a range of future scenarios and then, simulation-optimization is applied to evaluate available treatments under each of these scenarios. For each available initial treatment and each scenario, one optimal treatment path and its corresponding total cost is identified. After all simulations, a distribution of performance can be assigned to each initial treatment option. Based on this distribution, two optimal treatment alternatives are identified based on the decision-maker's risk preferences. Next, the PTPD model moves to the network level where integer programing is applied with the consideration of several constraints and a risk level to make a final treatment decision for each segment in the pavement network. The following sections describe these elements of the PTPD model.

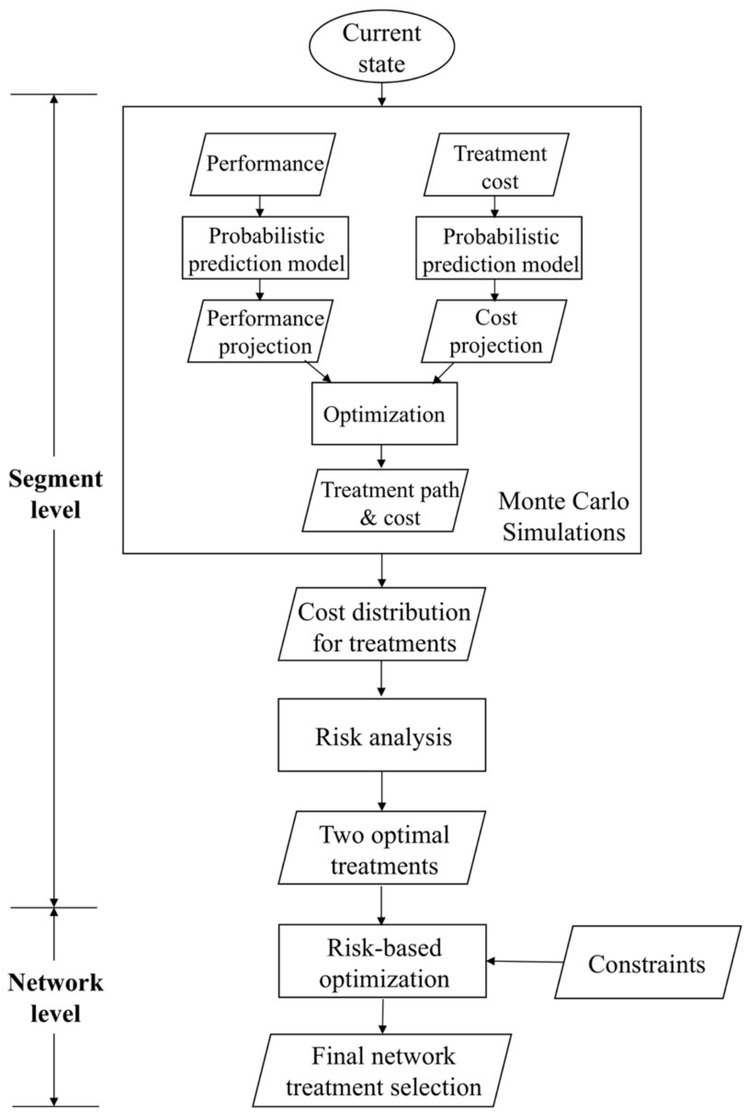


Figure 3-1. Flowchart of PTPD model (Oval represents the start of the model, rectangle indicates a computation or a process, parallelogram is the input or output of a computation.)

3.3.1 Probabilistic prediction models

During budget allocation, prediction models are used to estimate how pavements and context will change over time. Since treatment cost and pavement deterioration could influence the choice and timing of treatment actions, probabilistic prediction models of these two factors are incorporated in the proposed PTPD model.

Most allocation models use constant values for treatment cost. However, treatment cost could be influenced by many factors, like material and labor costs. Prices of different treatments may have different volatilities. A probabilistic treatment cost prediction model in [81] is applied in the PTPD model. This model predicts long-run prices of two important paving materials, asphalt and concrete. Equations (3.1) and (3.2) describe price predictions of asphalt and concrete, respectively, where *P* represents price, *N* is a random number that follows a normal distribution and *t* represents the time (in years). These equations provide theoretical uncertainty bounds that represent future price volatilities.

$$P^t_{asphalt} = 1.41P^t_{crushed\ stone} + 0.20P^t_{oil} - 61.6 + N\left(0, 3.5\right) \tag{3.1}$$

$$P^t_{concrete} = 0.51P^t_{crushed\ stone} + 0.44P^t_{cement} \_ 5.3 + N\left(0, 1.6\right) \tag{3.2}$$

When the corresponding journal paper for this chapter was published, the weighted multi-output model in Chapter 2 was still in the development process. Hence, a model based on a difference-stationary process in literature was adopted here [21]. Since the difference between the PTPD and the conventional benefit cost ratio model is mainly about the budget allocation process, the adoption of the deterioration model will not influence the main conclusions for this chapter. The adopted model assumes that pavement deterioration follows a random walk with drift and uncertainties that have a permanent influence on future deterioration levels, so the variance of future pavement performance increases over time. Age, average annual daily truck traffic (AADTT), and structural number (SN) / thickness of a pavement are incorporated in the deterioration model which are suggested to be influential factors by previous study [124]. The random error of the deterioration process is assumed to follow a Gaussian distribution with a constant standard deviation. The deterioration process is shown in equation (3.3), in which α and β are determined for specific pavement types.

$$\Delta IRI_{t,i} = \alpha Age_{t-1,i}^{\beta_1} AADTT_{t-1,i}^{\beta_2} Thickness_{t-1,i}^{\beta_3} + N\left(0, \beta_3\right) \quad (3.3)$$

3.3.2 Treatment evaluation on segment level

Problem formulation

The goal of the segment-level analysis is to evaluate and identify the best treatment $a_{i,1}^*$ for each segment i at the beginning of segment analysis period (e.g., t_s=1) when there is no budget constraint. During the evaluation process, available treatment alternatives $\boldsymbol{N}^{(m)}$ are related with pavement types $\boldsymbol{M}$ (where $m \in \boldsymbol{M}$). Hence, the goal is to evaluate $\boldsymbol{N}^{(m_0)}$, where m_0 is initially known before the analysis.

To allow for the impact of a budget constraint in the network level analysis, top two alternatives are determined for each segment, namely, $a_{i,1}^* = \left[a_{i,t_s=1}^{*1}, a_{i,t_s=1}^{*2}\right]$. The evaluation is based on the long-term benefits of treatment alternatives. The action with a smaller total cost given an analysis period is preferable. Available treatment alternatives $\boldsymbol{N}^{(m_0)}$ are evaluated by simulation-optimization, which integrates optimization into simulation analysis [125]. Monte Carlo simulations are used to generate a range of possible future scenarios. In this case, each scenario represents a specific projection for deterioration (random sample from equation (3.3)) and treatment cost (random sample from equations (3.1) and (3.2)). For each scenario and for each possible treatment in $\boldsymbol{N}^{(m_0)}$, an optimal treatment path and its corresponding total cost *TC* are determined.

To evaluate action $\boldsymbol{N}^{(m_0)}(\alpha)$, suppose the number of Monte Carlo simulations for the segment-level analysis is K_s. For the k_s^{th} simulation, the optimization process is formulated as the following mathematical model:

min: $\quad TC_{\alpha}^{k_s} \quad (3.4)$

s.t. $\quad a_1 = \boldsymbol{N}^{(m_0)}\left(\alpha\right) = \boldsymbol{N}_1\left(\alpha\right) \quad (3.5)$

$$\sum_{n=1}^{N_{t_s}} x_{n,t_s} \le 1, \quad \text{for } t_s = 2,...,\mathrm{T}_s \tag{3.6}$$

$$IRI_{t_s} = \left(IRI_{t_s-1} + \Delta IRI_{t_s}\right)\cdot\left(1-\sum_{n=1}^{N_{t_s}} x_{n,t_s}\right) + \left(IRI_{new} + \Delta IRI_{new}\right)\cdot\sum_{n=1}^{N_{t_s}} x_{n,t_s} \tag{3.7}$$

$$IRI_{t_s} \le IRI_{threshold} \tag{3.8}$$

$$uc_{t_s} = \beta\cdot\left\langle IRI_{t_s} - 1\right\rangle \quad \text{for } t_s = 1,2,...,\mathrm{T}_\mathrm{s} \tag{3.9}$$

$$a_{t_s} = \sum_{n=1}^{N_{t_s}} x_{n,t_s}\cdot \boldsymbol{N}_{t_s}\left(n\right) \quad \text{for } t_s = 1,2,...,\mathrm{T}_\mathrm{s} \tag{3.10}$$

$$m_{t_s} = g\left(m_{t_s-1}, a_{t_s}\right) \quad \text{for } t_s = 1,2,...,\mathrm{T}_\mathrm{s} \tag{3.11}$$

$$\boldsymbol{N}_{t_s} = \boldsymbol{N}^{\left(m_{t_s}-1\right)} \quad \text{for } t_s = 1,2,...,\mathrm{T}_\mathrm{s} \tag{3.12}$$

$$ac_{t_s} = p\left(ac_0, P^t_{asphalt}, P^t_{concrete}\right)\cdot area \tag{3.13}$$

$$TC_\alpha^{k_s} = \sum_{t=1}^{T_s}\frac{1}{\left(1+r\right)^{t_s}}\left(\sum_{n=1}^{N_{t_s}} x_{n,t_s}\cdot ac_{t_s}\left(n\right) + uc_{t_s}\right) \tag{3.14}$$

$$x_{n,t_s} \in \left\{0,1\right\} \quad \text{for } t_s = 1,2,...,\mathrm{T}_\mathrm{s}, \text{ and } \forall n \tag{3.15}$$

Table 3-1. Definitions of all variables in the segment-level optimization process

Variable	Meaning
T_s	Segment level analysis period
K_s, k_s	The total number and the ordinal of Monte Carlo simulations
TC	Total cost given the segment level analysis period
m_t	Pavement material type at time *t*. When $t = 0$, it represents the initial pavement type
r	Discount rate
$\boldsymbol{N}, n, a, \alpha$	***N*** is the set of treatment actions, *n* is the ordinal of the actions in ***N***, i.e. ***N(n)*** represents the n_{th} action *a* in *N*, α is the ordinal of the evaluated action.
x_{n,t_s}	Decision variable. If the n_{th} action in $\boldsymbol{N}_{t_s}$ is selected at year t_s, $x_{n,t_s} = 1$. Otherwise, $x_{n,t_s} = 0$.

ΔIRI_{t_s}	Pavement deterioration without treatment
ΔIRI_{new}	Pavement deterioration after a treatment
$\Delta IRI_{threshold}$	The performance threshold value for IRI.
uc_{t_s}	User cost at year t_s
β	Coefficient to calculate user cost.
ac_{t_s}	Agency cost at year t_s

Explanation of the equations in the segment-level optimization

The goal of the optimization analysis is to evaluate the α_{th} treatment action *a* in N_1 (equation (3.5)). For example, $N_1 = \{$do nothing, surface treatment, asphalt overlay, asphalt reconstruction$\}$, then the fourth (α_{th}) treatment action (*a*) is asphalt reconstruction. The segment-level optimization objective is to minimize the total agency cost *ac* plus user cost *uc* for a given analysis period T_s (equations (3.4) and (3.14)). x_{n,t_s} is a binary variable, which represents treatment action *n* is selected at year t_s if x_{n,t_s} is equal to 1. It is important to point out that agency (*ac*) and user costs (*uc*) are added together to compute total cost. This implicitly assumes that both are weighted equally in the evaluation of alternatives. In terms of the weight ratio between agency and user costs, some studies use the weight ratio of 1:1 or the ratio of 1:0.6268 [25], [78], [126]. This chapter assumes the weight ratio is 1:1. This ratio can be modified based on the requirements of a transportation agency.

At any year t_s, at most one action could be selected as shown in equation (3.6). Equation (3.7) describes roughness (IRI) at the end of year t_s based on the IRI at year t_s-1 and the treatment action at year t_s. A treatment action is applied at the beginning of each year. If a treatment action is applied, segment performance is improved and IRI decreases to IRI_{new}. IRI_{new} can be obtained through a performance jump model, which is usually a function of the IRI values before a treatment [51], [61]–[63]. When the corresponding journal paper for this chapter was published, the performance jump model was in the development process. Considering that the IRI values before a treatment are typically very similar (i.e., they are all at or near the threshold) due to the existence of a performance threshold, it is assumed that IRI_{new} is the same for different treatment actions. Even though IRI_{new} is the same, the deterioration rates for each treatment are different since the age, thickness and pavement types could be changed. Together, these phenomena capture some of the aspects of performance jump models described in the literature.

Before calculating ΔIRI by equation (3.3), age and thickness should be updated first based on the treatment type. If the treatment type is reconstruction, then the age is reset to 0 and thickness is set to the thickness of the reconstructed pavement. For other treatments, the age is not changed and continues to progress as before. If the treatment type is a surface treatment, the thickness is assumed to stay the same. If the treatment type is overlay, the new thickness is equal to the old thickness plus the overlay thickness and minus the mill thickness. The prediction of future traffic level of a single segment should be based on the pavement network and can be influenced by many factors [127]. To simplify the analysis, the traffic volume is assumed to remain the same for the whole analysis period.

Equation (3.8) is the performance constraint. Apart from agency cost, user cost is also an important component for the life-cycle cost. User cost is related with pavement impacts on fuel consumption through pavement-vehicle interaction (PVI), and traffic delay cost by work zone closures. Total delay cost is quite small compared to PVI cost given a whole analysis period, so in this analysis the user cost only temporarily considers fuel consumption caused by roughness-induced PVI [128]. In Chapter 4, the scope of user cost has been extended to incorporate both roughness-induced and deflection-induced PVI. Equation (3.9) describes the user cost, which is related with traffic volume, segment length and performance condition. Since the analysis focuses on a single segment, user cost can be regarded as a linear function of IRI, where $\langle x \rangle = x$ if $x > 0$, otherwise $\langle x \rangle = 0$.

Equation (3.10) describes the action a_{t_s} taken at year t_s. Material type m_{t_s} at year t_s can be decided by material type at year t_s-1 and the treatment taken at year t_s as shown in equation (3.11), and then corresponding treatment alternatives could be decided (equation (3.12)). Equation (3.13) describes the agency cost, which equals to the multiplication of unit treatment cost and segment area. The unit treatment cost changes with unit concrete and asphalt cost. Due to limited cost information, it is assumed that cost of concrete treatment actions changes at the same rate as the cost of the concrete material. Asphalt treatment actions changes at the same rate as the cost of the asphalt material. If no material is applied, such as diamond grinding, then treatment actions changes at the same rate as the construction cost index (CCI) [129].

Model solution

The model as framed in the preceding section is not a typical integer programming problem. Segment condition at year t_s is a function of the year previous (t_s-1) because the treatment action chosen at year t_s-1 (or some earlier year) determines the condition information at year t_s. This means that condition variables at year T_s are a polynomial function of $\prod_{t_s=1}^{T_s=1} x_{n,t_s}$. The degree of unknown variables is T_s -1. This level of non-linearity increases computational expense.

The most common approach that has applied to the segment-level optimization problem is a dynamic programming framework. For the case described here, the state space of the dynamic program would be large because each state would need to be described by many factors including pavement roughness, thickness, age, material, asphalt cost and concrete cost. A number of researchers have pointed out that dynamic programming can become computationally intensive when the state space is large due to the curse of dimensionality [115]. To address this challenge, several heuristic approaches have been proposed, such as genetic algorithms [37], [54], approximate dynamic programming [68], [77], [115], and reinforcement learning [118], [119]. While these approaches should be evaluated in the future, the goal of this chapter is to understand the implications of considering cost uncertainty and treatment path dependence on the budget allocation problem. As such, a simple backtrack-search algorithm is applied to solve this problem. For the specific problem, this turned out to be sufficiently fast and efficient.

As for the problem in the previous section, it is expected to find an optimal treatment schedule $\left(a_1, a_2, ..., a_{T_s}\right)$ from the Cartesian product space $\boldsymbol{N}_1 \times \boldsymbol{N}_2 \times ... \times \boldsymbol{N}_{T_s}$, which has the minimal total cost (agency plus user) given a period of T_s years. Let M_i be the number of treatment actions (including 'do nothing') in $\boldsymbol{N}_i$, then the total number of possible schedules is $M_{tot} = \prod_{i=1}^{T_s} M_i$. To solve this problem, a backtrack-search algorithm is designed to yield the global optimal solution as with the brute-force approach but with far fewer trials than M_{tot} [130].

The goal of the search is to find the schedule with the smallest cost. Initially, the smallest cost is set equal to infinity. Starting from the first action in $\boldsymbol{N}_1$, at each step, the backtrack-search algorithm extends the current partial treatment schedule $(a_1, a_2, ..., a_i)$ to a larger partial schedule $(a_1, a_2, ..., a_i, a_{i+1})$ by selecting one action in $\boldsymbol{N}_{i+1}$. After choosing the treatment a_{i+1}, its corresponding agency cost and user cost can be determined. During the step of extending treatment schedule by one action, the backtrack algorithm tests the partial treatment schedule by comparing the total cost of the partial schedule and the smallest total cost that has been found among all schedules traversed so far. If the former is larger than the latter, then the algorithm eliminates large branches of treatment a_{i+1} from further consideration. If not, the algorithm extends one action in the next step. When the algorithm extends to the end of the treatment schedule, if total cost of the current schedule is smaller than the existing smallest cost then it updates the smallest cost to the newly discovered one.

The computational efficiency of the backtrack-search algorithm usually depends on when the global optimal solution can be found [131]. After the global optimal solution is found, other schedules are usually partially cut off during the search process since its total cost is larger than the 'optimal' schedule. Therefore, the order of the search process is very important. In terms of the segment-level optimization problem, the optimal treatment schedule usually has two important characteristics: 1) Treatment actions are not applied every year. After a treatment action, there are several years for 'do nothing' until the next treatment action. After both upper and lower bound performance constraints are considered, the number of feasible treatment schedules is much smaller than M_{tot} [132]; 2) The cost differences for surface treatment, overlay, and reconstruction are large.

After considering these two characteristics, the backtrack search process for this problem follows three main strategies:

- There are two main constraints: 1) for each year, the pavement condition must satisfy the performance constraint; 2) The total cost of the current partial schedule must be less than the smallest total cost that has been found.
- For each step, 'do nothing' is always the first action to evaluate. This can help us avoid 'useless' search processes because 'do nothing' accounts for a large portion of any optimal schedule. If 'do nothing' satisfies constraints, there might be no need to search the branches of other treatment actions.
- If 'do nothing' does not satisfy constraints, all treatment actions are evaluated according to the order of their cost. Namely, expensive treatment cost actions are evaluated first. When the analysis period is short, surface treatment actions are usually preferable. In this case, the reconstruction or overlay actions usually don't need follow-up actions. Hence, the search process will converge to surface treatments rapidly. When the analysis period is long, reconstruction or overlay actions are more beneficial. Since they are evaluated first, the search process can also find the optimal schedule quickly.

Appendix A presents the pseudocode to find the optimal treatment schedule and illustrates its computational efficiency in terms of the running time for a small case study. When the analysis period is 20 years, for 10,000 random segments, the maximum search step number is less than 10^6 while the step number for the full brute-force search process is 6×10^{19}. The running time is less than 0.2s in MATLAB on a laptop (3.5 GHz Intel Core i7, RAM 16GB).

3.3.3 Treatment selection on segment level

Each simulation in Section 3.3.2 could provide an optimal treatment schedule and its corresponding total cost $TC_n^{k_s}$. After all simulations, future cost distributions $\left\{TC_n^{k_s}\right\}_{k_s=1}^{K_s}$ for each available treatment n in $\boldsymbol{N}^{(m_0)}$ are obtained. Based on these cost distributions, all treatment alternatives are evaluated and ranked by

$$\textbf{min:} \qquad z_n = \mathrm{E}_n + \theta \cdot SD_n \tag{3.16}$$

E_n represents the mean value of total cost distribution for treatment action n, SD_n is the standard deviation, and θ is the risk-aversion coefficient that is used to describe the tradeoff between mean cost and variation. After risk analysis, z_n could be obtained for each treatment alternative n in $\boldsymbol{N}^{(m_0)}$. Then two optimal (the two lowest z values) treatment alternatives $a_i^* = \left\{a_{i,1}^{*1}, a_{i,1}^{*2}\right\}$ are identified for each segment i.

The segment-level analysis (Section 3.3.2 and 3.3.3) evaluates the influence of treatment path dependence, incorporates that into an assessment of segment performance, and allows the decision-maker to make explicit trade-offs between expected and risk-based performance. These initial treatment selections on the segment level are passed on to the network level for further analysis.

3.3.4 Network-level analysis

On the network level, the goal is to make a final treatment decision for each segment using a risk-based optimization process. For each segment i, the alternatives are to choose one of the two selected alternatives a_i^* from the segment-level analysis or do nothing. The proposed risk-based optimization model makes treatment decisions on a yearly basis. It updates network performance based on decisions for the current year. Then it makes decisions for the next year based on the updated performance. At year t, the mathematical formulation of the network-level analysis is shown as follows:

$$\textbf{min:} \quad \sum_{i=1}^{I} \left(\mathrm{E}\Delta TC_{i,t} + \theta \cdot \Delta SD_{i,t} \right) \tag{3.17}$$

$$\textbf{s.t.} \quad y_{i,1} + y_{i,2} \le 1 \quad \text{for } i = 1,2,...,I \tag{3.18}$$

$$\sum_{i=1}^{I} \left(y_{i,1} \cdot ac_t\left(a_i^{*1}\right) + y_{i,2} \cdot ac_t\left(a_i^{*2}\right) \right) \le B_t \tag{3.19}$$

$$\mathrm{E}\Delta TC_{i,t} = \left(\mathrm{E}TC_{i,t}(0) - \mathrm{E}TC_{i,t}\left(a_i^{*1}\right) \right) \cdot y_{i,1} + \left(\mathrm{E}TC_{i,t}(0) - \mathrm{E}TC_{i,t}\left(a_i^{*2}\right) \right) \cdot y_{i,2} \quad \text{for } i = 1,2,...,I \tag{3.20}$$

$$\Delta SD_{i,t} = \left(SD_{i,t}(0) - SD_{i,t}\left(a_i^{*1}\right) \right) \cdot y_{i,1} + \left(SD_{i,t}(0) - SD_{i,t}\left(a_i^{*2}\right) \right) \cdot y_{i,2} \quad \text{for } i = 1,2,...,I \tag{3.21}$$

$$y_{i,1}, y_{i,2} \in \{0,1\} \quad \text{for } i = 1,2,...,I \tag{3.22}$$

Table 3-2. Definitions of all variables in the network-level optimization process

Variable	Meaning
I	Segment number
$\mathrm{E}\Delta TC_{i,t}$	The decrease of mean total cost given a segment analysis period T_s after a treatment is taken for segment *i* at year *t*
$SD_{i,t}$	The standard deviation of total cost given a segment analysis period T_s for segment *i* at year *t*
$\mathrm{E}\Delta SD_{i,t}$	The decrease of variation of total cost given a segment analysis period T_s after a treatment is taken for segment *i* at year *t*
θ	Risk-aversion coefficient for the network-level analysis
a_i^{*1}, a_i^{*2}	Two optimal treatment alternatives obtained on the segment level analysis
$y_{i,1}, y_{i,2}$	Decision variables. If a_i^{*1} is selected, then $y_{i,1} = 1$; If a_i^{*2} is selected, then $y_{i,2} = 1$. If neither a_i^{*1} or a_i^{*2} is selected, then $y_{i,1} = y_{i,2} = 0$.
B_t	Available budget at year *t*

The Markowitz formulation [133] was developed to design portfolios based on a conscious tradeoff between average return and risk. In this context, risk is represented by the uncertainty in future total cost. A system with a large risk (i.e., large standard deviation (*SD*) of total cost) has a high probability that the system will experience poor pavement network performance. Therefore, the optimization objective is to maximize the total decrease of expected total cost for a given period T_s as suggested by [78], [126], and also to minimize the standard deviation of total cost (i.e., risk) at the same time, as shown in equation (3.17). Since for a given year *t* and a segment *i*, $\mathrm{E}TC_{i,t}(0)$ and $SD_{i,t}(0)$ can be considered as constant values, the objective in equation (3.17) is essentially to minimize the average of total cost for a given period T_s and to minimize the standard deviation of total cost. θ is the risk-aversion coefficient, which is the same as the one on the segment level. A decision-maker can select the emphasis on expected performance and risk-aversion by changing the θ parameter.

Equation (3.18) requires that at most one treatment alternative could be chosen for each segment. $y_{i,1}$ and $y_{i,2}$ are binary variables as shown in equation (3.22), which represent treatment action a_i^{*1} or a_i^{*2} is selected at year *t* if $y_{i,1}$ or $y_{i,2}$ is equal to 1. Equation (3.19) is the budget constraint. Equation (3.20) describes the expected decrease of total cost for a period T_s, which considers three cases: action a_i^{*1} is chosen ($y_{i,1}=1$), a_i^{*2} is chosen ($y_{i,2}=1$), or no action ($y_{i,1}=y_{i,2}=0$). Equation (3.21) describes the decrease of standard deviation of total cost.

The network-level optimization problem is an integer programming problem, which is solved by the software *GUROBI*. By solving the optimization problem at year *t*, treatment decisions could be made for each segment *i*, namely $a_{i,t}=y_{i,1}\cdot a_i^{*1}+y_{i,2}\cdot a_i^{*2}$, and treatment decisions for the whole network can be expressed as $A_t=\left\{a_{i,t}\right\}_{i=1}^{I}$.

3.3.5 Model evaluation approach

In this part, a second set of Monte Carlo simulations are applied to evaluate the PTPD model's performance for a multi-year period. These simulations have incorporated future agency cost and deterioration uncertainties. Let *ac* and εIRI represent sets of possible future sequences of agency cost and deterioration uncertainty given a period, respectively. Both *ac* and εIRI are independent and identically distributed.

Suppose the total number of Monte Carlo simulation is *K* and for each simulation the analysis period is T_n. Let $\left\{ac^k\right\}_{k=1}^{K}$ and $\left\{\varepsilon IRI^k\right\}_{k=1}^{K}$ be a sequence of independent samples extracted from *ac* and εIRI, respectively. Then, input parameters for the model system, $\left\{W^k\right\}_{k=1}^{K}$, can be expressed as a sequence of independent sets based on $\left\{ac^k\right\}_{k=1}^{K}$ and $\left\{\varepsilon IRI^k\right\}_{k=1}^{K}$, where $W^k=\left\{ac^k,\varepsilon IRI^k\right\}$. For the k^{th} simulation, considering the T_n-year analysis period, W^k can be expressed as a sequence of $\left\{W_t^k\right\}_{t=1}^{T_n}$. Similarly, $W_t^k=\left\{ac_t^{\ k},\varepsilon IRI_t^{\ k}\right\}$. Assume pavement network condition is S_{t-1}^k at year *t-1* for k^{th} Monte Carlo simulation. Based on the proposed PTPD model, at year t treatment decisions A_t^k could be made, namely, $A_t^k = PTPD\left(S_{t-1}^k, W_t^k\right)$. Then pavement network condition at year t could be predicted based on S_{t-1}^k and A_t^k, which can be expressed as $S_t^k = prediction\left(S_{t-1}^k, A_t^k\right)$.

After all simulations, pavement network condition $\mathbb{S}$ could be obtained, where $\mathbb{S} = \{S_t^k : t \in [0, T_n], k \in [1, K]\}$. Then two forms of distribution curves are used to evaluate $\mathbb{S}$ - cumulative probability curves for the average performance of the analysis period $\mathbb{S}^1 = \{\mathbb{E}_t[S_t^k | k = k'] : k' \in [1, K]\}$, and annual performance distribution curves $\mathbb{S}^2 = \{\mathbb{E}_k[S_t^k | t = t'] : t' \in [1, T_n]\}$.

3.4 Case Study

Three case studies are presented here to illustrate the application and benefits of the PTPD model. The first one focuses on the segment-level analysis, and the second one focuses on the network level. The influence of the risk-aversion coefficients on the segment-level treatment selections and on the network-level performance are explored, respectively. The third case study compares the PTPD model with a benefit-cost ratio (B/C) model. It aims to show the benefits of incorporating uncertainties and treatment path dependence during treatment selections.

Across all three sets of analysis, it is assumed that pavement costs evolve according to equations (3.1) and (3.2), and that performance deteriorates according to equation (3.3).

3.4.1 Segment-level decision-making

This case study is concerned with a common hot mix asphalt (HMA) segment that has the attributes listed in Table 3-3. There are seven treatment actions available at $t_s = 1$ including preservation, overlay, and reconstruction (Table 3-4). Estimating treatment costs for planning-related decisions is always challenging [134]. For this study, expected cost data are based on an analysis of one year of publically available bid data for highway projects [20], [53]. Since the initial pavement type is HMA, its available treatments do not include diamond grinding (first row) for the first year. If a concrete-related action is taken during the analysis period, diamond grinding could be chosen after that. As such, this action is also listed in the table.

Table 3-3. Example segment attributes. (These values represent one segment in the system. Detailed analysis of this segment is described.)

Pavement Type	Age	Thickness	IRI	AADT	AADTT	Area
HMA	12	240mm	1.8m/km	6000	3500	1 yard^2

Table 3-4. Characteristics of available treatment actions used in the case study. Cost information is based on analysis of one year of publically available bid data [20], [53].

Action Type	Name of Action	Applicable Sections	Expected Cost ($/yard^2)
Preservation	Diamond grinding (DG)	Concrete top layer only	6.87
Preservation	2" mill & fill (MF)	Asphalt top layer only	8.03
Overlay	4" asphalt overlay (AC)	Concrete or asphalt top layer	12.18
Overlay	4" concrete overlay (AC)	Concrete or asphalt top layer	16.67
Reconstruction	New 8" asphalt (AC)	Concrete or asphalt top layer	26.10
Reconstruction	New 12" asphalt (AC)	Concrete or asphalt top layer	39.15
Reconstruction	New 8" JPCP (PCC)	Concrete or asphalt top layer	33.33
Reconstruction	New 12" JPCP (PCC)	Concrete or asphalt top layer	50.00

An analysis period T_s of 5 years is chosen. FHWA recommends that the choice of discount rate be based on the OMB rate, which is 1.3 – 1.5% for the calendar year 2019 [135]. The discount rate is set at 1.5% in this case study.

Figure 3-2 shows total cost (agency plus user) distributions, $\left\{TC_n^{K_s}\right\}_{k_s=1}^{K_s}$, derived from the application of the segment level model for the seven applicable treatment actions for the example segment described in Table 3-3. For this case, preservations like 2" mill & fill (blue dot line) and overlays like concrete (orange dash line) and asphalt overlays (blue dash line) have a smaller total cost. Due to the existence of uncertainties, only one treatment action is needed when the deterioration rate is small, otherwise two actions are required. This explains the step phenomenon for cost distributions of preservations and overlays. Among the treatments analyzed, 2" mill & fill is most likely to have two actions.

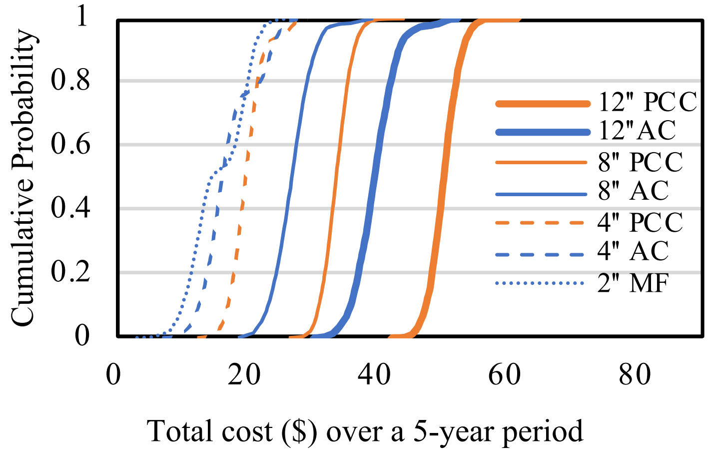


Figure 3-2 Total cost distributions for different treatment actions

Using the risk model described in equation (3.16), optimal treatment alternatives for different risk-aversion coefficients are listed in Table 3-5. When the risk-aversion is low (θ=0 to 1), 2" mill & fill and 4" asphalt overlay are preferable since they have relatively low initial costs and have the lowest total mean cost. By contrast, when the risk-aversion is high, concrete overlays and concrete reconstruction (thin solid blue line) become optimal alternatives. This is due in part to the fact that the modeled price volatility of concrete is lower than that of asphalt and that concrete has lower user costs.

Table 3-5. Optimal treatment alternatives

Risk-aversion	Optimal Alternatives	
	1st	2nd
$\boldsymbol{\theta}$**=0**	2" mill & fill	4" asphalt overlay
$\boldsymbol{\theta}$**=1**	2" mill & fill	4" asphalt overlay
$\boldsymbol{\theta}$**=5**	4" concrete overlay	2" mill and fill
$\boldsymbol{\theta}$**=10**	4" concrete overlay	New 8" concrete

From this example, it is found that risk-aversion can influence the preferred treatment. When the risk-aversion coefficient is small, treatments with small expected costs are preferable. Otherwise, treatments with smaller uncertainty are chosen. A sensitivity analysis of these results to the choice of discount rate was carried out and is presented in the Appendix B. This analysis shows that results are not strongly affected by discount rate except in cases where the analysis period is long and the risk parameter (θ) is low.

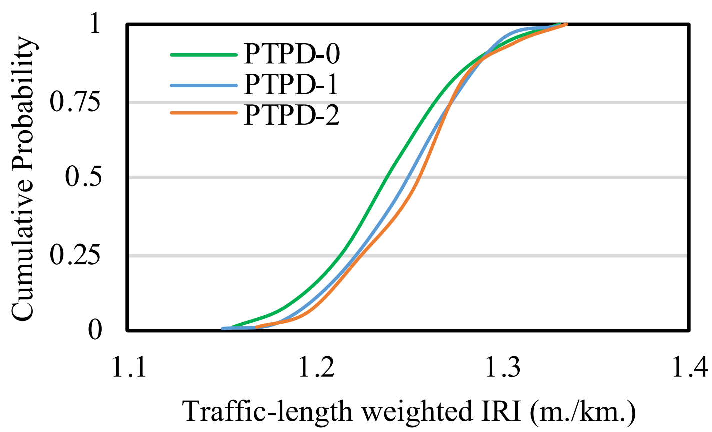
3.4.2 Network-level performance

The second case study explores the influence of different risk-aversion coefficients on network-level performance using the PTPD model. The analyzed pavement network consists of 30 segments, including four pavement types, namely HMA, concrete, asphalt overlay composite (AOC), and concrete overlay composite (COC) pavements. Other available information includes IRI, age, structure, and traffic volume for each segment at the time of the analysis. Five risk-aversion coefficients are analyzed, namely, $\theta = 0$, 0.5, 1, 1.5, and 2. When the coefficient is 0, risk is not incorporated, and treatment decisions are only based on expected total cost for a period T_s (segment level). The comparisons of these five coefficients are based on 100 Monte Carlo simulations with the consideration of deterioration process and treatment cost uncertainties. The network and segment analysis periods are 20 and 10 years, respectively, for all simulations. Available treatment actions are listed in Table 3-4.

