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Data-driven algorithms for enhanced transportation infrastructure asset management

by

Ahmed F Abdelaty Ahmed

A dissertation submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Civil Engineering (Construction Engineering and Management)

Program of Study Committee:
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Iowa State University

Ames, Iowa

2017

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ABSTRACT

State highway agencies collect a considerable amount of digital data to document as well as support a variety of decision-making processes. This data is used to develop insights and extract information to enhance serval decision-making systems. However, digital data collected by highway agencies has been consistently underutilized especially in supporting data-driven or evidence-based decision-making systems. This underutilization is a result of a poor established connection between the data collected and its final possible usage.

This study analyzes the digital data collected by highway agencies to enhance the reliability of decision-making systems by utilizing Geographic Information Systems (GIS) and data analytics. This study will a) develop an enhanced Life-Cycle Cost Analysis (LCCA) for pavement rehabilitation investment decisions by establishing a novel cost classification system , b) identifying the barriers and challenges faced by agencies to adopt a data-driven pavement performance evaluation process, and c) develop a dynamic pavement delineation algorithm that aggregates the pavement condition data at the distress level. In order to achieve these objectives, the study uses different digital dataset including a) pavement rehabilitation historical bid-data, b) pavement rehabilitation as-built drawings, c) pavement condition data, and d) pavement maintenance and rehabilitation geospatial data. The study developed an enhanced life-cycle cost analysis practice that would significantly improve the economic evaluation accuracy of investment decisions. Additionally, the study identified seven major barriers and challenges that hinder the adoption of a data-driven pavement performance evaluation. Finally, the study developed and automated a pavement delineation algorithm using Python programming language.

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This study is expected help highway agencies utilize their historical digital datasets to support a variety of decision-making systems. Furthermore, the study paves the way to adopting and implementing data-driven and evidence based decision-making processes.

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CHAPTER I: INTRODUCTION

Background and Motivation

Civil infrastructure systems have a significant impact on the nation's economy by providing reliable and economic transportation, communication, and other services that directly contribute to the growth of the nation's economy. Managing different types of infrastructure assets is a fundamental task for governmental agencies to achieve their mission. The Federal Highway Administration (FHWA) defines infrastructure asset management as programs that aim to help practitioners manage their physical assets effectively and efficiently through a systematic and strategic process of operation, maintenance and improvements (FHWA 2012). These programs help agencies provide an acceptable level of service and prevent the assets from further deterioration caused by a variety of stressors. Infrastructure asset management covers different types of physical assets such as pavement structures, bridges, sewer networks, etc. This study focuses on pavement assets and their management practices which are the fundamental components in building an economic and efficient transportation system. In the last decades, there has been a steady evolution of several asset management areas of decision making (Hicks et al. 2000 and Jahren et al. 2007), performance evaluation (Hall et al. 2002 and Dong and Huang 2012), economic evaluation (Pittenger et al. 2011 and Irfan et al. 2009), and pavement condition data delineation (Misra and Das 2004 and El Gendy and Shalaby 2004). However, there is a need for improvement in these distinct areas to efficiently utilize the growing amount of digital data collected and stored in different forms of databases which will consequently enhance and support data-driven asset management plans.

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State highway agencies use automated data collection methods such as laser scanning and ultrasonic waves to collect pavement condition data. The use of automated data collection methods has resulted in collecting an enormous amount of pavement condition data. For instance, Iowa DOT collects pavement condition data every 52 feet which results in more than a half million pavement condition records for its pavement network stored annually in the DOT's Geographic Information System (GIS) database. Additionally, state highway agencies have moved towards digital data storage for different daily business operations such as daily work reports, maintenance and rehabilitations contracts, etc. The availability of this digital data is both a challenge and an opportunity. The challenge is how agencies can manage and analyze the collected historical data while the opportunity is the valuable knowledge that agencies can extract from this digital data to improve the business practices and decision-making processes.

The knowledge that can be extracted from the digital collected data can significantly improve the practices of asset management in terms of economic analysis and performance measurement which in turn can facilitate the implementation of acts including the Intermodal Surface Transportation Efficiency Act (ISTEA), the Moving Ahead for Progress in 21st Century Act (MAP-21), and the Fixing America's Surface Transportation (FAST) Act. In 1991, the Intermodal Surface Transportation Efficiency Act (ISTEA) was signed and it required the consideration of the life-cycle costs in the design of pavements. A few years later, the Federal Highway Administration (FHWA) issued the Life-Cycle Cost Analysis (LCCA) in pavement design guide which is now used by over 80% of the Departments of Transportation (DOTs) to evaluate the economic effectiveness of investment decisions (Chan et al. 2008). Additionally, the guide provides guidelines for analyzing risks and uncertainties associated with the investment decisions such as agency costs and other sources of uncertainties.

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MAP-21 requires State Highway Agencies (SHAs) to develop performance-based plans and risk-based asset management plans. Thus, agencies need to accurately assess the performance of their prior investments to improve their future performance-based plans. Many studies addressed the performance and economic evaluation in terms of maintenance and rehabilitation treatments of pavements (Hall et al. 2002, Dong and Huang 2012, and Lu and Tolliver 2012). However, the opportunities to realistically establish data-driven asset management practices are growing as agencies collect more digital data efficiently.

Problem Statement

The main challenge that faces state highway agencies is how to manage and analyze their digital infrastructure data in order to extract useful knowledge that can improve their asset management practices such as economic analysis, performance evaluation, digital data management and decision-making.

Economic analysis of alternatives is conducted by agencies to evaluate the economic value of several alternatives by considering life cycle costs incurred during the future life of the alternative. However, there are uncertainties associated with the LCCA that question the credibility of the analysis results. Several studies analyzed the use of LCCA and the uncertainties associated with it (Abaza 2002, Salem et al. 2003, Ozbay et al. 2004, Chan et al. 2008, Li and Madanu 2009, and Swei et al. 2013). However, the prevailing understanding of these uncertainties associated with the agency costs is still limited. Therefore, there is a need to study this uncertainty to help practitioners choose the right decision based on rigorous economic analysis.

As for performance evaluation, estimating treatment service lives is a challenging and fundamental task since it is directly associated with the analysis period of the LCCA and

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performance evaluation of prior investments. Several studies addressed the performance evaluation issues of maintenance and rehabilitation treatments of pavements (Hall et al. 2002, Dong and Huang 2012, and Lu and Tolliver 2012). The majority of the studies use the data from the long-term pavement performance (LTPP) database that does not necessarily reflect the performance of treatments at the state level. Other studies used highly controlled data collected by state agencies (Jahren et al. (1998), Labi and Sinha (2004), Labi et al. (2007), Irfan et al. (2009), Liu et al. (2010), and Chen et al. (2009). Most of the previous studies used highly controlled data collected by state highway agencies. With the increasing amount of digital data collected by agencies, there is a need to evaluate and identify the challenges and barriers associated with using the collected data to establish a data-driven treatment performance evaluation process.

As agencies strive to manage their assets, they heavily invest in automated data collection methods such as laser and ultrasound scanning which result in an enormous amount of pavement condition data. For instance, Iowa DOT collects more than half a million pavement condition records for its pavement network annually. In fact, many DOTs collect pavement condition data for very short sections (i.e., 52 feet in Iowa). As such, there is a need to develop a scientific and dynamic method to aggregate the pavement condition data to from reasonably long segments that are suitable for pavement management purposes. This method should also overcome the limitations of other algorithms including the cumulative difference approach (AASHTO 1993) and other statistical methods proposed by several studies (Divinsky et al. 1997, Kenedy et al. 2000, Shalaby 2004, Yang et al. 2009, and D'Apuzzo and Nicolosi 2012)

Agencies can realize a high return on their investment from their ever growing digital databases in terms of the knowledge extracted from the historical data. As such, this study

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addresses this issue by analyzing the data collected by SHAs to extract meaningful information that should improve SHAs practices. The research questions that this study will aim to answer are:

1. How are the LCCA results affected by the historical cost data of pavement treatments and the variability of treatments service lives?
2. What are the challenges and barriers that hinder the adoption of a data-drive treatment performance evaluation?
3. How can agencies delineate their pavement condition data effectively in order to accurately represent the pavement condition?