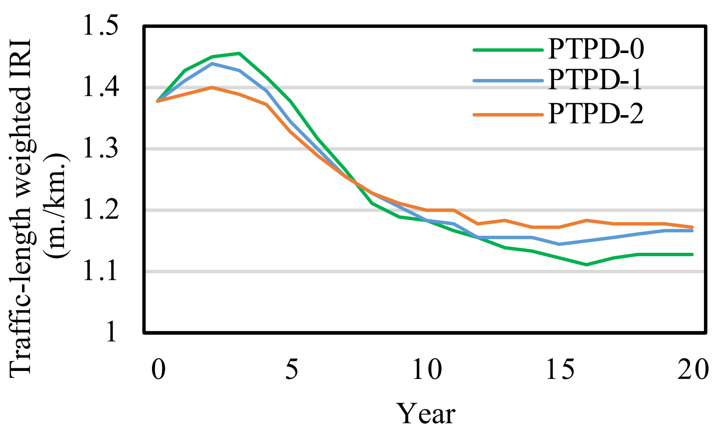
As mentioned earlier in Section 3.3.1, IRI is chosen as the pavement condition metric for each segment. In terms of pavement network performance, traffic-length weighed IRI (TWIRI) is adopted as the performance metric, as shown in equation (3.23), where AADT represents annual average daily traffic. TWIRI reflects both the performance condition of each segment and its significance in the pavement network as measured by its length and traffic volume.

$$TWIRI_i = \frac{AADT_i \cdot Length_i}{\sum_{i=1}^{I} AADT_i \cdot Length_i} \cdot IRI_i \tag{3.23}$$

The comparison results are shown in Figure 3-3. PTPD-1 represents the curve whose risk-aversion coefficient is equal to 1. The curves that represent PTPD-0.5 and PTPD-1.5 lie between PTPD-1 and PTPD-2 curves but are not shown to improve clarity in the figure. Table 3-6 summarizes the average (AVG) and standard deviation (STD) of network performance. From these results, there is a tradeoff between the mean and variance of performance. With the increase of the risk-aversion coefficient the slope of the cumulative probability curve becomes steeper, and the mean value of the curve increases slightly. This phenomenon is strongly correlated with materials chosen to maintain pavements. Figure 3-4 shows the ratios of pavement types at the beginning and the end of the analysis period for different risk-aversion coefficients. When the risk-aversion coefficient increases, the ratios of concrete and concrete overlay composite pavements increase, which means concrete is applied more frequently than asphalt. This is because concrete has lower future cost uncertainty than asphalt in these simulations.



(a). CDF of average TWIRI over 20 years under different risk-aversion factors



(b). Annual average TWIRI distribution under different risk-aversion factors

Figure 3-3. Network-level performance under different risk-aversion coefficients for PTPD model (PTPD-0.5 and PTPD-1.5 curves lie between PTPD-1 and PTPD-2 curves but are not shown to improve clarity).

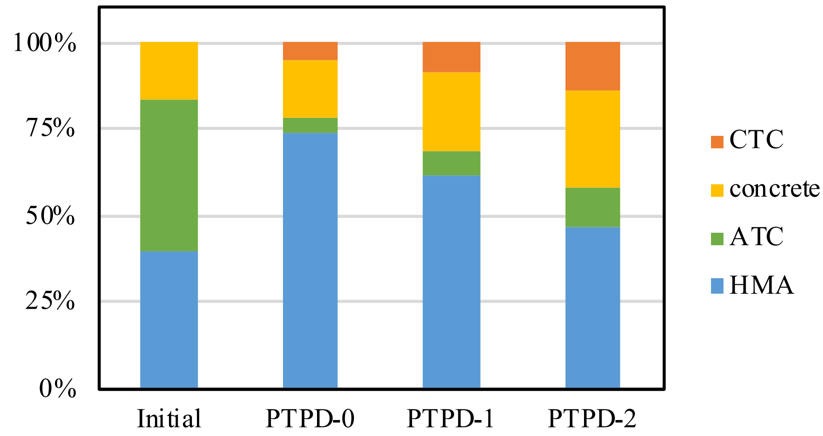


Figure 3-4. Pavement type distributions at year=0 and year=20 for different risk-aversion coefficients (0, 1, and 2)

Table 3-6 summarizes key statistical characteristics of the solutions from the PTPD model, including the mean (AVG), standard deviation (STD), and 10% value at risk (VAR10). The VAR10 value provides indication of elevated high-TWIRI risk – that is higher risk of ending up with poor performing networks. From Table 3-6, PTPD-0 has the lowest average result (bold value), PTPD-2 has the smallest standard variation, and PTPD 0.5 has the lowest VAR10 result. As there is no completely dominating option, a case from the middle of the range tested – the PTPD-1 – is selected to compare with a B/C model in the next case study. The PTPD-1 solution provides a balance, with nearly optimal average return and nearly optimal high-TWIRI risk management.

Table 3-6. Average and standard deviation of network performance for five risk-aversion coefficients (0, 0.5, 1, 1.5, and 2). VAR10 is 10% value at risk. Bold values are discussed in the text.

	AVG	STD	VAR10
PTPD-0	**1.241**	0.0596	1.296
PTPD-0.5	1.245	0.0578	**1.290**
PTPD-1	1.248	0.0575	1.291
PTPD-1.5	1.249	0.0571	1.291
PTPD-2	1.251	**0.0562**	1.297

In general, the risk-aversion coefficient represents the tradeoff between the mean and variance of performance. It influences the distribution of pavement types and the pavement network performance.

3.4.3 Comparison with B/C model

The PTPD model is compared here with a benefit-cost ratio (B/C) model [53], [129]. This B/C model is also based on the two-stage bottom-up framework. On the segment level of the B/C model, different treatment alternatives are ranked by the benefit-cost ratio. The benefit mainly refers to the expected performance difference between the case where there is no treatment action and the case where a treatment action *n* is applied at year t* given a period of *T* years. Figure 3-5 illustrates how to calculate a treatment alternative's benefit (the light blue shaded area *B*). On the network level, the objective is to maximize the total traffic weighted benefits for the whole pavement network.

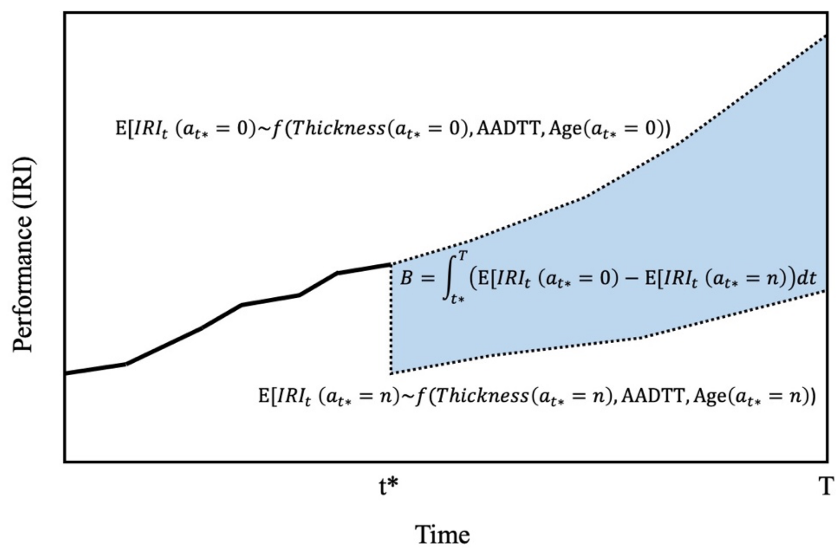
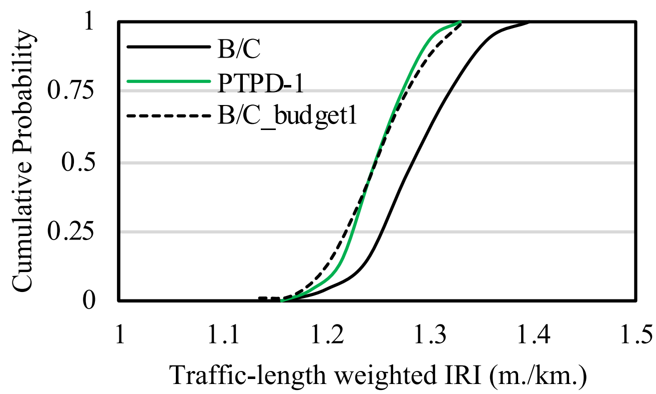
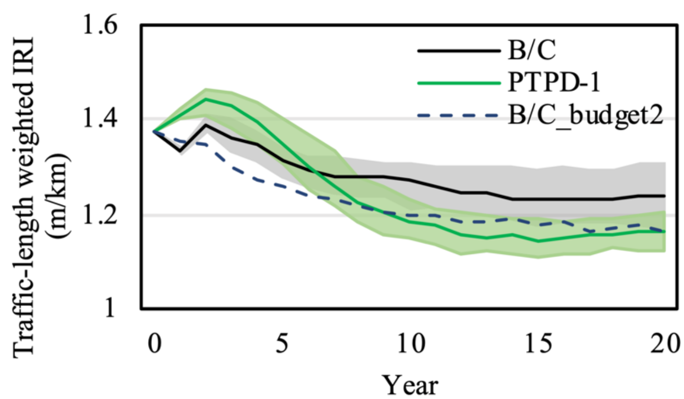


Figure 3-5. Representation of benefits in the B/C model

The B/C model only evaluates the analyzed treatment action itself and the evaluation process is deterministic. By contrast, the PTPD model tries to evaluate the analyzed treatment by considering possible future treatment schedules. By comparing these two models, benefits of incorporating cost uncertainties and treatment path dependence could be discovered. Based on the previous case study, the risk-aversion coefficient is chosen as 1 and the discount rate is 1.5%. The comparison process is based on 100 Monte Carlo simulations. The cumulative probability of average traffic-length weighted IRI for the whole pavement network over 20 years and annual traffic-length weighted IRI distribution are shown in Figure 3-6.



(a). CDF of average TWIRI over 20 years



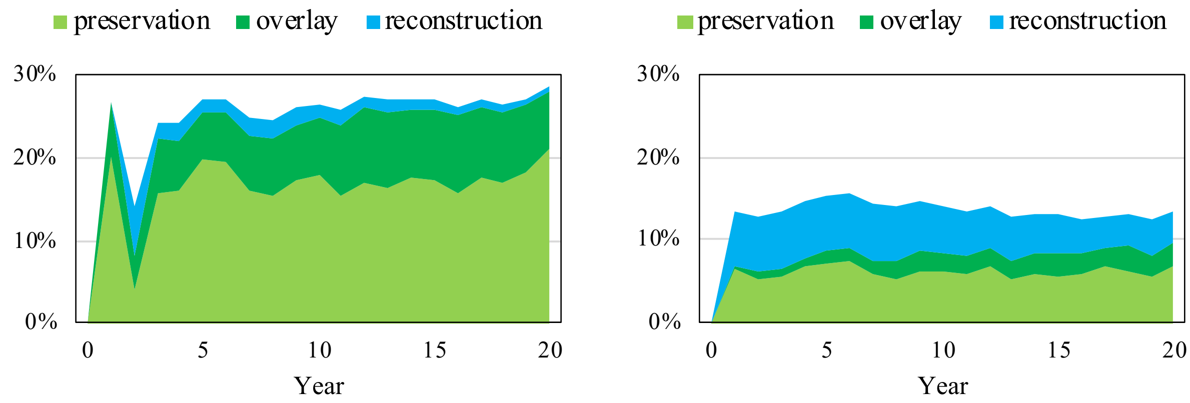
(b). Annual TWIRI distribution

Figure 3-6. Network-level performance for B/C and PTPD-1 models

It is clear that, in the long run, the PTPD model has a better average performance since it has a smaller average and final traffic-length weighted IRI. To explore the value of this performance difference, the B/C model is re-executed with a progressively higher budget. To achieve a similar mean performance level, the B/C model needs to increase its budget by 10.4%, as shown by B/C_budget1 (the black dash line) in Figure 3-6(a).

Figure 3-6(b) plots the evolution of TWIRI over the analysis period for the PTPD model and the B/C model run at two budget levels (same as PTPD = B/C and 16.7% higher = B/C_budget2). The shaded areas in Figure 3-6(b) show the interquartile range (from 25% to 75%) of the modeled annual distribution of traffic-length weighted IRI. The solid and dashed lines represent the median values of distributions of the three model results. The dashed line (B/C_budget2) in Figure 3-6(b) represents the results of a scenario where the budget level was raised until the B/C model would achieve a similar performance level at the end of the analysis period (20 years) as the PTPD model. This analysis suggests that the B/C model needs to increase its budget by 16.7% to yield a performance similar to PTPD at the end of year 20.

From Figure 3-6(b), the B/C model performs better (i.e., TWIRI is lower) for the first five years, while the PTPD model has a faster decreasing rate and has a smaller average traffic-length weighted IRI after 6 years. This phenomenon is strongly correlated with the treatment actions that both models have chosen. Figure 3-7 shows treatment type distributions for both models. At the first year of the analysis period, the ratios of preservations are very high for the B/C model (the spike in Figure 3-7(a)). This phenomenon is related with the performance conditions of segments in the pavement network. For the current pavement network, many segments need preservations in the first year. If the initial performances of segments were changed, the spike phenomenon might disappear. Compared to the B/C model, the PTPD model chooses more reconstruction actions, especially for the first 10 years. Since these actions are very expensive, the total number of segments that can be maintained is smaller than the B/C model for the first 10 years. This explains why traffic-length weighted IRI of the PTPD model increases at the beginning of the analysis period. However, after the first few years, the long-term benefits of reconstructions are felt throughout the network, which enables a shift to preservations and overlays for the last 10 years. In this case, the PTPD model chooses more reconstructions and less preservations and overlays compared to the B/C model.



(a). B/C model (b). PTPD-1 model

Figure 3-7. Ratios of treated segments by different treatment types for B/C and PTPD-1 models

It is important to note that the magnitude and specifics of these results would certainly shift for different cases, under different budget levels, and for different levels of risk preference. A sensitivity analysis of these results to the choice of discount rate was carried out and is presented in the Appendix B. This analysis shows that results are not strongly affected by discount rate. In terms of the given range of discount rates, PTPD model has a better performance than the B/C model. Future work should carefully map out other trade-offs that exist across these aspects of the pavement management problem. Nevertheless, the results shown here suggest that there is promising is in explicit consideration of cost uncertainty in pavement management.

In general, after considering treatment path dependence, segment decisions are based on the benefits of both current evaluated treatment action and its following actions, which can adapt to uncertainties. By doing so, the proposed model proactively deals with an uncertain future.

3.5 Conclusions and Discussions

This chapter proposes a new probabilistic, bottom-up model for the budget allocation process in pavement management systems with the consideration of uncertainty in deterioration, cost and also treatment path dependence. On the segment level, simulation-optimization is applied to evaluate each available treatment. Monte Carlo simulations generate future scenarios with the consideration of future deterioration processes and treatment cost uncertainties. For each scenario, an optimization model is applied to determine the optimal treatment path given an analysis period.

The optimization model is solved by a backtrack-search algorithm. Total cost distributions for each evaluated treatment are obtained using the simulation results. The best two treatment alternatives are selected for each segment based on a risk model. On the network level, an optimal treatment decision is made for each segment after considering several constraints using a risk-based optimization model.

Three case studies are presented to test the PTPD model. The first two are mainly concerned with the influence of risk-aversion coefficients on segment-level treatment selections and network-level performance. These cases demonstrate that considering risk in the PTPD model influences network performance by changing the types of treatments that are selected. The third case study highlights the benefits of considering both current evaluated treatment and its following actions, along with uncertainty in costs and deterioration. In the case study presented, the PTPD model yields a better predicted network performance compared to a B/C model at a constant budget level. To achieve a similar performance level, the B/C model requires a 10.4 % higher budget in terms of the average performance of the analysis period and a 16.7 % higher budget for the annual performance distribution. This is partly due to the selection of different types for treatments. The PTPD model tends to use more reconstructions and overlays for the first few years and then shifts to preservations.

As more technologies emerge to measure pavement condition and to create or repair pavements, the job of the DOT planner becomes more complex. This dynamic landscape makes the use of effective network planning models even more important. Although much work needs to be done to adapt the model presented here to all the specifics of real-world pavement asset management, the results presented here suggest that this model formulation holds promise to identify budget allocation decisions that could improve network performance even when budget levels are currently insufficient. Elements of the model presented here – notably the consideration of uncertainty in deterioration and cost, treatment path dependence, and explicit risk tradeoffs – could be incorporated into the tools being increasingly deployed by departments of transportation to support pavement network planning. If implemented with the appropriate supporting data and analyses, the model presented here should provide a more complete picture of the long-term value of various treatment strategies. This does depend heavily on the development of robust models of pavement deterioration, performance jump on treatment, and treatment cost – both present and future. Many in the academic community and beyond, seem to think that such models (and the data on which they depend) must be already robust and ubiquitous. Our research team's experience in this space suggests that while there are many agencies that meet this standard, there remain many more at various stages along the journey to that reality. Models like the one described here are poised to turn this emerging data into information that will allow planners to better leverage emerging measurement and paving technologies and to shepherd their pavement networks to a better state than has been possible before.

Despite this potential, much work is needed to improve the model described herein. One important topic is to upgrade the adopted deterioration model to better differentiate the impact of region including the influence of climate. For some cases, the climate could play a significant role in the deterioration process. In addition, the current analysis focuses on only a single performance measure – pavement roughness. In practice, there are other metrics to describe pavement conditions (e.g., cracking, rutting or faulting). A single metric cannot give a comprehensive description of pavement condition. Finally, it is important for future work to incorporate a true performance jump model to calculate the condition values after treatment. These gaps will be discussed and solved in the Chapter 4.

CHAPTER 4 ENVIRONMENTAL AND ECONOMIC EVALUATIONS OF TREATMENT STRATEGIES FOR PAVEMENT NETWORK PERFORMANCE-BASED PLANNING

This chapter evaluates the role of problem framing in the form of different available treatment strategies that consist of treatment materials, treatment types, and evaluation period for treatments. The analyses are conducted based on the PTPD model introduced in Chapter 3. Both environmental and economic performance is evaluated for different problem framing in the context of a case based on the Iowa U.S. route network. Results show that the proposed strategy that uses both concrete and asphalt, different treatment types, and a long evaluation period could both improve pavement network performance and reduce greenhouse gas (GHG) emissions. Compared to a conventional 5-year asphalt-only strategy, the proposed strategy can accomplish this with an annual budget that is 32% smaller and reduce associated GHG emissions by 21%. These results can provide transportation agencies with insights to achieve a sustainable pavement network.

4.1 Introduction

Inadequate budgets have been a pervasive problem faced by transportation agencies in the U.S [2]. Pavements in poor condition can lead to both a decrease of driving comfort and safety and an increase in fuel consumption and GHG emissions. To improve pavement network condition, the Moving Ahead for Progress in the 21st Century (MAP-21) Act compels transportation agencies to develop efficient pavement management systems (PMS). PMSs are broadly concerned with the evaluation of current conditions, the prediction of future conditions, and the planning of various treatments, including preservation, overlay, and reconstruction (POR) for a pavement segment or a network [4].

Performance-based planning (PBP) is the practice of using data from PMSs to support POR decisions based on the predicted network performance, available budgets, and treatment strategies. To improve the effectiveness of these decisions, a significant body of research has emerged on mathematical budget allocation algorithms, which improve and evaluate an algorithm in terms of reduction in cost or improvement in network conditions. By focusing on the algorithm, these studies do not explore the influence of how the budget allocation problem is framed on those same metrics of performance. In particular, analyses are usually constrained to a single treatment strategy, which consists of a limited, fixed portfolio of treatment actions. For example, a set of available treatment actions that only use asphalt materials might be called an asphalt-only strategy. Framing the analysis around a single treatment strategy limits the possible solution space and may preclude the discovery of optimal treatment plans. There are few studies that explore the influence of including different treatment strategies within the problem framing on pavement network condition and / or cost of maintaining the network.

Additionally, existing research reported in the literature focuses on the economic aspects of pavement treatment decisions. To date, analyses that consider the associated environmental impacts (specifically GHG emissions), have not accounted for the growing influence of EVs or deflection-induced excess GHG emissions. Also, PBP models described in the literature are usually based on a single condition metric, such as the international roughness index (IRI), pavement condition index (PCI), pavement surface rating (PSR), or combined condition index (CCI), to evaluate network performance. However, real-world decisions are made based on the consideration of several condition metrics, such as IRI, various cracks, rutting, or faulting. Hence, treatment decision-making should incorporate multiple metrics.

The author is not aware of a previous study to explore the influence of including different treatment strategies within the problem framing on expected pavement network condition and environmental impact that considers multiple condition metrics within the algorithm.

To address these gaps, three issues that influence the size of the possible solution space are considered. These issues are 1) available pavement materials, 2) available treatment types, and 3) scope of the evaluation period for treatments. The exploration is based on the PTPD model introduced in Chapter 3. This model has been updated to make treatment decisions based on multi-condition metrics and incorporate environmental effects. The explorations of different treatment strategies are based on the Iowa U.S. route network. Results show that the combinations of various materials and treatment types, and a long evaluation period could improve the pavement network condition and reduce GHG emissions effectively. Compared to a 5-year asphalt-only strategy, the proposed strategy leads to the same level of performance with an annual budget that is 32% smaller and reduces associated GHG emissions by 21%. In addition, it is difficult to decrease GHG emissions even by increasing the budget when applying the 5-year asphalt-only strategy since any slight decrease in GHG emissions due to improved road condition (and therefore reduced excess fuel consumption) does not offset the increased embodied emissions needed to achieve this.

4.2 Literature Review

Existing studies of PBP approaches focus on the allocation algorithm applied to select optimal treatment actions. More specifically, in the majority of papers on the topic, one or more algorithms are tested against a fixed set of available treatment actions. These alternative algorithms are typically evaluated in terms of their improvement of the objective function either budget required to achieve a level of performance or level of performance at a fixed budget. Here, a treatment action is defined as a specific technology, and applied at a specified intensity (e.g., two-inch asphalt overlay, four-inch asphalt overlay, diamond grinding). A treatment strategy as a portfolio of related treatment actions (e.g., preservation treatments, asphalt treatments). The set of available treatment strategies may be influenced by many factors, such as policy, budget, material availability, and past experience of the decision-makers.

The distinction between treatment action and treatment strategy is not merely semantic. Adding additional available actions to a problem will not deteriorate, and may improve, the solution. For such an addition to offer improvement, however, those additions must be Pareto efficient to expand the solution space. Generally, different treatment strategies represent such additions in that they often offer diverse characteristics. For network budget allocation problems, this mostly manifests as alternatives with diverse investments (effecting the budget constraint) and diverse deterioration or other in-use behavior (effecting life-cycle costs or impacts). As an example, preservations would be expected to require lower investment than reconstruction, but also offer lower life-cycle benefits. Although the scope of available treatment strategies may impact the optimal solution, its influence is largely ignored in both real-world application and exiting literature.

As noted previously, most existing research on PBP focuses on the development and evaluation of allocation algorithms. As such, most studies consider few alternative treatment actions, only describe these actions in general terms (e.g., “preventative maintenance”, “rehabilitation”, “reconstruction”), and do not specify the type of pavement material involved [57], [70], [71], [73],

[76], [77], [87]. In fact, all the studies in this group consider four or fewer available treatment actions. Another set of literature is more specific about the types of treatment actions available (e.g., crack sealing, full-depth patch, milling with two-inch overlay). These studies may limit available alternatives to asphalt treatments [25], [59], [74] or do not specify the pavement material [4], [47], [58], [86]. On average, these studies consider a slightly larger number of treatment alternatives, but all still limit the set to six or fewer alternatives. A notable exception is Denysiuk et al. that considers 16 specific, asphalt treatment alternatives [136]. In focusing on algorithmic improvements, none of these studies explicitly evaluate how problem framing, especially expansion or contraction of the alternative set or, more generally, changes to the solution space effects the optimal solution.

Three previous studies have been identified, outside of previous work by the author, which have examined the impact of problem framing on the optimal solution. Torres-Machi et al explore the impact of the available budget on the alternatives selected from eleven available asphalt treatments and four concrete treatments. Results show that a 20% increase in budget can lead to a 21% increase in long-term effectiveness and 13% decrease of GHG emissions [137]. Irfan et al [132] expressly considered the impact of including five asphalt treatment alternatives – preventative maintenance and rehabilitation – and found that incorporating both preventative maintenance and rehabilitation is superior to just using preventative maintenance or rehabilitation. Lee et al [115] analyzed the influence of including three different treatment alternatives – maintenance, resurfacing, and reconstruction – and found the optimal treatment policy is the joint optimization of maintenance and reconstruction. Two previous papers by CSHub at MIT, Akbarian et al [138] and Guo et al [139], have raised the issue of the role of problem framing, but did not systematically analyze this across the full range of characteristics discussed in this chapter and, as detailed subsequently, did not apply a state-of-the-art optimization algorithm.

Looking at the existing literature, no previous study has explicitly evaluated the impact of considering a set of treatment strategies that includes both a range of specific treatment strategies and multiple pavement material types. This is a notable exception because asphalt and concrete solutions typically represent interestingly diverse characteristics including differences in initial investment and life-cycle implications. From the perspective of objectives in the budget allocation models, most of them focus on economic aspects of the problem by maximizing pavement network condition within a limited budget [25], [66], [83] or minimizing total cost to satisfy a condition requirement [43], [59]. Recent literature has noted that, in addition to economic considerations, it is also important to consider environmental impacts during the pavement management process. One common approach to evaluate environmental impact is life cycle assessment (LCA), which calculates the total GHG emissions of a pavement segment throughout its life cycle – from material extraction to end-of-life [39]–[42]. To simultaneously incorporate both the environmental and economic considerations, a life cycle assessment – life cycle cost analysis (LCA-LCCA) framework has been proposed [54], [140]–[142]. The analysis scope for both LCA and LCCA focuses on a single pavement segment (or project). Several researchers have also incorporated environmental assessment for network (or system) level analyses through different allocation models such as a benefit cost ratio (B/C) framework [137], dynamic programing [45], [143], Lagrangian dual solution methodology[144], and a multi-year optimization framework [145]. These studies all consider the GHG emissions associated with materials and construction equipment used to complete treatment actions. In this chapter, these emissions are referred as embodied emissions. For analyses reported to-date, the environmental impacts of the pavement use phase have been limited to roughness-induced excess GHG emissions for conventional internal combustion engines vehicles (ICEVs). In recent years, however, the number of electrical vehicles (EVs) has gradually increased [146]. Considering their different environmental impacts [147], it is necessary to differentiate them during the analysis for pavement-induced GHG emissions. In addition, the deflection-induced excess GHG emissions should also be incorporated [148]–[150].

Most existing PBP allocation models in the literature usually use a single condition metric as the decision criteria, such as condition state in Markovian model, IRI, PCI, PSR and CCI, etc. However, in reality, treatment decisions are made based on several condition metrics. Although some models use an overall condition metric (e.g., PCI, CCI), this alone does not capture all important aspects of individual deterioration metrics. For example, when a segment's PCI is above the threshold value (implying there is no need for maintenance), an individual metric, such as longitudinal crack, may be below the threshold value (implying a need maintenance). (More details can be found in Appendix C.3). Hence, it is necessary to make treatment decisions considering all relevant condition metrics instead of a single condition metric. To address this gap, the multi-output deterioration model introduced in Chapter 2 is applied, which can simultaneously predict all condition metrics and incorporate their correlations during the prediction process.

To summarize, existing PBP research focuses on the development and performance of allocation algorithms and ignores the influence of problem framing, especially on the scope of the available solution space. In addition, most pavement network analyses focus on economic effects, and for analyses involving environmental effects, they have not incorporated the growing influence of EVs or deflection-induced excess GHG emissions. In these analyses, pavement treatment decisions are usually based on a single condition metric. Considering current gaps, this chapter applies a comprehensive – environmental and economic – analyses to explore the influence of three issues that alter the size of the available solution space. These issues are 1) available pavement materials, 2) available treatment types, and 3) scope of the evaluation period for treatments. These are tested in the context of Iowa's U.S route pavement network using the PTPD allocation model. In this model, all metrics are considered within the model constraints, which only IRI directly effects the objective function through its impact of excess fuel consumption. The influence of EVs has been incorporated as well.

4.3 Methodology

To evaluate the impact of problem framing, PTPD model is applied to a specific case under a range of different scenarios. The pavement deterioration prediction is based on the weighted multi-output model described in Chapter 2. In this section, a modified PTPD model is presented first to fill the gaps about pavement maintenance decision-making based on multi condition metrics, and the consideration of EVs and PVI-deflection induced excess fuel consumptions. Then, a set of performance jump models are proposed to evaluate the effectiveness of different treatment actions. At last, evaluation metrics are provided to evaluate pavement network condition and environmental impacts.

4.3.1 Budget allocation model - PTPD

PTPD model introduced in Chapter 3 only focuses on a single condition metric, i.e., IRI. In order to incorporate multi-condition metrics, the segment-level analysis in the PTPD model has been modified, which can be found in Appendix C.1.1.

In the PTPD model, both the segment-level and network-level objectives are to minimize the expected total cost (agency cost plus user cost) and to minimize the standard deviation of the total cost as well. The agency cost mainly consists of the cost for treatment actions. The future treatment cost is predicted based on a probabilistic model introduced in the Section 3.3.1. The user cost is dominated by the excess fuel consumption caused by pavement-vehicle interaction (PVI) [128], [151], including both roughness-induced and deflection-induced PVI. Corresponding PVI models are introduced in detail in Appendix C.1.2. Although roughness is known to increase vehicle wear and tear, Zaabar and Chatti found that roughness-induced vehicle operating costs due to wear-and-tear are much smaller than the roughness-induced excess fuel cost [152]. As such, operating costs due to wear-and-tear are ignored here.

PVI models described in the literature are based on conventional internal combustion engines vehicles (ICEVs), and expressly predict excess fuel consumption measured in gallons of gasoline and/or diesel. However, with the increase of electrical vehicles (EVs), it is necessary to adapt these models for a more current context. This adaptation is accomplished by considering the relative energy intensity per mile for ICEVs and EVs. Using this information, the expected energy consumption, in terms of kWh of electricity, are computed for the fraction of vehicles that are assumed to EVs (details are in Appendix C.1.3). During the analysis, the average gasoline and diesel cost for the state of Iowa are from American Automobile Association (AAA) [153].

Even though the optimization objective includes only economic terms, when applied to real-world cases, it also captures many of the key drivers of environmental impacts. This is true because of a strong correlation between dominant costs and dominant drivers of emissions. Within the objective function, the user cost term is represented by excess fuel consumption which, in turn, is the dominant driver of transportation emissions for the pavement use. The agency cost term is dominated by the quantity of treatment actions, which is also the dominant driver for the embodied emissions. Because of the correspondence of these two effects, the proposed budget allocation model, PTPD, does provide useful insight into the influence of different treatment strategies on both the pavement network condition and its environmental effect.

Essentially, this optimization problem is a multi-objective one, i.e., to minimize the budget (reflected by the agency cost) and to minimize the GHG emissions (reflected by the agency cost and user cost) at the same time. By assigning different weights to different sub-objectives, different optimal results can be obtained, and a corresponding Pareto frontier can be generated. The point on the frontier can be considered as the smallest GHG emissions given a budget constraint level. Since the goal of this chapter is to explore the influence of different treatment strategies on pavement condition and environmental effects, the analyses of different weights for multi objectives are ignored in this chapter. Instead, it focuses on results for a critical budget level; that is the budget at which network performance would stay relatively constant. Results for different budget constraint levels are provided in Appendix C.2. At the end of the exploration of different strategies, the Pareto frontier is provided for a comparison between a proposed strategy and a 5-year asphalt-only strategy.

In this framework, treatments are incorporated into the optimum solution either because they play a role in optimizing the objective function (lowest total cost) or because their performance falls below a critical threshold. Only the condition metric IRI directly influences the optimization objective through the extra user cost caused by roughness-induced PVI. Nevertheless, several other pavement condition metrics (rutting, faulting, and different cracks) influence the decision-making process. Specially, if any condition metric falls below its critical threshold value, the corresponding pavement segment is identical to immediately receive a treatment. To summarize, the treatment decision of a segment is determined by both threshold value and the cost-oriented optimization process.

4.3.2 Pavement performance jump model

The deterioration model in Chapter 2 is used to predict pavement condition over time assuming no treatment action occurs. In addition to this, it is also necessary to predict the effect of different treatment actions on pavement condition. This kind of prediction model is called a *performance jump model*, which is usually a function of the pavement condition before a treatment is applied [61]. Because the Iowa PMS dataset contains very limited data points for each treatment action type, only a simple polynomial model is trained as suggested in [25]. For a 4" asphalt/concrete overlay, the performance jump model can be expressed as:

$$IRI_{new} = IRI_{old} - \left(-0.4517 + 0.3735 \cdot IRI + 0.1206 \cdot IRI^2\right) \quad (4.1)$$

$$rut_{new} = 2 \quad (4.2)$$

$$LCRACK_{new} = 0.1322 \cdot LCRACK_{old} \tag{4.3}$$

$$TCRACK_{new} = 0.1171 \cdot TCRACK_{old} \tag{4.4}$$

Due to the lack of available data for the maintenance of concrete pavements, it is assumed that *fault* becomes 0 after an overlay (equation (4.5)). In addition, it is also assumed that ACRACK follows the same performance jump model as TCRACK for asphalt pavements, and LWCRACK follows the same model as LCRACK for asphalt pavements (equations (4.6) and (4.7)).

$$fault_{new} = 0 \tag{4.5}$$

$$ACRACK_{new} = 0.1171 \cdot ACRACK_{old} \tag{4.6}$$

$$LWCRACK_{new} = 0.1322 \cdot LWCRACK_{old} \tag{4.7}$$

For overlays with other thicknesses, performance is interpolated linearly between the values found for the 4” asphalt/concrete overlay and those for a 13” reconstruction. It is important to note that this interpolation likely overstates the performance of overlays larger than 4” overlay. Nevertheless, the lack of data precludes more sophisticated modeling. After a 13” reconstruction, values for IRI, rut, fault, ACRACK, LCRACK, LWCRACK, and TCRACK are assumed to be 0.5 m/km, 0 mm, 0 mm, 0 m^2/km, 0 m/km, 0 m/km, 0 count/km, respectively.

Iowa PMS dataset contains limited data on preservation treatment actions. To accommodate this, the Long-term Pavement Performance (LTPP) dataset was applied to generate the performance jump model for IRI as shown in equation (4.8). The performance jump models for rutting and faulting (equation (4.9)) are assumed to be the same as overlay actions. All cracks after a preservation are assumed to be reduced by 40% based on the limited data in the Iowa dataset (equation (4.10)).

$$IRI_{new} = IRI_{old} - \left(-0.2684 - 0.3565 \cdot IRI + 0.1592 \cdot IRI^2\right) \tag{4.8}$$

$$rut_{new} = 2,\ fault_{new} = 0 \tag{4.9}$$

$$CRACK_{new} = 0.6 \cdot CRACK_{old} \tag{4.10}$$

4.3.3 Evaluation metrics

To evaluate different treatment strategies, two main evaluation metrics are proposed. The first one is traffic-length weighted PCI (TWPCI), which is used to describe the pavement network condition. PCI is the overall condition metric used by the state of Iowa. To reflect the significance of a segment i in the network, PCI is weighted by traffic and length of the segment, as shown in equation (4.11), where AADT represents annual average daily traffic, I is the total number of segments.

$$TWPCI_i = \frac{AADT_i \cdot length_i}{\sum_{i=1}^{I} AADT_i \cdot length_i} \cdot PCI_i, \quad \text{and } TWPCI = \sum_{i=1}^{I} TWPCI_i \tag{4.11}$$

The second evaluation metric is cumulative life-cycle GHG emissions, including embodied emissions, PVI-induced excess GHG emissions, and global warming potential related to radiative forcing.

The embodied impacts incorporate the life-cycle GHG emissions associated with the realization of the segment treatment. Here this includes all activities from resource extraction until the end of life of treatment actions, excluding use phase impacts (which are explicitly accounted separately). Regional practices of asphalt and concrete production were adopted from the national databases [154], [155]. The projection of materials technologies was incorporated in the study to include the future changes in the embodied emission during the analysis period. Details of life cycle inventories and assumption values and sources for the energy consumptions and mix designs are provided in the Appendix C.1.4.

The PVI-induced excess GHG emissions can be obtained as shown in equation (4.12). $\delta IFC_{R,car}$ represents the excess gasoline caused by roughness-induced PVI for cars. Due to their comparatively lower mass compared to trucks, deflection-induced PVI is ignored for cars. $\delta IFC_{R,truck}$ and $\delta IFC_{D,truck}$ represent excess diesel consumptions for trucks in terms of roughness-induced and deflection-induced PVI, respectively. GHG emissions associated with fuel consumption are based on estimates from U.S. EPA, namely, 8,887 grams CO_2/ gallon for gasoline ($\alpha_{gasoline}$) and 10,180 grams CO_2/ gallon for diesel (α_{diesel}) [156].

$$GHG = \alpha_{gasoline} \cdot \delta IFC_{R,car} + \alpha_{diesel} \cdot \left(\delta IFC_{R,truck} + \delta IFC_{D,truck}\right) \tag{4.12}$$

The surface reflectivity of pavements (measured as albedo) can directly contribute to climate change by inducing a radiative forcing (RF) at the top of the atmosphere. In this analysis, the RF-induced global warming potential (GWP) was estimated and included in the life cycle assessment according to the calculation steps described in the Appendix C.1.5 and in [157]. Location-specific RF impacts due to changes in pavement albedo were estimated as a function of the intensity of incoming radiation, atmospheric transmittance, and the change in albedo. Incoming radiation estimates were based on the county coordinates.

In addition to these two metrics, traffic-length weighted IRI (TWIRI) is tracked as a measure of overall system performance. Its calculation is described in Appendix C.1.6 and its corresponding results are presented in Appendix C.2.

4.4 Case Study

The impacts of different treatment strategies that transportation agencies may use in PBP on network performance improvement are explored, including 1) the selection of materials (asphalt concrete (AC) only, portland cement concrete (PCC) only, or both); 2) the selection of treatment types (short-term actions only, long-term actions only, or mix); and 3) segment analysis period (SAP), which represents the period to evaluate treatment benefits. Different strategies are compared with a proposed strategy, which uses both AC and PCC materials, both short-term and long-term treatments, and an SAP of 20 years. These treatment strategies are analyzed and compared under a critical budget which is the minimum annual budget to maintain pavement network condition under the proposed strategy.

The explorations of different treatment strategies are based on initial network conditions derived from data for Iowa's U.S. route system for year 2017. This dataset includes, for all 9,550 lane miles, information on age, AADT, AADTT, pavement thickness, layer type, construction and maintenance history, and different condition metrics, etc. All PMS information can be found on the website of Iowa DoT Open Data [110]. During the analysis period, the traffic volume is modeled to increase. Due to the limited traffic prediction information for the state of Iowa, the future traffic volumes for conventional ICEV, EV and trucks are based on the national prediction for vehicle miles traveled (VMT) from EIA [146].

Table 4-1 lists the available treatment actions for the U.S. route pavement network suggested by pavement engineers, which may not be the same as the ones taken by Iowa DoT. The treatment types include preservation (P), overlay (O), and reconstruction (R). Based on the duration of their benefits, these actions are divided into two groups: short-term actions (preservation, 4" concrete and asphalt overlays), and long-term actions (thick overlays and reconstruction), as shown in the column *Duration*. The *Design* column represents the pavement type that can be maintained by the corresponding treatment action. Expected cost data are based on an analysis of 5 years (2014-2018) of publically available bid data for Iowa highway projects [20]. For the actions that are suitable for both PCC and AC, two cost values are given, respectively.

Table 4-1. Treatment actions.

Name	**Type**	**Duration**	**Design**	**Expected cost ($/S.Y.)**
Diamond grinding	Preservation	Short-term	PCC	2.77
Micro-surfacing	Preservation	Short-term	AC	3.03
4" asphalt overlay	Overlay	Short-term	AC & PCC	8.97 & 8.97
4" concrete overlay	Overlay	Short-term	AC	13.21
6" asphalt overlay	Overlay	Long-term	AC & PCC	12.97 & 12.97
6" concrete overlay	Overlay	Long-term	AC & PCC	17.38 & 16.14
9" asphalt overlay	Overlay	Long-term	AC	19.16
8.5" concrete overlay	Overlay	Long-term	AC & PCC	22.60 & 21.36
13" new asphalt	Reconstruction	Long-term	AC & PCC	57.05
11" new concrete	Reconstruction	Long-term	AC & PCC	53.65

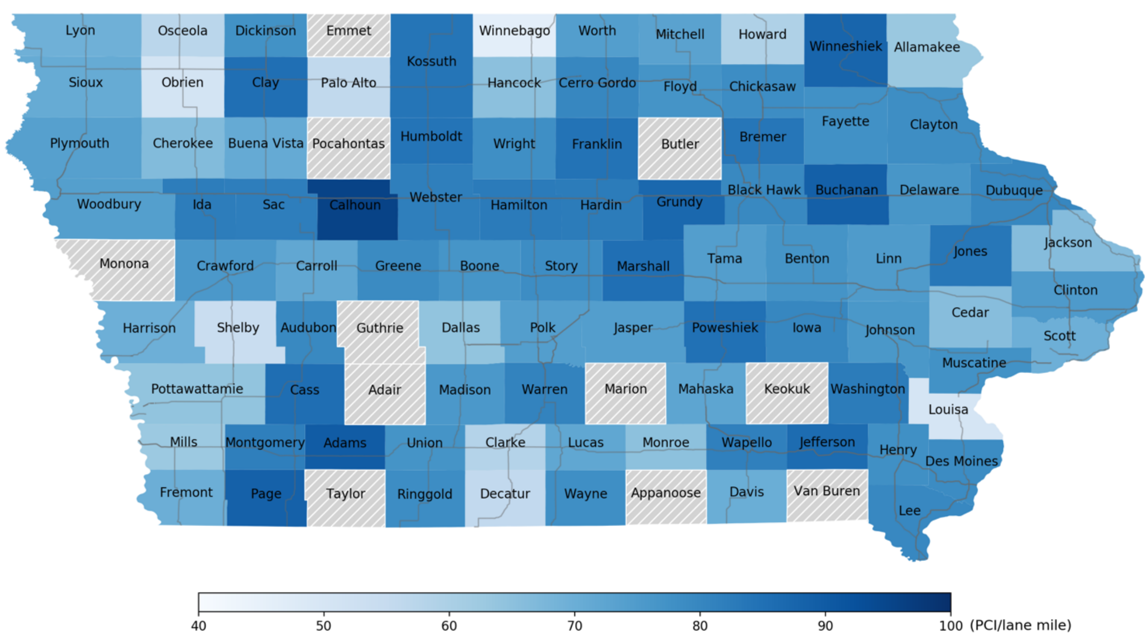
S.Y.: squared yard

4.4.1 Proposed strategy

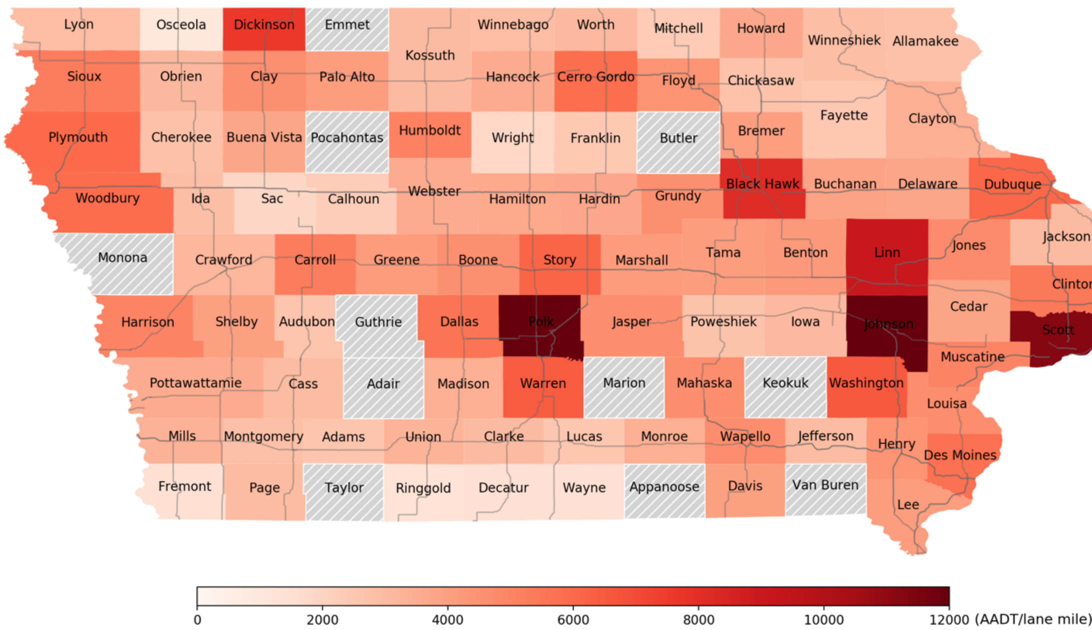
The proposed strategy is as follows: the network analysis period is 30 years; treatment materials include both AC and PCC; treatment types include both short-term and long-term treatments; the segment analysis period is 20 years.

Figure 4-1 shows the distributions for initial PCI (Figure 4-1(a)) and traffic volume (Figure 4-1(b)) on the county level for the Iowa U.S. route network. In both sub figures, grey lines represent the routes. Counties shown with grey hatches do not contain U.S. route pavements. Adams, Calhoun and Page counties have the best road condition with the highest average PCI. By contrast, Winnebago and Louisa have the lowest PCI per lane mile. Polk, Johnson, and Scott have the largest traffic volume. These counties exhibit a medium condition level, but due to their large traffic volume, they are associated with large excess GHG emissions due to PVI. (See Appendix C.2.1) From these plots, it is clear that pavement condition and context vary widely across the state, making it challenging to allocate the available budget in an efficient way.

At year 0, the initial TWPCI for the whole pavement network is 76.3. To maintain the TWPCI after 30 years as the same as year 0 for TWPCI, the annual budget must be \$132.5M for the proposed scenario. This value was found through iterative search. This is referred to as the critical budget (i.e., the budget required to maintain network performance over the analysis period for the proposed strategy). The actual budget can be much larger than this proposed critical budget since some costs are not included in the analysis, such as traffic management, engineering, and striping, etc. At year 30, for the proposed strategy, average TWPCI is 76.2. At year 0, the ratios for asphalt, asphalt overlay composite and concrete pavements are 6%, 59% and 35%.



(a). Initial PCI distribution



(b). Initial AADT distribution

Figure 4-1. Initial (a). PCI and (b). AADT distributions for Iowa U.S. route network on the county level based on Iowa PMS 2017 (counties in hatch don't have U.S route pavements).

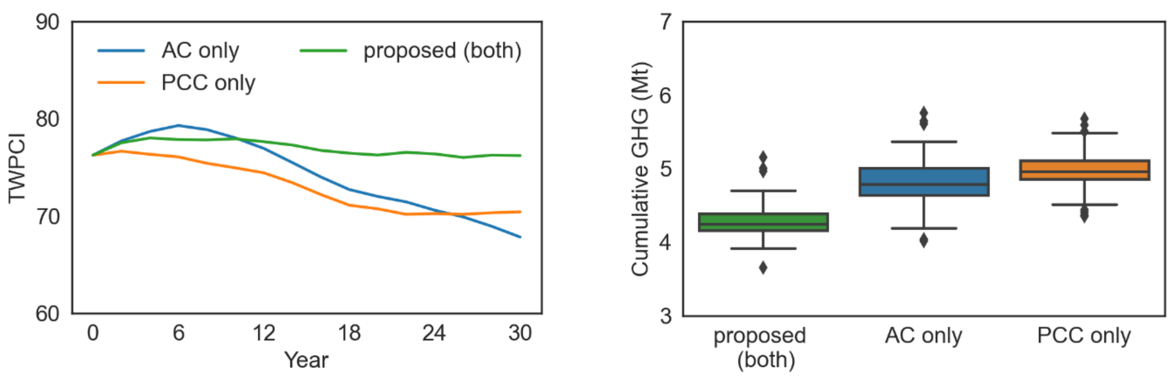
4.4.2 Influence of treatment materials

AC and PCC are the two primary materials used for pavement treatments. In this section, three treatment strategies concerning material selection are compared, including the proposed strategy (both materials used in the network), an AC only strategy, and a PCC only strategy.

Figure 4-2 presents the comparisons among these three strategies. Figure 4-2(a) shows that incorporating both materials in the available treatment options, the proposed strategy, leads to the best average pavement network performance. At year 30, the TWPCI for the AC only strategy and the PCC only strategy is 11% and 7.6% less than the proposed strategy, respectively. Figure 4-2(b) shows the cumulative life-cycle GHG emissions as discussed in Section 4.3.3, including embodied emissions, emissions due to PVI and emissions due to radiative forcing. By using both AC and PCC, the cumulative GHG emissions are also the lowest. The proposed strategy could save around 0.52 Mt (12.2%) of GHG emissions compared to AC only strategy and around 0.69 Mt (16%) compared to PCC only strategy.

Interestingly, among these three alternatives, the AC only strategy has a higher TWPCI for the first 10 years than the proposed strategy. However, starting from the 6th year, the pavement network performance becomes worse year by year. This phenomenon is mainly due to the characteristics of AC materials. Generally, AC pavements require lower upfront investment than PCC, but their condition typically deteriorates over a shorter time period. By contrast, since PCC treatments can be more expensive to build, the total paved area that can be maintained in a given year with the PCC only strategy is smaller compared to the AC only and proposed strategies. As a result, for the first few years within AC only strategy conditions can improve more rapidly. However, as time passes, the long-term benefits of the PCC treatments start to stand out. In terms of TWPCI, the PCC only strategy has a slower decreasing rate than the AC only strategy. Starting from 26th year, the PCC only strategy provides a better pavement network performance than the AC only strategy.

The comparisons of treatment material strategies under different budget levels can be found in Appendix C.2.2. The proposed strategy always provides the best pavement network performance compared to the AC only and PCC only strategies. Results suggests that as budget levels increase more PCC solutions should be applied.



(a) (b)

Figure 4-2. Comparisons of different treatment material strategies. (a) is annual mean TWPCI, (b) is the distributions for cumulative life-cycle GHG emissions for 30 years.

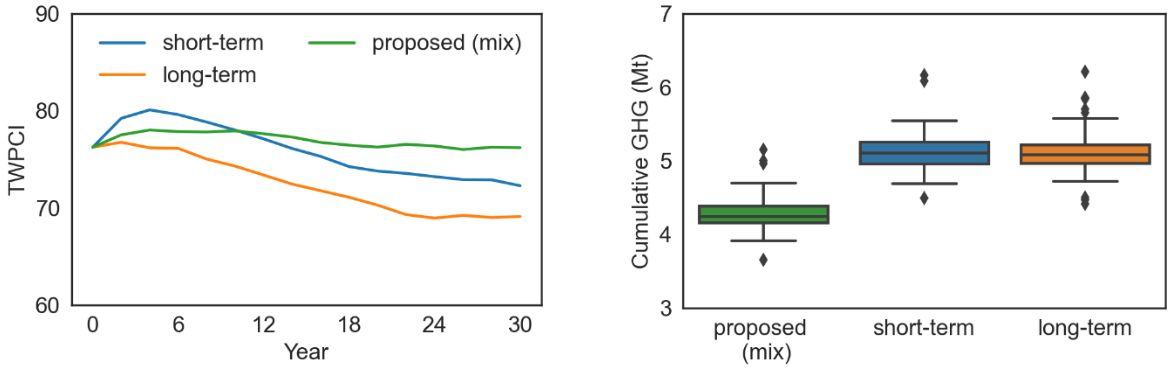
4.4.3 Influence of treatment types

Treatment types can be divided into two categories: short-term and long-term treatments. Short-term treatments include preservation and thin overlays. These treatment actions have a low price but a short impact on deterioration development. In addition, being thinner, they have small embodied emissions but may not be effective to reduce GHG emissions caused by deflection-induced PVI. Long-term treatments include thick overlays and reconstructions. They are expensive but have a longer impact on pavement condition. They have large embodied emissions but are also effective at reducing GHG emissions caused by deflection-induced PVI. In this section, three treatment strategies concerning treatment types are explored, including a short-term (only) strategy, a long-term (only) strategy, and the proposed strategy (a mixed strategy).

In Figure 4-3(a), the proposed strategy leads to the best average pavement network performance after 30 years, whose TWPCI is 5.1% higher than the short-term strategy and 9.3% higher than the long-term strategy. Figure 4-3(b) shows that by using mixed treatment types, the cumulative life-cycle GHG emission for 30 years is also the smallest. The proposed strategy could save around 0.82 Mt (19.2%) of GHG emissions compared to the short-term strategy and around 0.83 Mt (19.4%) compared to the long-term strategy.

The short-term strategy only applies inexpensive treatments and hence, it could fix more pavement area than the other two strategies. It has the highest TWPCI for the first 10 years. However, even though more pavement area is maintained, short-term treatments do not last for a long time. That's the main reason why TWPCI eventually goes down. By contrast, the long-term strategy can only fix a small amount of pavement area due to the higher costs. With a limited budget, this leads to the worst performance among these three strategies.

The comparisons of treatment type strategies under different budget levels can be found in Appendix C.2.3. Results suggest using more short-term treatments when the budget is low, but shifting to more long-term treatments as budget levels increase.



(a) (b)

Figure 4-3. Comparisons of different treatment type strategies. (a) is annual mean TWPCI, (b) is the distributions for cumulative life-cycle GHG emissions for 30 years.

4.4.4 Influence of segment analysis period

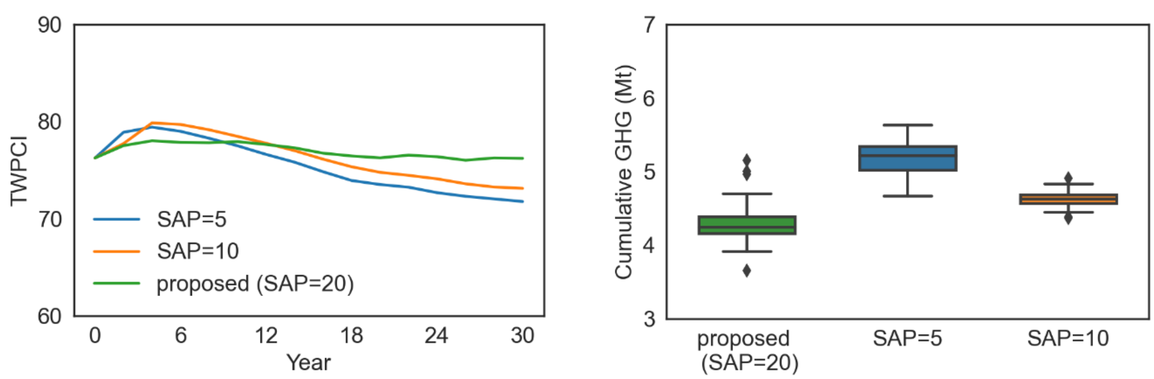
Segment analysis period (SAP) represents the period of time used to evaluate available treatment actions based on their total cost (agency plus user cost). When the analysis period is short, agency costs account for most of the total cost. In such cases, inexpensive treatments like preservation, thin overlays, and asphalt treatments are more likely to be selected. But these treatments usually deteriorate more rapidly. On the other hand, when the analysis period is large, user costs related to pavement condition accounts for a large fraction of total costs. Since reconstruction, thick overlays, and concrete treatments usually provide long-term benefits (in terms of pavement condition and lower user costs), they are more likely to be chosen when the analysis period is large.

When the budget level is high enough, it would be expected that an optimization model would make use of more long-term treatments when evaluated using a large SAP. However, larger SAPs exponentially increases the computational burden [55]. Furthermore, conventional PBP analyses usually use SAPs on the order of five years. Hence, only three SAPs are discussed: SAP=5, SAP=10 and SAP=20 (i.e., the proposed strategy).

In Figure 4-4(a), SAP=20 leads to the best average pavement network performance after 30 years, which is 5.8% higher than the SAP=5 strategy and 4.1% higher than the SAP=10 strategy. Figure 4-4(b) shows the SAP=20 strategy also has considerably smaller total GHG emissions. The proposed strategy could save around 0.89 Mt (20.6%) and 0.34 Mt (7.8%) of GHG emissions compared to the SAP=5 and SAP=10 strategy, respectively.

When the SAP is small, treatments with short-term benefits are preferred. These treatments are inexpensive, and more pavement areas can be maintained. The SAP=5 strategy leads to a higher TWPCI for the first 10 years compared to the SAP=20 strategy. However, as discussed before, these treatments do not last long. Hence, after 12 years, the proposed scenario (SAP=20) has a higher TWPCI than the SAP=5 strategy.

The comparisons of treatment evaluation period under different budget levels can be found in Appendix C.2.4. The SAP=20 strategy performs better than the SAP=5 and SAP=10 strategy for all budget levels.



(a) (b)

Figure 4-4. Comparisons of different segment analysis periods. (a) is annual mean TWPCI, (b) is the distributions for cumulative life-cycle GHG emissions for 30 years.

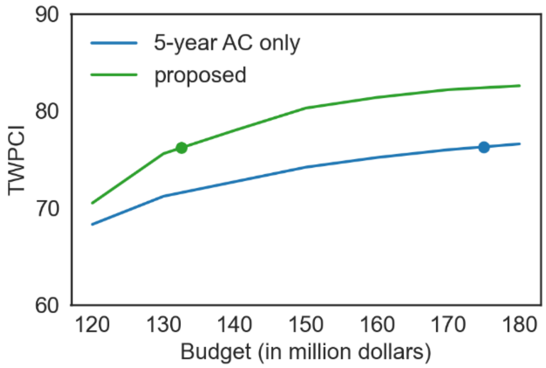
4.4.5 Proposed strategy vs. 5-year AC only strategy

Finally, the proposed strategy is compared with a 5-year, AC only strategy that only considers short-term treatments. Based on a national analysis of Oman bid data over the last 10 years, more than 40% states spend less than 5% of paving budget on concrete paving projects. In addition, after consulting with several state transportation agencies and experienced pavement engineers, one common practice is to develop pavement treatment schedules considering only a short analysis period, like 5 or 10 years. Hence, the 5-year AC only strategy is selected as the baseline strategy to be compared with the proposed strategy. Figure 4-5(a) shows the performance of these two strategies in terms of TWPCI at year 30 across a range of available budgets. Points on any horizontal line on this figure represent equal levels of performance. To have a similar network condition performance at year 30, the 5-year AC only (SAP=5 years) strategy (blue dot in Figure 4-5(a)) would require a budget that is 32% larger than required by the proposed strategy (green dot in Figure 4-5(a)). For comparison, in Chapter 3, it shows that the improvement of budget allocation algorithm can save about 17% of the annual budget. Under the critical budget ($132.5M), the propose strategy can reduce GHG emissions by 21% compared to the 5-year only strategy. As budget levels increase, the GHG emissions for the 5-year AC only strategy increase all the time. But for the proposed strategy, GHG emissions decrease first and then increase. These phenomena are strongly due to the trade-off between the embodied emissions and PVI-induced emissions.

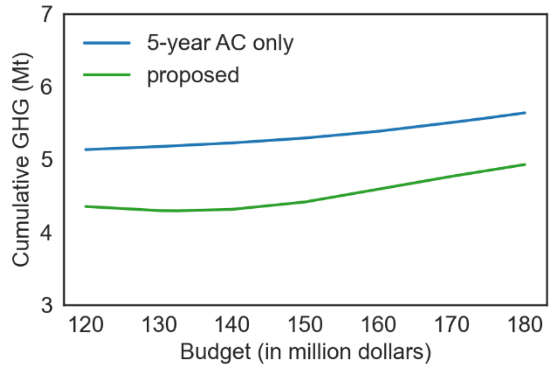
The 5-year AC only strategy only uses asphalt materials and primarily thinner treatments. These actions deteriorate more rapidly, leading to larger GHG emissions due to roughness-induced PVI. Additionally, these actions have a lower modulus and/or stiffness, and will always create a network with a larger deflection-induced PVI compared to one applying longer-term (typically thicker) treatments and, in particular, any strategy that incorporates concrete materials. In this case, even though more treatment actions are applied as budget levels increase, the slight decrease of emissions due to PVI cannot offset the increase of embodied emissions as shown in Figure 4-5(c).

As for the proposed strategy, when the budget is less than $132.5M, as budget levels increase, the decrease of emissions due to PVI can offset the increase of embodied emissions as shown in Figure 4-5(d). Hence, the total GHG emissions decrease. However, when the budget is larger than the $132.5M, the average road condition is already good. In this situation, the marginal decrease of emissions due to PVI does not offset the increase of embodied emissions. Hence, the total GHG emissions increase.

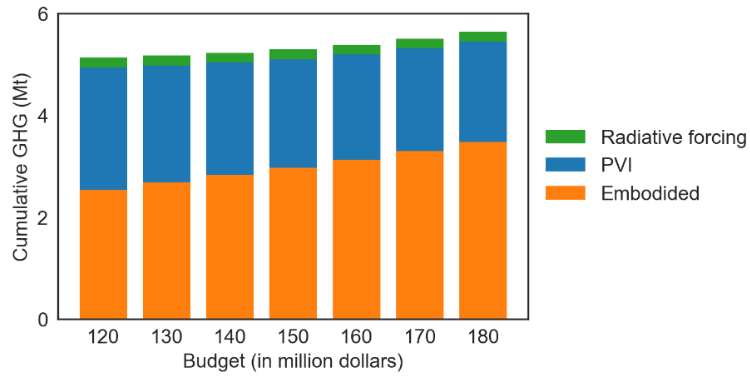
These results make it clear that the framing of the network optimization problem, in particular the selection of broad range of available treatment strategies and considering a long-time horizon, can have at least equal, if not more, importance as the improvement of the budget allocation algorithm.



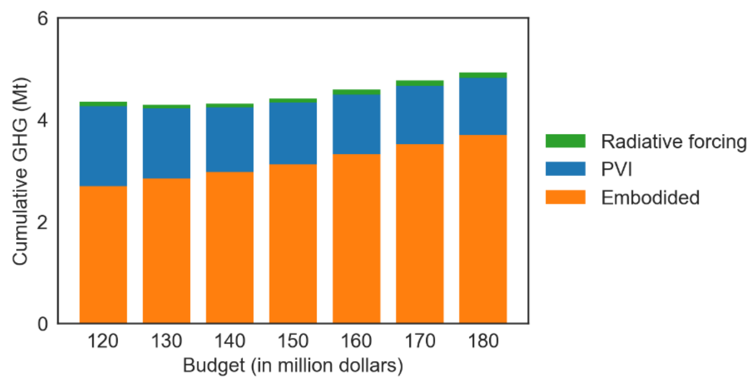
(a)



(b)



(c)



(d)

Figure 4-5. Comparisons of 5-year AC only strategy and the proposed strategy. (a) is the TWPCI at year 30 (the green dot represents the critical budget for the proposed strategy, and the blue dot represents the budget level at which the 5-year AC only strategy has a similar network performance as the proposed strategy), (b) is Pareto frontier: minimal GHG emissions under budget constraints, (c) is GHG emission distributions for the 5-year only strategy under different budgets, (d) is GHG emission distributions for the proposed strategy under different budgets.

4.5 Conclusions

This chapter has explored the influence of problem framing, in particular framing that can alter the size of the available solution space, on the outcome of performance-based planning for a road network. Specifically, it examined three issues that influence the size of the possible solution space. These issues are 1) available pavement materials, 2) available treatment types, and 3) scope of the evaluation period for treatments.

The impact of these on pavement network condition and GHG emissions was evaluated in a case of the Iowa U.S. route network. Results suggest the importance of applying a variety of materials and treatment types and using a long evaluation period to improve predicted pavement network performance and reduce GHG emissions. Compared to a commonly used 5-year AC only strategy, the proposed strategy was shown to deliver the same network performance at a budget that was 32% lower and reduce GHG emissions by 21%. In addition, due to the use of asphalt material and thin overlays, even as budget levels increase, for the 5-year AC only strategy, the increase of embodied GHG emissions is not offset by the slight decrease of GHG emissions caused by improved road condition (and therefore lower roughness-induced PVI). From the sensitivity analysis in Appendix C.2, the ratios of treatment materials and treatment types can be influenced by budget levels. Essentially, in optimal solutions, short-term, asphalt treatments are suggested to be used more frequently when the budget level is low, and concrete, long-term treatments are suggested to used more when the budget level is high. These research findings can provide policy insights for transportation agencies in terms of road maintenance.

All analyses presented here are based on several assumptions as dictated by the availability of data. For example, the deterioration model could not be tailored to every class of pavement due to a lack of data. The performance jump values for some treatment actions are based on the linear interpolation, which likely overstates the performance of overlays larger than 4 inches. As data quality improves, more sophisticated modeling should be developed. As for the budget allocation model, since existing excess fuel consumption models are only based on IRI, the objective only incorporates IRI, which implicitly gives IRI more importance during the optimization process. In the future, with the development of the relationship between excess fuel consumption and other condition metrics, those metrics would influence the optimization objective as well. At last, during the analyses, the influence of future climate change on pavement deterioration is ignored.

Future work should aim to solve these current limitations. After obtaining enough data, the deterioration model for concrete overlay composite pavements can be developed. In addition, the current weighted multi-output model is based on a Markovian assumption. In the future, it is necessary to explore the influence of historical dependence on the model prediction performance. After solving these limitations, a better set of results is expected to be obtained.

CHAPTER 5 IMPROVING PAVEMENT NETWORKS THROUGH PERFORMANCE-BASED PLANNING WITH OPTIMAL MANAGEMENT POLICIES

This chapter proposes three pavement management policies that can help improve pavement networks, including decision-making flexibility, long-term planning, and market diversification. The evaluation of these three policies is based on U.S pavement networks. After incorporating all three management policies, the total excess vehicle fuel cost reduction through improved road conditions is 28% relative to a business-as-usual scenario, which is about 62 billion dollars saved for the whole U.S. pavement network from 2017 to 2050. All states can benefit from the proposed management policies. These results can provide transportation agencies and stakeholders with insights for pavement management policies to improve pavement networks.

5.1 Introduction

The U.S. road system has been assigned a grade of D in *The Report Card for America's Infrastructure* published by American Society of Civil Engineers (ASCE) since 1998. Over 40% of the system is in poor or mediocre condition. This is in part because transportation agencies are underfunded: the backlog in repairing existing roads has increased to $435 billion [2]. According to ASCE's report *Failure to act: Economic impacts of status quo investment across infrastructure systems*, if no action is taken, the U.S. is forecasted to lose $10.3 trillion in GDP, $2.4 trillion in exports, and 3 million jobs from 2020-2039 [1].

To improve the pavement network condition, the enactment of the Moving Ahead for Progress in the 21st Century (MAP-21) Act compels transportation agencies to develop efficient pavement management systems (PMS) to improve current pavement networks. PMSs are broadly concerned with the evaluation of current conditions, the prediction of future conditions, and the planning of various treatments, including preservation, overlay, and reconstruction (POR) for a segment or a pavement network [4]. Performance-based planning (PBP) is the practice of using data from PMSs to support analyses on the predicted network performance based on available budgets and treatment strategies.

Most existing research usually focuses on the development of mathematical algorithms for budget allocation in PBP. However, an efficient budget allocation process is inadequate to improve the current road system considering the lack of funding. It is also necessary to apply the budget allocation process under the right policies. As suggested in the *The Report Card for America's Infrastructure 2021* [2], both the state and local transportation asset management plans should consider long-term planning and incorporate life-cycle cost analysis (LCCA), which implicitly refers to two potential management policies: long-term planning and decision-making flexibility. Essentially, the first policy focuses on a treatment's long-term benefit when it is evaluated. The second policy aims to relax constraints for treatment selection, such as a constraint that asphalt pavements can only be maintained by asphalt overlays. Under the policy of decision-making flexibility, the selection of treatments is based on life cycle cost analysis and the treatment alternatives include both asphalt and concrete materials.

Another potential management policy is to increase market diversification, which can reduce the unit prices for both asphalt and concrete materials [88]. For most states in the U.S., asphalt is dominant in the paving market. Hence, by proactively increasing the concrete market share, i.e., the market diversification, the unit prices for both materials are expected to decrease, and more pavements are expected to be maintained.

In this chapter, these three management policies are evaluated for each state in the U.S., with the exception of Alaska and Hawaii due to limited data availability. Their evaluations are based on four PBP scenarios with the consideration of different numbers of policies. Under the same budget level, the excess vehicle fuel costs due to pavement vehicle interaction (PVI) are calculated for five scenarios. After incorporating all three policies, the excess vehicle fuel cost reduction is 28% or 62 billion dollars saved compared to the business-as-usual (BAU) scenario from 2017 to 2050. All states can benefit from proposed policies. States in the wet freeze climate zone, Washington, and California have larger benefits compared to other states. When states have high initial IRI and large traffic volume, it is possible for them to have large benefits. On the other hand, when a state has a large cost ratio between concrete and asphalt prices, and a large ratio of concrete pavements, then it tends to have a small benefit from these policies.

5.2 Literature Review

Existing studies of PBP usually focus on the development of mathematical algorithms for budget allocation. Only a few studies have explored the influence of how the allocation problem is framed on the pavement network conditions, including the systematic exploration of different treatment strategies in Chapter 4. Both the development of mathematical algorithms (Chapter 3) and the evaluation of different treatment strategies (Chapter 4) are in the scope of the budget allocation process. In addition to an efficient budget allocation process, it is also necessary to have appropriate management policies to support the allocation process. However, the discussion and evaluation about the influence of different policies on pavement networks are very few in literature to date.

The Report Card for America's Infrastructure 2021 [2] recommends "develop[ing] state and local level comprehensive transportation asset management plans that link asset management efforts to long-term transportation planning and incorporate the use of life-cycle cost analysis", which implies two potential management policies: long-term planning and decision-making flexibility. For current transportation agencies, especially the local ones, the selection of treatment actions for a pavement segment (or project) is usually by prescribed decision-trees, which are built based on expert options or past experiences. However, due to the limitations from past experiences or existing policies, the selection criteria based on the decision is very constrained. For example, pavements can only be maintained by asphalt materials in some states in the New England region of the U.S. In order to relax such constraints, both asphalt and concrete materials, and different treatment types should be considered. LCCA can be applied to evaluate different treatments as suggested by the report card [37], [54], [57], [66]–[68]. The implementation of the above two aspects are incorporated into the first policy, decision-making flexibility.

LCCA involves consideration of initial construction costs, costs of overlay and preservation (i.e., agency costs), and in some cases, user costs associated with excess vehicle fuel consumption caused by PVI and vehicle operations. The total life-cycle cost (LCC) usually equals the sum of initial construction or treatments costs and discounted future agency and user costs. As discussed in [38], an efficient way to determine the treatment schedule is based on an optimization process, whose objective is to minimize the total LCC, either by genetic algorithm [37], [54], [140], dynamic programming [142] or the backtrack algorithm [38]. For analyses reported to-date, the user cost usually ignores the excess vehicle fuel cost due to deflection-induced PVI, which plays a significant role in the use phase [148]–[150]. In recent years, considering the number of electric vehicles (EVs) has gradually increased [146], it is necessary to differentiate them during the analysis for roughness-induced PVI. In addition, LCCA usually aims for a pavement project. Only a very few studies have incorporated LCCA for the segment level analysis in a so-called two-stage bottom-up (TSBU) model [55], [57].

The second implied management policy from the report card is the long-term planning. As discussed in Chapter 4, a long evaluation period could lead to a better pavement network condition compared to short ones. When using long-term planning, the pavement network tends to use many reconstructions and thick overlays for the first few years, and then shift to the thin overlays and preservations later. Hence, the pavement network condition is a little worse compared to the scenario using the short evaluation period for the first few years, and then it becomes much better in the following years since the long-term benefits start to stand out.

Another potential management policy is to increase market diversification. There usually exists a negative and significant correlation between the number of bidders for a project and its cost growth [158], [159], which implies that increasing intra-industry competition can lead to the decrease of infrastructure cost. Asphalt and concrete are two common paving materials. For all states in the U.S., asphalt has the dominant market share in the paving market. There are only about 6 states whose concrete market share is larger than 30%. Based on the research by [88], increasing number of bidders and the decreasing market concentration can bring down the unit prices for both materials. Hence, there exists a big opportunity to fix more pavement areas and improve pavement networks by proactively advocating the market diversification policy. However, the author is not aware of a previous study to evaluate the benefit of incorporating market diversification for pavement networks from the state or national level analysis.

To summarize, most research focuses on the budget allocation process by improving the allocation algorithms, and very few studies work on the exploration of different treatment strategies. However, the influence of potential management policies under which the budget allocation process happens is seldomly evaluated. To bridge these gaps, the benefits of three management policies are evaluated across the U.S., including decision-making flexibility, long-term planning, and market diversification. The benefit is in the form of excess vehicle fuel cost due to PVI. Two types of budget allocation models are applied, including one based on the prescribed decision tree, and another one based on dynamic LCCA. The word dynamic is chosen to reflect the fact that pavement conditions, treatment cost, and traffic volume change every year. Five scenarios based on these two allocation models are proposed with the consideration of different number of policies, and corresponding excess vehicle fuel costs are obtained for the period from 2017 to 2050. Then the benefit for each policy can be expressed as the cost savings between two scenarios for the whole nation and each state as well. Finally, potential influential factors for the benefit are explored.