Research Objectives

In order to address the aforementioned problems, this research has three main objectives as follows:

1. Evaluate the effect on pavement LCCA results by differentiating historical pavement rehabilitation costs into pavement and non-pavement cost items and develop a process for accurate pavement LCCA.
2. Identify the challenges and barriers that hinder the adoption of a data-driven treatment evaluation process of pavement treatments.
3. Develop an algorithm that dynamically delineates the pavement condition data to form longer pavement segments for pavement management purposes.

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Methodology and Organization

Three major tasks are conducted to fulfill the objectives of this research. Figure 1-1 illustrates the overall methodology and organization of this dissertation. The first objective of this research is to develop an enhanced LCCA that considers the associated inherent uncertainties which are the cost distribution of historical rehabilitation cost data. In order to address this uncertainty, historical bid data and as-built drawings were collected and analyzed. Statistical analysis methods, distribution fitting and Monte Carlo simulation were used to ultimately conduct a probabilistic LCCA. The results of the probabilistic LCCA are then used to evaluate the effect of misusing the historical cost data on the feasibility and effectiveness of competing investment decisions.

The second objective of this study is to identify the barriers and challenges that hinder the adoption of a data-driven performance evaluation process of pavement treatments. Those barriers and challenges are identified by mimicking the typical performance evaluation process used by many agencies and researchers. The study used a spatial integration to integrate the pavement condition data and entire historical treatment projects data in a GIS platform. Additionally, the pavement distress data were tracked before and after treatment applications to determine the barriers and challenges associated with using the historical data to support a data-driven pavement performance evaluation.

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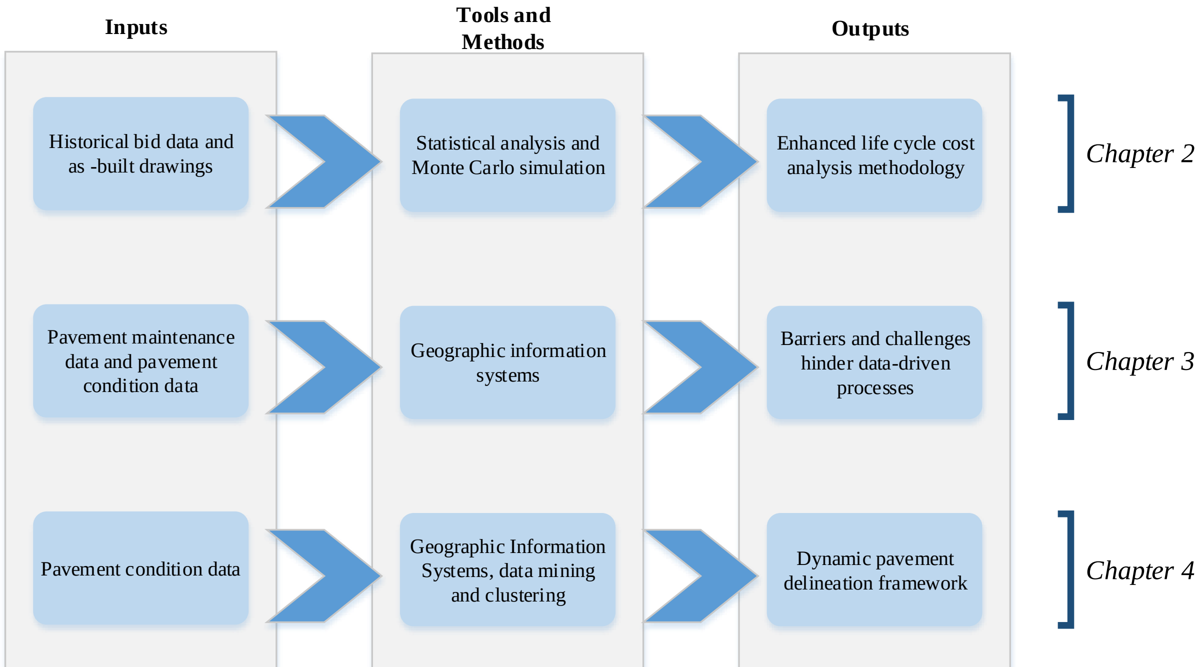

Figure 1-1 Overall research methodology and dissertation organization

Finally, the last component of this study aims to develop a segmentation algorithm for pavement sections based on the collected condition data by one state highway agency. The segmentation or delineation algorithm uses the affinity propagation clustering technique to find homogenous pavement segments at the distress level. A case study was conducted to show the capabilities of the proposed segmentation methodology in terms of condition representation.

This dissertation consists of three papers that aims to achieve each of the aforementioned objectives. Further details on each paper is discussed below.

Paper #1: Enhancing life cycle cost analysis with a novel cost classification framework for pavement rehabilitation projects

This paper presented a comprehensive literature review on LCCA practices and uncertainties. Based on the literature analysis, it was found that the majority of previous studies have misused the historical data of rehabilitation costs to evaluate the effectiveness of investment

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decisions. Few studies have pointed out that contract details of pavement rehabilitation projects should be studied carefully to differentiate between pavement items and non-pavement items. As such, this paper presented a comprehensive cost classification framework that differentiates between pavement and non-pavement cost items.

This cost classification framework was developed by analyzing the historical bid data along with the as-built drawings. Three major rehabilitation treatments were studied in this paper including:

- Hot Mix Asphalt (HMA) resurfacing
- HMA with milling
- HMA with Cold in-place Recycling (CIPR)

Based on the data analysis of approximately 100 pavement rehabilitation projects, the cost classification items was developed. Furthermore, a stochastic LCCA was conducted to show the effect of including non-pavement cost items in evaluating economic effectiveness of investment decisions. By addressing this major point of uncertainty, agencies will be able to enhance their LCCA practices and increase the reliability of the analysis.

Paper #2: Barriers to implementing data-driven pavement treatment performance evaluation process

This paper identified the barriers and challenges that face agencies in order to use their historical digital data to evaluate the performance of pavement treatments. From the literature review, it was found that the service life of pavement treatment have major variations according to the performance indicator used in the evaluation process. It was also observed that most agencies and researchers use data from highly controlled sites to evaluate the performance of specific treatments. With increasing efforts to collect digital data on pavement performance,

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there is an opportunity to tap into the historical data collected and enhance the pavement treatment performance evaluation process. However, there are existing barriers and challenges that hinder the full utilization of the historical data. Thus, this paper identified those barriers and presented a set of recommendation to overcome them.

Paper #3: Dynamic multidimensional pavement delineation approach

Highway agencies are now able to collect continuous pavement condition data using modern technological advancements including laser scanner, image processing and sensor technology. Continuous pavement condition data are often collected for very short distances which enhances the agency's confidence in identifying the existing conditions. However, it is challenging to use the raw and high density pavement condition data to support a variety of decision making systems. As such, this paper presented a novel approach that dynamically delineates the pavement condition data at the distress level using a powerful data clustering technique. Pavement condition data collected by the Iowa DOT were used as a case study to demonstrate the capabilities of the proposed algorithm.

Expected Contribution

This study investigated and clarified major inherent uncertainty associated with LCCA by statistically analyzing the historical cost data of prior investments which will improve the credibility of LCCA results. Additionally, this study identified major barriers and challenges that hinder the use of performance-based plans. A set of recommendations to overcome those barriers and challenges were provided.

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Furthermore, the study proposes a scientific and dynamic approach to segment roadways based on the pavement condition assessment data to accurately represent the pavement condition. This approach is expected to help agencies aggregate the collected pavement condition data to accurately represent the condition of pavement segments and hence improve several decision-making practices.

In summary, the outcomes of this study is expected to significantly improve the practices of transportation asset management by improving their economic analysis procedures, and establishing a data-driven treatment evaluation process and pavement condition data delineation approach. As such, agencies can conduct accurate economic evaluation of their investment decisions, adjust their data collection practices to address the identified barriers and challenges, and manage their collected data effectively which can create an efficient business cycle that can optimize the use of available resources.