5.3 Methodology

In this section, two types of allocation models are presented first, including decision-tree based and dynamic LCCA based allocation models. Both models are based on the TSBU framework. The models first focus on the segment level to determine the optimal treatment alternative(s), and then move to the network level to determine which segments should receive the treatments with the consideration of budget and performance constraints. For the business-as-usual (BAU) scenario, the decision-tree based allocation model is applied. On the segment level, the optimal treatment is determined by a decision tree based on past experiences or expert opinions. Three proposed management policies are realized by a dynamic LCCA based allocation model. On the segment level, two optimal alternatives are determined by the dynamic LCCA, during which the pavement condition, traffic level, and treatment cost change annually.

Next, a numerical model to describe the influence of market concentration on the unit prices of paving materials is introduced. Finally, the benefits of management policies are mainly described by the excess vehicle fuel cost, including gasoline and diesel cost for internal combustion engine vehicles (ICEVs), and electricity cost for EVs.

5.3.1 Decision-tree based allocation model

In terms of the allocation model for the BAU scenario, on the segment level, the optimal treatment for each segment is based on decision trees whose decision criteria are pavement condition (IRI) and pavement age. Figure 5-1 shows the decision tree used in the analyses. The Federal Highway

Administration (FHWA) suggests that when IRI is larger than 2.68 m/km, then the road condition is evaluated as having a poor condition. Hence, this value is used for the reconstruction criterion. IRI_{thre} is mainly related to the current pavement network condition, which differs for different states and different road systems. For example, interstate systems usually have better road conditions than the local systems, so the IRI_{thre} for an interstate system (less than 1.6 m/km) is usually smaller than a local system (around 2.0 m/km).

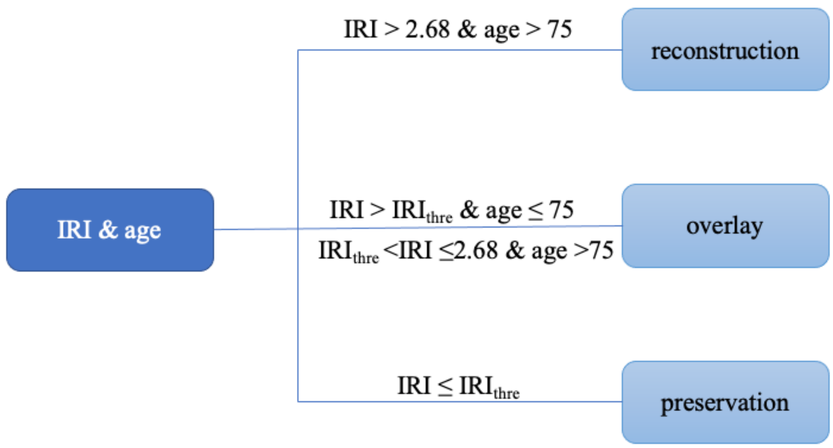


Figure 5-1. Treatment decision tree

After determining the optimal treatment for each segment, the allocation model moves to the network level to select which segments should receive treatments under the budget constraint. The selection approach is mainly based on the prioritization method [138]. First, the treatment benefit for segment *i* is calculated by the equation (5.1):

$$benefit^i = \left(IRI^i_{fixed} - IRI^i_{non-fixed}\right) \cdot AADT^i \tag{5.1}$$

where IRI^i_{fixed} represents the IRI value if segment *i* receives its optimal treatment, and $IRI^i_{non-fixed}$ is the IRI value if segment *i* chooses to do nothing. $AADT^i$ is the annual average daily traffic. By multiplying IRI difference and AADT, the benefit can roughly represent the excess vehicle fuel consumptions caused by roughness-induced PVI. Given a system in a state, the pavement segment length is the same as discussed in Appendix D.1, hence equation (5.1) does not incorporate length.

Next, the allocation model ranks all segments based on their benefits as shown in the following equation,

$$r_j = rank\left(benefit_j\right) \tag{5.2}$$

where r_j is the ranked pavement network, and the segment with the largest benefit ranks first. With the consideration of budget constraint, segments that can be maintained are selected by:

$$S = \arg\min_{r_j}\left(\sum_{S,i \subseteq S, S \subseteq r_j} cost_i - B\right) \tag{5.3}$$

$$s.t \quad B - \sum_{S,i \subseteq S} cost_i \geq 0 \tag{5.4}$$

where S is the set of selected segments, $cost_i$ represents the treatment cost for segment i, and B is the available budget.

In the analyses, the budget allocation process is on an annual basis. Initial pavement condition and treatment cost are provided. Then a set of treatment decisions is made for the whole pavement network through the allocation model. Then, the pavement segment information is updated, and the process moves on to the next year. At the beginning of the next year, the treatment cost is updated based on the cost prediction models, which can be found in the Section 3.3.1. Then the budget allocation model is applied to make the treatment actions for the whole pavement network. The whole process is repeated until the end of the analysis period.

5.3.2 Dynamic LCCA based allocation model

On the segment level of the dynamic LCCA allocation model, different treatments are evaluated and then two optimal alternatives are selected. On the network level, the goal is to minimize the total life cycle cost (LCC) for the whole pavement networks within the budget constraint.

Segment level analysis

The goal of the segment-level analysis is to evaluate and identify the best treatment $a_{i,1}^*$ for each segment i at the beginning of segment analysis period (e.g., t_s=1) when there is no budget constraint. During the evaluation process, available treatment alternatives $\boldsymbol{N}^{(m)}$ are related with pavement types $\boldsymbol{M}$ (where $m \in \boldsymbol{M}$). Hence, the goal is to evaluate $\boldsymbol{N}^{(m_0)}$, where m_0 is initially known before the analysis.

To allow for the impact of a budget constraint in the network level analysis, the top two alternatives are identified for each segment, namely, $a_{i,1}^{*} = \left[a_{i,t_s=1}^{*1}, a_{i,t_s=1}^{*2}\right]$. The evaluation is based on the LCC given an analysis period. The action with a smaller LCC is preferable.

To evaluate action $\boldsymbol{N}^{(m_0)}(\alpha)$, its minimal LCC is determined by the following optimization process:

min: LCC_{α} (5.5)

s.t. $a_1 = \boldsymbol{N}^{(m_0)}(\alpha) = \boldsymbol{N}_1(\alpha)$ (5.6)

$$\sum_{n=1}^{N_{t_s}} x_{n,t_s} \le 1 \quad \text{for } t_s = 2,\ldots,\mathrm{T}_s \tag{5.7}$$

$$IRI_{j,t_s} = \left(IRI_{j,t_s-1} + \Delta IRI_{j,t_s}\right)\cdot\left(1-\sum_{n=1}^{N_{t_s}} x_{n,t_s}\right) + \left(IRI_{j,new} + \Delta IRI_{j,new}\right)\cdot\sum_{n=1}^{N_{t_s}} x_{n,t_s} \tag{5.8}$$

for $t_s = 1,2,\ldots,\mathrm{T}_\mathrm{s}$

$$IRI_{j,t_s} \le IRI_{j,threshold} \tag{5.9}$$

$$uc_{t_s} = fc_{R,t_s} + fc_{D,t_s} \quad \text{for } t_s = 1,2,\ldots,\mathrm{T}_\mathrm{s} \tag{5.10}$$

$$a_{t_s} = \sum_{n=1}^{N_{t_s}} x_{n,t_s} \cdot \boldsymbol{N}_{t_s}(n) \quad \text{for } t_s = 1,2,\ldots,\mathrm{T}_\mathrm{s} \tag{5.11}$$

$$m_{t_s} = g\left(m_{t_s-1}, a_{t_s}\right) \quad \text{for } t_s = 1,2,\ldots,\mathrm{T}_\mathrm{s} \tag{5.12}$$

$$\boldsymbol{N}_{t_s} = \boldsymbol{N}^{\left(m_{t_s}-1\right)} \quad \text{for } t_s = 1,2,\ldots,\mathrm{T}_\mathrm{s} \tag{5.13}$$

$$ac_{t_s} = p\left(ac_0, P_{asphalt}^{t}, P_{concrete}^{t}\right)\cdot area \tag{5.14}$$

$$LCC_\alpha = \sum_{t=1}^{T_s} \frac{1}{\left(1+r\right)^{t_s}} \left(\sum_{n=1}^{N_{t_s}} x_{n,t_s} \cdot ac_{t_s}\left(n\right) + uc_{t_s} \right) \tag{5.15}$$

$$x_{n,t_s} \in \left\{0,1\right\} \quad \text{for } t_s = 1,2,...,\mathrm{T_s}, \text{ and } \forall n \tag{5.16}$$

Table 5-1. Definitions of all variables in the segment-level optimization process

Variable	**Meaning**
T_s	Segment level analysis period
LCC	Life cycle cost given the segment level analysis period
m_t	Pavement material type at time *t.* When $t = 0$, it represents the initial pavement type
r	Discount rate
$\boldsymbol{N}, n, a, \alpha$	***N*** is the set of treatment actions, *n* is the ordinal of the actions in ***N***, i.e. ***N(n)*** represents the n_{th} action *a* in *N*, α is the ordinal of the evaluated action.
x_{n,t_s}	Decision variable. If the n_{th} action in $\boldsymbol{N}_{t_s}$ is selected at year t_s, $x_{n,t_s} = 1$. Otherwise, $x_{n,t_s} = 0$.
$\Delta IRI_{j,t_s}$	Pavement deterioration without any treatment
$\Delta IRI_{j,new}$	Pavement deterioration after a treatment
$\Delta IRI_{j,threshold}$	The performance threshold value for condition metric *j*.
uc_{t_s}	User cost at year t_s
fc_{R,t_s}	Excess fuel cost induced by roughness-induced PVI at year t_s
fc_{D,t_s}	Excess fuel cost induced by deflection-induced PVI at year t_s
ac_{t_s}	Agency cost at year t_s

The goal of the optimization analysis is to evaluate the α_{th} treatment action *a* in $\boldsymbol{N}_1$ (equation (5.6)). For example, $\boldsymbol{N}_1 = \{$do nothing, surface treatment, asphalt overlay, asphalt reconstruction$\}$, then the fourth (α_{th}) treatment action (*a*) is asphalt reconstruction. The segment-level optimization objective is to minimize the total LCC including agency cost *ac* plus user cost *uc* for a given analysis period T_s (equations (5.5) and (5.15)). x_{n,t_s} is a binary variable, which represents treatment action *n* is selected at year t_s if x_{n,t_s} is equal to 1. The weight ratio between agency and user costs is assumed to be 1:1. This ratio can be modified based on the requirements of a transportation agency.

At any year t_s, at most one action could be selected as shown in equation (5.7). Equation (5.8) describes IRI at the end of year t_s based on the IRI at year t_s-1 and the treatment action at year t_s. A treatment action is applied at the beginning of each year. If a treatment action is applied, segment performance is improved and IRI decreases to IRI_{new}. IRI_{new} can be obtained through a set of performance jump models, which are introduced in Appendix D.5. The calculation of ΔIRI is based on the deterioration models introduced in Appendix D.4. Equation (5.9) describes the performance constraints for IRI. Equation (5.10) describes the user cost, including excess fuel consumption cost caused by both roughness- and deflection-induced PVI. Corresponding equations can be found in Appendix C.1.2.

Equation (5.11) describes the action a_{t_s} taken at year t_s. Material type m_{t_s} at year t_s can be decided by material type at year t_s-1 and the treatment taken at year t_s as shown in equation (5.12), and then corresponding treatment alternatives could be decided (equation (5.13)). Equation (5.14) describes the agency cost, which equals to the multiplication of unit treatment cost and segment area. The unit treatment cost changes with unit concrete and asphalt cost. Due to limited cost information, it is assumed that cost of concrete treatment actions changes at the same rate as the cost of the concrete material. Asphalt treatment actions change at the same rate as the cost of the asphalt material. If no material is applied, such as diamond grinding, then treatment actions change at the same rate as the construction cost index (CCI) [129].

The solution of this optimization model is based on the backtrack algorithm (Appendix A). Two optimal treatment alternatives $a_i^* = \left\{a_{i,1}^{*1}, a_{i,1}^{*2}\right\}$ with the smallest LCC are identified for each segment *i*.

Network level analysis

On the network level, the goal is to make a final treatment decision for each segment based on an optimization process. For each segment *i*, the goal is to choose one of the two selected alternatives

a_i^* from the segment-level analysis or do nothing. The proposed optimization model makes treatment decisions on an annual basis. It updates network performance based on decisions for the current year. Then it makes decisions for the next year based on the updated performance. At year *t*, the mathematical formulation of the network-level analysis is shown as follows:

max: $\sum_{i=1}^{I} \Delta LCC_{i,t}$ (5.17)

s.t. $y_{i,1} + y_{i,2} \le 1 \quad \text{for } i = 1,2,...,I$ (5.18)

$$\sum_{i=1}^{I} \left(y_{i,1} \cdot ac_t\left(a_i^{*1}\right) + y_{i,2} \cdot ac_t\left(a_i^{*2}\right) \right) \le B_t \tag{5.19}$$

$$\Delta LCC_{i,t} = \left(LCC_{i,t}\left(0\right) - LCC_{i,t}\left(a_i^{*1}\right) \right) \cdot y_{i,1} + \left(LCC_{i,t}\left(0\right) - LCC_{i,t}\left(a_i^{*2}\right) \right) \cdot y_{i,2} \tag{5.20}$$

for $i = 1,2,...,I$

$$y_{i,1}, y_{i,2} \in \{0,1\} \quad \text{for } i = 1,2,...,I \tag{5.21}$$

Table 5-2. Definitions of all variables in the network-level optimization process

Variable	**Meaning**
I	Segment number
$\Delta LCC_{i,t}$	The decrease of life cycle cost given a segment analysis period T_s after a treatment is taken for segment *i* at year *t*
a_i^{*1}, a_i^{*2}	Two optimal treatment alternatives obtained on the segment level analysis
$y_{i,1}, y_{i,2}$	Decision variables. If a_i^{*1} is selected, then $y_{i,1} = 1$; If a_i^{*2} is selected, then $y_{i,2} = 1$. If neither a_i^{*1} or a_i^{*2} is selected, then $y_{i,1} = y_{i,2} = 0$.
B_t	Available budget at year *t*

The optimization objective is to maximize the total decrease of life cycle cost for a given period T_s as suggested by [78], [126], as shown in equation (5.17). Equation (5.18) requires that at most one treatment alternative could be chosen for each segment. $y_{i,1}$ and $y_{i,2}$ are binary variables as shown in equation (5.21), which represent treatment action a_i^{*1} or a_i^{*2} is selected at year *t* if $y_{i,1}$

or $y_{i,2}$ is equal to 1. It should be noted that if the condition metric of a pavement segment is less than its performance threshold, then this segment will be guaranteed to receive a treatment by setting $y_{i,1} + y_{i,2} = 1$. Equation (5.19) is the budget constraint. Equation (5.20) describes the decrease of total LCC for a period T_s, which considers three cases: action a_i^{*1} is chosen ($y_{i,1} = 1$), a_i^{*2} is chosen ($y_{i,2} = 1$), or no action ($y_{i,1} = y_{i,2} = 0$).

The network-level optimization problem is an integer programming problem, which is solved by the software *GUROBI*. By solving the optimization problem at year *t*, treatment decisions could be made for each segment *i*, namely $a_{i,t} = y_{i,1} \cdot a_i^{*1} + y_{i,2} \cdot a_i^{*2}$.

5.3.3 Market diversification

As suggested by [88], states with more uniform market shares among pavement materials, namely, with a higher market diversification, can pay lower prices for all materials. In order to evaluate the relationship between indicators of competition – number of bidders and dominant market share - and bid pricing for pavement systems, panel data regression models are developed using the bid data for concrete and asphalt related pay items that span 10 years for 47 states in the U.S. These models embed several covariates that account for cross-sectional and time-varying heterogeneity. The panel data regression model can be expressed as:

$$Y_{i,t} = \beta_0 + \beta_1 \cdot X_{it,1} + \cdots \beta_p \cdot X_{it,p} + \varepsilon_{it} \tag{5.22}$$

Where $Y_{i,t}$ is the logarithmic unit-price for asphalt and concrete pay items, which is a function of covariates (X) and their associated effects (β) as well as an error term (ε). In the budget allocation analysis, due to the limited information about the bidders and other covariates, only the linear relationship between the logarithmic unit-price and dominant market share is considered. The coefficients of dominant market share for asphalt and concrete materials are 0.34 and 1.39, respectively. In this case, with the unit change of dominant market share, the corresponding change for the unit price can be inferred for both materials.

In order to increase the market diversification in the dynamic LCCA based allocation model, on the network level, given a year, the spending for both asphalt and concrete materials are calculated and the corresponding dominant market share is determined. Then, for the next year, both the asphalt and concrete cost are updated based on the cost projection model described in the Section 3.3.1 and the change of dominant market share (equation (5.22)). On the segment level, if there is no proactive policy to reduce the market concentration, then the treatment cost values from the network level are used. If there is a proactive policy, for example, reduce the dominant market share by 10%, then the treatment cost values for the segment level analysis should be modified. Suppose the initial asphalt market share is 90%, and the goal is to reduce it to 80%. At a certain year, the asphalt market share is 85%, then during the segment level analysis, it is assumed that the asphalt market share will continue to decrease to 80% in the future, and there should be a corresponding change for the treatment cost since the dominant market share should decrease by another 5%. By doing so, the segment level analysis assumes that the unit prices should decrease in the future.

5.3.4 Excess vehicle fuel cost

Excess vehicle fuel consumption is mainly caused by PVI and the corresponding PVI models are described in Appendix C.1.2. The fuel cost is equal to the unit fuel price multiplied by the quantity of excess fuels as shown in equation (5.23). $\delta IFC_{R,ICEV\,car}$ represents the excess gasoline caused by roughness-induced PVI for cars that use internal combustion engines. Due to their light weight compared to trucks, deflection-induced PVI is ignored for cars. $\delta IFC_{R,truck}$ represents excess diesel consumptions for trucks in terms of roughness-induced PVI. Existing PVI models are based on the ICEV. Considering the increasing number of EVs, the adopted PVI model is adjusted based on the relative energy intensity per mile for ICEVs and EVs. Using this information, the expected energy consumption, in terms of kWh of electricity, are computed for the fraction of vehicles that are assumed to EVs (details are in Appendix C.1.3). $\delta IFC_{R,EV\,car}$ represents excess electricity consumptions for cars that belong to EV in terms of roughness-induced PVI. In the analysis, the deflection-induced PVI is only considered for trucks, and δIFC_{D} represents excess diesel consumptions for trucks in terms of deflection-induced PVI.

The initial gasoline and diesel cost are based on [153]. The initial electricity cost for each state is based on the state electricity profiles from EIA [160]. The projections of future gasoline, diesel, and electricity cost are from the table *Energy Prices by Sector and Source* provided by [161].

$$Fuel\ Cost = \alpha_{gasoline} \cdot \delta IFC_{R,ICEV\ car} + \alpha_{diesel} \cdot \left(\delta IFC_{R,truck} + \delta IFC_{D}\right) + \alpha_{electricity} \cdot \delta IFC_{R,EV\ car} \quad (5.23)$$

5.4 Case Study

Three proposed management policies are evaluated for all states across the U.S with the exception of Alaska and Hawaii due to a lack of data. Five scenarios are proposed as listed in Table 5-3. Their differences mainly lie in three aspects: (1) treatment evaluation approach, which is used to select the optimal treatment alternative for a pavement segment; (2) treatment evaluation period, which represents the period during which a treatment is evaluated for its benefit; (3) market diversification, which shows whether the influence of market concentration is considered and whether the policy to increase the market diversification is proactively considered. These three aspects are concerned with the proposed management policies, and the scenarios in Table 5-3 can be compared to reflect the benefits of policies as shown in Table 5-4.

Table 5-3. Scenarios to evaluate pavement management policies

Scenario	Evaluation approach	Evaluation period	Market diversification
BAU	decision tree	-	No
dLCCA 5	dynamic LCCA	5 years	No
dLCCA 20	dynamic LCCA	20 years	No
dLCCA mkt0	dynamic LCCA	20 years	Yes
dLCCA mkt	dynamic LCCA	20 years	proactively consider it

Table 5-4. Evaluation objectives for different comparisons among scenarios

Scenario comparisons	Evaluation objectives
BAU - dLCCA 5	benefit of the decision-making flexibility policy
dLCCA 5 - dLCCA 20	benefit of the long-term planning policy
dLCCA 20 - dLCCA mkt0	influence of the awareness of market concentration
dLCCA mkt0 - dLCCA mkt	benefit of advocating for market diversification
BAU - dLCCA mkt	benefit of incorporating all three policies

For all scenarios, the network analysis period is from 2017 to 2050. The pavement management system data are sampled by statistical inference from the FHWA road statistics and LTPP dataset. The sampling process for each state can be found in Appendix D.1. The initial unit prices for concrete and asphalt paving materials are the 5-year (2016-2020) average cost exacted from the Oman data (details can be found in Appendix D.2). Notably, there is almost no concrete pavement projects in the past 5 years in several states including Massachusetts, Maine, New Hampshire, New Jersey, Rhode Island, Vermont and Mississippi. Hence, for the BAU scenario, these states only use asphalt materials. But for dLCCA related scenarios, concrete materials are applied and it is assumed that the unit concrete price is equal to the 75th percentile of the distribution for the unit concrete prices across the U.S. In addition, for some states, like Montana, have very high concrete prices but their neighbor states can have quite low prices. In this case, it may be more economic to transport concrete from neighbor states. Here, it is assumed that if the concrete price of a state is larger than 75th percentile of the distribution for the unit concrete prices, then its concrete price is equal to the average of concrete prices from its neighbor states whose price is lower than the 75th percentile of the distribution for the unit concrete prices.

Future material cost is projected by a prediction model introduced in the Section 3.3.1. Due to limited information of treatment actions for all states, it is assumed that states in the same climate zone have the same set of treatment actions, which are listed in Appendix D.3.

The determination of treatment schedules is usually based on the future conditions of pavement segments. During this process, the pavement deterioration model is used to predict pavement condition without any treatments, and the performance jump model is applied to describe the pavement condition after a treatment. Corresponding models can be found in Appendix D.4 and D.5.

For all scenarios, due to different importance levels, given a state, each road system (i.e., interstate, arterial, collector, and local) is analyzed separately. Each system has its own critical budget, which is the minimum annual budget to maintain pavement network condition under the BAU scenario over the network analysis period. Figure 5-2 shows the average IRI over the network analysis period for the BAU scenario. The high traffic roads include interstate and arterial systems, and the low traffic roads include the collector and local systems.

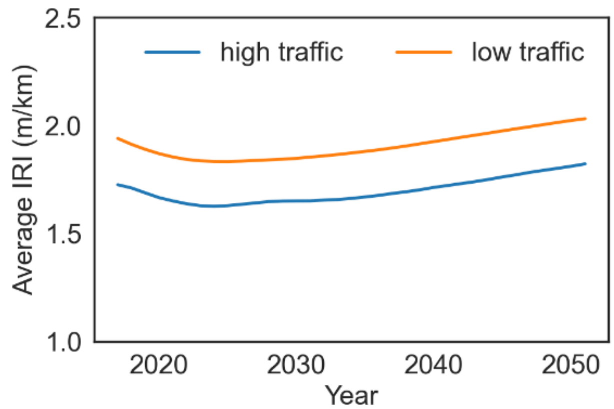


Figure 5-2. Average IRI over the network analysis period for the BAU scenario

5.4.1 Total savings for vehicle fuel cost

The total excess vehicle fuel costs from 2017 to 2050 across the U.S are calculated for the five scenarios in Table 5-3 and presented in Figure 5-3. Generally, the proposed policies reduce the vehicle fuel cost significantly. After incorporating all three policies, the total excess vehicle fuel cost (e.g., the comparison between BAU and dLCCA mkt) is reduced by 28%, a savings of about 62 billion dollars.

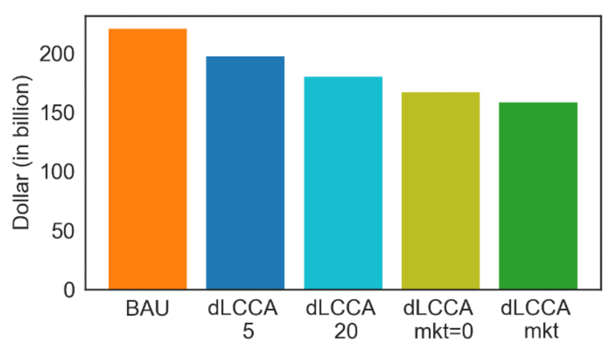
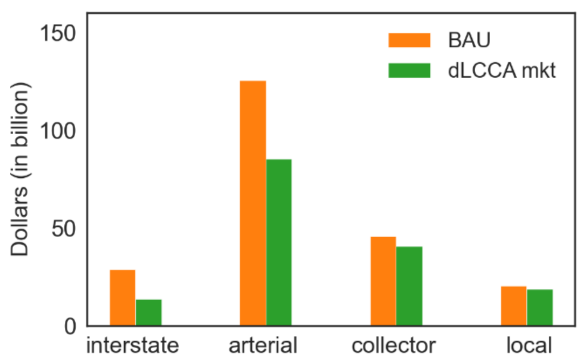
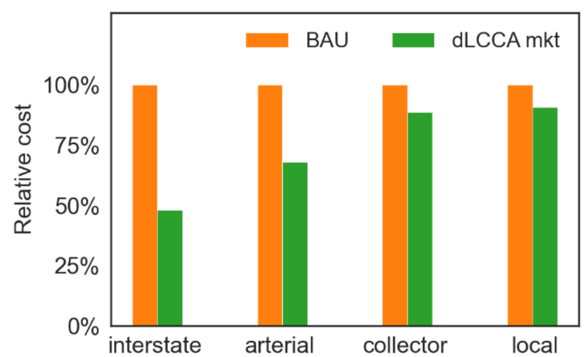


Figure 5-3. Total excess vehicle fuel costs for different scenarios from 2017 to 2050 across the U.S excluding Alaska and Hawaii

The excess vehicle fuel costs for different systems are shown in Figure 5-4. Figure 5-4(a) shows the absolute total cost for different systems, and the arterial system provides the largest saving when comparing the BAU and the dLCCA mkt scenarios, which is equal to 40.3 billion dollars. Figure 5-4(b) shows the relative total fuel cost compared to the BAU scenario for different systems, and the interstate system provides the largest relative saving, about 52%. The interstate and arterial systems provide large savings due to the shift from using asphalt materials to concrete materials, as shown in Figure 5-5(a). The ratio of concrete-surfaced pavements (e.g., concrete pavements and concrete overlay composite pavements, COC) has increased from 10% to 59% for high traffic roads. Concrete pavements usually have a slower deterioration rate and are stiffer than the asphalt pavements. For the high traffic roads, concrete-surfaced pavements usually require less treatment actions compared to asphalt-surfaced pavements. Hence, the annual average life cycle cost for concrete is usually smaller than that for asphalt roads. After incorporating the flexibility in decision making (e.g., asphalt pavement can be maintained by concrete overlays), considering the long-term benefits and unit prices' reduction due to market diversification, the high traffic roads will tend to use more concrete materials. For low traffic loads, the pavement deterioration is usually at a slow rate and hence, the number of maintenances is smaller than the high traffic roads. In this case, the benefit of concrete material is not eminent compared to asphalt. As shown in Figure 5-5(b), after incorporating three management policies, most roads are still asphalt-surfaced ones.

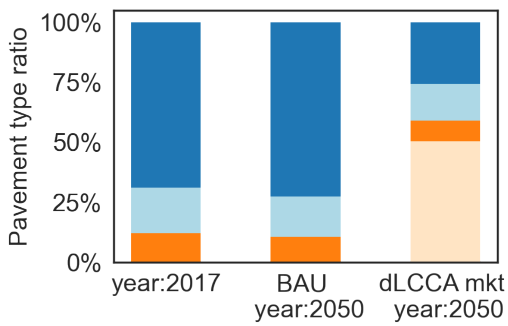


(a)

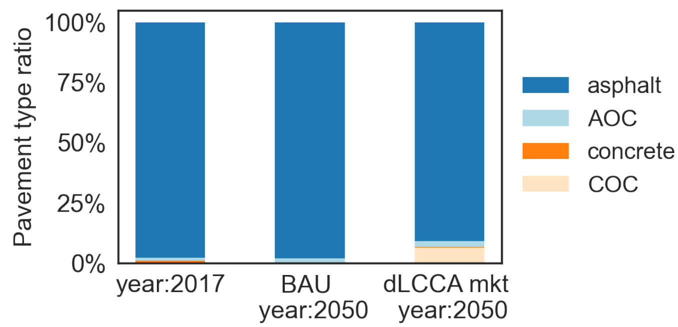


(b)

Figure 5-4. (a) Total excess vehicle fuel cost and (b) excess vehicle fuel cost ratios compared to the BAU scenario for different systems scenarios of BAU and dLCCA mkt.



(a)



(b)

Figure 5-5. Pavement type distribution for (a) high traffic roads and (b) low traffic roads.

5.4.2 State-level vehicle fuel cost saving due to decision-making flexibility

As shown in the Section 5.4.1, the total excess vehicle fuel cost saving due to decision-making flexibility is about 23.4 billion dollars from 2017 to 2050 based on the comparison between BAU and the dLCCA 5 scenario. For the BAU scenario, the decision-making process is based on a prescribed decision tree. For example, asphalt pavements can only be maintained by the asphalt materials, and the treatment type is mainly determined by the IRI and age thresholds. Compared to the BAU scenario, the dLCCA 5 scenario, which is based on the dynamic LCCA allocation model, relaxes the decision-making process so that any type of pavement can be maintained by both asphalt and concrete materials, and the optimal treatment action is determined by the LCCA process.

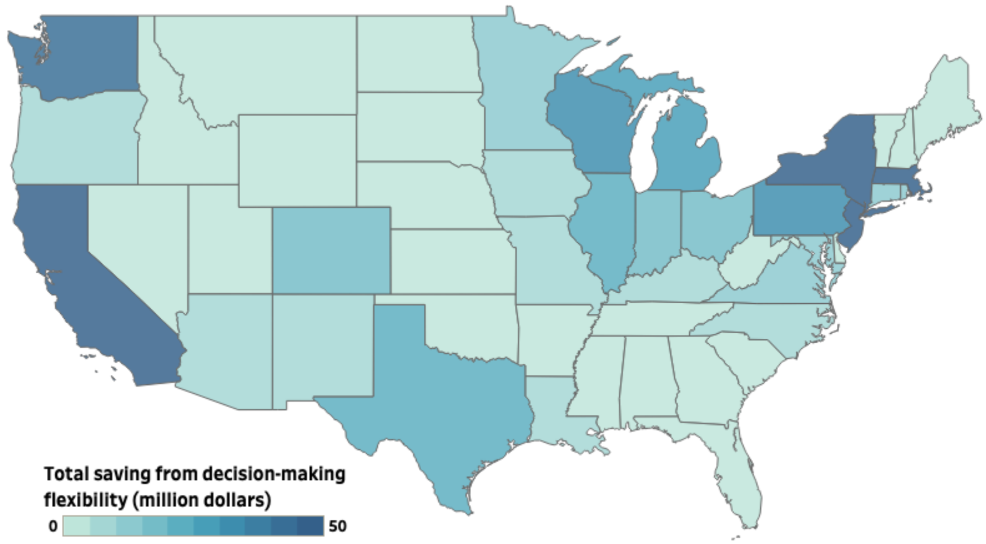
Figure 5-6(a) shows the annual average total savings for each state in the U.S. There are three states whose savings are larger than 50 million dollars. Figure 5-6(b) shows the annual average savings per lane mile for each state in the U.S. There are 7 states whose savings are larger than 300 dollars per lane mile. In general, all states can benefit from the decision-making flexibility policy, especially for California, Washington, and states near New York. The states in the wet nonfreeze climate zone tend to have small cost savings.

Next, potential factors that influence the magnitude of the savings due to the decision-making flexibility policy are explored. Two types of factors are considered for each road system, including (1) pavement network condition: the average IRI, the average AADT, the pavement type distribution, pavement area ratios for different systems; (2) economic factors: budget level, unit prices for both asphalt and concrete, and cost ratio between concrete and asphalt unit prices. Then, the correlation coefficients between each factor and the state-level savings due to the decision-making flexibility are calculated. If the correlation coefficient of a factor is larger than 0.35 or smaller than -0.3, then this factor is considered influential.

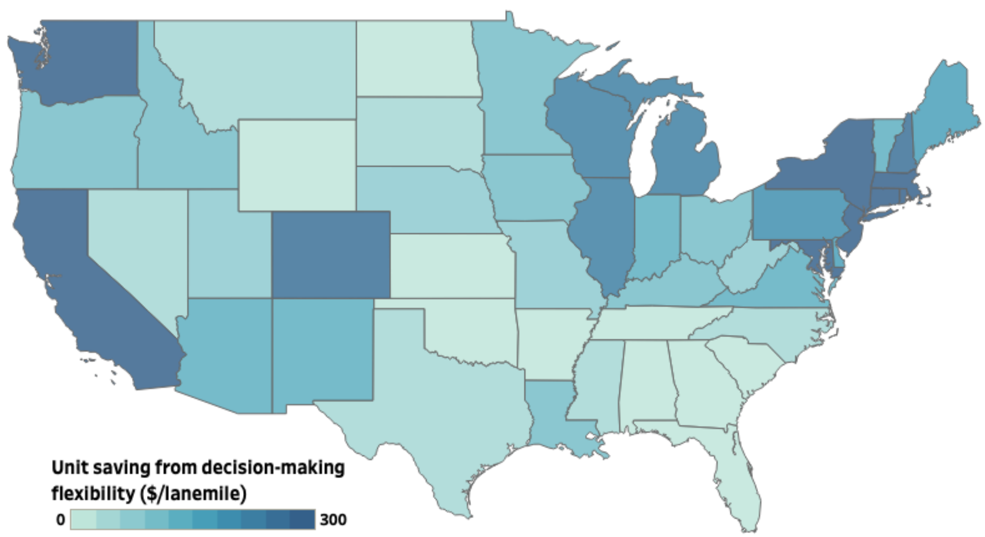
As seen from Figure 5-6(b), New Jersey, Rhode Island, and Massachusetts have the largest unit saving per lane mile (more than $1000 per lane mile), and their savings are much larger than other states (less than $500 per lane mile). One potential reason is that the pavement networks for these states are in very bad condition, especially for arterial, collector, and local systems. Due to their huge differences from other states in terms of unit cost saving, these three states are considered outliers and are removed from the correlation analysis.

The positive factors mainly include the average IRI for all systems, the average AADT for interstate, arterial and collector systems, and the asphalt price. Notably, the average AADT for the local system also has a relatively large correlation coefficient (0.3). When the initial pavement network is in bad condition and the traffic level is large, a state has a higher chance to witness a big saving due to the decision-making flexibility policy. When the asphalt price is high, the cost difference between asphalt overlay and reconstruction becomes large, and the cost difference between asphalt and concrete becomes small. In this case, for some extremely bad roads (i.e., IRI is larger than 2.68), where the BAU scenario uses the reconstruction, the dLCCA 5 scenario will use more asphalt and concrete overlays in order to fix as many as pavement segments as possible.

The only negative factor is the cost ratio between concrete and asphalt unit prices. When the cost ratio is large, only asphalt materials are applied, leading to potentially high excess vehicle fuel cost due to deflection-induced PVI.



(a)



(b)

Figure 5-6. State-level annual cost saving due to decision-making flexibility policy: (a) total saving, (b) unit saving per lane mile.