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CHAPTER 2: ENHANCING LIFE CYCLE COST ANALYSIS WITH A NOVEL COST CLASSIFICATION FRAMEWORK FOR PAVEMENT REHABILITATION PROJECTS

Abstract

Life cycle cost analysis (LCCA) procedures have been used over the past decades to justify the choice of one pavement design alternative over the others. However, many ambiguities associated with the life cycle cost input values, such as the discount rate and future cost estimates have questioned the credibility of the analysis results. Another unrecognized source of errors in pavement LCCA is the misunderstanding of pavement treatment costs when historical costs are typically used for estimating those costs. The historical costs of pavement rehabilitation projects typically include a significant amount of non-pavement related costs, which may result in a wrong LCCA if not treated appropriately. This paper addresses this specific source of error and proposes a solution to eliminating this error by using a novel cost classification framework that successfully differentiates mainline roadway costs from non-pavement cost items. A case study using Monte Carlo simulation is conducted to evaluate the probabilistic LCCA results. The results of the case study indicate that the conventional approach of using total rehabilitation project costs in LCCA may even lead to a wrong investment decision. The findings of this study will help practitioners and researchers better understand the nature of pavement rehabilitation project cost distributions

Keywords: Stochastic life cycle cost analysis, Monte Carlo simulation, pavement maintenance and rehabilitation, highway infrastructure, asset management, construction projects

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Introduction

The extensive road infrastructure in the United States, which consists of more than 4 million miles (ASCE 2013), represents a huge financial burden on the state and local governments. Though highway agencies strive to keep their pavement assets at an acceptable condition, the existing funding gap has resulted in delaying many rehabilitation projects (Xu and Tsai 2012). The current road infrastructure requires periodic maintenance and rehabilitation treatments to be maintained at an acceptable level of functional and structural performance. At the same time, maintenance and rehabilitation investment decisions have to be economically justifiable to yield the highest return on investments by evaluating their economic effectiveness.

Life Cycle Cost Analysis (LCCA) is a set of procedures used to evaluate the economic value of different design alternatives at the design stage of the project development process. Highway agencies have been using LCCA procedures to justify the selection of one pavement design alternative over the others. In addition, the agencies use life cycle concepts to evaluate the economic value of maintenance and rehabilitation decisions. The procedures, which have been well documented by most highway agencies describing the detailed implementation of pavement LCCA, consider different cost input values associated with the pavement over its service life. For example, the technical bulletin issued by The Federal Highway Administration (FHWA 1998) presents one of the most widely accepted guidance and recommendations in conducting LCCA. Additionally, the use of LCCA by agencies is widespread. Over 80% of the state DOTs perform LCCA to select the economic pavement alternative (Chan et al. 2008).

However, the LCCA procedures contain inherent uncertainties and some misconceptions. For instance, LCCA is highly sensitive to the discount rate when the asset's analysis period is long. Thus, there is clear understanding and agreement on the need to discount future costs but

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there is no clear consensus on what discount rate would be appropriate. Federal Highway Administration (FHWA) recommends 4% as an appropriate discount rate for LCCA and state highway agencies typically use a discount rate ranging from 3-5% as a discount rate. Jawad and Ozbay (2006) concluded that using a fixed average discount rate for a long-term monetary cost estimation can significantly skew the accuracy of the estimation. Another example of the inherent uncertainties in the LCCA stems from possibly different sequences and timing of maintenance and rehabilitation treatments. Pour and Jeong (2012) discovered that in reality, more than ten different sequences of treatments with different application timing were available by analyzing historical I-40 highway project records in Oklahoma. The reality of different treatment sequences and application timing might be caused by funding gaps as noted by Xu and Tsai (2012) and/or different aging patterns due to external loading conditions, material and construction qualities. However, most LCCA procedures use a fixed sequence and a fixed timing of future pavement treatments. To overcome the uncertainties of those input values, the LCCA communities have embraced the concept of probabilistic LCCA by representing those input values in probability distribution curves. This probabilistic LCCA approach may avoid the risk of one point estimate from a deterministic LCCA approach but it does not eliminate the fundamental uncertainties associated with the LCCA results.

Another relatively unknown point of error in pavement LCCA is the misunderstanding of pavement treatment costs when historical costs are typically used for estimating those costs. Unlike the inherent LCCA uncertainties discussed in the previous paragraph, this source of error can be completely eliminated if the LCCA users understand the structure of historical pavement treatment project costs and correctly make adjustments to estimate the pavement treatment costs for LCCA.

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Historical pavement rehabilitation project cost data are archived in a database called the bid tabulations/tabs, which contain the summary of the bids submitted by contractors who responded to the bidding process. It is important to note that the pavement rehabilitation project costs stored in the bid tabs database include all work items for the project and the common practice of state highway agencies is that a pavement rehabilitation project includes not only the original mainline roadway rehabilitation but also other non-pavement related work items such safety enhancements, traffic signal installation, etc.. However, the work item description in the bid tabs data does not necessarily indicate whether a work item is related to the mainline roadway or not. As a result, if the total cost of a pavement rehabilitation project is directly used to estimate the unit cost of a pavement rehabilitation type for LCCA without understanding the cost breakdown of pavement rehabilitation projects, it may result in an incorrect LCCA, leading to a wrong selection of a pavement design or a treatment.

The main objective of this paper is to develop a cost classification framework that discerns between pavement and non-pavement related costs of pavement rehabilitation projects for LCCA applications. This proposed framework can be used as a basis for conducting a fair LCC comparison between different alternatives and test the hypothesis that LCCA results can be significantly skewed because of the inclusion of non-pavement related costs. The study also aims at finding a good-fit probability distribution of total rehabilitation costs and mainline roadway costs for different rehabilitation types. Based on the cost classification framework and using the good-fit probability distributions, a case study that involves estimating the LCC of a pavement system probabilistically is conducted with the Monte Carlo simulation (MCS) to evaluate the effect of using the total rehabilitation costs on the pavement alternative selection process. The implications of the cost classification framework presented here will help practitioners and

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researchers understand the nature of pavement rehabilitation cost distribution. The cost classification of past rehabilitation projects is essential to enhance a highway agency's decision making processes and accurately assess the economic value of different pavement systems.

Background

The concept of LCCA is not a new concept however estimating LCCA involves many risks and uncertainties that affect the reliability and accuracy of its results. As such, early efforts have been focused on how to address those risks and uncertainties. For instance, Flanagan et al. (1987) integrated risk management and LCCA to address different sources of risks and uncertainties such as discount rate, initial capital cost and running costs. The study also proposed using sensitivity analysis to study the effect of uncertain parameters on the LCC. Flanagan et al. (1987) also integrated the probability analysis by using Monte Carlo simulation to generate several numbers of simulations of the LCC based on a probability distribution associated with different uncertain parameters. Bromillow and Pawsey (1987) laid the theoretical background for buildings LCCA that involves considering the capital investment, maintenance and operation costs, and time value of money over the asset life. The methods and concepts of earlier studies can be easily adapted to estimate the LCC for any type of civil infrastructure.

LCCA has also gained importance in different sectors especially for decision makers. For instance, Ranasinghe (1996) developed a simplified model for decision makers to calculate the total project costs and considers cost escalation during construction. Those previous attempts have paved the way toward applying LCCA in the field of transportation asset management.

The transportation asset management community has realized the importance of pavement LCCA over the past decades. Many studies have investigated the use of LCCA by state highway agencies and evaluated treatment cost effectiveness (Ozbay et al. 2004, Chan et al.

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2008, Li and Madanu 2009 and Abaza 2002). Additionally, many DOTs have developed their own probabilistic LCCA procedures using their historical cost records and probability distributions (Rangaraju et al. 2008). However, the use of total costs reported in the historical cost records can overestimate the pavement life cycle cost and underestimate its economic effectiveness because the historical records do not differentiate between pavement and non-pavement related costs. In Canada, a probabilistic LCCA that uses the best-fit probability distributions for pavement item costs was developed (Tighe 2001). The study used the cost data provided by the Ministry of Transportation of Ontario as "an average item price from the three lowest bid prices". The study fitted the cost distribution for different pavement materials such as asphalt binders and granular materials using the (χ^2) test. By categorizing cost items by quantities, the study concluded that the lognormal distribution is the best-fit distribution for pavement material costs. Khurshid et al. (2014) then developed a methodology to evaluate the cost effectiveness of asphalt concrete overlays using treatment performance and cost. The agency's historical costs were comprised of the initial construction costs and annual maintenance cost per lane kilometer.