5.4.3 State-level cost saving due to long-term planning

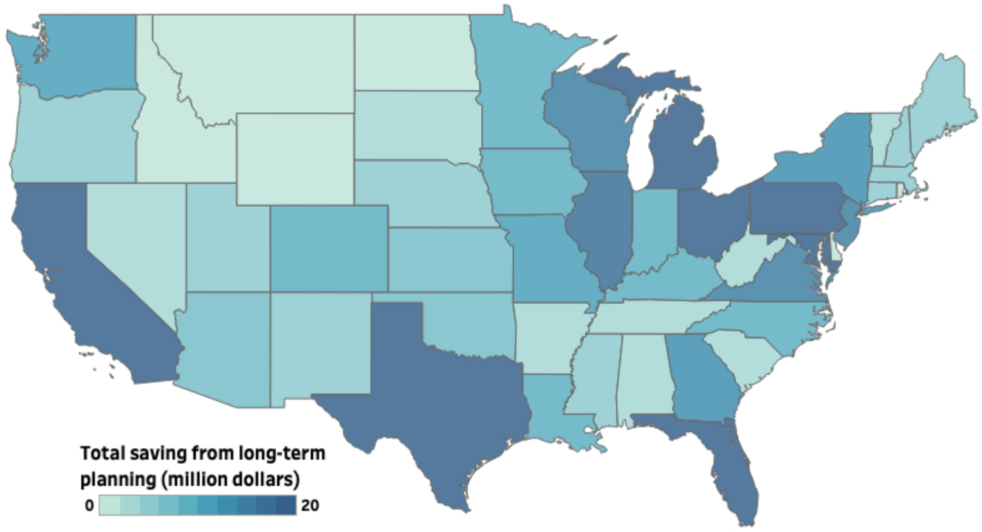
The total excess vehicle fuel cost savings due to long-term planning policy is about 17.4 billion dollars from 2017 to 2050, as shown in Figure 5-3. Compared to the dLCCA 5 scenario, the dLCCA 20 scenario evaluates treatments based on their long-term performance. In this case, more overlays and reconstructions are expected to be applied.

Figure 5-7(a) shows the annual average total savings due to the long-term planning policy for each state in the U.S. There are 5 states whose total annual benefits are larger than 20 million dollars. Figure 5-7(b) shows the annual average unit saving per lane mile for each state in the U.S. There are 3 states whose annual benefits are larger than $250 per lane mile, including Maryland, California and New Jersey. In general, all states can benefit from the long-term planning policy. States in wet-freeze climate zone tend to benefit more from the long-term planning policy.

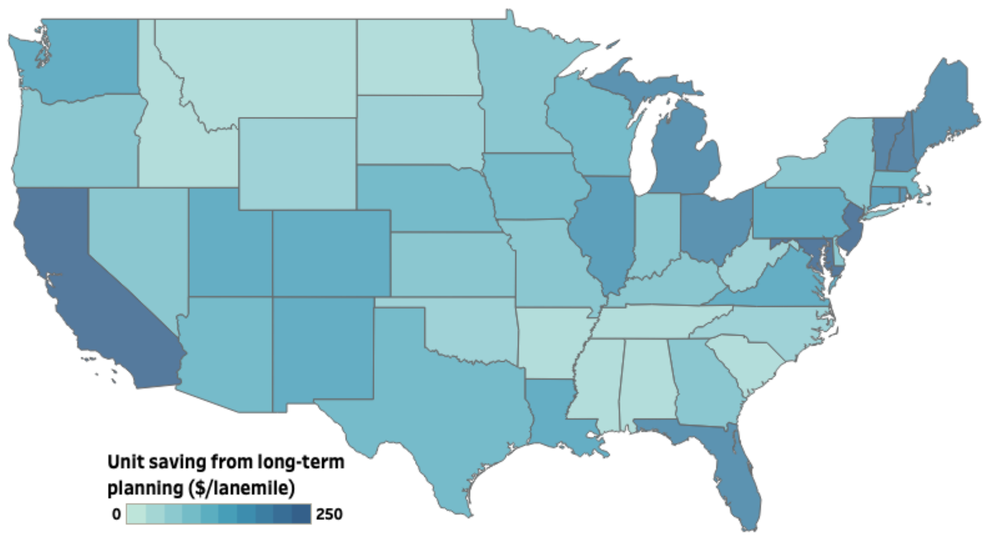
Next, potential factors that influence the magnitude of the savings due to the long-term planning are explored. Potential factors are the same as those introduced in the Section 5.4.2. Maryland, California, and New Jersey are removed from the correlation analysis, whose unit cost savings are larger than $250 per lane mile.

The positive factors mainly include the average IRI for the arterial system, the average AADT for arterial and collector systems, the asphalt price, and the budget level for interstate system. When the initial pavement network is in bad condition and the traffic level is large, a state has a higher chance to witness a big saving due to the long-term planning policy. In this case, long-term treatments, i.e., overlays, reconstructions, and concrete materials, are expected to be used more. When the budget level is large, long-term treatments can also be used more.

The only negative factor is the ratio for the concrete pavements in the interstate system. Due to the high traffic volume, it is better to use concrete material due to its long-term durability and high stiffness. Hence, when the ratio for the concrete pavements in the interstate system is large, there is a small improvement by increasing the ratio of concrete pavements, leading to small cost saving due to the long-term planning policy.



(a)



(b)

Figure 5-7. State-level annual cost saving due to long-term planning policy: (a). total saving, (b). unit saving per lane mile.

5.4.4 State-level cost saving due to market diversification

For most existing budget allocation analyses, the influence of market concentration is ignored, namely, the prices of treatment materials are not influenced by the market concentration. However, as shown in Figure 5-3, after being aware of the market concentration, the total vehicle cost saving is about 12.8 billion dollars from year 2017 to 2050. Figure 5-8 shows the annual total cost saving per lane mile for each state. States in the East tend to have large cost savings. The positive factors include the budgets for collector system, and the average IRI for the interstate system. The only negative factor is the cost ratio between concrete and asphalt prices. These factors influence the usage of concrete material, and thus have an impact on the unit prices for both asphalt and concrete materials.

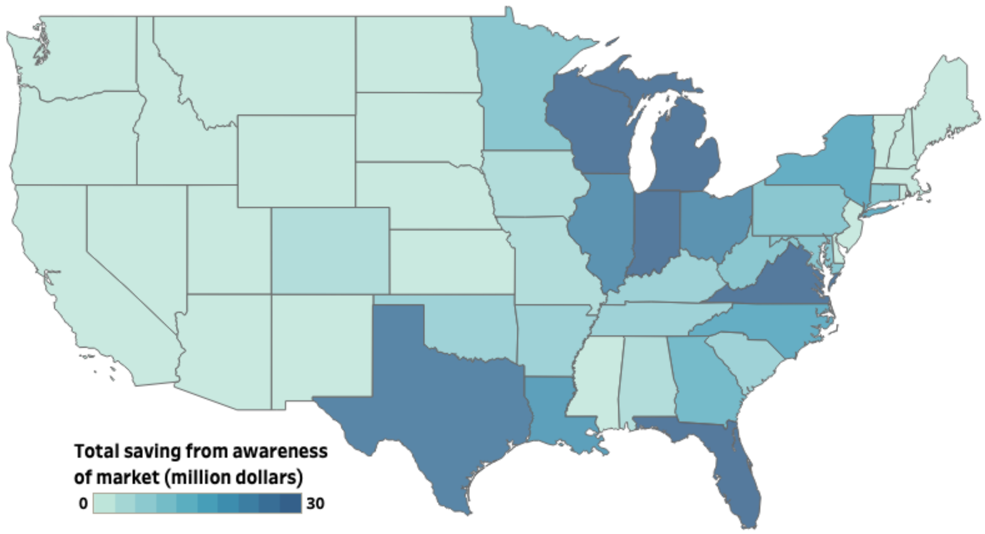


Figure 5-8. State-level annual cost saving per lane mile due to the awareness of market concentration.

Next, by proactively diversifying the paving market, another 8.7 billion dollars for vehicle fuel cost can be saved from 2017 to 2050 as shown in Figure 5-3. Considering different states have different initial conditions and material prices, different states may have different objectives in terms of how much asphalt market share should be decreased. For each state, 5 objectives are compared, including 0%, 5%, 10%, 15% and 20%. The total excess vehicle fuel costs are obtained for each objective, and then the one that provides the smallest excess vehicle fuel cost is considered as the optimal objective. Figure 5-9 shows the optimal objective for each state. All states can benefit from the proactive market diversification, except for the state of Wyoming due to its high concrete price. The main influential factor for the optimal objective is the initial market share for asphalt materials. When the initial market share is large, a state tends to have a large optimal objective.

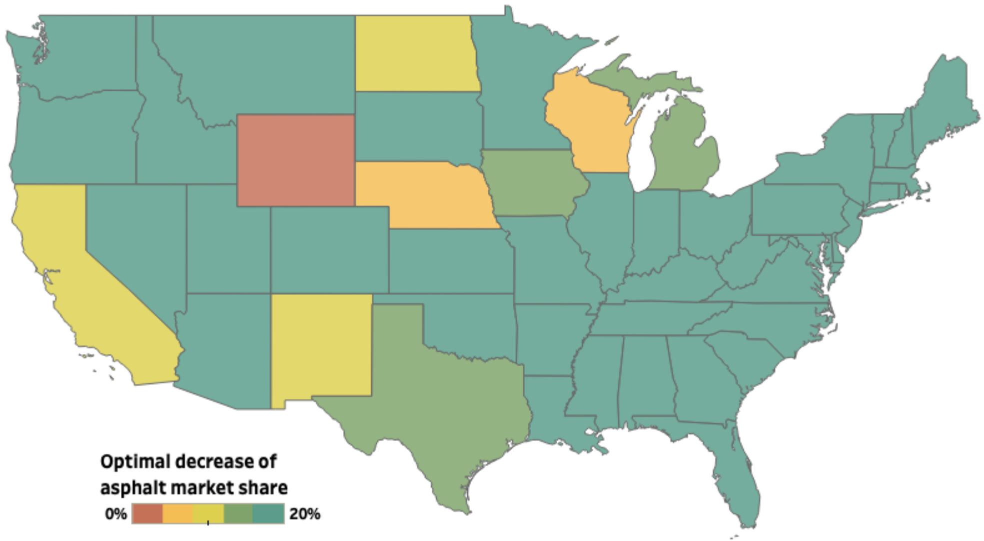


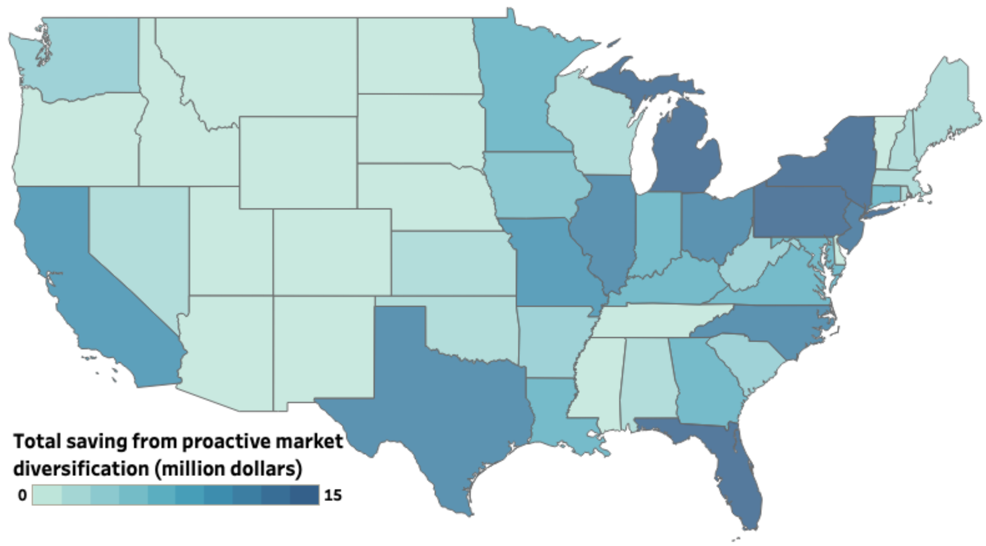
Figure 5-9. Optimal objectives to decrease the asphalt market share for each state.

Figure 5-10(a) shows the annual average total savings due to proactive market diversification for each state in the U.S. There are 4 states whose total annual benefits are larger than 15 million dollars. Figure 5-10(b) shows the annual average savings per lane mile for each state in the U.S. There are 11 states whose annual benefits are larger than \$100 per lane mile. In general, all states except Wyoming can benefit from the proactive market diversification. States in wet freeze climate zone tends to benefit more and states in dry nonfreeze climate zone tend to have small savings.

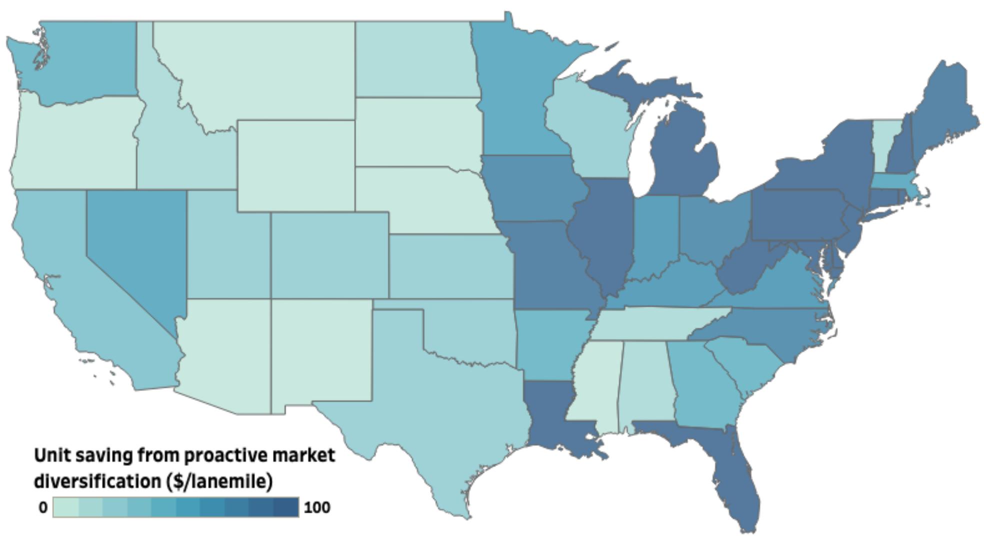
Next, potential factors that influence the magnitude of the benefits due to the proactive market diversification are explored. Potential factors are the same as those introduced in the Section 5.4.2. Rhode Island, New Jersey, and Connecticut are removed from the correlation analysis, whose unit cost savings are larger than \$200 per lane mile.

The positive factors mainly include the average AADT for interstate, arterial, and collector systems, the budget levels for collector system, and the asphalt price. These factors can promote the concrete usage and reduce the market concentration for asphalts.

The negative factor is cost ratio between the concrete and asphalt prices. When this ratio is large, concrete becomes less preferable, and asphalt continues to be dominant in the paving market.



(a)



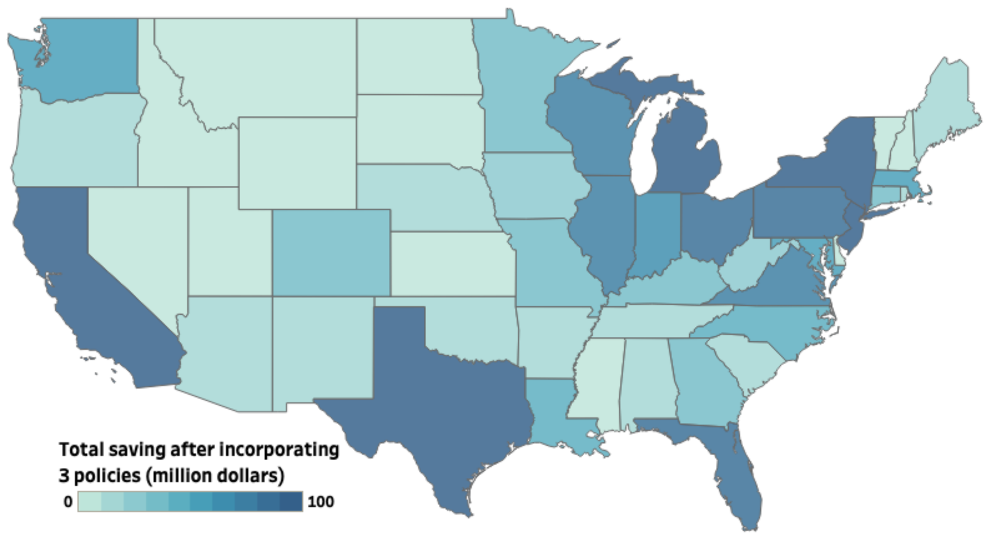
(b)

Figure 5-10. State-level annual cost saving due to the proactive increase of market diversification: (a). total saving, (b). unit saving per lane mile.

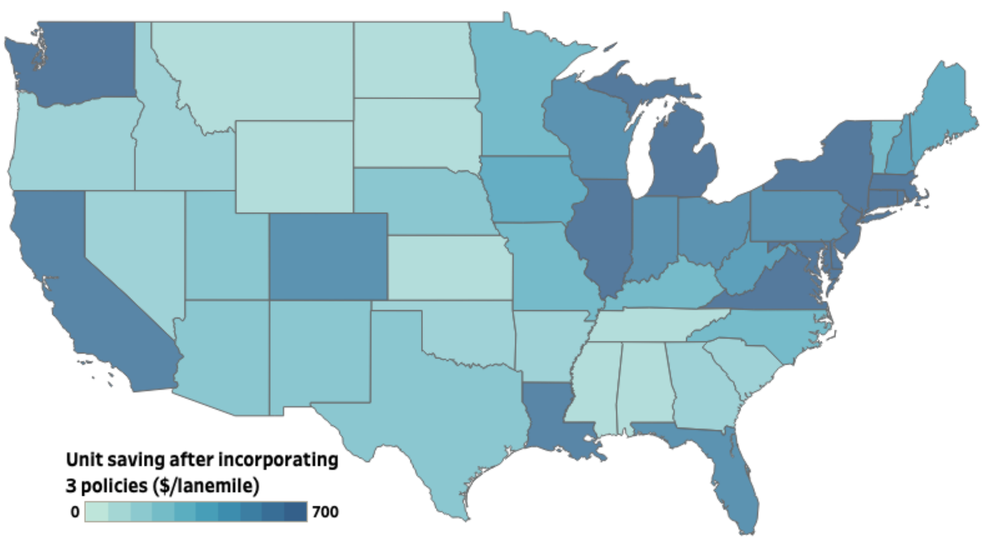
5.4.5 State-level total cost saving

Figure 5-11(a) shows the annual average total savings after incorporating all management policies for each state in the U.S. There are 4 states whose total annual benefits are larger than 100 million dollars. Figure 5-11(b) shows the annual average savings per lane mile for each state in the U.S. There are 8 states whose annual benefits are larger than $700 per lane mile. All states benefit from the proposed management policies. States in the wet freeze climate zone, the state of California, and Washington provide larger unit savings compared to other states.

The influential factors have been discussed in the previous sections. To summarize, positive factors mainly include the average IRI, AADT, asphalt price, and budget levels. The negative factors mainly include cost ratio between concrete and asphalt prices, and the ratio of concrete pavements in the interstate system.



(a)



(b)

Figure 5-11. State-level total annual cost saving: (a). total saving, (b). unit saving per lane mile.

5.5 Conclusions

This chapter has evaluated the benefits of three management policies across the U.S based on five scenarios. Compared to the BAU scenario, after incorporating the policies of decision-making flexibility, long-term planning, and market diversification, the total excess vehicle fuel cost due to PVI can be reduced by 28%, which is approximately 62 billion dollars, for the period from 2017 to 2051. The arterial system provides the largest absolute cost saving of about 40 billion dollars, and the interstate system provides the largest relative cost saving about 52%. These policies also influence the distribution for pavement types. For high-traffic roads (interstate and arterial), the ratio of concrete-surfaced pavements increases from 10% to 59%. For low traffic roads, the ratio increases from 0% to 6%. The increasing usage for concrete materials can provide long-term benefits for the pavement network and decrease the unit prices for both asphalt and concrete materials.

All states can benefit from proposed three management policies. States in the wet freeze climate zone, California and Washington, have larger unit saving per lane mile compared to other states. The positive influential factors include the average IRI, traffic volume, asphalt price, and budget levels. The negative influential factors mainly include the cost ratio between the concrete and asphalt, and the ratio of concrete pavements in the interstate system.

There are several limitations for the analyses. First, the pavement management system data is mainly based on the statistical inference from the FHWA road statistics and LTPP database. Second, due to limited data, states in the same climate zone assume to have the same deterioration rate, and the deterioration model lacks the consideration of the influence of future temperature rise. With a high resolution of data in the future, these limitations could be solved, and a better set of results is expected to be obtained.

CHAPTER 6 CONCLUDING REMARKS AND FUTURE WORK

Performance-based planning is an efficient way to improve pavement networks. By using a robust pavement deterioration model, an efficient budget allocation algorithm, appropriate treatment strategies and management policies, current pavement networks can be improved significantly even within an already tight budget. This chapter summarizes the main conclusions that derive from this thesis as well as its limitations and suggested future work to address those. The answers to research question in Section 1.4 are embedded in the dissertation summary and conclusions.

6.1 Summary and Conclusions

This dissertation presents a comprehensive study of pavement modeling approaches, pavement treatment strategies and management policies, with the ultimate objective of improving performance-based planning and, therefore, pavement networks.

Pavement deterioration prediction model

A new weighted multi-output neutral network model for pavement deterioration prediction has been proposed, which can predict multi pavement condition metrics simultaneously. This model provides convenience for pavement management systems whose treatment decisions are based on composite, multi-condition metrics such as the pavement condition index (PCI). Considering the fact that different condition metrics may have different importance levels, each metric to be predicted must be assigned a weight during the model training process.

Compared to single-output models, an appropriately weighted, multi-output model performs better at estimating PCI (13% lower MSE) than an estimate derived from multiple, individually optimized single-output models. These results make it clear, that multi-output models can improve prediction performance in cases where correlation exists. Furthermore, careful variable weighting is important to achieve the optimal balance of prediction performance among the various metrics.

Budget allocation model

A new probabilistic, bottom-up model for the budget allocation process in pavement management systems has been proposed, which is called the probabilistic treatment path dependence (PTPD) model. PTPD modelling incorporates uncertainty in pavement deterioration, treatment cost and also treatment path dependence brought by future uncertainties. Different from most existing allocation models, the PTPD model evaluates treatments based on both its own immediate benefit and also the expected benefits of its possible subsequent treatments. In this thesis, the evaluation metric used to frame the objective function is the total system cost for given an analysis period, including both agency cost and user cost. In this case, if the price of a treatment action increases, then the model will avoid using this treatment, which is actually the benefit of considering treatment path dependence.

This PTPD model provides a decision-maker an opportunity to control the uncertainty of future pavement networks through a risk-based optimization process. When the risk-aversion coefficient is large, the model tends to choose treatments that provide lower future uncertainties, and the predicted future pavement network has a small performance uncertainty.

Compared to a conventional allocation model based on the benefit-cost ratio (B/C) approach, PTPD yields a better predicted network performance. In the presented case study, to achieve a similar performance level, the B/C model requires a 10 % higher budget to deliver the same average performance over the analysis period and a 17 % higher budget for the end of analysis period. This is partly due to the selection of different types for treatments. The PTPD model tends to use more reconstructions and overlays for the first few years and then shifts to preservations. By doing so, the pavement network can benefit from the long-term treatments and the network condition can be improved gradually.

Pavement treatment strategies

Pavement modeling itself is not enough to improve pavement networks, it is also necessary to consider how the budget allocation problem is framed. In this thesis, the influence of problem framing has been evaluated from both environmental and economic perspectives, in particular framing that can alter the size of the available solution space, on the outcome of performance-based planning for a road network. The problem framing is reflected by different treatment strategies, which are concerned with treatment materials, treatment types and evaluation period.

Results suggest the importance of applying a variety of materials and treatment types and using a long evaluation period to improve predicted pavement network performance and reduce GHG emissions. Compared to commonly used 5-year AC only strategy, the proposed strategy was shown to deliver the same network performance at a budget that was 32% lower and reduce associated GHG emissions by 21%. In addition, due to the use of asphalt materials and thin overlays, even though more treatment actions are applied as budget levels increase, the slight decrease of emissions due to PVI cannot offset the increase of embodied emissions. Based on a sensitivity analysis, the proportions of treatment materials and treatment types found in the optimal solution are influenced by budget levels. Essentially, in optimal solutions, short-term, asphalt treatments are observed to be used more frequently when the budget level is low, and concrete, long-term treatments are observed to used more when the budget level is high.

Pavement management policies

Performance-based planning cannot deliver on its full potential without appropriate pavement management policies. Three management policies were evaluated in this thesis based on the U.S. pavement networks, including decision-making flexibility, long-term planning, and market diversification. Essentially, these policies try to relax selection criteria for pavement treatments, consider long-term performance, and also reduce unit prices for both asphalt and concrete materials.

Compared to the BAU scenario, after incorporating the three proposed policies, the total excess vehicle fuel cost can be reduced by 28%, i.e., 62 billion dollars for the period from 2017 to 2051. Of this, the arterial system provides the largest absolute cost saving of about 40 billion dollars, and the interstate system provides the largest relative cost saving at about 52%. These policies also influence the distribution of pavement types. For high-traffic roads (interstate and arterial), the ratio of concrete-surfaced pavements increases from 10% to 59%. For low traffic roads, the ratio increases from 0% to 6%. The increasing use of concrete materials can provide long-term benefits for pavement networks and decrease the unit prices for both asphalt and concrete materials.

All states can benefit from the proposed policies explored in this thesis. States in the wet freeze climate zone, California, and Washington have larger unit cost savings per lane mile compared to other states. The positive influential factors include the average IRI, traffic volume, asphalt price, and budget levels. The negative influential factors mainly include the cost ratio between concrete and asphalt and the ratio of concrete pavements in the interstate system.

6.2 Limitations and Future Work

The proposed framework for PBP is efficient and feasible to improve current pavement networks. It provides guidance for transportation agencies regarding how to allocate a limited budget more efficiently, and insights for stakeholders as to how to promote appropriate management policies. However, due to the limitation of available data and model algorithms, there are still some limitations for this dissertation work.

Pavement deterioration prediction model

The proposed weighted multi-output neural network model is based on the Markovian assumption, which ignores the historical dependence during the prediction process, namely, the prediction at year t+1 is only based on the information at t. Even though the proposed variables can reflect the treatment history, the prediction algorithm itself cannot incorporate historical dependence.

In order to solve this limitation, the author has developed several recurrent neural networks for IRI, RUT and ACRACK based on the LTPP dataset [162]. These models are all single-output ones. Compared to the conventional feed-forward neural network models (i.e., they are built based on the Markovian assumption), the recurrent neural network models have better prediction performances.

For future work, it is better to build a multi-output recurrent neural network model, which can both incorporate the correlations among different condition metrics, and also consider the historical dependence during the prediction process. In addition, telematics data have attracted more and more attention in both academia and industry (e.g., Carbin developed at CSHub). In the near future, it can be foreseen that there will be prediction models based on telematics-derived data of road condition. Considering the convenience of data collection, it may be necessary to develop some online models for pavement condition prediction.

Budget allocation model

The proposed PTPD model incorporates uncertainties for pavement treatment cost and pavement deterioration. In addition to these two uncertainty sources, there is also budget uncertainty, which can be influenced by economic conditions, or federal and state policies. In a TSBU framework, the budget uncertainty does not influence the evaluation of treatment actions on the segment level. Instead, it influences how many segments can be maintained.

The consideration of uncertainties increases the computational cost. Even though the proposed backtrack algorithm is already very efficient compared to existing algorithms, it is still necessary to improve the calculation process for large-scale analyses.

During the analyses, all segments are assumed to be independent, namely, their relative geographic relationships are ignored. However, in the real-world application, there may exist some constraints about geographic locations. For example, when road segments are maintained, the algorithm should make sure that cars have a reasonable detour route around the roads under repair so that the traffic flow will be not influenced dramatically.

For future work, first, the cost projection model should be updated. The cost projection model applied in this thesis is based on data at least before year 2016. It is better to update the cost projection model based on an updated dataset. Second, the influence of budget uncertainty should be explored. For example, how budget uncertainty influences the selection of treatment materials. Next, considering the huge computational cost from the segment-level analyses, it is suggested to develop a look-up table or a deep learning model to 'memorize' all possible segment-level results. The deep learning model has the capacity to memorize all training data when it is complex enough (i.e., overfitting). Last but not least, the dependences among segments should be incorporated. On the one hand, it would provide insights on treatment feasibility due constraints associated with geographic location. On the other hand, this would also allow the model to incorporate the consideration of economy scale, i.e., the unit price for pavement treatment decreases with an increase in project size.

Pavement treatment strategies

During the evaluation of different treatment strategies, several assumptions are made due to limitations of available data and the PTPD algorithm. First, due to limited records in the Iowa PMS dataset, it is infeasible to develop a robust performance jump model for overlays with different thicknesses, or a model for the preservation. Hence, linear interpolation is applied for overlay models, and the preservation model is based on the LTPP dataset. In the future, with the increasing resolution of Iowa's PMS data, a set of robust performance jump models are expected.

The deterioration model is developed based on the historical PMS data. In the future, with the improvement of material properties for both asphalt and concrete materials, it is necessary to update the deterioration model as well based on the new data in the future.

Pavement management policies

The evaluation of different management policies is based on all states in the U.S. excluding Hawaii and Alaska. However, due to the limitation of available data, the PMS data for each state is sampled based on FHWA road statistics, and age and thickness are statistically inferred from the LTPP dataset. In the future, with the increasing resolution of PMS data for each state, it should be possible to use real data for each road segment. For example, the Carbin tool developed at MIT's CSHub is collecting road condition data across the U.S.

Due to the limited data, in this thesis, only four sets of deterioration models are developed for each climate zone. For future work, to increase the robustness for pavement deterioration prediction, it is better to develop state-specific pavement deterioration models. In addition, applied deterioration models cannot incorporate the influence of climate change, namely, under different climate scenarios, two pavement segments would have the same deterioration rates as long as they have the same age, thickness and traffic volume. Considering the potential for climate change, it is necessary to incorporate temperature and precipitation in the model with the increasing collection of PMS data in the future.

Finally, the improvement of pavement networks should not only rely on this or other research works. It is also necessary and important to communicate research findings with transportation agencies and stakeholders. In the future, some research work should also focus on how to better communicate the value of changing network management practices to key stakeholders.

Bibliography

[1] ASCE, “Failure to act: Economic impacts of status quo investment across infrastructure systems,” Reston, VA, 2021.

[2] ASCE, “2021 Report Card for America’s Infrasturcture,” Reston, VA, 2021.

[3] ASCE, “2017 Report Card for America’s Infrastructure,” Reston, VA, 2017.

[4] S. Madanat, S. Park, and K. Kuhn, “Adaptive optimization and systematic probing of infrastructure system maintenance policies under uncertainty,” *J. Infrastruct. Syst.*, vol. 12, no. 3, pp. 192–198, 2006.

[5] D. C. Baker, N. G. Sipe, and B. J. Gleeson, “Performance-based planning: perspectives from the United States, Australia, and New Zealand,” *J. Plan. Educ. Res.*, vol. 25, no. 4, pp. 396–409, Jun. 2006.

[6] Highway Research Board, “The AASHO Road Test, Special Reports No. 61-AE.,” Washington, D.C., 1962.

[7] Federal Highway Administration, “LTPP InfoPave,” 2019. [Online]. Available: https://infopave.fhwa.dot.gov/. [Accessed: 13-Aug-2019].

[8] M. Ben-Akiva and R. Ramaswamy, “An approach for predicting latent infrastructure facility deterioration,” *Transp. Sci.*, vol. 27, no. 2, pp. 174–193, 1993.

[9] S. Owusu-Ababio, “Effect of neural network topology on flexible pavement cracking prediction,” *Comput. Civ. Infrastruct. Eng.*, vol. 13, no. 5, pp. 349–355, 1998.

[10] C. A. Roberts and N. O. Attoh-Okine, “A comparative analysis of two artificial neural networks using pavement performance prediction,” *Comput. Civ. Infrastruct. Eng.*, vol. 13, no. 5, pp. 339–348, 1998.

[11] S. Inkoom, J. Sobanjo, A. Barbu, and X. Niu, “Prediction of the crack condition of highway pavements using machine learning models,” *Struct. Infrastruct. Eng.*, vol. 15, no. 7, pp. 940–953, 2019.

[12] C. Y. Chu and P. L. Durango-Cohen, “Estimation of infrastructure performance models using state-space specifications of time series models,” *Transp. Res. Part C Emerg. Technol.*, vol. 15, no. 1, pp. 17–32, 2007.

[13] F. Hong and J. A. Prozzi, “Roughness model accounting for heterogeneity based on in-service pavement performance data,” *J. Transp. Eng.*, vol. 136, no. 3, pp. 205–213, 2010.

[14] J. Yu, E. Y. Chou, and Z. Luo, “Development of linear mixed effects models for predicting individual pavement conditions,” *J. Transp. Eng.*, vol. 133, no. 6, pp. 347–354, 2007.

[15] F. D. Rosa, L. Liu, M. Asce, N. G. Gharaibeh, and M. Asce, “IRI prediction model for use in network-level pavement management systems,” *J. Transp. Eng. Part B Pavements*, vol. 143, no. 1, pp. 1–8, 2017.

[16] C. Liu, D. Wu, Y. Li, and Y. Du, “Large-scale pavement roughness measurements with vehicle crowdsourced data using semi-supervised learning,” *Transp. Res. Part C Emerg. Technol.*, vol. 125, 2021.

[17] M. Botshekan, E. Asaadi, J. Roxon, F.-J. Ulm, M. Tootkaboni, and A. Louhghalam, "Smartphone-enabled road condition monitoring: from accelerations to road roughness and excess energy dissipation," *Proc. R. Soc. A Math. Phys. Eng. Sci.*, vol. 477, no. 2246, p. 20200701, 2021.

[18] M. Botshekan *et al.*, "Roughness-induced vehicle energy dissipation from crowdsourced smartphone measurements through random vibration theory," *Data-Centric Eng.*, vol. 1, 2020.

[19] A. Skar and E. Levenberg, "Live road condition assessment with in-vehicle sensors," in *Transportation Research Board 2021 Annual Meeting*, 2021.

[20] Oman Systems Inc, "Bid Table," Nasheville, TN, 2020.

[21] O. Swei, J. Gregory, and R. Kirchain, "Does pavement degradation follow a random walk with drift? Evidence from variance ratio tests for pavement roughness," *J. Infrastruct. Syst.*, vol. 24, no. 4, p. 04018027, Dec. 2018.

[22] M. Mahmood, M. Rahman, and S. Mathavan, "A multi-input deterioration-prediction model for asphalt road networks," *Proc. Inst. Civ. Eng. - Transp.*, vol. 172, no. 1, pp. 12–23, 2019.

[23] American Association of State Highway and Transportation Officials, "AASHTO guide for design of pavement structures," Washington, DC, 1993.

[24] American Association of State Highway and Transportation Officials, "Mechanistic-empirical pavement design guide. A manual of practice," Washington, D.C., 2008.

[25] G. Lamptey, S. Labi, and Z. Li, "Decision support for optimal scheduling of highway pavement preventive maintenance within resurfacing cycle," *Decis. Support Syst.*, vol. 46, no. 1, pp. 376–387, Dec. 2008.

[26] Z. Lou, M. Gunaratne, J. J. Lu, and B. Dietrich, "Application of neural network model to forecast short-term pavement crack condition: Florida case study," *J. Infrastruct. Syst.*, vol. 7, no. 4, pp. 166–171, 2001.

[27] B. J. Lee and H. D. Lee, "Position-invariant neural network for digital pavement crack analysis," *Comput. Civ. Infrastruct. Eng.*, vol. 19, no. 2, pp. 105–118, 2004.

[28] D. T. Thube, "Artificial neural network (ANN) based pavement deterioration models for low volume roads in India," *Int. J. Pavement Res. Technol.*, vol. 5, no. 2, pp. 115–120, 2012.

[29] H. Gong, Y. Sun, W. Hu, and B. Huang, "Neural networks for fatigue cracking prediction using outputs from pavement mechanistic-empirical design," *Int. J. Pavement Eng.*, 2019.

[30] M. Mazari and D. D. Rodriguez, "Prediction of pavement roughness using a hybrid gene expression programming-neural network technique," *J. Traffic Transp. Eng. (English Ed.*, vol. 3, no. 5, pp. 448–455, 2016.

[31] Nii O. Attoh-Okine, "Predicting roughness progression in flexible pavements using artificial neural networks," in *3rd International Conference on Managing Pavements*, 1994.

[32] F. Guo, X. Zhao, J. Gregory, and R. Kirchain, "A weighted multi-output neural network model for the prediction of rigid pavement deterioration," *Int. J. Pavement Eng.*, pp. 1–13, 2021.

[33] H. Gong, Y. Sun, W. Hu, P. A. Polaczyk, and B. Huang, "Investigating impacts of asphalt

mixture properties on pavement performance using LTPP data through random forests," *Constr. Build. Mater.*, vol. 204, pp. 203–212, Apr. 2019.

[34] N. F. Pan, C. H. Ko, M. Der Yang, and K. C. Hsu, "Pavement performance prediction through fuzzy regression," *Expert Syst. Appl.*, vol. 38, no. 8, pp. 10010–10017, 2011.

[35] J. Santos, A. Ferreira, and G. Flintsch, "An adaptive hybrid genetic algorithm for pavement management," *Int. J. Pavement Eng.*, vol. 20, no. 3, pp. 266–286, 2019.

[36] O. Swei, J. Gregory, and R. Kirchain, "Probabilistic life-cycle cost analysis of pavements," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2523, no. 2523, pp. 47–55, 2015.

[37] J. Santos and A. Ferreira, "Life-cycle cost analysis system for pavement management at project level," *Int. J. Pavement Eng.*, vol. 14, no. 1, pp. 71–84, 2013.

[38] F. Guo, J. Gregory, and R. Kirchain, "Probabilistic life-cycle cost analysis of pavements based on simulation optimization," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2673, no. 5, pp. 389–396, May 2019.

[39] N. J. Santero, E. Masanet, and A. Horvath, "Life-cycle assessment of pavements. Part I: Critical review," *Resour. Conserv. Recycl.*, vol. 55, no. 9–10, pp. 801–809, 2011.

[40] J. Santos, A. Ferreira, and G. Flintsch, "A life cycle assessment model for pavement management: methodology and computational framework," *Int. J. Pavement Eng.*, vol. 16, no. 3, pp. 268–286, Mar. 2015.

[41] A. Noshadravan, M. Wildnauer, J. Gregory, and R. Kirchain, "Comparative pavement life cycle assessment with parameter uncertainty," *Transp. Res. Part D Transp. Environ.*, vol. 25, pp. 131–138, Dec. 2013.

[42] H. Azarijafari, A. Yahia, and M. Ben Amor, "Life cycle assessment of pavements: Reviewing research challenges and opportunities," *Journal of Cleaner Production*, vol. 112. Elsevier Ltd, pp. 2187–2197, 20-Jan-2016.

[43] K. Golabi, R. B. Kulkarni, and G. B. Way, "A statewide pavement management system," *Interfaces (Providence).*, vol. 12, no. 6, pp. 5–21, 1982.

[44] P. L. Durango and S. M. Madanat, "Optimal maintenance and repair policies in infrastructure management under uncertain facility deterioration rates: An adaptive control approach," *Transp. Res. Part A Policy Pract.*, vol. 36, no. 9, pp. 763–778, 2002.

[45] J. Lee, S. Madanat, and D. Reger, "Pavement systems reconstruction and resurfacing policies for minimization of life-cycle costs under greenhouse gas emissions constraints," *Transp. Res. Part B Methodol.*, vol. 93, pp. 618–630, 2016.

[46] Q. Bai, S. Labi, and K. C. Sinha, "Trade-off analysis for multiobjective optimization in transportation asset management by generating pareto frontiers using extreme points nondominated sorting genetic algorithm II," *J. Transp. Eng.*, vol. 138, no. 6, pp. 798–808, Jun. 2012.

[47] K. D. Kuhn and S. M. Madanat, "Model uncertainty and the management of a system of infrastructure facilities," *Transp. Res. Part C Emerg. Technol.*, vol. 13, no. 5–6, pp. 391–404, 2005.

[48] G. Morcous and Z. Lounis, "Maintenance optimization of infrastructure networks using

genetic algorithms," *Autom. Constr.*, vol. 14, no. 1, pp. 129–142, Jan. 2005.

[49] K. Murakami and M. A. Turnquist, "Dynamic model for scheduling maintenance of transportation facilities," in *Transportation Research Record*, 1985, no. 1030, pp. 8–14.

[50] F. Hong, E. Perrone, M. Mikhail, and A. Eltahan, "Planning pavement maintenance and rehabilitation projects in the new pavement management system in Texas," in *Transportation Research Board TRB 2017 Annual Meeting*, 2017, pp. 1–22.

[51] A. Ahmed, S. Labi, Z. Li, and T. Shields, "Aggregate and disaggregate statistical evaluation of the performance-based effectiveness of long-term pavement performance specific pavement study-5 (LTPP SPS-5) flexible pavement rehabilitation treatments," *Struct. Infrastruct. Eng.*, vol. 9, no. 2, pp. 172–187, Nov. 2013.

[52] C. Torres-Machi, A. Chamorro, C. Videla, E. Pellicer, and V. Yepes, "An iterative approach for the optimization of pavement maintenance management at the network level," *Sci. World J. Artic.*, vol. 2014, pp. 1–11, 2014.

[53] O. Swei, J. Gregory, and R. Kirchain, "Embedding flexibility within pavement management: a technique to improve expected performance of roadway systems," *J. Infrastruct. Syst.*, vol. 25, no. 3, p. 05019007, 2019.

[54] J. Santos, A. Ferreira, and G. Flintsch, "A multi-objective optimization-based pavement management decision-support system for enhancing pavement sustainability," *J. Clean. Prod.*, vol. 164, pp. 1380–1393, Oct. 2017.

[55] F. Guo, J. Gregory, and R. Kirchain, "Incorporating cost uncertainty and path dependence into treatment selection for pavement networks," *Transp. Res. Part C Emerg. Technol.*, vol. 110, pp. 40–55, 2020.

[56] M. Bektas, Fatih; Smadi, Omar G.; and Al-Zoubi, "Pavement management performance modeling: evaluating the existing PCI equations," 2014.

[57] H. Yeo, Y. Yoon, and S. Madanat, "Maintenance optimization for heterogeneous infrastructure systems: evolutionary algorithms for bottom-up methods," in *Sustainable and Resilient Critical Infrastructure Systems*, Berlin, Heidelberg: Springer, 2010, pp. 185–199.

[58] G. Zhou and L. Wang, "Co-location decision tree for enhancing decision-making of pavement maintenance and rehabilitation," *Transp. Res. Part C Emerg. Technol.*, vol. 21, no. 1, pp. 287–305, 2012.

[59] T. Fwa, W. Chan, and C. Tan, "Genetic-algorithm programming of road maintenance and rehabilitation," *J. Transp. Eng.*, vol. 122, no. 3, pp. 246–253, 1996.

[60] J. R. Menendez and N. G. Gharaibeh, "Incorporating risk and uncertainty into infrastructure asset management plans for pavement networks," *J. Infrastruct. Syst.*, vol. 23, no. 4, p. 04017019, 2017.

[61] M. Irfan, M. B. Khurshid, S. Labi, and W. Flora, "Evaluating the cost effectiveness of flexible rehabilitation treatments using different performance criteria," *J. Transp. Eng.*, vol. 135, no. 10, pp. 753–763, Oct. 2009.

[62] M. B. Khurshid, M. Irfan, and S. Labi, "An analysis of the cost-effectiveness of rigid pavement rehabilitation treatments," *Struct. Infrastruct. Eng.*, vol. 7, no. 9, pp. 715–727,

Sep. 2011.

[63] M. B. Khurshid, M. Irfan, A. Ahmed, and S. Labi, “Multidimensional benefit-cost evaluation of asphaltic concrete overlays of rigid pavements,” *Struct. Infrastruct. Eng.*, vol. 10, no. 6, pp. 792–810, Jun. 2014.

[64] Q. Bai, A. Ahmed, Z. Li, and S. Labi, “A hybrid pareto frontier generation method for trade-off analysis in transportation asset management,” *Comput. Civ. Infrastruct. Eng.*, vol. 30, no. 3, pp. 163–180, Mar. 2015.

[65] Q. Bai, S. Labi, K. C. Sinha, and P. D. Thompson, “Multiobjective optimization for project selection in network-level bridge management incorporating decision-maker’s preference using the concept of holism,” *J. Bridg. Eng.*, vol. 18, no. 9, pp. 879–889, Sep. 2013.

[66] H. Yeo, Y. Yoon, and S. Madanat, “Algorithms for bottom-up maintenance optimisation for heterogeneous infrastructure systems,” *Struct. Infrastruct. Eng.*, vol. 9, no. 4, pp. 317–328, 2013.

[67] L. Zhang, L. Fu, W. Gu, Y. Ouyang, and Y. Hu, “A general iterative approach for the system-level joint optimization of pavement maintenance, rehabilitation, and reconstruction planning,” *Transp. Res. Part B Methodol.*, vol. 105, pp. 378–400, 2017.

[68] J. Lee and S. Madanat, “A joint bottom-up solution methodology for system-level pavement rehabilitation and reconstruction,” *Transp. Res. Part B Methodol.*, vol. 78, pp. 106–122, Aug. 2015.

[69] L. Gao, C. Xie, Z. Zhang, and S. T. Waller, “Network-level road pavement maintenance and rehabilitation scheduling for optimal performance improvement and budget utilization,” *Comput. Civ. Infrastruct. Eng.*, vol. 27, no. 4, pp. 278–287, 2012.

[70] B. K. A. Abaza, S. A. Ashur, S. A. Abu-eisheh, and A. Rabay, “Macroscopic optimum system for management of pavement rehabilitation,” *J. Transp. Eng.*, vol. 127, no. 6, pp. 493–500, 2001.

[71] F. Wang, Z. Zhang, and R. Machemehl, “Decision-making problem for managing pavement maintenance and rehabilitation projects,” *Transp. Res. Rec. J. Transp. Res. Board*, vol. 1853, no. 1, pp. 21–28, 2003.

[72] M. Ng, Z. Zhang, and S. Travis Waller, “The price of uncertainty in pavement infrastructure management planning: An integer programming approach,” *Transp. Res. Part C Emerg. Technol.*, vol. 19, no. 6, pp. 1326–1338, 2011.

[73] J. C. Chu and K.-H. Huang, “Mathematical programming framework for modeling and comparing network-level pavement maintenance strategies,” *Transp. Res. Part B Methodol.*, vol. 109, pp. 1–25, 2018.

[74] W. T. Chan, T. F. Fwa, and K. Zahidul Hoque, “Constraint handling methods in pavement maintenance programming,” *Transp. Res. Part C Emerg. Technol.*, vol. 9, no. 3, pp. 175–190, 2001.

[75] K. C. Sinha, S. Labi, and Q. Bai, “Uncertainties in transportation infrastructure development and management,” in *Proceedings of the International Symposium on Engineering under Uncertainty: Safety Assessment and Management (ISEUSAM - 2012)*, India: Springer India, 2013, pp. 55–71.

[76] P. Chootinan, A. Chen, M. R. Horrocks, and D. Bolling, "A multi-year pavement maintenance program using a stochastic simulation-based genetic algorithm approach," *Transp. Res. Part A Policy Pract.*, vol. 40, no. 9, pp. 725–743, 2006.

[77] A. Medury and S. Madanat, "Incorporating network considerations into pavement management systems: A case for approximate dynamic programming," *Transp. Res. Part C Emerg. Technol.*, vol. 33, pp. 134–150, 2013.

[78] A. Medury and S. Madanat, "Simultaneous network optimization approach for pavement management systems," *J. Infrastruct. Syst.*, vol. 20, no. 3, pp. 1–7, 2014.

[79] M. Ben-Akiva, F. Humplick, S. M. Madanat, and R. Ramaswamy, "Infrastructure management under uncertainty: Latent performance approach," *J. Transp. Eng.*, vol. 119, no. 1, pp. 43–58, 1993.

[80] S. Madanat, "Optimal infrastructure management decisions under uncertainty," *Transp. Res. Part C*, vol. 1, no. 1, pp. 77–88, 1993.

[81] O. Swei, J. Gregory, and R. Kirchain, "Probabilistic approach for long-run price projections: case study of concrete and asphalt," *J. Constr. Eng. Manag.*, vol. 143, no. 1, p. 05016018, Jan. 2016.

[82] W. B. Powell, *Approximate dynamic programming : solving the curses of dimensionality*, Second Edi. New Jersey: A JOHN WILEY & SONS, INC., PUBLICATION, 2011.

[83] P. L. Durango-Cohen and P. Sarutipand, "Maintenance optimization for transportation systems with demand responsiveness," *Transp. Res. Part C Emerg. Technol.*, vol. 17, no. 4, pp. 337–348, Aug. 2009.

[84] P. Durango-Cohen and P. Sarutipand, "Multi-facility maintenance optimization with coordinated interventions," in *Proceedings of the Eleventh World Conference on Transport Research*, 2007.

[85] P. L. Durango-Cohen and P. Sarutipand, "Capturing interdependencies and heterogeneity in the management of multifacility transportation infrastructure systems," *J. Infrastruct. Syst.*, vol. 13, no. 2, pp. 115–123, 2007.

[86] P. L. Durango-Cohen and N. Tadepalli, "Using advanced inspection technologies to support investments in maintenance and repair of transportation infrastructure facilities," *J. Transp. Eng.*, vol. 132, no. 1, pp. 60–68, Jan. 2006.

[87] Z. Wu, G. W. Flintsch, and M. Asce, "Pavement preservation optimization considering multiple objectives and budget variability," *J. Transp. Eng.*, vol. 135, no. 5, pp. 305–315, 2009.

[88] O. Swei, T. R. Miller, M. Akbarian, J. Gregory, and R. Kirchain, "Effects of market concentration and competition in the paving sector."

[89] K. Kobayashi, K. Kaito, and N. Lethanh, "A statistical deterioration forecasting method using hidden Markov model for infrastructure management," *Transp. Res. Part B Methodol.*, vol. 46, no. 4, pp. 544–561, 2012.

[90] N. Lethanh and B. T. Adey, "Use of exponential hidden Markov models for modelling pavement deterioration," *Int. J. Pavement Eng.*, vol. 14, no. 7, pp. 645–654, 2013.

[91] J. A. Prozzi and S. Madanat, "Development of pavement performance models by combining experimental and field data sets," *J. Infrastruct. Syst.*, vol. 10, no. 1, pp. 9–22, 2004.

[92] J. H. Choi, T. M. Adams, and H. U. Bahia, "Pavement roughness modeling using back-propagation neural networks," *Comput. Civ. Infrastruct. Eng.*, vol. 19, no. 4, pp. 295–303, 2004.

[93] M. I. Hossain, L. S. P. Gopisetti, and M. S. Miah, "International roughness index prediction of flexible pavements using neural networks," *J. Stomatol.*, vol. 145, no. 1, 2019.

[94] H. P. Hong and S. S. Wang, "Stochastic modeling of pavement performance," *Int. J. Pavement Eng.*, vol. 4, no. 4, pp. 235–243, 2003.

[95] K. A. Abaza, "Back-calculation of transition probabilities for Markovian-based pavement performance prediction models," *Int. J. Pavement Eng.*, vol. 17, no. 3, pp. 253–264, 2016.

[96] J. A. Prozzi and S. M. Madanat, "Incremental nonlinear model for predicting pavement serviceability," *J. Transp. Eng.*, vol. 129, no. 6, pp. 635–641, 2003.

[97] W. Zhang and P. L. Durango-Cohen, "Explaining heterogeneity in pavement deterioration: clusterwise linear regression model," *J. Infrastruct. Syst.*, vol. 20, no. 2, p. 04014005, 2013.

[98] M. J. Heidari, A. Najafi, and S. Alavi, "Pavement deterioration modeling for forest roads based on logistic regression and artificial neural networks," *Croat. J. For. Eng.*, vol. 39, no. 2, pp. 271–287, 2018.

[99] X. Chen, Q. Dong, X. Gu, and Q. Mao, "Bayesian analysis of pavement maintenance failure probability with Markov chain Monte Carlo simulation," *J. Transp. Eng. Part B Pavements*, vol. 145, no. 2, p. 04019001, 2019.

[100] K. A. Abaza, "Deterministic performance prediction model for rehabilitation and management of flexible pavement," *Int. J. Pavement Eng.*, vol. 5, no. 2, pp. 111–121, 2004.

[101] F. Hong and J. A. Prozzi, "Estimation of pavement performance deterioration using Bayesian approach," *J. Infrastruct. Syst.*, vol. 12, no. 2, pp. 77–86, 2006.

[102] J. P. Aguiar-Moya, J. A. Prozzi, and A. de Fortier Smit, "Mechanistic-empirical IRI model accounting for potential bias," *J. Transp. Eng.*, vol. 137, no. 5, pp. 297–304, 2011.

[103] N. O. Attoh-Okine, S. Mensah, and M. Nawaiseh, "A new technique for using multivariate adaptive regression splines (MARS) in pavement roughness prediction," *Proc. Inst. Civ. Eng. - Transp.*, vol. 156, no. 1, pp. 51–55, 2003.

[104] A. Bianchini and P. Bandini, "Prediction of pavement performance through neuro-fuzzy reasoning," *Comput. Civ. Infrastruct. Eng.*, vol. 25, no. 1, pp. 39–54, 2010.

[105] A. G. Karlaftis and A. Badr, "Predicting asphalt pavement crack initiation following rehabilitation treatments," *Transp. Res. Part C Emerg. Technol.*, vol. 55, pp. 510–517, 2015.

[106] L. Yao, Q. Dong, J. Jiang, and F. Ni, "Establishment of prediction models of asphalt pavement performance based on a novel data calibration method and neural network," *Transp. Res. Rec.*, vol. 2673, no. 1, pp. 66–82, 2019.

[107] N. Kargah-Ostadi, S. M. Stoffels, and N. Tabatabaee, "Network-level pavement roughness prediction model for rehabilitation recommendations," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2155, pp. 124–133, 2010.

[108] G. Press, "Cleaning big data: most time-consuming, least enjoyable data science task, survey says," *Forbes*, 23-Mar-2016.

[109] Federal Highway Administration, "Highway Statistics 2017," 2017. [Online]. Available: https://www.fhwa.dot.gov/policyinformation/statistics/2017/. [Accessed: 13-Aug-2019].

[110] "Iowa DOT Open Data." [Online]. Available: https://data.iowadot.gov/datasets/. [Accessed: 30-Jul-2019].

[111] C. Y. Chu and P. L. Durango-Cohen, "Estimation of dynamic performance models for transportation infrastructure using panel data," *Transp. Res. Part B Methodol.*, vol. 42, no. 1, pp. 57–81, 2008.

[112] J. A. Rice, *Mathematical Statistics and Data Analysis*. Belmont, CA, USA: Cengage Learning, 2006.

[113] C. M. Bishop, *Pattern recognition and machine learning (Information Science and Statistics)*. Secaucus, NJ, USA: Springer-Verlag New York, Inc., 2006.

[114] J. Heaton, *Introduction to neural networks for Java, 2nd Edition*, vol. 99. Chesterfield, MO, USA: Heaton Research, Inc., 2008.

[115] J. Lee and S. Madanat, "Jointly optimal policies for pavement maintenance, resurfacing and reconstruction," *EURO J. Transp. Logist.*, vol. 4, no. 1, pp. 75–95, Mar. 2015.

[116] P. L. Durango-Cohen, "A time series analysis framework for transportation infrastructure management," *Transp. Res. Part B Methodol.*, vol. 41, no. 5, pp. 493–505, 2007.

[117] J. Yoo and A. Garcia-Diaz, "Cost-effective selection and multi-period scheduling of pavement maintenance and rehabilitation strategies," *Eng. Optim.*, vol. 40, no. 3, pp. 205–222, Mar. 2008.

[118] L. Yao, Q. Dong, J. Jiang, and F. Ni, "Deep reinforcement learning for long-term pavement maintenance planning," *Comput. Civ. Infrastruct. Eng.*, vol. 35, no. 11, pp. 1230–1245, 2020.

[119] S. Renard, B. Corbett, and O. Swei, "Minimizing the global warming impact of pavement infrastructure through reinforcement learning," *Resour. Conserv. Recycl.*, vol. 167, p. 105240, Apr. 2020.

[120] O. Swei, "Forecasting infidelity: why current methods for predicting costs miss the mark," *J. Constr. Eng. Manag.*, 2019.

[121] O. Swei, "Long-run construction cost trends: Baumol's cost disease and a disaggregate look at building material price dynamics," *J. Constr. Eng. Manag.*, vol. 144, no. 7, p. 04018058, Jul. 2018.

[122] S. M. Shahandashti and B. Ashuri, "Forecasting engineering news-record construction cost index using multivariate time series models," *J. Constr. Eng. Manag.*, vol. 139, no. 9, pp. 1237–1243, Sep. 2013.

[123] V. P. Deshpande, I. D. Damnjanovic, and P. Gardoni, "Reliability-based optimization models for scheduling pavement rehabilitation," *Comput. Civ. Infrastruct. Eng.*, vol. 25, no. 4, pp. 227–237, May 2010.

[124] Y. Lee, A. Mohseni, and M. Darter, "Simplified pavement performance models," *Transp.*

Res. Rec., vol. 1397, pp. 7–14, 1993.

[125] M. C. Fu, "Optimization for simulation: Theory vs. Practice," *INFORMS J. Comput.*, vol. 14, no. 3, pp. 192–215, Aug. 2003.

[126] A. Furuya and S. Madanat, "Accounting for network effects in railway asset management," *J. Transp. Eng.*, vol. 139, no. 1, pp. 92–100, 2013.

[127] Y. Yin, S. Lawphongpanich, and Y. Lou, "Estimating investment requirement for maintaining and improving highway systems," *Transp. Res. Part C Emerg. Technol.*, vol. 16, no. 2, pp. 199–211, 2008.

[128] A. Louhghalam, M. Akbarian, and F. J. Ulm, "Carbon management of infrastructure performance: Integrated big data analytics and pavement-vehicle-interactions," *J. Clean. Prod.*, vol. 142, pp. 956–964, 2017.

[129] O. Swei, "Material diversification in pavement management: A technique to proactively deal with an uncertain future," MIT, 2016.

[130] S. W. Golomb and L. D. Baumert, "Backtrack programming," *J. ACM*, vol. 12, no. 4, pp. 516–524, Oct. 1965.

[131] J. J. McGregor, "Backtrack search algorithms and the maximal common subgraph problem," *Softw. Pract. Exp.*, vol. 12, no. 1, pp. 23–34, Jan. 1982.

[132] M. Irfan, M. B. Khurshid, Q. Bai, S. Labi, and T. L. Morin, "Establishing optimal project-level strategies for pavement maintenance and rehabilitation – A framework and case study," *Eng. Optim.*, vol. 44, no. 5, pp. 565–589, May 2012.

[133] H. M. Markowitz, "Portfolio selection," *Finance*, vol. 7, no. 1, pp. 77–91, 1952.

[134] M. Irfan, M. B. Khurshid, A. Ahmed, and S. Labi, "Scale and condition economies in asset preservation cost functions: Case study involving flexible pavement treatments," *J. Transp. Eng.*, vol. 138, no. 2, pp. 218–228, Feb. 2012.

[135] Office of Management and Budget, "Circular A-94 Guidelines and discount rates for benefit-cost analysis of federal programs," 2019.

[136] R. Denysiuk, A. V. Moreira, J. C. Matos, J. R. M. Oliveira, and A. Santos, "Two-stage multiobjective optimization of maintenance scheduling for pavements," *J. Infrastruct. Syst.*, vol. 23, no. 3, p. 04017001, 2017.

[137] C. Torres-Machi, E. Pellicer, V. Yepes, and A. Chamorro, "Towards a sustainable optimization of pavement maintenance programs under budgetary restrictions," *J. Clean. Prod.*, vol. 148, pp. 90–102, Apr. 2017.

[138] M. Akbarian, J. Gregory, R. Kirchain, and F.-J. Ulm, "Economic and environmental analysis of pavement management system parameters for performance based planning opportunities: A case study of North Carolina's interstate system," in *Transportation Research Board TRB 2019 Annual Meeting*, 2019.

[139] F. Guo, J. Gregory, and R. Kirchain, "Exploration of treatment strategies in pavement management system: A case study of Iowa's interstate system," in *Transportation Research Board 2020 Annual Meeting*, 2020.

[140] D. Chong, Y. Wang, Z. Dai, X. Chen, D. Wang, and M. Oeser, "Multiobjective optimization

of asphalt pavement design and maintenance decisions based on sustainability principles and mechanistic-empirical pavement analysis," *Int. J. Sustain. Transp.*, pp. 1–12, 2018.

[141] R. Liu, B. W. Smartz, and B. Descheneaux, "LCCA and environmental LCA for highway pavement selection in Colorado," *Int. J. Sustain. Eng.*, vol. 8, no. 2, pp. 102–110, 2015.

[142] B. Yu, Q. Lu, and J. Xu, "An improved pavement maintenance optimization methodology: Integrating LCA and LCCA," *Transp. Res. Part A*, vol. 55, pp. 1–11, 2013.

[143] J. Lee and S. Madanat, "Optimal policies for greenhouse gas emission minimization under multiple agency budget constraints in pavement management," *Transp. Res. Part D Transp. Environ.*, vol. 55, pp. 39–50, Aug. 2017.

[144] D. Reger, S. Madanat, and A. Horvath, "The effect of agency budgets on minimizing greenhouse gas emissions from road rehabilitation policies," *Environ. Res. Lett.*, vol. 10, no. 11, 2015.

[145] J. France-Mensah and W. J. O'Brien, "Developing a sustainable pavement management plan: tradeoffs in road condition, user costs, and greenhouse gas emissions," *J. Manag. Eng.*, vol. 35, no. 3, p. 04019005, May 2019.

[146] EIA, "Light-Duty Vehicle Miles Traveled by Technology Type." [Online]. Available: https://www.eia.gov/outlooks/aeo/data/browser/#/?id=51-AEO2020&cases=ref2020&sourcekey=0. [Accessed: 01-Sep-2019].

[147] D. Wu *et al.*, "Regional heterogeneity in emissions benefits of electrified and lightweighted light-duty vehicles," *Environ. Sci. Technol.*, vol. 53, no. 18, pp. 10560–10570, 2019.

[148] H. AzariJafari, J. Gregory, and R. Kirchain, "Potential Contribution of Deflection-Induced Fuel Consumption to U.S. Greenhouse Gas Emissions," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2674, no. 8, pp. 931–937, Aug. 2020.

[149] M. Akbarian, S. S. Moeini-Ardakani, F.-J. Ulm, and M. Nazzal, "Mechanistic approach to pavement-vehicle interaction and its impact on life-cycle assessment," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2306, pp. 171–179, 2012.

[150] X. Xu, M. Akbarian, J. Gregory, and R. Kirchain, "Role of the use phase and pavement-vehicle interaction in comparative pavement life cycle assessment as a function of context," *J. Clean. Prod.*, vol. 230, pp. 1156–1164, Sep. 2019.

[151] A. Louhghalam, M. Akbarian, and F.-J. Ulm, "Scaling relationships of dissipation-induced pavement–vehicle interactions," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2457, no. 1, pp. 95–104, Jan. 2014.

[152] I. Zaabar and K. Chatti, "Estimating vehicle operating costs caused by pavement surface conditions," *Transp. Res. Rec.*, vol. 2455, pp. 63–76, 2014.

[153] "AAA Gas Prices." [Online]. Available: https://gasprices.aaa.com/. [Accessed: 20-May-2020].

[154] NAPA, "Asphalt Pavement Industry Survey on Recycled Materials and Warm-Mix Asphalt Usage," 2018.

[155] NRMCA, "Sustainability: Industry-average EPD program," 2020. [Online]. Available: https://www.nrmca.org/sustainability/EPDProgram/. [Accessed: 01-Apr-2020].

[156] EPA, "Greenhouse gas emissions from a typical passenger vehicle." [Online]. Available: https://www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle. [Accessed: 20-May-2020].

[157] X. Xu, O. Swei, L. Xu, C. A. Schlosser, J. Gregory, and R. Kirchain, "Quantifying Location-Specific Impacts of Pavement Albedo on Radiative Forcing Using an Analytical Approach," *Environ. Sci. Technol.*, vol. 54, no. 4, pp. 2411–2421, 2020.

[158] P. G. Carr, "Investigation of Bid Price Competition Measured through Prebid Project Estimates, Actual Bid Prices, and Number of Bidders," *J. Constr. Eng. Manag.*, vol. 131, no. 11, pp. 1165–1172, Nov. 2005.

[159] P. P. Shrestha and N. Pradhananga, "Correlating bid price with the number of bidders and final construction cost of public street projects," *Transp. Res. Rec.*, no. 2151, pp. 3–10, Jan. 2010.

[160] EIA, "State Electricity Profiles," 2020. [Online]. Available: https://www.eia.gov/electricity/state/. [Accessed: 02-Feb-2021].

[161] EIA, "Energy Prices by Sector and Source," 2021. [Online]. Available: https://www.eia.gov/outlooks/aeo/data/browser/#/?id=3-AEO2021&cases=ref2021&sourcekey=0. [Accessed: 06-May-2021].

[162] F. Guo, J. Gregory, and R. Kirchain, "Comparison of feedforward and recurrent neural networks for predicting pavement roughness," in *Transportation Research Board TRB 2021 Annual Meeting*, 2021.

[163] C. R. Bennett and I. D. Greenwood, "Volume 5: HDM-4 Calibration Reference Mannual, International Study of Highway Development and Mangement Tools (ISOHDM), Wrold Road Association (PIARC)," 2003.

[164] M. Q. Wang, "Development and use of GREET 1.6 fuel-cycle model for transportation fuels and vehicle technologies.," p. 39, Aug. 2001.

[165] EPA, "New fuel economy and environment labels for a new generation of vehicles.," 2011.

[166] EIA, "Light-Duty fuel economy: conventional cars: Gasoline." [Online]. Available: https://www.eia.gov/outlooks/aeo/data/browser/#/?id=50-AEO2020&cases=ref2020&sourcekey=0. [Accessed: 20-May-2020].

[167] CSI/IEA, "Technology Roadmap Low-Carbon Transition in the Cement Industry," 2017.

[168] C. Chen, G. Habert, Y. Bouzidi, A. Jullien, and A. Ventura, "LCA allocation procedure used as an incitative method for waste recycling: An application to mineral additions in concrete," *Resour. Conserv. Recycl.*, vol. 54, no. 12, pp. 1231–1240, Oct. 2010.

[169] Asphalt Insitute, "Life Cycle Assessment of Asphalt Binder," 2019.

[170] IPCC, *Climate change 2013: the physical science basis: Working Group I contribution to the Fifth assessment report of the Intergovernmental Panel on Climate Change*. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press (CUP), 2013.

[171] H. Li, J. Harvey, Y. He, Z. Chen, and P. Li, "Pavement treatment practices and dynamic albedo change in urban pavement network in California," *Transp. Res. Rec.*, vol. 2523, pp. 145–155, 2015.

[172] Federal Highway Administration, “Evaluation of long-term pavement performance (LTPP) climatic data for use in mechanistic-empirical pavement design guide (MEPDG) calibration and other pavement analysis.” [Online]. Available: https://www.fhwa.dot.gov/publications/research/infrastructure/pavements/ltpp/15019/008.cfm. [Accessed: 01-Jul-2020].

[173] L. Titus-Glover, M. I. Darter, and H. Von Quintus, “Impact of environmental factors on pavement performance in the absence of heavy loads,” Champaign, IL, 2019.

Appendix A: Backtrack-Search Algorithm

Pseudocode

In the pseudocode, *a* represents the partial schedule which uses integers to represent treatment actions. For example, 0 represents 'do nothing', and 1 represents the first action in the set of available treatments denoted by *N*. *T* is the analysis period. The search process can be described by a recursive process, i.e., the function called BSA(a). The role of function FIRST(a) is to generate the first extension of partial schedule *a*. The role of function NEXT(a) is to generate the next alternative extension of partial schedule *a.*

```
min_cost = inf
Function BSA(a):
    global min_cost
    if TC(a) > min_cost: return None
    if TC(a) < min_cost & length(a) = T:
        min_cost = TC(a)
        return min_cost
    n ← FIRST(a)
    while n ≠ None:
        BSA(a)
        n ← NEXT(a)

Function FIRST(a):
    if length(a) = T: return None
    else: return (a[0], a[1], ..., a[k], 0)

Function NEXT(n):
        k ← length(n)
    if n[k] = length(N): return None
    else: return (n[0], n[1], ..., n[k-1], n[k]+1)

Function TC(a):
    return the total cost for the partial schedule a
```

Computational Performance

To test the computational performance of the backtrack-search algorithm, four analysis periods are analyzed, including 5, 10, 15, and 20 years. For each analysis period, 10,000 segment samples are generated. Each of them has different age, thickness, traffic, material type, all of which influence the deterioration rate. During the analysis period, uncertainties of treatment cost and deterioration are considered to generate future scenarios. During the search process, the future scenario is fixed. But the deterioration uncertainty is different for each year. The cost of the same treatment action is different for each year. 8 treatment actions are considered, as listed in the Table 3-4 in Section 3.4.1.

The computational performance is evaluated by the number of visited steps. Suppose M is the number of available treatment actions, and T is the analysis period, then the total number of possible treatment schedules is $(M+1)^T$ and each schedule includes T steps. Hence, the number of visited steps for the brute-force approach is $T(M+1)^T$. Table A1 shows the computational performance based on the number of visited steps. The analyses are conducted in MATLAB. The results show that the real number of visited steps is much smaller than the brute-force approach. In addition, even for 20 years, in terms of the maximum number of visited steps, the total running time is still less than 0.2s on a laptop (3.5 GHz Intel Core i7, RAM 16GB).

Table A-1. Number of visited steps

	mean	**std**	**min**	**max**	**brute-force**
5 years	153	74	45	684	2.95×10^5
10 years	1,237	1,182	90	10,800	1.74×10^{10}
15 years	7,118	9,066	135	94,653	1.03×10^{15}
20 years	36,199	60,536	180	745,506	6.08×10^{19}

Note: (1). The results are based on 10,000 random segments; (2). 1,000,000 steps take about 0.2 second in MATLAB

Appendix B: Supplementary Materials for Chapter 3

In Section 3.4.3, the proposed PTPD model is compared with a B/C model. It is important to note that the magnitude and specifics of these results would certainly shift for different cases, under different budget levels, and for different levels of risk preference. As an example of this, an analysis of the sensitivity of model results to the choice of discount rate is presented here.

Considering that the segment-level decision-making process is mainly based on the total cost distributions, the rank preference of different treatment actions could be influenced by the discount rate. Here, a sensitivity analysis of the influence of discount rate on both segment- and network-level result is presented.

The US Federal Highway Administration (FHWA) recommends using OMB discount rates for the life-cycle cost analysis of highway projects [a]. The United States Government Office and Management and Budget (OMB) through circular A-94 "Guidelines and Discount Rates for Benefit-Cost Analysis of Federal Programs." suggests a discount rate of 1.3-1.5% for calendar year 2019 [b]. FHWA suggested that discount rate use the OMB rate, i.e., 1.3%. Many existing papers use a discount rate of 4%. Therefore, the discount rates *r* for the sensitivity analysis are chosen as 0, 1.5%, 3%, 4% and 5%. Here are the results:

Segment-level Analysis

The segment-level analysis is based on the same segment in Section 3.4.1. Table B-1 and Table B-2 show the optimal treatment alternatives for different discount rates (*r*) and risk-aversion coefficients (θ) when the analysis period is 5 and 10 years, respectively.

---

[a] Kane, AR, *FHWA Policy Memorandums: National Highway System Designation Act; Life-Cycle Cost Analysis Requirements*, April 19,1996. Retrieved from https://www.fhwa.dot.gov/legsregs/directives/policy/lcca.htm on April 17, 2019.