Many studies have focused on addressing the uncertainty issues in LCCA. Swei et al. (2013) characterized the uncertainty of unit cost construction activities of pavement maintenance to probabilistically quantify uncertainty in the life cycle costs of pavements. The study conducted case studies to demonstrate the benefit of using the distress prediction models of the mechanistic empirical design guide and the Oman Systems bidTabs database to determine the timing and unit prices of rehabilitation treatments and materials. The study presented a reliable method to sequence the rehabilitation treatments, however the use of historical cost data directly from the

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bid tabs can significantly skew the LCCA results. Pour and Jeong (2012) developed realistic LCCA using typical sequential patterns of pavement maintenance and rehabilitation. The study presented a considerable leap towards determining the typical sequential patterns of pavement treatments activities by using the association analysis. Salem et al. (2003) established a risk-based life cycle costing of infrastructure rehabilitation using the probability theory and simulation application to determine the rehabilitation and construction costs of pavements. Despite unique contributions of the aforementioned studies, most of them failed to recognize the fact that pavement rehabilitation costs include a significant amount of non-pavement related costs that should be excluded from LCCA. However, a few prior studies did recognize this issue. The LCCA practices used by Michigan DOT were evaluated by comparing the predicted and the actual pavement life cycle costs (Chan et al. 2008). It was concluded that the actual costs were overestimated in most cases due to the overestimation in materials quantities (Chan et al. 2008). Irfan et al. (2009) recommended examining the contract details of treatment projects to exclude non-pavement activities. Lee et al. (2011) used the LCCA procedures to select a pavement rehabilitation method for the I-710 Long Beach rehabilitation project in California. Agency cost estimates consisted of construction costs and non-pavement costs, such as pavement cost, traffic handling cost, drainage cost and so forth. The historical bid database was used to estimate the unit prices of pavement items and non-pavement costs were calculated simply by using multipliers (Lee et al. 2011). For example, traffic handling costs were calculated as 8% of the total costs. The study pointed out the issue of non-pavement cost items in LCCA. However, the use of multipliers to calculate the non-pavement cost items is not an accurate approach. Hegazy and Saad (2014) developed a mathematical optimization model that aims at obtaining optimum fund-allocation rehabilitation decisions by considering assets' life cycle costs. The optimization

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model was validated using a pavement case study which aimed at allocating limited funds to optimize the network ride quality. However, the case study conducted did not differentiate between pavement and non-pavement costs. In summary, most rehabilitation projects include work items that are not related to the pavement structure. The inclusion of these costs in the LCCA can result in a biased decision making process. Table 2-1 summarizes the research objectives of some relevant studies discussed above and whether they differentiated between pavement and non-pavement costs or not.

Table 2-1. Summary of Recent LCCA studies

Literature	Research Goal	Differentiation between pavement and non-pavement costs
Rangaraju et al. (2008)	Probabilistic approach to determining life cycle costs	No
Tighe (2001)	Guidelines for probabilistic life cycle costing analysis	No
Khurshid et al. (2014)	Benefit-cost analysis of asphalt concrete overlays	No
Swei et al. 2013	Quantify uncertainty in life cycle costs of pavements	No
Pour and Jeong (2012)	Development of realistic life cycle costing model	No
Salem et al. (2003)	Risk based life cycle costing approach of pavement rehabilitation	No
Chan et al. (2008)	Evaluation of life cycle cost practices used by Michigan DOT	Yes
Irfan et al. (2009)	Evaluation of pavement rehabilitation cost effectiveness	Yes
Lee et al. (2012)	Using LCCA to select pavement rehabilitation	Yes

Research Methodology

This research uses descriptive statistical measures and probability theory to analyze mainline pavement and non-pavement related costs. Figure 2-1 illustrates the research approach used to classify and analyze pavement rehabilitation costs. First, a sample of historical pavement

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treatment projects are selected and extensively analyzed using the bid tab data and the as-built drawings to segregate and quantify pavement and non-pavement cost items. This process develops a cost breakdown structure of pavement rehabilitation projects for LCCA. Second, a statistical analysis is conducted on those historical projects to determine the major cost drivers. Third, a goodness of fit test using the Komogorov-Smirnov (K-S), Anderson-Darling (A-D), and Chi-squared (χ^2) tests are done to determine a good fit distribution for total rehabilitation and mainline roadway costs. Finally, the good fit distributions are then used to perform a MCS for a probabilistic LCCA and demonstrate the value of using the proposed approach. The probability distributions are directly incorporated into spreadsheet by using @risk software. A MCS uses the defined distribution to cover all the possible outcomes to calculate the LCC for each scenario and associate the calculated LCC with an estimated probability.

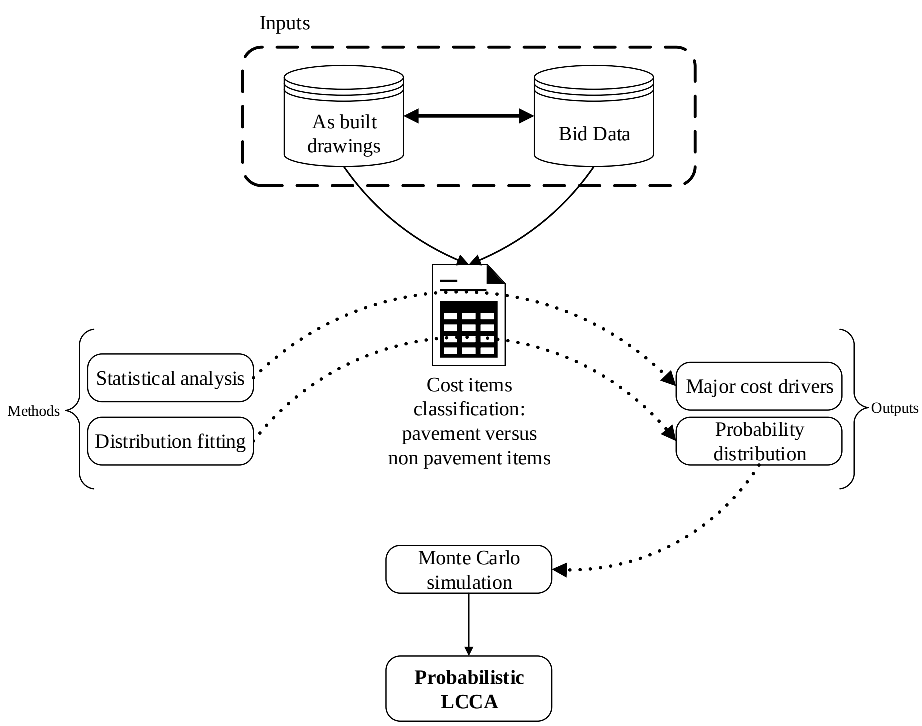

Figure 2-1. Research Methodology

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Data Sources

The bid database used in this research was obtained from Iowa DOT. Each record in the database contains item prices, letting date, project location, project length and so forth for pavement rehabilitation projects. However, there is some missing information that are not recorded. For example, the thickness and the number of lanes for each project are not available. Due to this reason, as-built drawings for the selected projects were obtained to determine the thickness of the pavement treatment, number of lanes, and to classify cost items in details. Because of the data structure in the bid tabs, it is very difficult to differentiate between the quantities of pavement and non-pavement related cost items. For example, an asphalt binder item recorded in the bid tabs data may contain work items related to the mainline roadway and paved shoulder at the same time. As such, the use of as built drawings is essential to separate the quantities and costs of pavement and non-pavement cost items. In this research, three major rehabilitation treatments, which are hot mix asphalt (HMA) resurfacing, HMA resurfacing with cold in-place recycling (CIPR) and HMA resurfacing with milling, used by Iowa DOT are considered. These three types of rehabilitation are most common in Iowa. Projects from 2011 to 2013 are selected for the analysis conducted. The number of projects used is 30, 33 and 36 for HMA resurfacing, HMA resurfacing with CIPR and HMA resurfacing with milling respectively. All costs are brought to 2014 dollars using the construction cost indexes provided by the office of contract at Iowa DOT (2015).

Cost Items Classification Framework

The classification framework of cost items is developed using the expertise of Iowa DOT pavement engineers. It is found that the nature of rehabilitation projects is different from the regular preservation or minor maintenance projects. For most minor preservation and

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maintenance projects, the project typically includes only directly pavement related work items. However, rehabilitation projects usually include non-pavement related work items such as safety work items or updating the roadway to specific standards. As such, a consensus of classifying pavement rehabilitation costs into five cost classes that represent specific types of work items was reached. Table 2-2 summarizes the five classes of cost items for pavement rehabilitation projects with a sample of typical work tasks for each class. These five classes are mainline roadway, safety, necessary, update, and miscellaneous costs.

Mainline roadway costs include any direct costs associated within the 12 feet driving lanes, such as HMA, milling/scarification, base course, intermediate course, binder and so forth. Safety Costs are any costs related to improving the safety of the roadway, such as guardrail and associated costs, crash cushions, lighting and signs, rumble strips, pipe work, paved shoulders, and climbing lanes. Paved shoulders are defined as pavement outside of the mainline that is not part of a turn lane, climbing lane, or ramp. The inclusion of the paved shoulders under safety cost items may be debatable especially if the paved shoulder is tied to the roadway to enhance the performance of the pavement system. However, it was decided to include paved shoulders under safety costs class since roadway shoulders are used for motorists safety. However, if tied shoulders are used to enhance the performance of the mainline roadway, the agency should consider adding the shoulder costs to the mainline roadway costs.

Necessary costs are any costs for required items when resurfacing, but not depending directly on the type or depth of resurfacing. This includes subdrains, patching, granular shoulders, earth shoulders, and pavement markings. Update Costs are any costs associated with bringing the roadway up to current specifications or updating existing features such as bridge approach replacement, turn lanes (new, extended, or resurfaced,), ramps, superelevation updates,

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and urban works. Finally, miscellaneous costs are any costs not included in the previous cost classes, such as incentives, traffic control, and mobilization.

Table 2-2. Classification of pavement rehabilitation costs

Cost Class	Examples of cost items
Mainline roadway	Widening, resurfacing, grading and replacing, and scarification
Safety	Guardrail, crash cushions ,lighting and signs ,rumble strips, pipes and aprons extensions, paved shoulders, and climbing lane
Necessary	Sub-drain, patching, and pavement marking
Update	Bridge approaches, turn lane, ramps, wedges, dowel bar, retrofitting, urban work (manholes and sidewalks)
Miscellaneous	Incentives, median crossovers, traffic control, mobilization, sampling, erosion control, runouts/return, miscellaneous (clearing, insurance, grubbing…)

Mainline roadway costs are expressed as per pavement thickness and number of lane miles because of their nature. The cost of safety and necessary items tend to increase as the project size increases and hence, safety and necessary costs are expressed as per lane mile. On the other hand, the nature of the update cost items are different from the aforementioned cost classes. For example, a project may have many update work items such as bridge approach replacement or adding turn lanes while another project might not have any update costs. As a result, expressing the update costs as per lane mile will be meaningless and misleading and hence, update costs should be expressed as total cost per project. Finally, costs of miscellaneous work items are expressed as costs per lane mile since they tend to increase as the project size increases. The cost classification framework developed is essential to analyzing rehabilitation project costs accurately and to remove the ambiguity associated with non-pavement related costs. For example, an excavation item recorded in the bid tabs data may contain work items related to the mainline roadway and safety at the same time. As a result, the differentiation between such cost items by using the proposed classification framework that can assign different work tasks to

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the right category or split the cost between the categories becomes more important to analyze historical cost data records.

Cost Data Analysis of Rehabilitation Projects

The data analysis conducted for the three major rehabilitation treatments provides a true understanding of the cost distribution of pavement rehabilitation projects over different cost classes. Table 2-3 summarizes the average, minimum, maximum, and standard deviation of percentage of cost items to total costs.

For HMA resurfacing with milling, mainline roadway costs is as high as 77.88% and as low as 31.94%. In some cases, other non-pavement related items represent more than 65% of the total project costs, which indicates that non-related pavement cost items can govern rehabilitation total projects costs. Safety cost items, which is the second cost driver, reached more than 35% in many projects. The aforementioned statistical measures indicate that mainline road construction cost items are not always the major driver for the total project costs. For HMA resurfacing, mainline roadway and safety cost are the major cost drivers. The maximum percentage of mainline road construction cost to total project cost is approximately 54% while the minimum percentage is approximately 16%. Similarly, the percentage of safety cost items to total project cost is as high as approximately 60% and as low as 0%, which indicates that safety costs for HMA resurfacing vary significantly according to the project's requirements. It is worth noting that the two aforementioned treatments tend to be used on pavements that have great variance in condition, as observed by the DOT's engineers, and hence the variation in different cost classes was expected.

Unlike other treatments analyzed in this research, the mainline roadway costs for HMA resurfacing with CIPR are found to be consistent with low standard deviation. It was also noted,

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by the DOT's engineers, that this treatment typically tend to be used on roads that are in similar condition and the treatment application is fairly consistent. The average percentage of mainline road construction costs to the total project cost is approximately 50% associated with a relatively low standard deviation.

The average percentage of safety cost items to total costs is approximately 27% while the maximum and minimum safety costs to total costs percentage are 40% and 14% respectively. Necessary, update, and miscellaneous costs are found to have minor contribution on average to total project costs. The statistical analysis of the rehabilitation projects cost classes shows the variation of cost classes contribution to total costs. The average mainline roadway costs for each rehabilitation type is different and the amount of non-pavement related work items vary significantly from one project to another. These variations are the main ambiguity associated with pavement rehabilitation costs.

Goodness of Fit

The K-S, A-D, and χ^2 goodness of fit tests are performed using @risk software to determine good fit distributions for total costs and mainline roadway costs for each pavement rehabilitation type. The goodness of fit test are conducted two times for each rehabilitation project. The first test is conducted to find a good fit probability distribution for the rehabilitation project's total costs per lane mile while the second test is conducted to find the good fit probability distribution for mainline roadway costs only. Finding good fit distributions for pavement and non-pavement related cost items is essential to implementing probabilistic LCCA. The dataset for each type of rehabilitation treatment projects is used to find a good fit probability distribution and then conduct a probabilistic LCCA using MCS.

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Table 2-3. Cost data analysis summary for different pavement rehabilitation treatments

	Class	Average Cost	Standard deviation	Unit	Average % to total cost	Standard deviation	Maximum	Minimum
HMA resurfacing with milling	Mainline road	$28,792	$8,266	per inch per lane mile	48.13%	11.52%	77.88%	31.94%
	Safety	$50,858	$35,513	per lane mile	24.25%	14.66%	51.02%	0.00%
	Necessary	$23,705	$14,400	per lane mile	12.49%	5.83%	27.16%	1.06%
	Update	$76,099	$120,380	per project	3.59%	5.15%	17.26%	0.00%
	Miscellaneous	$22,046	$16,162	per lane mile	11.55%	5.30%	28.30%	4.22%
HMA resurfacing	Mainline road	$30,201	$7,399	per inch per lane mile	36.30%	8.98%	54.14%	15.88%
	Safety	$71,823	$41,283	per lane mile	25.42%	13.09%	59.22%	0.00%
	Necessary	$57,198	$34,520	per lane mile	18.90%	8.39%	49.12%	4.28%
	Update	$213,712	$307,936	per project	6.71%	7.92%	31.60%	0.00%
	Miscellaneous	$45,180	$50,955	per lane mile	12.67%	7.35%	34.62%	3.62%
HMA resurfacing with CIPR	Mainline road	$37,230	$4,425	per inch per lane mile	50.33%	5.84%	62.13%	39.01%
	Safety	$66,396	$19,743	per lane mile	26.96%	5.53%	40.80%	13.72%
	Necessary	$28,983	$12,870	per lane mile	11.83%	4.74%	20.10%	3.40%
	Update	$37,071	$45,076	per project	1.23%	2.29%	12.58%	0%
	Miscellaneous	$23,871	$10,169	per lane mile	9.66%	2.93%	17.19%	4.49%

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Before conducting the goodness of fit test, data cleaning is done to clean the sample data from outliers based on extreme low and high mainline roadway costs. The extreme values are calculated based on the quartiles values, which is one of the statistical outlier detection techniques (Hodge and Austin 2004). The extreme low and high threshold values are calculated by dividing and multiplying 25^{th} and 75^{th} quartiles by 1.5 respectively. As a result, records that have mainline roadway costs more than the upper extreme value or less than the lower extreme value are excluded for the goodness of fit test. Based on the aforementioned data cleaning criteria, three projects are excluded from the HMA resurfacing with milling and only one project is excluded from the HMA resurfacing datasets. As a result, the sample sizes used to conduct the goodness of fit test are 29, 33 and 33 for HMA resurfacing, HMA resurfacing with CIPR and HMA resurfacing with milling respectively.