[b] https://www.whitehouse.gov/wp-content/uploads/2018/12/M-19-05.pdf

When the analysis period is 5 years, the influence of discount rate is insignificant. When the analysis period is 10 years and risk-aversion coefficient is small, optimal treatment alternatives shift to lower initial-cost actions like mill and fill (MF), and asphalt overlay (4" AC). (See light yellow shaded cells.). When the analysis period is 10 years and the risk-aversion coefficient is large, two optimal treatment alternatives stay the same but their order may change.

Table B-1. Optimal treatment alternatives for different discount rates and risk-aversion coefficients when the analysis period is 5 years.

	Optimal Alternatives (analysis period = 5 years)									
	$r = 0$		$r = 0.015$		$r = 0.03$		$r = 0.04$		$r = 0.05$	
	1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd
θ=0	2" MF	4" AC	2" MF	4" AC	2" MF	4" AC	2" MF	4" AC	2" MF	4" AC
θ=1	2" MF	4" AC	2" MF	4" AC	2" MF	4" AC	2" MF	4" AC	2" MF	4" AC
θ=5	4" PCC	2" MF	4" PCC	2" MF	4" PCC	2" MF	4" PCC	2" MF	4" PCC	2" MF
θ=10	4" PCC	8" PCC	4" PCC	8" PCC	4" PCC	8" PCC	4" PCC	8" PCC	4" PCC	8" PCC

Note: MF=mill & fill, AC=asphalt, PCC=concrete

Table B-2. Optimal treatment alternatives for different discount rates and risk-aversion coefficients when the analysis period is 10 years.

	Optimal Alternatives (analysis period = 10 years)									
	$r = 0$		$r = 0.015$		$r = 0.03$		$r = 0.04$		$r = 0.05$	
	1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd
θ=0	4" AC	4" PCC	4" AC	2" MF	4" AC	2" MF	2" MF	4" AC	2" MF	4" AC
θ=1	4" PCC	2" MF	2" MF	4" PCC	2" MF	4" PCC	2" MF	4" AC	2" MF	4" AC
θ=5	4" PCC	2" MF	4" PCC	2" MF	2" MF	4" PCC	2" MF	4" PCC	2" MF	4" PCC
θ=10	4" PCC	2" MF	4" PCC	2" MF	4" PCC	2" MF	2" MF	4" PCC	4" PCC	2" MF

Note: MF=mill & fill, AC=asphalt, PCC=concrete

Network-level Analysis

For the network-level analysis, the risk-aversion coefficient is chosen as 1. Except for the discount rate, all other information is the same as that in Section 3.4.3. The B/C model considers current period costs and non-monetary benefits that accrue over time. As such, the discount rate does not alter the B/C metric of the B/C model results.

Figure B-1 shows the cumulative probability curves of average TWIRI over 20 years under different discount rates. For all discount rates, the PTPD model performs better than B/C model.

The discount rate will influence the segment-level treatment decisions and thus influence pavement network performance. With the increase of discount rate, the long-term benefits of treatments are diminished. This leads the segment-decision process to select more treatments with low upfront costs, but less long-term benefit. In turn, this leads to a network with higher variability in performance over the long term.

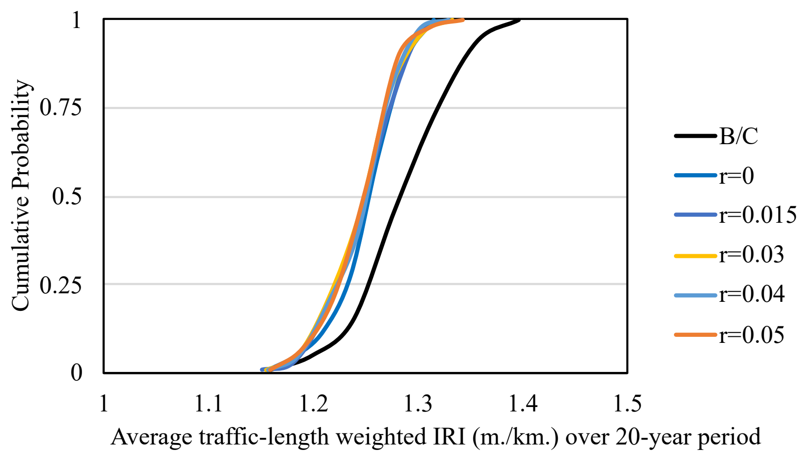


Figure B-1. CDF of average TWIRI over 20 years under different discount rates

Summary

In addition to the discount rate, there are other parameters that could influence the model performance, future work should extend current model to sensitivity analysis to explore the influence of different parameters. Nevertheless, the results shown here suggest that it is promising to explicitly consideration of cost uncertainty in pavement management.

Appendix C: Supplementary Materials for Chapter 4

C.1. Methodology

C.1.1 Modified PTPD model

The segment level analysis in the PTPD model is modified to incorporate multi condition metrics. The objective is still to minimize both the expectation and standard deviation of total life cycle cost. Instead of a single condition threshold for IRI in Chapter 3, each condition metric has its own condition threshold. The user cost is only concerned with IRI, so the treatment decision of a segment is determined by both threshold value and cost-oriented optimization process

Segment level analysis

The goal of the segment-level analysis is to evaluate and identify the best treatment $a_{i,1}^{*}$ for each segment i at the beginning of segment analysis period (e.g., t_s=1) when there is no budget constraint. During the evaluation process, available treatment alternatives $\boldsymbol{N}^{(m)}$ are related with pavement types $\boldsymbol{M}$ (where $m \in \boldsymbol{M}$). Hence, the goal is to evaluate $\boldsymbol{N}^{(m_0)}$, where m_0 is initially known before the analysis.

To allow for the impact of a budget constraint in the network level analysis, the top two alternatives are identified for each segment, namely, $a_{i,1}^{*} = \left[a_{i,t_s=1}^{*1}, a_{i,t_s=1}^{*2}\right]$. The evaluation is based on the long-term benefits of treatment alternatives. The action with a smaller total cost given an analysis period is preferable. Available treatment alternatives $\boldsymbol{N}^{(m_0)}$ are evaluated by simulation-optimization, which integrates optimization into simulation analysis [38], [125]. Monte Carlo simulations are used to generate a range of possible future scenarios. In this case, each scenario represents a specific projection for deterioration and treatment cost. For each scenario and for each possible treatment in $\boldsymbol{N}^{(m_0)}$, an optimal treatment path and its corresponding total cost *TC* are determined.

To evaluate action $\boldsymbol{N}^{(m_0)}(\alpha)$, suppose the number of Monte Carlo simulations for the segment-level analysis is K_s. For the k_s^{th} simulation, the optimization process is formulated as the following mathematical model:

min: $TC_{\alpha}^{k_s}$ (C.1)

s.t. $a_1 = \boldsymbol{N}^{(m_0)}(\alpha) = \boldsymbol{N}_1(\alpha)$ (C.2)

$\sum_{n=1}^{N_{t_s}} x_{n,t_s} \leq 1$, for $t_s = 2,...,\mathrm{T_s}$ (C.3)

$CM_{j,t_s} = \left(CM_{j,t_s-1} + \Delta CM_{j,t_s}\right)\cdot\left(1-\sum_{n=1}^{N_{t_s}} x_{n,t_s}\right) + \left(CM_{j,new} + \Delta CM_{j,new}\right)\cdot\sum_{n=1}^{N_{t_s}} x_{n,t_s}$ (C.4)

for $t_s = 1,2,...,\mathrm{T_s}$

$CM_{j,t_s} \leq CM_{j,threshold}$ (C.5)

$uc_{t_s} = fc_{R,t_s} + fc_{D,t_s}$ for $t_s = 1,2,...,\mathrm{T_s}$ (C.6)

$a_{t_s} = \sum_{n=1}^{N_{t_s}} x_{n,t_s} \cdot \boldsymbol{N}_{t_s}(n)$ for $t_s = 1,2,...,\mathrm{T_s}$ (C.7)

$m_{t_s} = g\left(m_{t_s-1}, a_{t_s}\right)$ for $t_s = 1,2,...,\mathrm{T_s}$ (C.8)

$\boldsymbol{N}_{t_s} = \boldsymbol{N}^{\left(m_{t_s}-1\right)}$ for $t_s = 1,2,...,\mathrm{T_s}$ (C.9)

$ac_{t_s} = p\left(ac_0, P_{asphalt}^t, P_{concrete}^t\right)\cdot area$ (C.10)

$TC_{\alpha}^{k_s} = \sum_{t=1}^{T_s} \frac{1}{(1+r)^{t_s}}\left(\sum_{n=1}^{N_{t_s}} x_{n,t_s} \cdot ac_{t_s}(n) + uc_{t_s}(n)\right)$ (C.11)

$x_{n,t_s} \in \{0,1\}$ for $t_s = 1,2,...,\mathrm{T_s}$, and $\forall n$ (C.12)

Table C-1. Definitions of all variables in the segment-level optimization process

Variable	Meaning
T_s	Segment level analysis period
K_s, k_s	The total number and the ordinal of Monte Carlo simulations
TC	Total cost given the segment level analysis period
m_t	Pavement material type at time *t*. When $t = 0$, it represents the initial pavement type
r	Discount rate
$\boldsymbol{N}, n, a, \alpha$	***N*** is the set of treatment actions, *n* is the ordinal of the actions in ***N***, i.e. ***N(n)*** represents the n_{th} action *a* in *N*, α is the ordinal of the evaluated action.
x_{n,t_s}	Decision variable. If the n_{th} action in $\boldsymbol{N}_{t_s}$ is selected at year t_s, $x_{n,t_s} = 1$. Otherwise,

	$x_{n,t_s} = 0$.
CM_j	Condition metric, $j \in \{IRI, RUT, FAULT, ACRACK, LCRACK, LWCRACK, TCRACK\}$
$\Delta CM_{j,t_s}$	Pavement deterioration for condition metric *j* without any treatment
$\Delta CM_{j,new}$	Pavement deterioration of condition metric *j* after a treatment
$\Delta CM_{j,threshold}$	The performance threshold value for condition metric *j*.
uc_{t_s}	User cost at year t_s
fc_{R,t_s}	Excess fuel cost induced by PVI roughness at year t_s
fc_{D,t_s}	Excess fuel cost induced by PVI deflection at year t_s
ac_{t_s}	Agency cost at year t_s

The explanation for each equation is similar to the one in Section 3.3.2. The solution of this optimization model is based on the backtrack algorithm (Detailed information is in Appendix A). Then each simulation provides an optimal treatment schedule and its corresponding total cost $TC_n^{k_s}$. After all simulations ($K_s = 100$), future cost distributions $\left\{TC_n^{k_s}\right\}_{k_s=1}^{K_s}$ for each available treatment *n* in $\boldsymbol{N}^{(m_0)}$ are obtained. Based on these cost distributions, all treatment alternatives are evaluated and ranked by

$$\textbf{min:} \quad z_n = \mathrm{E}_n + \theta \cdot SD_n \tag{C.13}$$

E_n represents the mean value of total cost distribution for treatment action *n*, SD_n is the standard deviation, and θ is the risk-aversion coefficient that is used to describe the tradeoff between mean cost and variation. After risk analysis, z_n could be obtained for each treatment alternative *n* in $\boldsymbol{N}^{(m_0)}$. Then two optimal (the two lowest z values) treatment alternatives $a_i^* = \left\{a_{i,1}^{*1}, a_{i,1}^{*2}\right\}$ are identified for each segment *i*.

C.1.2 Pavement-vehicle interaction models

Pavement-vehicle interaction (PVI) has a large impact on the use phase of high traffic volume pavements [128], [151]. The rolling resistance caused by PVI can reduce fuel efficiency. Considering different mechanisms, PVI can be divided into two types – roughness-induced and deflection-induced PVI.

Road roughness has an impact on excess vehicle fuel consumptions. This can be quantified by the Highway Development Management-4 (HDM-4) model [163]. The HDM-4 model uses IRI as the metric, and the roughness-induced excess fuel consumption can be calculated by equation (C.14), which is a function of IRI, traffic, speed, and pavement segment length [128]. β_C and γ_C are related with vehicle type, and V represents the vehicle velocity.

$$\delta IFC_R = \beta_C \langle IRI, IRI_0 \rangle \left(1 + \gamma_C \frac{V}{3.6} \right) \tag{C.14}$$

The second type of PVI is related with the dissipation of mechanical work provided by vehicles. Weights of moving vehicles can cause viscous deformation within the pavement structure, which leads to rolling resistance and causes excess fuel consumptions. To capture the impact of deflection-induced PVI, Louhghalam et al. developed a numerical model as shown in equation (C.15). The excess dissipated energy δE caused by deflection-induced PVI is influenced by pavement stiffness E, subgrade stiffness k, temperature T, thickness h, width b, vehicle axle load P, speed V, and pavement density, etc. The dissipated energy can be converted to instaneous change in fuel consumption (equation (C.16)). Results shows that the excess fuel consumption caused by cars is negligible compared to trucks in terms of PVI-deflection [128]. Hence, only deflection-induced PVI caused by trucks is considered. The energy emission rate ξ_f for diesel is about 146.11 MJ/gallon as suggested in the GREET model [164].

$$\delta E = \frac{V_{cr}}{V} \frac{P^2}{l_s^2 bk} 10^{F(\Pi_1, \Pi_2)} \tag{C.15}$$

$$\delta IFC_D = \delta E / \xi_f \tag{C.16}$$

C.1.3 Equivalent conversion from gasoline to electricity

The roughness-induced PVI model provides the excess fuel consumption for a conventional ICEV in terms of gasolines. As for EVs, it is necessary to convert gasolines equivalently to electricity (kWh). Suppose the excess fuel consumption for ICEV is 1 gallon ($fule_{ICEV}$). Then the corresponding miles can be obtained based on the fuel economy for ICEV (MPG_{ICEV}),

$$mile_{ICEV} = MPG_{ICEV} \cdot fule_{ICEV} \tag{C.17}$$

Given the same mile and the equivalent fuel economy for EV ($MPG_{EV,\,gas\ equiv}$), the equivalent gasoline consumption for EV is calculated,

$$fuel_{EV,\,gas\ equiv} = \frac{mile_{ICEV}}{MPG_{EV,\,gas\ equiv}} \tag{C.18}$$

By substituting (C.17) into (C.18),

$$fuel_{EV,\,gas\ equiv} = \frac{MPG_{ICEV}}{MPG_{EV,\,gas\ equiv}} \left(unit : gallon \right) \tag{C.19}$$

As reported in [165], the energy emitted by 1 gallon of gasoline is equivalent to 33.7 kWh. Then the excess fuel consumption for EVs can be obtained by,

$$fuel_{EV,\,electricity} = fuel_{EV,\,gas\ equiv} \cdot 33.7 kWh / gallon \tag{C.20}$$

The fuel economies for ICEV and EV (i.e. MPG_{ICEV} and $MPG_{EV,\,gas\ equiv}$) can be found in [166].

C.1.4 Embodied GHG emissions

The assumptions and life cycle inventory data for each material in the foreground system are provided in Table C-2. Since the trend for low-carbon construction materials is continuing its momentum, various suppliers are striving to lower the carbon footprint of their supply chain while keeping their costs in a reasonable range so as not to lose their market share. Hence, several technologies have been adopted in different regions. For the concrete procurement, the incorporation of alternative binders, such as slag, fly ash, and limestone, up to 50% have been applied on a large scale in the field and reported in the environmental product declarations [155]. Moreover, according to the Cement Sustainability Initiative projection[167], on average, 25% of the cement plants will be equipped with carbon capture technologies by 2050. For the asphalt pavements, the warm mix asphalt has completely replaced the hot mix market in certain states, such as Tennessee [154]. Also, reclaimed asphalt pavements have been incorporated up to 50%, and the trend towards full natural gas in asphalt plants is reported as a goal towards embodied impact reduction in the future. These assumptions were linearly implemented from the currently-implemented level (Table C-2) until 2050 to capture the temporal dynamics in the life cycle inventory of GHG emissions.

Table C-2. Concrete and asphalt input data for embodied impact calculation

Process	**Bill of materials data source**	**Value**	**Allocation factors**
Portland Cement (kg/m3)	[155]	341.7	-
Fly Ash (kg/m3)	[155]	39.7	[168]
Slag Cement (kg/m3)	[155]	24.3	[168]
Mixing Water (kg/m3)	[155]	163.7	-
Crushed Coarse Aggregate (kg/m3)	[155]	822.8	-
Natural Coarse Aggregate (kg/m3)	[155]	132.9	-
Natural Fine Aggregate (kg/m3)	[155]	791.9	-
High Range Water Reducer (% cement content)	[155]	0.2	-
Accelerator (% cement content)	[155]	0.3	-
Truck (km)	[155]	80.0	-
Rail (km)	[155]	65.0	-
Ocean (km)	[155]	56	-
Barge (km)	[155]	10	-
Electricity Midwest Reliability Organization (MRO) (kWh/m3)	[155]	1.14	-
Natural Gas (m3/m3)	[155]	0.4	-
Fuel Oil (lit/m3)	[155]	0.1	-
Diesel (lit/m3)	[155]	2.2	-
Concrete technology projection	[167]	-	-
Bitumen mass asphalt (% mass)	[7]	5%	[169]
Gravel mass asphalt (% mass)	[154]	47%	-
Sand mass asphalt (% mass)	[154]	47%	-

Truck (km)	[169]	35	-
Asphalt heating fuel (Btu/ton)	[155], Asphalt EPD	2.89E+05	-
Electricity (kWh/ton)	[155], Asphalt EPD,	3.30	-
Reclaimed asphalt content at the beginning of analysis period	[154]	18%	
Warm mixed asphalt proportion at the beginning of analysis period	[154]	53%	

Note: unit is kg/m3 unless otherwise stated; [155]: NRMCA Industry-wide EPD program, 2020; [167]: CSI/IEA, 2017; [7]: LTPP; [154]: NAPA Annual report, 2018; [169]: Asphalt Institute, 2019; [168]: Chen et al. 2010

C.1.5 Radiative forcing

The road surface albedo can induce a radiative forcing (RF) by perturbing the shortwave radiation budget. In fact, RF is the change in net irradiance at the top of the atmosphere (TOA). For shortwave forcing agents like surface albedo changes, the instantaneous RF at the TOA is linked to surface temperature change and can be used instead of the stratospheric-adjusted RF at the tropopause. Therefore, RF at TOA due to pavement albedo change can be calculated as the change of shortwave radiation at TOA [157]:

$$RF_{TOA} = -R_{TOA}\Delta\alpha_p \tag{C.21}$$

Where R_{TOA} is downward solar radiation at the TOA and $\Delta\alpha_p$ is defined as the variation in planetary albedo. Following a procedure widely reported in the literature, changes in planetary albedo $\Delta\alpha_p$ can be approximately linearly related to changes in surface albedo $\Delta\alpha_s$:

$$\Delta\alpha_p = f_a\Delta\alpha_s \tag{C.22}$$

Where f_a is a two-way transmittance factor accounting for the absorption and reflection of solar radiation throughout the atmosphere. Combining equations (C.21) and (C.22):

$$RF_{TOA} = -R_{TOA}\Delta\alpha_p = -R_{TOA}f_a\Delta\alpha_s \tag{C.23}$$

RF at the TOA can also be computed using the solar radiation at the earth's surface:

$$RF_{TOA} = -R_sT_a\Delta\alpha_s \tag{C.24}$$

From these equations, the albedo induced RF is a function of three quantities: the intensity of incoming radiation (R_{TOA} or R_s), atmospheric transmittance (f_a or T_a) and the change in albedo, $\Delta\alpha_s$. Of these factors, transmittance is particularly challenging to estimate. Generally, $\Delta\alpha_s$ would be known for a given situation of interest. Both R_{TOA} and R_s were extracted from NASA Atmospheric Science Data Center: Surface meteorology and Solar Energy database. The transmittance factor f_a or T_a was estimated for each state using research work at MIT CSHub [157].

The next step is to calculate the absolute global warming potential (AGWP) induced by this RF change. By dividing the AGWP of RF change to AGWP of CO2, the RF-induced GWP is calculated as:

$$GWP_{RF} = \frac{\int_0^{AP} RF_{TOA}\, dt}{\int_0^{TH} RF_{CO2}\, dt} \tag{C.25}$$

For the purpose of this analysis, the 9.17E-14 W.yr/m2/kgCO2 is the value corresponding to the 100-year time horizon for GWP calculation (the denominator) [170]. The average albedo values of 0.1 and 0.3 (for asphalt and concrete, respectively) for the state network are assumed constant in time according to several city-level analyses of Li et al [171].

C.1.6 Evaluation metrics

IRI is commonly used to describe the pavement condition in both literature and real-world practice. To reflect the significance of a segment *i* in the network, IRI is weighted by traffic and length of the segment, as shown in equation (C.26), where AADT represents annual average daily traffic, *I* is the total number of segments.

$$TWIRI_i = \frac{AADT_i \cdot length_i}{\sum_{i=1}^{I} AADT_i \cdot length_i} \cdot IRI_i, \quad \text{and } TWIRI = \sum_{i=1}^{I} TWIRI_i \tag{C.26}$$

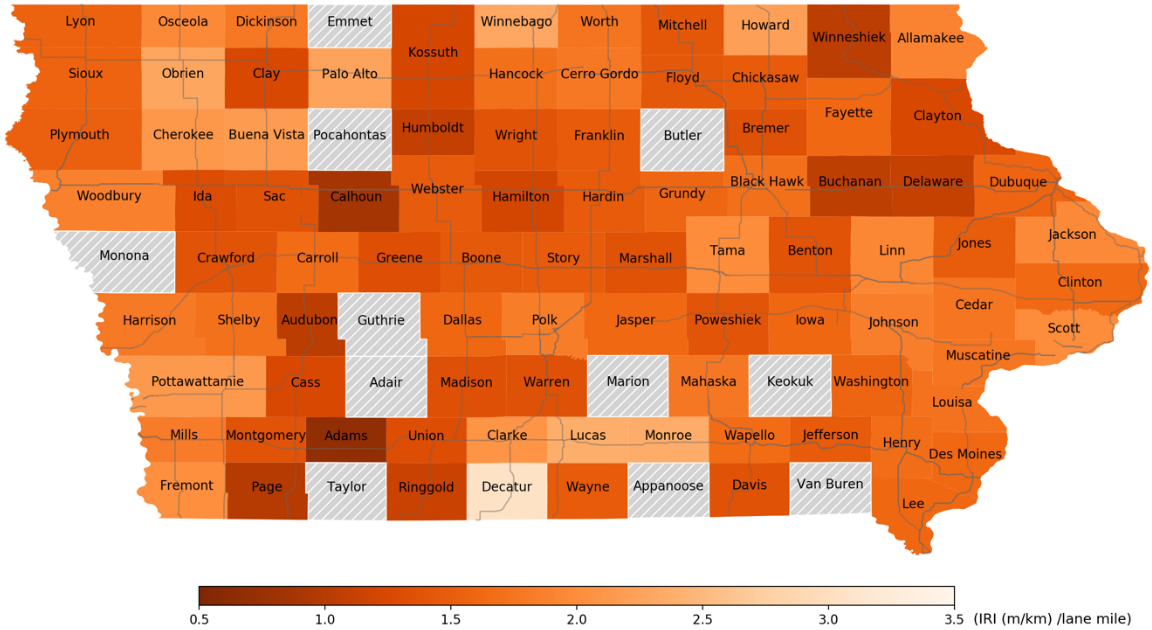
To better relate TWPCI and TWIRI, TWIRI is converted into a TWIRI index, which also ranges from 0 to 100 as shown in equation (2.4) in Chapter 2.

C.2. Case Study

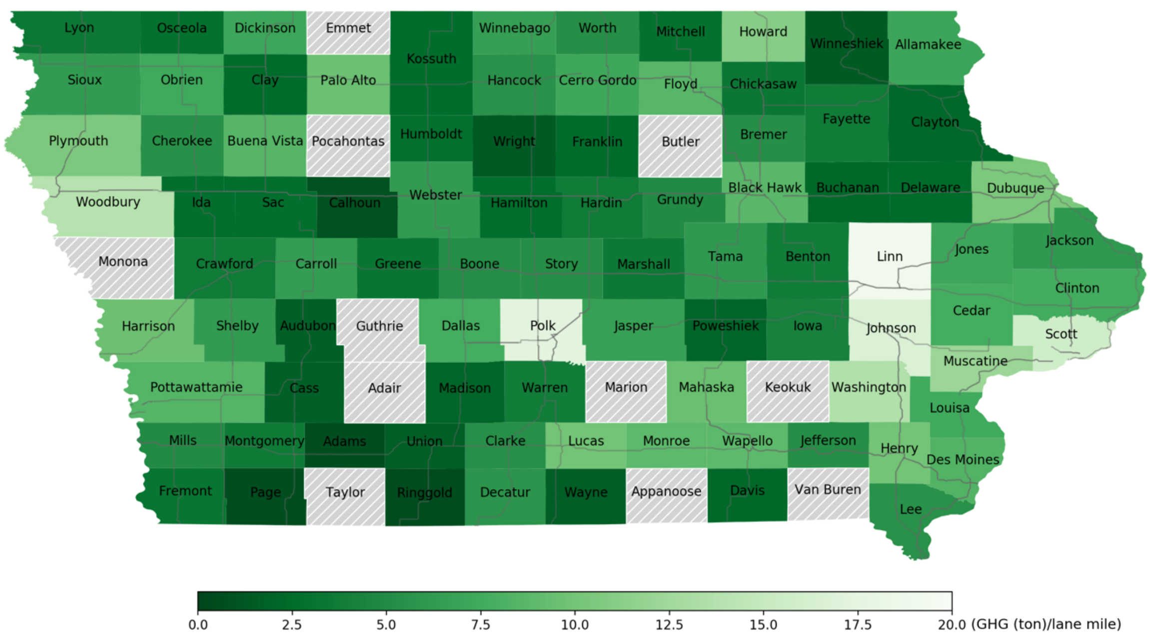
C.2.1 Proposed strategy

Figure C-1(a) and (b) show the distributions for initial IRI and PVI-induced GHG emissions on the county level for the Iowa U.S. route network. 11 counties don't have U.S. route pavements, which are shown in hatch. Grey lines represent the routes. Adams, Calhoun and Page counties have the best roughness condition with the smallest IRI. By contrast, Winnebago and Obrien have the largest average IRI. In terms of environmental effect, Ringgold, Page and Adamas provide the smallest PVI-induced GHG emissions since these counties have good pavement condition and small traffic volume. By contrast, Polk, Johnson, and Scott have the largest GHG emissions due to their large traffic volume.

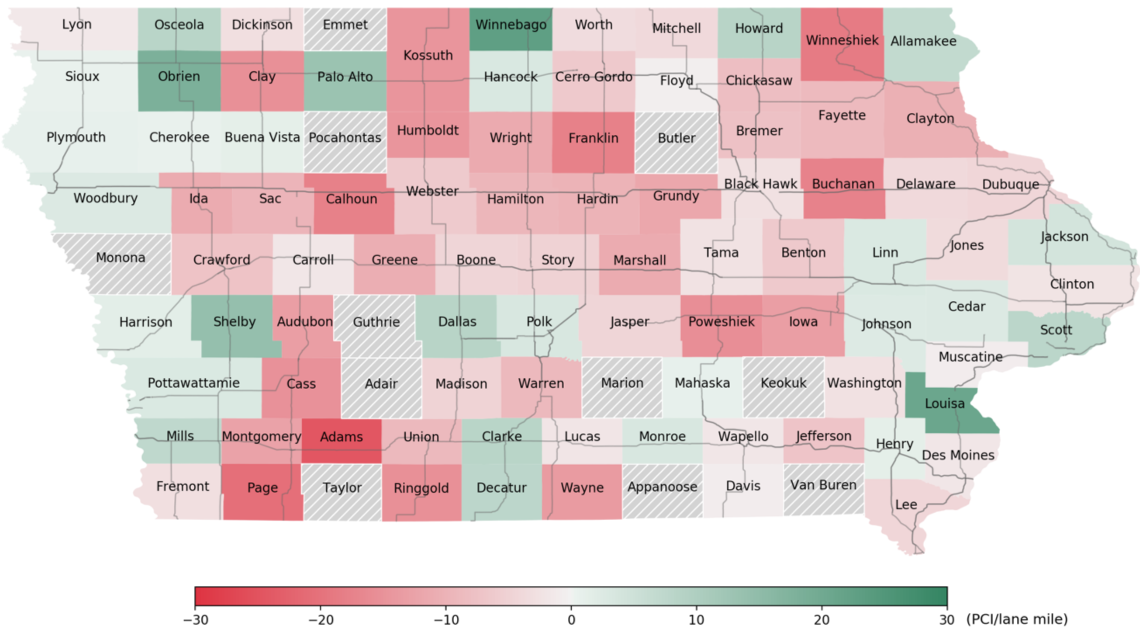
Figure C-1(c) shows the average change in PCI per lane mile for each county after 30 years of applying the proposed strategy with the critical budget. Using PCI as an example, the value for each county equals to average PCI at year 30 minus the average PCI at year 0. The most notable feature of this plot is that although the overall system maintains a relatively constant level of performance, results within specific counties can vary widely. For example, after 30 years under the scenario of the proposed strategy, Adam, Calhoun and Page counties (the three counties with the best initial condition) experience a decrease in pavement condition, while pavement conditions in Winnebago, Louisa and Obrien improve. Considering the goal of the proposed strategy is to maintain the network condition stable after 30 years, the PTPD model tries to improve pavements in bad condition at the sacrifice of the pavements in good condition, and make the network condition more uniformly distributed. The same phenomenon is also observed in Figure C-1(d) for PVI-induced GHG emissions and Figure C-1(e) for IRI.



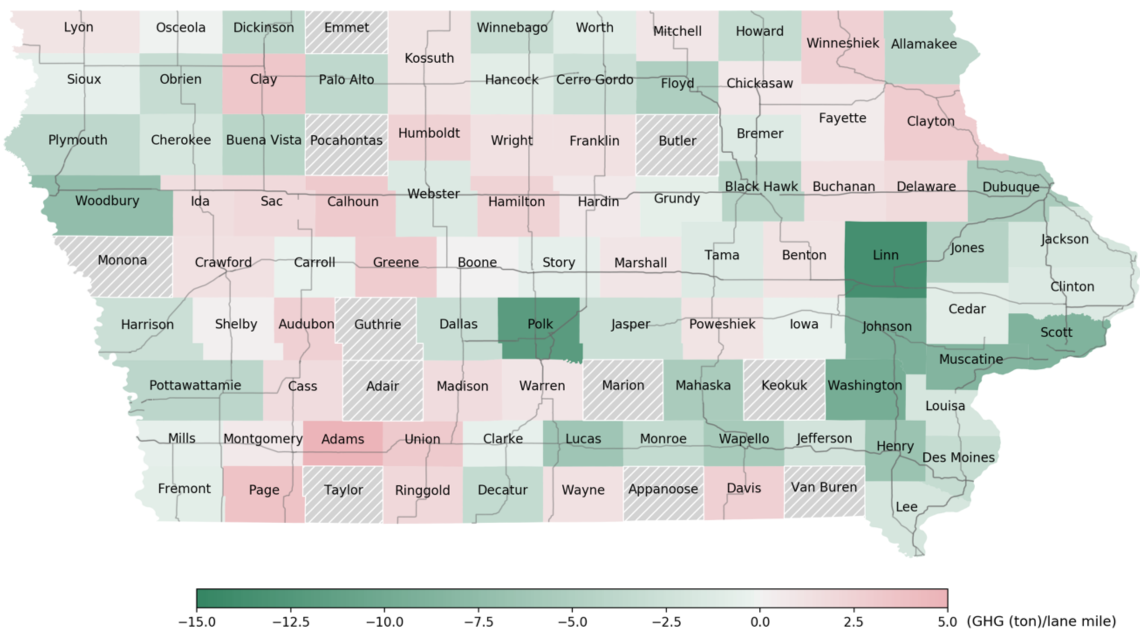
(a). Initial IRI distribution



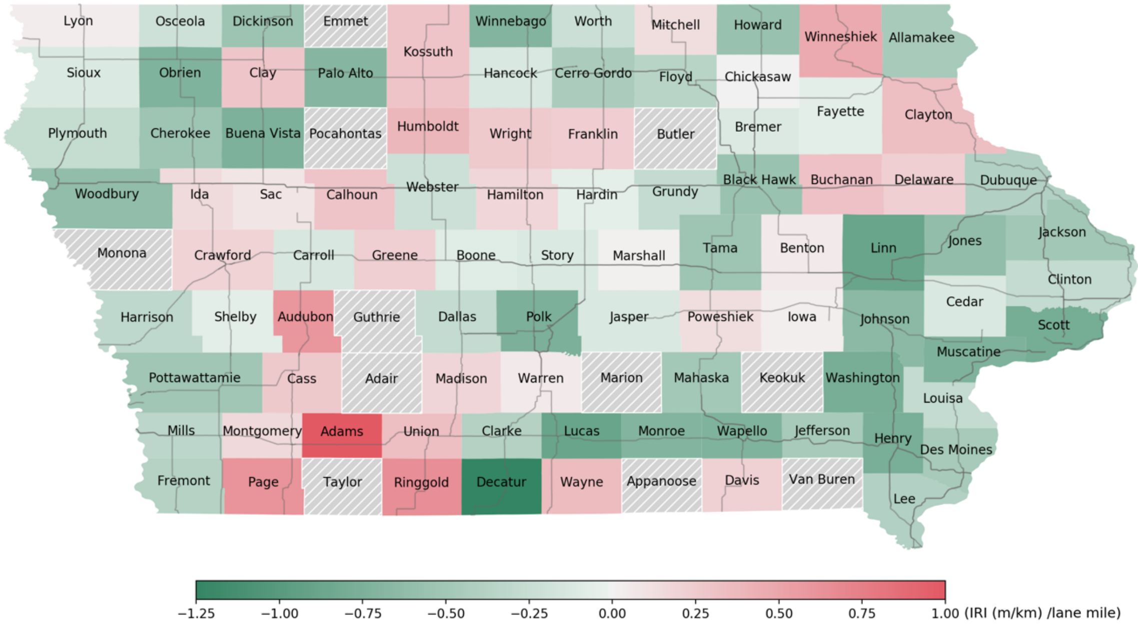
(b). Initial distribution for PVI-induced GHG emissions



(c). PCI variation between year=0 and year=30



(d). PVI-induced GHG variation between year=0 and year=30



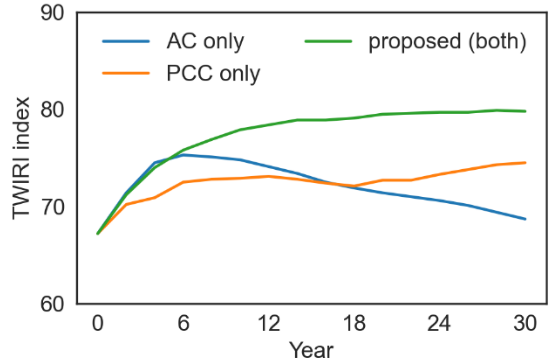
(e). IRI variation between year=0 and year=30

Figure C-1. Initial (a). IRI and (b). PVI-induced GHG distributions for Iowa U.S. route network on the county level based on Iowa PMS 2017; (c). PCI, (d) GHG emissions due to PVI and (e). IRI variations for each county after 30 years based on the proposed strategy under the critical budget (counties in hatch don't have U.S route pavements).

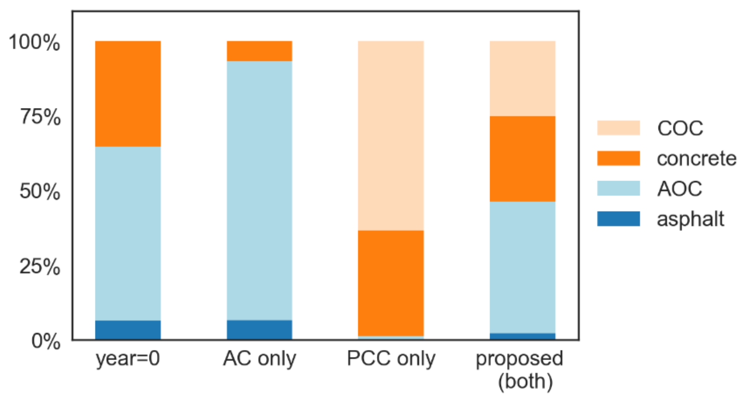
C.2.2 Influence of treatment materials

Figure C-2 (a) presents the TWIRI comparisons among three treatment material strategies under the critical budget. It shows that incorporating both materials leads to the best average pavement network performance in terms of TWIRI index. As for the AC only strategy, the TWIRI index goes up first and then goes down. As for the PCC only strategy, it takes time to reflect its long-term benefit. After 18 years, PCC only strategy performs better than AC only strategy in terms of TWIRI index. Figure C-2(b) shows the pavement type distribution at the beginning and the end of the analysis period. Corresponding explanations can be found in the Section 4.4.2.