In the present study, the χ^2 test is used to measure the goodness of fit that is one of the most generally applicable tests of fit since it can be applied to discrete, continuous, univariate or multivariate data (Moore 1986). It was developed to test the hypothesis that a random sample has a specific distribution function. The χ^2 value is calculated based on equation 2-1 (Moore 1986).

$$\chi^2 = \sum_{i=1}^{n} \frac{(N_i - np_i)^2}{np_i} \qquad (1)$$

Where, n is the number of observations,

N_i is the observed frequency of the i^{th} cell, and

np_i is the expected frequency for the i^{th} cell.

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However, the χ^2 test has a major drawback since there is no clear methodology for selecting the number and locations of bins. As such, the K-S and A-D tests are also conducted to reach a consensus about finding good fit distributions. It is worth noting, that the K-S and A-D tests do not require binning.

A good fit distribution would have a small value of test statistic. All input data records are fitted based on the following assumptions: input data is a continuous sample data, 95% confidence level, and cells are equiprobable. The p-value associated with the goodness of fit tests is 0.05. Table 2-4 summarizes the best-fit distribution for each pavement rehabilitation type.

Log-logistic, Log-normal and Log-logistic distributions are found to be good fit probability distributions for the total cost per lane mile for HMA resurfacing with milling, HMA resurfacing and HMA resurfacing with CIPR respectively. The distribution parameters, shift factors and test statistics values are reported in Table 4. Similarly, the mainline roadway costs of HMA resurfacing with milling and HMA resurfacing are fitted to a log-logistic distribution while the mainline roadway costs of HMA resurfacing with CIPR is fitted to a Weibull distribution.

The log-normal distribution parameters are the mean and standard deviation while the Weibull, and Log-logistic distributions parameters' are shape and scale factors. The shift factor of a distribution is used to shift the domain of the distribution toward the right or the left on the x-axis in which a positive shift factor indicates a right shift on the x-axis and a negative shift factor indicates a left shift.

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Table 2-4. Fitted distributions for each rehabilitation treatment

Description		HMA resurfacing with milling	HMA resurfacing	HMA resurfacing with CIPR
Total cost per lane mile	Distribution (parameters)	Loglogistic (201401;36540)	Lognormal (166529.2;116373.6)	Loglogistic (240218; 23340)
	Shift factor		138615	
	(χ^2) (Rank)	7.515 (6)	5.96 (5)	0.7273 (1)
	K-S (Rank)	0.0822 (1)	0.1271 (2)	0.0777 (1)
	A-D (Rank)	0.2463 (1)	0.322 (1)	0.3668 (1)
Mainline roadway costs per inch per lane mile	Distribution (parameters)	Loglogistic(10121;18097;5.6577)	Loglogistic (8810.8; 21073; 5.66)	Weibull (2.24; 10565)
	Shift factor			27, 870
	(χ^2) (Rank)	5.39 (6)	5.55 (1)	1.15 (2)
	K-S (Rank)	0.0974 (1)	0.1577 (2)	0.079 (2)
	A-D (Rank)	0.2448 (1)	0.5292 (1)	0.1397 (1)

Probabilistic Life Cycle Cost Analysis

A probabilistic LCCA is adopted to study the effect of using the historical total costs per lane mile on pavement investment decision. The LCCA procedure recommended by the FHWA (1998) is used in this research. The first step in the LCCA procedure is to establish pavement design alternatives for a specified analysis period. In this study, an existing flexible pavement system is assumed and a rehabilitation treatment is needed at year 20 to buy time until the next total reconstruction.

HMA resurfacing with CIPR, HMA resurfacing with milling and HMA resurfacing are assumed to be three feasible alternatives. The technical feasibility of each rehabilitation treatment depends on the existing pavement distresses. For example, HMA resurfacing with CIPR may not be a technically feasible alternative if the pavement surface exhibits high extent alligator cracks (Illinois DOT 2010). In this case study, it is assumed that the three rehabilitation alternatives are technically feasible. It is worth mentioning that the treatment sequencing for each

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design alternative will vary according to the initial design of the pavement system, fund availability, traffic volumes, agency practice and future pavement condition. Figure 2-2 shows the timeline of the assumed maintenance and rehabilitation activities which can be feasible in many cases. It is also assumed that crack sealing, microsurfacing, rehabilitation treatment and crack sealing are applied at years 6, 12, 20 and 24 respectively. The timing sequence assumed is validated as a common sequence by discussing with pavement engineers in Iowa. It is worth mentioning that each agency has developed its own design strategy. For instance, California department of transportation (CalTrans 2013) has developed typical pavement maintenance and rehabilitation schedules that consider several factors such as environmental conditions. pavement type, and service level. As such, the maintenance and rehabilitation schedule in this study is assumed to be the same for all scenarios to simplify the LCCA calculations and neutralize rehabilitation schedule effects.

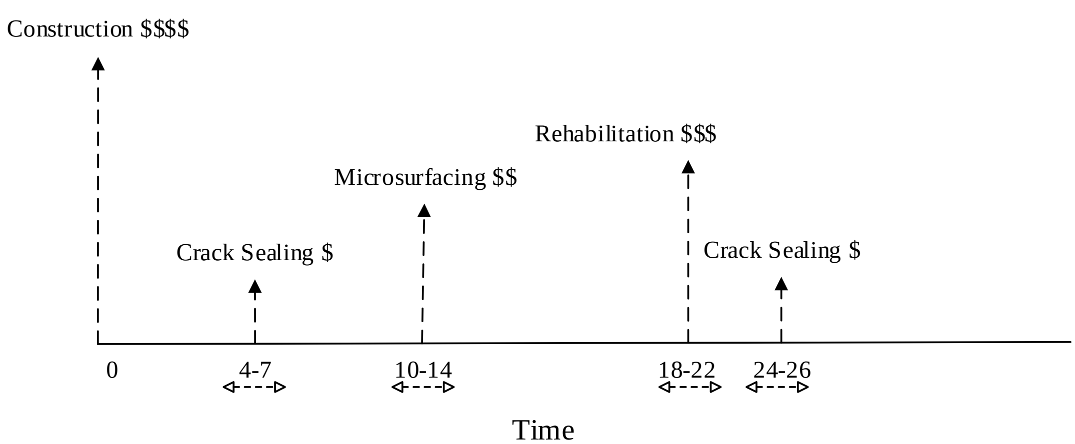

Figure 2-2. Time line for pavement life cycle maintenance and rehabilitation

The second step in the LCCA procedures is to determine the performance period for each alternative. The average performance period of HMA resurfacing with CIPR, HMA resurfacing with milling and HMA resurfacing are 10, 12 and 15 years respectively based on experience of

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the Iowa DOT, City and County engineers,. Since there is no data available to find probability distributions for the performance periods, triangular distributions are assumed for each performance period. Thus, the most likely value is the average performance period while the minimum and maximum values are calculated as plus or minus two years from the most likely value.

The third step in the LCCA procedures is to estimate the agency costs by determining the quantities and unit prices (FHWA 1998). FHWA also recommends determining the unit prices from the agency's historical data. In this case study, the probabilistic LCCA is conducted using a similar approach. The treatment thicknesses are assumed three inches and the length of the project is assumed one lane mile. The total cost per lane mile and the mainline roadway costs are estimated based on the assumed thickness and length. Other agency costs, user costs, and salvage values are assumed the same across all alternatives and hence these costs are not considered in the LCCA.

A MCS is then conducted to perform a probabilistic LCCA two times. The first LCCA is conducted using the total costs of rehabilitation projects per lane while the second LCCA is conducted using the mainline roadway costs only. The effect of using the total costs per lane mile in LCCA is analyzed using the equivalent uniform annual cost (EUAC) since the use of net present value (NPV) to compare the cost effectiveness of different treatments has major problem in determining the analysis period (Pittenger et al. 2011). As such, the EUAC presents a fair comparison when treatments have different performance periods. The EUAC is calculated for each alternative based on the stated assumptions and using a discount rate of four percent, as suggested by the FHWA (1998). Table 2-5 summarizes the results of the LCCA for the three alternatives. MCS is conducted to estimate the EUAC at different confidence levels using the

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good-fit distributions. In addition, the average EUAC and its standard deviation for each alternative is calculated.

Table 2-5. Comparison of LCCA Results

EUAC	**HMA resurfacing with CIPR**	**HMA resurfacing with milling**	**HMA resurfacing**
$EUAC_{(1)}$ (standard deviation)	$30,455 ($5,472)	$24,053 ($7,914)	$35,680 ($12,903)
$EUAC_{(2)}$ (standard deviation)	$14,192 ($1,707)	$10,740 ($2,273)	$10,816 ($2,345)
$EUAC_{(1)}$ @ 50%	$30,389.85	$24,744.87	$32,416.06
$EUAC_{(2)}$ @50%	$13,993.49	$10,363.92	$10,510.19
$EUAC_{(1)}$ @75%	$33,621.59	$29,698.14	$40,853.59
$EUAC_{(2)}$ @75%	$15,268.85	$11,794.91	$12,199.07
$EUAC_{(1)}$ @90%	$39,178.12	$34,410.94	$61,477.15
$EUAC_{(2)}$ @90%	$16,391.32	$13,495.2	$15,667.05

Figures 2-3 and 2-4 show the cumulative probability curves of the EUACs for each alternative using the total rehabilitation project costs and mainline roadway costs. In the case of using the total rehabilitation project costs for calculating the EUAC, HMA resurfacing with milling is found to be the most economical alternative at different confidence levels. At the same time, HMA resurfacing and HMA resurfacing with CIPR have approximately an equivalent economic value at confidence level of 40% or less.

However, HMA resurfacing with CIPR has a higher economic value than HMA resurfacing at the confidence level of 40% or more. On the other hand, HMA resurfacing with milling and HMA resurfacing have approximately equivalent economical values at different confidence levels when only the mainline roadway costs are used. However, HMA resurfacing with CIPR has the lowest economical value.

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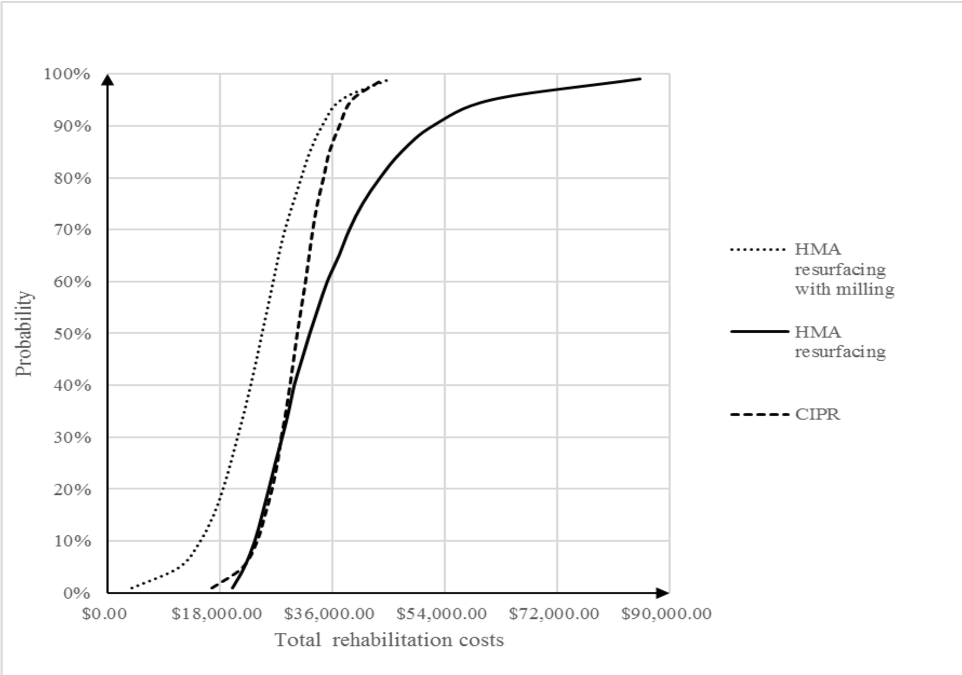

Figure 2-3. Cumulative probability curves using total rehabilitation costs

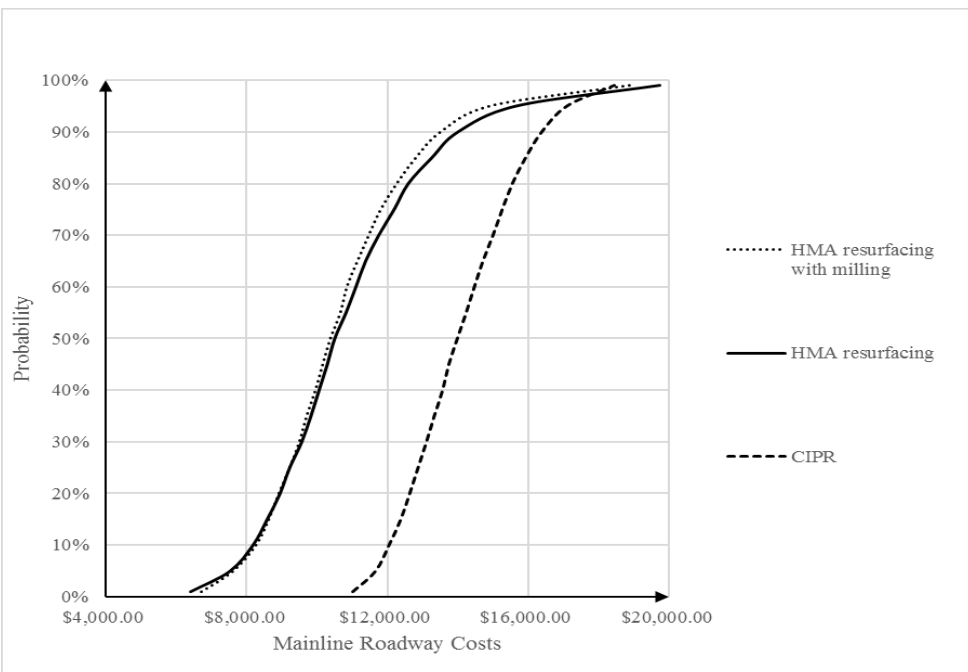

Figure 2-4. Cumulative probability curves using mainline roadway costs only

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Sensitivity Analysis

It is found that the results of LCCA is influenced by different uncertainties and risks associated with different parameters such as discount rate and treatment timing. For instance, Pratico (2007) pointed out that LCCA has inherent problems in terms of uncertainty of engineering and economic values of inputs. Huang (2006) also indicated that the results of LCCA is questionable because the analysis inputs are based on the analyst's experience.

As such, a sensitivity analysis is conducted to test the effect of changing different parameters on the final decision. First, the discount rate is changed to vary from 1% to 6% at the increment of 1%. As such, the MCS is conducted five additional times using different discount rates. When the simulation is conducted using the total rehabilitation costs, it is found that the ranking of treatment selection based on the EUAC did not change at different confidence levels. However, it is found that the EUAC difference between HMA resurfacing and HMA resurfacing with milling shrinks at lower confidence levels and discount rates. On the other hand, the ranking of treatments based on the EUAC did not change when using the mainline roadway costs only at 75% and 50% confidence levels and HMA resurfacing becomes slightly favorable when a discount rate of 5% is used at 90% confidence level (see Figure 2-5).

Besides using different constant discount rates, a triangular distribution is assumed to conduct an additional MCS to study the effect of using a variable discount rate over the analysis period. The minimum, most likely, and maximum values were 2%, 4%, and 6% respectively. As such, values of the EUAC for different treatments have changed accordingly. However, the change recorded did not affect the ranking of treatments no matter which cost was used for calculations.