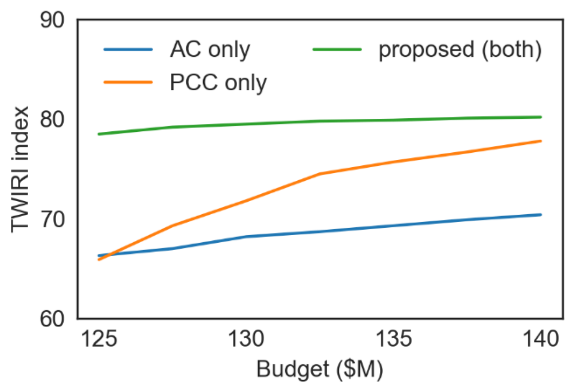
A sensitivity analysis is conducted to compare treatment material strategies under different budget levels, as shown in Figure C-2(c)~(e). For all budget levels, the proposed strategy performs the best. As budget levels increase, the TWIRI and TWPCI differences between the AC only and PCC only strategies increase, and the difference for GHG emissions decreases. It suggests that when the budget level is low, it is better to apply more AC solutions to fix more pavement areas, and with the increase of budget levels more PCC solutions should be invested.



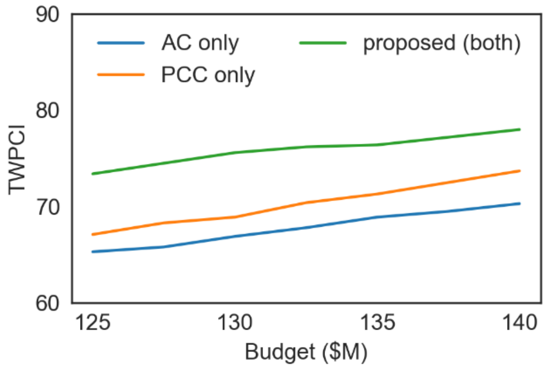
(a)



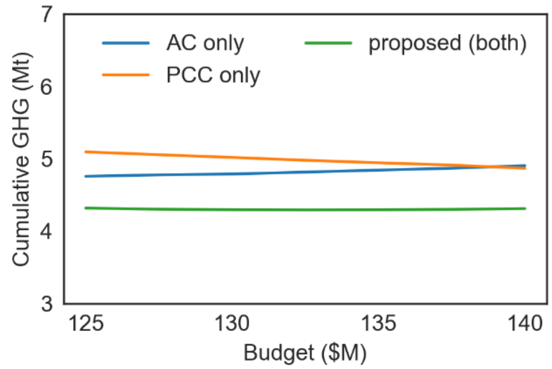
(b)



(c)



(d)



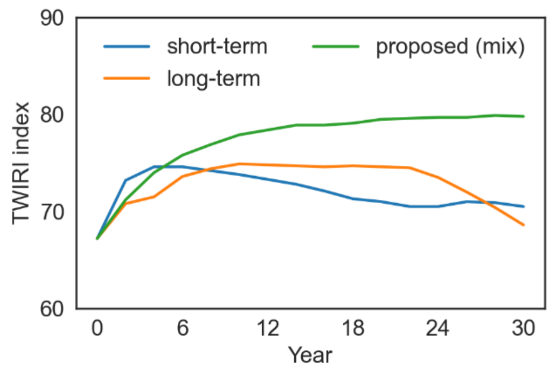
(e)

Figure C-2. Comparisons of different treatment material strategies. (a) is annual mean TWIRI index under the critical budget ($132.5M), (b) is the pavement type distribution at the beginning of analysis period (year=0) and the end of analysis period for each material strategy, (c) is the mean TWIRI index at year 30, (d) is the mean TWPCI at year 30 and (e) is the cumulative life-cycle GHG emissions for 30 years under different budgets.

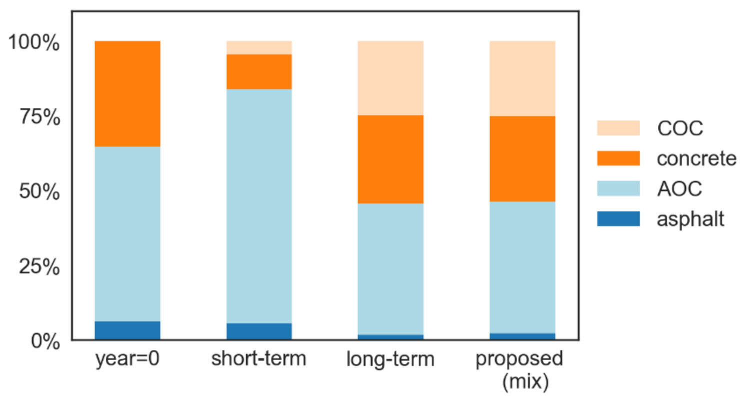
C.2.3 Influence of treatment types

Figure C-3(a) presents the TWIRI comparisons among three treatment type strategies under the critical budget. It shows that incorporating mix treatment types leads to the best average pavement network performance in terms of TWIRI index after year 4. The short-term only strategy performs the best for the first four years, then its performance drops quickly. The long-term only strategy performs the worst for the first 8 years, and then it performs better than the short-term only strategy due to its long-term benefits. It becomes the worst after year 24 due to its smallest maintained area. Figure C-3(b) shows the pavement type distribution at the beginning and the end of the analysis period. Corresponding explanations can be found in the Section 4.4.3.

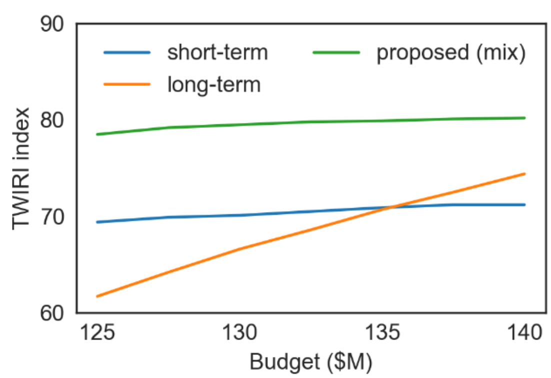
A sensitivity analysis is conducted to compare treatment type strategies under different budget levels, as shown in Figure C-3(c)~(e). For all budget levels, the proposed strategy (mix strategy) always has the best pavement network condition (i.e., TWIRI index and TWPCI) and smallest GHG emissions. With the increase of budget levels, the short-term strategy provides very limited improvement compared to the proposed and long-term only strategies. The difference between the short-term only strategy and the proposed strategy increases as the budget grows. These results suggest using more short-term treatments when the budget is low, and more long-term treatments when the budget is high.



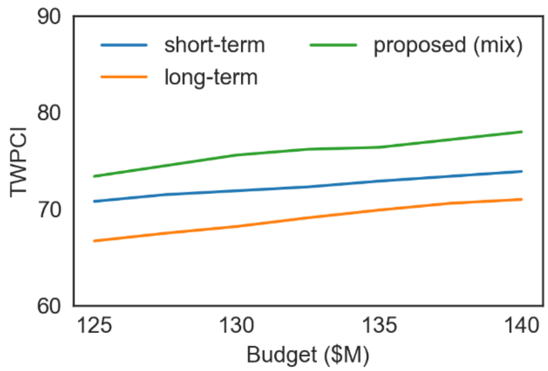
(a)

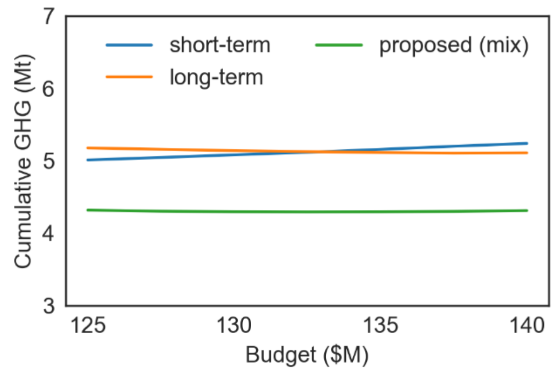


(b)



(c)





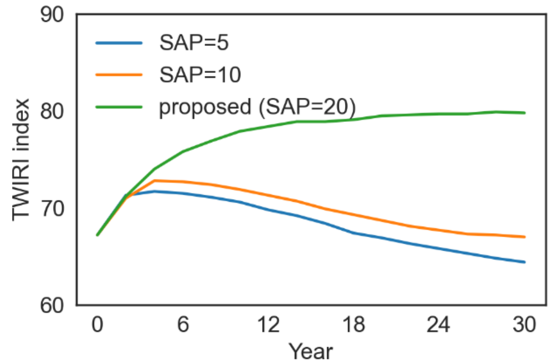
(d) (e)

Figure C-3. Comparisons of different treatment type strategies. (a) is annual mean TWIRI index under the critical budget ($132.5M), (b) is the pavement type distribution at the beginning of analysis period (year=0) and the end of analysis period for each treatment type strategy, (c) is the mean TWIRI index at year 30, (d) is the mean TWPCI at year 30, and (e) is cumulative life-cycle GHG emissions for 30 years under different budgets.

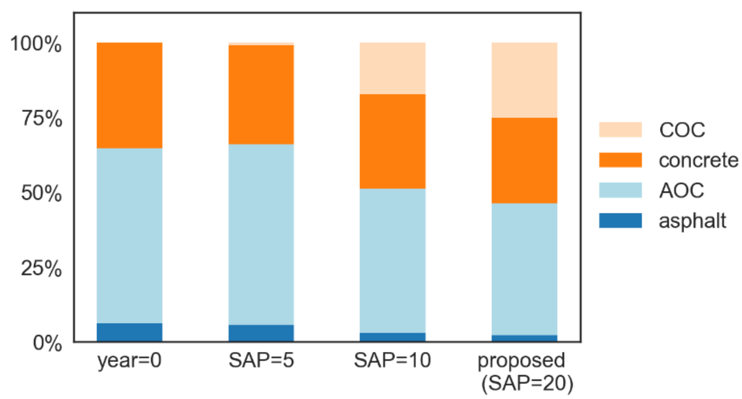
C.2.4 Influence of segment analysis period

Figure C-4(a) presents the TWIRI comparisons among three segment analysis periods under the critical budget. It shows that the differences for these three segment analysis periods are very tiny for the first 2 years. After that, the SAP=20 strategy leads to the best average pavement network performance in terms of TWIRI index. The second best is the SAP=10 strategy and the SAP=5 strategy performs the worst. Figure C-4(b) shows the pavement type distribution at the beginning and the end of the analysis period. Corresponding explanations can be found in the Section 4.4.4.

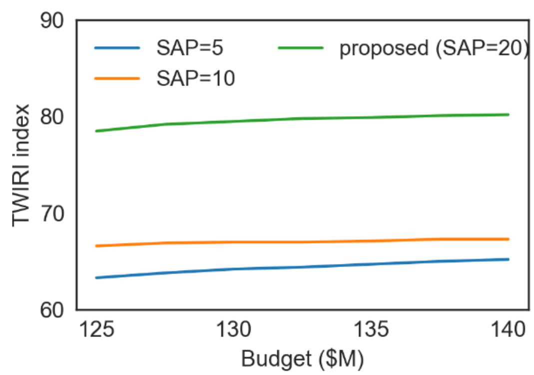
Figure C-4(c)~(e) present the sensitivity analysis for the comparison among three SAP strategies under different budget levels. The proposed strategy (SAP=20) always has a better pavement network condition (i.e., TWIRI index and TWPCI) and smaller GHG emissions. With the increase of budget levels, the difference between the SAP=5 strategy and the proposed strategy increases.


90
80
70
60
TWIRI index
SAP=5
SAP=10
proposed (SAP=20)
0
6
12
18
24
30
Year

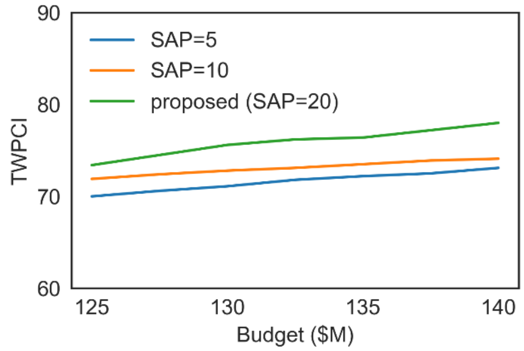
(a)


100%
75%
50%
25%
0%
year=0
SAP=5
SAP=10
proposed (SAP=20)
COC
concrete
AOC
asphalt

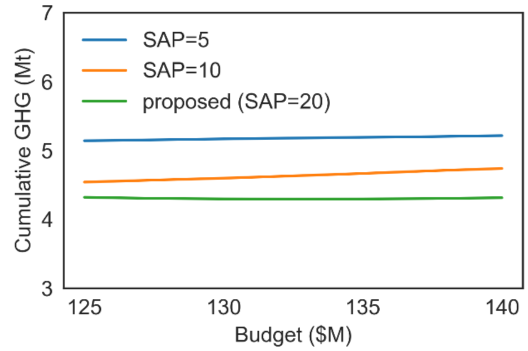
(b)


90
80
70
60
TWIRI index
SAP=5
SAP=10
proposed (SAP=20)
125
130
135
140
Budget ($M)

(c)



(d)



(e)

Figure C-4. Comparisons of different segment analysis periods. (a) is annual mean TWIRI index under the critical budget ($132.5M), (b) is the pavement type distribution at the beginning of analysis period (year=0) and the end of analysis period for each segment analysis period, (c) is the mean TWIRI index at year 30, (d) is the mean TWPCI at year 30, and (e) is the cumulative life-cycle GHG emissions for 30 years under different budgets.

C.3. Importance to consider multiple condition metrics

Many research papers use a single condition index (e.g., PCI), or condition state in a Markovian model as an overall condition description. Such metrics can incorporate multiple metrics, but it is different from considering multiple metrics distinctly, possible in concert with the PCI. As an example of the value of this distinction, Table C-3 shows the characteristics of an asphalt overlay composite pavement segment in Iowa. This PMS data is from year 2012. The ORIGKEY in the table can be considered as the unique name of a segment. For Iowa, PCI ranges from 0 to 100 where 100 represents the perfect condition. The PCI of this segment is 83. It is in a good condition and, based on Iowa standards there is no need to fix it because of overall poor condition. However, its level longitudinal cracking (1017 m/km) is more than double the threshold value, which is 500m/km. Hence, based on this criterion it requires to maintain this segment immediately.

Table C-3. Sample asphalt overlay composite pavement in Iowa

Year	ORIGKEY	IRI (m/km)	RUT (mm)	ACARCK (m^2/km)	LCARACK (m/km)	LWCRACK (m/km)	TCRACK (m/km)	PCI
2012	03512185 64192 7917	1.1	4.7	0	1017	1.5	48	83

Note: ACRACK=alligator crack; LCARCK=longitudinal crack, LWCRACK=longitudinal wheelpath crack, TCRACK=transverse crack

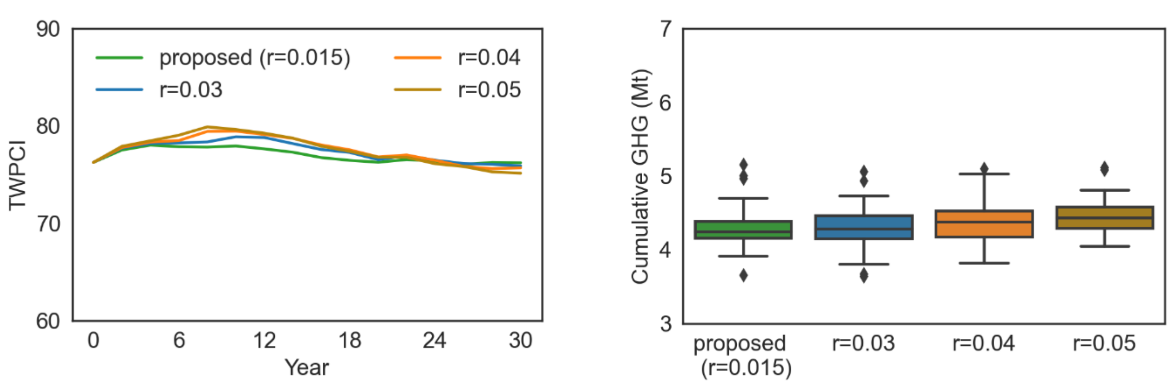
C.3. Sensitivity analysis for discount rates

It is important to note that the magnitude and specifics of results in Chapter 4 would certainly shift for different cases and for different levels of risk preference. As an example of this, an analysis of the sensitivity of model results to the choice of discount rate is presented here.

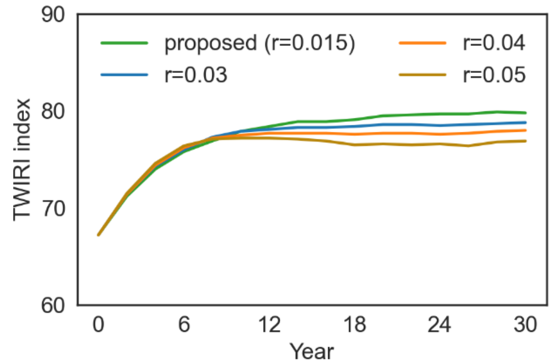
Federal highway administration (FHWA) recommends that the choice of discount rate be the real treasury interest rate as suggested by the OMB [135], which suggest a discount rate of 1.3-1.5% for calendar year 2019. For all analyses in Chapter 4 and Appendix C.2, the discount is chosen as 1.5%. Many existing papers use a discount rate of 4%. Therefore, the discount rates for the sensitivity analysis are chosen as 1.5%, 3%, 4% and 5%.

The sensitivity analysis only focuses on the proposed strategy with the critical budget, i.e., \$132.5M. Figure C-5(a) and (c) show that with the increase of discount rate, the pavement network performance increases first and the decrease, which is mainly due to the slight increase of asphalt material usages as shown in Figure C-5(d). As discount rates increase, the cumulative GHG emissions also increase as shown in Figure C-5(b).

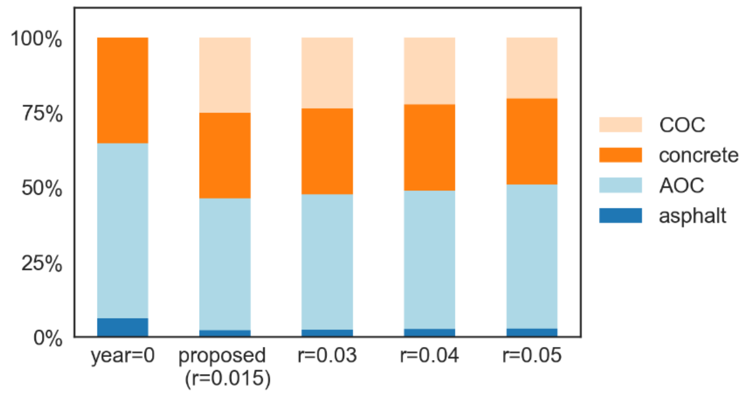
Notably, the influence of discount rate is very slight. When the discount rate increases from 1.5% to 5%, TWPCI decreases by 1.4%, total GHG emissions and TWIRI grow by 3.4% and 8%, respectively.



(a) (b)



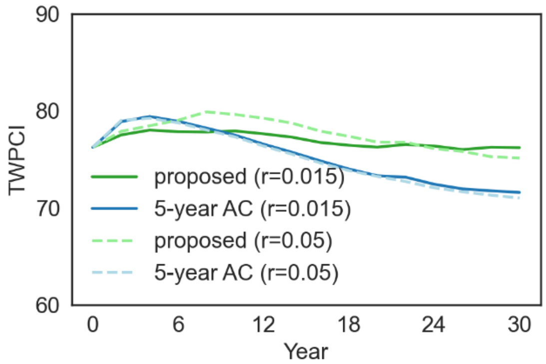
(c)



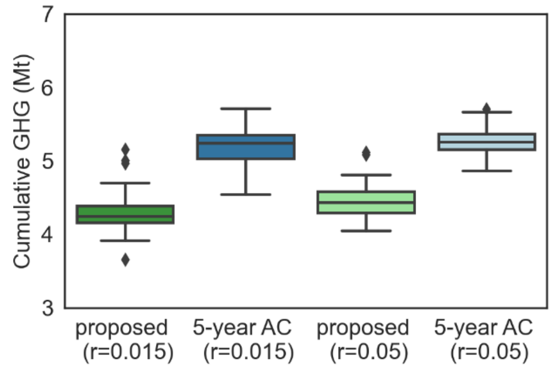
(d)

Figure C-5. Comparisons of different discount rates under the critical budget ($132.5M). (a) is annual mean TWPCI, (b) is the distributions for cumulative life-cycle GHG emissions for 30 years, (c) is the annual TWIRI index, (d) is the pavement type distribution at the beginning of analysis period (year=0) and the end of analysis period for each discount rate.

Next, the proposed strategy and the 5-year AC only strategy are compared under the critical budget in terms of two discount rates 1.5% and 5%. Figure C-6(a) shows that the change of discount rate has a very small influence on the comparison between these two strategies. TWPCI difference between these two strategies changes from 4.6 to 4.1when discount rate increases from 1.5% to 5%. Similarly, it also has a small influence on the cumulative life-cycle GHG emissions as shown in Figure C-6(b). The corresponding difference for the GHG emissions changes from 0.89Mt to 0.82Mt. Hence, the selection of different discount rates will not significantly influence the main conclusions in both Chapter 4 and Appendix C.2.



(a)



(b)

Figure C-6. Comparisons between the proposed strategy and 5-year AC only strategy under discount rates 1.5% and 5%. (a) is the annual mean TWPCI, (b) is the cumulative life-cycle GHG emissions for 30 years under the critical budget ($132.5M)

Appendix D: Supplementary Materials for Chapter 5

D.1 Pavement management system (PMS) data

PMS data is one of the key elements for determining treatment schedules. Ideally, it is better to use state-specific data for pavement management analyses. However, only a few states provide publicly available PMS data. To analyze all states in the U.S. with a reasonable resolution, two data sources are applied, including road statistics generated by the federal highway administration (FHWA), and the long-term pavement performance (LTPP) database.

FHWA road statistics

FHWA provides the road statistics for different road systems, including interstate, arterial, collector and local, for both rural and urban roads [109]. At present, statistics for year 2017 and 2018 are available online. However, when this project was started, only the data for year 2017 was available, so all analyses are only based on the year 2017 statistics. Even though it is not the up-to-date one, it will not influence the final conclusions.

The FHWA road statistics provide the distributions for international roughness index (IRI), annual average daily traffic (AADT), annual average daily truck traffic (AADTT), pavement types, pavement length, lane number and lane width in terms of miles for each system and route type. Corresponding data source for each variable is listed in Table D-1.

Given one variable, FHWA statistics divide its distribution into several buckets and provides the pavement length (in miles) for each bucket. Table D-2 provides an example for AADT distribution for rural interstate system in Massachusetts. For interstate system, it is assumed that each segment length is equal to 2.5 miles. For arterial, collector and local systems, segment length is assumed to be 10 miles. The segment number given one bucket is equal to the total length divided by 2.5 for interstate system, and by 10 for other systems. For example, in the bucket (10,000, 19,999), the segment number is equal to 3. Next, for each segment, its AADT value is uniformly sampled based on the bucket threshold values. For the same example, for bucket (10,000, 19,999), 3 segments' IRI values are uniformly sample form the range [10,000, 19,999].

During the analysis period, IRI values change each year due to the deterioration process and treatment selections. AADT and AADTT have annual growth rates as 0.6% and 1.2%, respectively [146].

Table D-1. Data source from FHWA road statistics

Variable	Table number	Variable	Table number
IRI	HM-64	AADT	HM-57
Pavement length	HM-50	Pavement type	HM-51
AADTT/AADT	VM-1	Lane number	HM-60/HM-20
Lane width	Highway Functional Classification Concepts, Criteria and Procedures		

Table D-2. Miles by AADT for rural interstate system in Massachusetts

State	<10,000	10,000~19,999	20,000~34,999	>35,000
Massachusetts	-	6	39	19

LTPP database

Pavement deterioration prediction is usually based on age, thickness, and traffic levels [124]. However, age and thickness are not provided by the FHWA road statistics. To obtain these two values, several linear relationships are developed based on the LTPP dataset (equations (D.1) - (D.3)).

$$TOTTHK = a_{1,1} \cdot IRI + a_{1,2} \cdot AADTT \tag{D.1}$$

$$SURTHK = a_{2,1} \cdot IRI + a_{2,2} \cdot AADTT \tag{D.2}$$

$$AGE = a_{3,1} \cdot IRI + a_{3,2} \cdot AADTT \tag{D.3}$$

Where TOTTHK represents the total thickness, and SURTHK represents the surface thickness. The reason to differentiate these two types of thicknesses is for the calculation of excess vehicle fuel consumption caused by deflection-induced pavement vehicle interaction (PVI).

It would be ideal to develop a set of inferring relationships for each state. However, the LTPP dataset only covers around 2,500 segments in both U.S and Canada. Some states have no data at all. Instead of state-specific relationships, four sets of inferring relationships are developed for each climate zone. Figure D-1 presents four climate zones for the U.S., as suggested by LTPP [172].

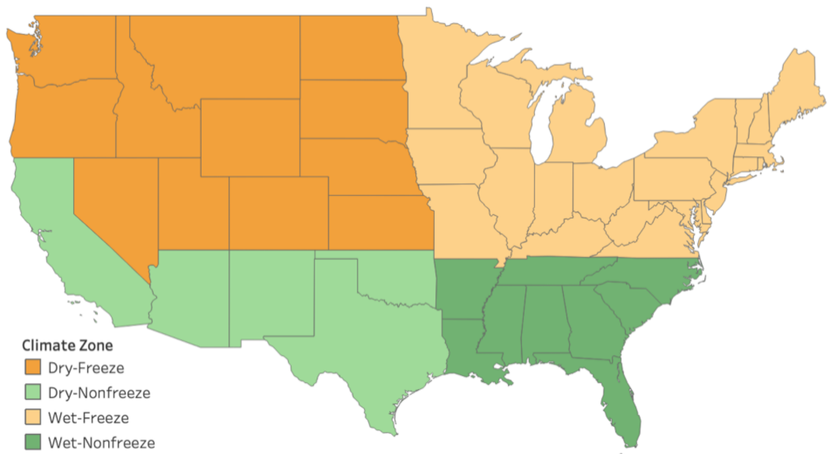


Figure D-1. Climate zones in the U.S. suggested by LTPP.

D.2 Pavement treatment cost

Treatment cost for different states are mainly generated based on the available bid data for highway projects from 2016 to 2020 [20]. In order to extract the unit prices for both asphalt and concrete materials, the original Oman dataset are filtered by the following criteria: (1). focusing on the winning bid; (2). the project size should be at least 1 mile; (3). focusing on the overlays and reconstructions while surface treatments are ignored. The third criterion is not trivial since different states may have different bid names for the same type of pavement projects. Hence, the filtering process was with the help of experienced pavement engineers.

After the filtering process, a set of projects can be obtained with their project size (i.e., the quantity of material usage) and corresponding total cost. Then the unit prices for concrete and asphalt materials can be generated by equation (D.4).

$$unit\ cost = \frac{\sum_{i=1}^{I} quantity_i \cdot cost_i}{\sum_{i=1}^{I} quantity_i} \tag{D.4}$$

D.3 Pavement treatment actions

For treatment actions, it would be great to use the real ones for each state. However, it is difficult to collect the treatment information for all states. Instead, the same treatment schedule is used for the same type of road systems (e.g., interstate roads) and assume that those states that fell in the same climate zone (Figure D-1) follow the same treatment actions that the representative state is following. The treatment actions for the representative states were adopted from their life cycle cost handbook published by the state department of transportations. Representative states for each climate zone are Colorado, Arizona, Iowa and Florida, respectively. Due to the lack of representative data for low-volume roads, certain assumptions are applied to different climate zones. For all the climate zones, the local and collector treatment actions are considered similar. Selected treatments for both asphalt-surfaced and concrete-surfaced pavements are listed in Table D-3 and Table D-4, respectively.

Table D-3. Treatment actions for asphalt-surfaced pavements

Climate Zone	System	Reconstruction	Overlay	Preservation
Dry-Freeze (CO)	interstate	14” new asphalt pavement	6” asphalt overlay	2” mill & fill
	arterial	9” new asphalt pavement	5” asphalt overlay	2” mill & fill
	collector	5.75” new asphalt pavement	0.75” mill & 3.25” fill	0.75” mill & 1.5” fill
	local	5.75” new asphalt pavement	2” asphalt overlay	0.75” mill & 1.5” fill
Dry-Nonfreeze (AZ)	interstate	13.5” new asphalt pavement	5” asphalt overlay	0.75” mill & 1.5” fill
	arterial	7.5” new asphalt pavement	5” asphalt overlay	0.75” mill & 1.5” fill
	collector	5.75” new asphalt pavement	0.75” mill & 3.25” fill	0.75” mill & 1.5” fill
	local	5.75” new asphalt pavement	2” asphalt overlay	0.75” mill & 1.5” fill
Wet-Freeze (IA)	interstate	13” new asphalt pavement	6” asphalt overlay	2” mill & fill
	arterial	7.5” new asphalt pavement	5” asphalt overlay	2” mill & fill
	collector	5.75” new asphalt pavement	0.75” mill & 3.25” fill	0.75” mill & 1.5” fill
	local	5.75” new asphalt pavement	2” asphalt overlay	0.75” mill & 1.5” fill
Wet-Nonfreeze (FL)	interstate	12.5” new asphalt pavement	3” mill & 4” fill	Crack and seal
	arterial	6” new asphalt pavement	2” mill & 3” fill	Crack and seal
	collector	5.75” new asphalt pavement	0.75” mill & 3.25” fill	0.75” mill & 1.5” fill
	local	5.75” new asphalt pavement	2” asphalt overlay	0.75” mill & 1.5” fill

* The thickness unit is inch.

Table D-4. Treatment actions for concrete-surfaced pavements

Climate Zone	System	Reconstruction	Overlay	Preservation
Dry-Freeze (CO)	interstate	10” new concrete pavement	5” concrete overlay	Diamond grinding
	arterial	7.5” new concrete pavement	5” concrete overlay	Diamond grinding
	collector	7.5” new concrete pavement	3.25” asphalt overlay	Diamond grinding
	local	7.5” new concrete pavement	2” asphalt overlay	Diamond grinding
Dry-Nonfreeze (AZ)	interstate	11” new concrete pavement	5” concrete overlay	Diamond grinding
	arterial	8.5” new concrete pavement	5” concrete overlay	Diamond grinding
	collector	7.5” new concrete pavement	3.25” asphalt overlay	Diamond grinding
	local	7.5” new concrete pavement	2” asphalt overlay	Diamond grinding
Wet-Freeze (IA)	interstate	11” new concrete pavement	6” concrete overlay	Diamond grinding
	arterial	8” new concrete pavement	5” concrete overlay	Diamond grinding
	collector	7.5” new concrete pavement	3.25” concrete overlay	Diamond grinding
	local	7.5” new concrete pavement	2” asphalt overlay	Diamond grinding
Wet-Nonfreeze (FL)	interstate	9” new concrete pavement	4” asphalt overlay	3% slab replacement
	arterial	9” new concrete pavement	4” asphalt overlay	3% slab replacement
	collector	7.5” new concrete pavement	3.25” concrete overlay	Diamond grinding
	local	7.5” new concrete pavement	2” asphalt overlay	Diamond grinding

* The thickness unit is inch.

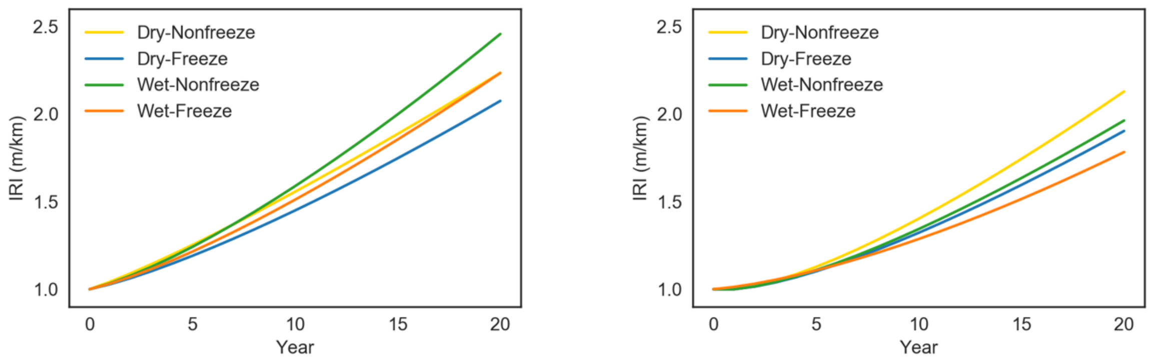
D.4 Pavement deterioration model

Prediction models for pavement conditions are used to estimate how pavement condition and context will change over time without a treatment action. Considering that environmental factors could influence pavement deterioration rates, four sets of deterioration models in terms of asphalt, concrete, asphalt overlay composite pavements are developed for four climate zones. Due to limited data, it is not possible to build a model for concrete overlay composite pavements. Hence, it is assumed that the concrete overlay composite pavements have the same deterioration rate as concrete pavements.

There are several types of pavement condition metrics, such as roughness, cracks, rut/fault, etc. Among them, roughness attracts the most attention in both academia and industry, and IRI is usually applied to describe road roughness conditions. The adopted pavement deterioration model is based on a difference-stationary process and was developed using data from LTPP. It is assumed that pavement deterioration follows a random walk with drift and uncertainties that have a permanent influence on future deterioration levels, so the variance of future pavement performance increases over time [21]. Age, AADTT, and total thickness (TOTTHK) of pavement are incorporated in the deterioration model which are suggested to be influential factors by a previous study [124]. The expected deterioration process is shown in equation (D.5):

$$\Delta IRI_{t,i} = \alpha \cdot AGE_{t-1,i}^{\beta_1} \cdot AADTT_{t-1,i}^{\beta_2} \cdot TOTTHK_{t-1,i}^{\beta_3} \tag{D.5}$$

where coefficients $\alpha, \beta_i \left(i = 1,2,3 \right)$ can be obtained through ordinary least squares (OLS). Figure D-2 presents examples of deterioration curves for an asphalt pavement segment and a concrete pavement segment in different climate zones, respectively. These curves provide similar trends as the findings in [173].



(a) asphalt (b) concrete

Figure D-2. Examples of deterioration curves for (a) asphalt and (b) concrete in terms of different climate zones

D.5 Performance jump model

Performance jump model is used to describe the effectiveness of different treatments, namely, after a treatment action, how the pavement condition changes. It is usually a function of the condition metric before a treatment is applied [61]. Based on the LTPP dataset, performance jump models are developed for asphalt pavement preservation, concrete pavement preservation, and asphalt overlay.

For each type of model, IRI before treatment (IRI_0), age, surface thickness are considered as dependent variables, and for asphalt overlay model, the overlay thickness is incorporated as well. Then linear regression is applied to find significant variables. Results show that IRI_0 is the only significant variables for both preservation models, and significant variables for the asphalt overlay model include IRI_0 , age, and overlay thickness. Next, generalized linear models are applied to develop three performance jump models in the form of equation (D.6).

$$\Delta IRI = a_0 + a_1 \cdot f_1\left(IRI_0\right) + a_2 \cdot f_2\left(age\right) + a_3 \cdot f_3\left(overlay\ thickness\right) \tag{D.6}$$

where functions f_1, f_2, and f_3 can be in linear, polynomial, exponential and logarithmic forms and they are mainly determined by Pearson correlation coefficient between the dependent variable and ΔIRI . Then, OLS is applied to determine coefficients $a_i\left(i = 0,1,2,3\right)$ in the model.