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It is also noted that the timing of different maintenance and rehabilitation treatments is deterministic and is based on engineering judgement. As such, another MCS is conducted to study the effect of applying a probabilistic timing for the rehabilitation treatments and a triangular distribution is assumed to have 18, 20 and 22 years as minimum, most likely, and maximum values respectively. It is found that the EUAC for each scenario has slightly changed except the EUAC for HMA resurfacing total costs which is found to be increasing significantly at 90% confidence level to be $52,156.85. However, the change observed did not influence the ranking of treatments irrespective of costs used for calculations.

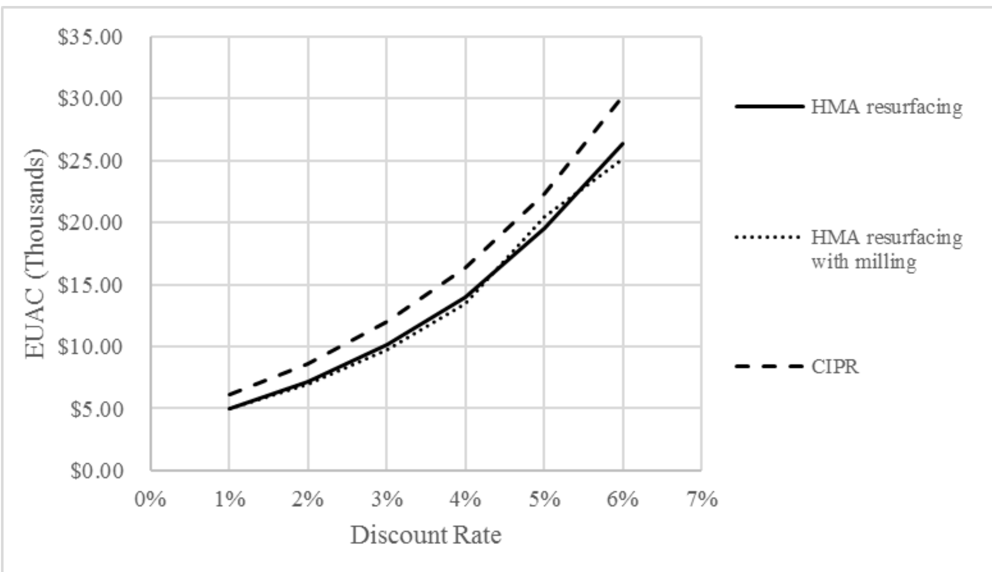

Figure 2-5. Mainline roadway EUAC at 90% confidence level

Discussions

The use of the total cost per lane mile in the LCCA makes HMA resurfacing with milling the most economical alternative based on the average EUAC. MCS calculates the EUAC at several levels of confidence. When two levels of confidence, 75% and 90%, are considered, HMA resurfacing with milling is still the most economical alternative. However, at 90% level of

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confidence, the EUAC for HMA resurfacing with milling and HMA resurfacing with CIPR are close to each other. In this case, the agency may consider that the two alternatives have equivalent economic values and hence the agency may consider other factors to select one of those alternatives.

In order to study the effect of using the total costs instead of the mainline roadway costs, a MCS is conducted using the mainline roadway costs only. In this case, the average EUAC for HMA resurfacing with milling and HMA resurfacing are very close to each other. In addition, the EUAC for HMA resurfacing with milling and HMA resurfacing at 75% and 90% confidence levels are still close to each other. Similarly, the agency may consider other factors to decide whether to apply HMA resurfacing with milling or HMA resurfacing.

The use of total costs per lane mile to evaluate treatment's LCC will definitely underestimate the economic value of some treatments. In this case study, the economic value of HMA resurfacing is significantly underestimated and the decision of the highway agency can be substantially skewed by using the total costs from the historical data. HMA resurfacing with CIPR is ranked as the second economic alternative when using the historical total costs per lane mile. However, the same treatment is deemed uneconomical if the mainline roadway costs are used in the LCCA.

The use of total costs from historical records without differentiating between the mainline roadway costs and other non-pavement related costs will definitely lead to biased results. The assumption that non-pavement related costs associated with the historical cost data records cannot affect the LCCA results is proved to be invalid. As such, agencies should use their historical records with great caution to accurately evaluate the economic effectiveness of rehabilitation treatments.

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Limitations

The study uses data obtained from Iowa DOT to evaluate the effect of including non-pavement costs on LCCA results. As such, the conclusions made in this study can not be generalized. However, government agencies that follow similar procedures and practices can benefit from the outcomes produced.

In calculating the LCCA, the study assumed the same maintenance and rehabilitation sequence for all the alternatives to neutralize the effect of applying different strategies on the LCCA results. For agencies seeking to replicate the study using their historical data, it is recommended to follow the agency practice in terms of maintenance and rehabilitation sequencing. Additionally, the study uses a constant discount rate and the same probabilistic discount rate over the alternative analysis period to calculate the EUAC. It is recommended adopting differential discount rates in case of comparing different alternatives that are expected to have different inflation/escalation patterns.

Summary and Conclusions

One major point of errors in the current pavement LCCA procedure stems from the ignorance of cost components of pavement rehabilitation projects. These rehabilitation projects usually include work items that are not related to the pavement structure itself such as widening, bridge approach, adding a turn lane and so forth. These items can be as expensive as the mainline roadway costs themselves or more. The statistical analysis conducted in this study shows that non-pavement related items account for at least more than 50% of the total project cost. Thus, when the entire rehabilitation project costs from historical bid data are used in LCCA, it is highly likely to lead to biased and sometimes wrong pavement investment decisions.

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The study developed a novel cost classification framework that can separate pavement rehabilitation project costs into five categories: mainline construction, safety, update, necessary, and miscellaneous costs. The cost classification framework can allow for extraction of costs of pavement related items only.

A goodness of fit test for total rehabilitation costs and mainline roadway costs for each pavement rehabilitation type was performed. The good fit probability distributions were used to probabilistically estimate the pavement LCC using MCS. A case study clearly showed that using the total rehabilitation project costs in LCCA would result in biased decisions. A treatment that is not economically effective can be selected because of the inclusion of a significant amount of non-pavement costs in LCCA. Based on the results of this research, it is recommended that agency costs in LCCA should only include the mainline roadway costs of rehabilitation treatments using the cost classification framework presented.

This research presented a methodological process for agencies to differentiate between mainline roadway costs and other non-pavement related costs. One of the most important research outcomes is that non-pavement related costs can exceed the pavement related costs. As such, the inclusion of the total rehabilitation costs to estimate the LCC will definitely skew the results. In addition, the study provided agencies with guidance for reasonably estimating rehabilitation costs in conducting probabilistic LCCA. State highway agencies are encouraged to adopt the cost classification framework presented in this study or at least differentiate between pavement and non-pavement related costs to eliminate any possibility of biased LCCA decisions due to inclusion of non-pavement related costs embedded in project bid data.

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CHAPTER 3: BARRIERS TO IMPLEMENTING DATA-DRIVEN PAVEMENT TREATMENT PERFORMANCE EVALUATION PROCESS

Abstract

State highway agencies have been collecting a massive amount of pavement condition data by using automated collection technologies. This rich historical dataset has great potential to support data driven pavement management decisions such as the selection and timing of pavement maintenance options. However, most agencies face various technical and data integration issues that result in serious underutilization of the collected data. Unless those barriers are clearly identified, communicated and resolved, it will significantly reduce the efficiency and effectiveness of the financial investments made to collect the pavement condition data and meet the Federal Highway Administration's direction of performance based project delivery and asset management through MAP-21 and FAST Acts. This study identifies technical challenges and data integration barriers that prevent the effective use of historical data when an agency tries to implement a data-driven process to evaluate the performance of pavement treatments. The study uses the historical data collected from one State Department of Transportation as a representative highway agency. A set of recommendations is presented to help state highway agencies to fully take advantage of the pavement condition data collection efforts for implementing pavement asset management.

Keywords: Performance Evaluation, pavement treatment, Pavement rehabilitation, Geographic information system, Pavement condition assessment data, asset management.

Introduction

The United States has one of the largest transportation networks in the world with a length of more than 4.3 million km of paved roads (USDOT 2013), which is a key success factor

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for supporting the nation's economy (GAO 2008 and Shirley 2011). With the existing massive transportation network and the completion of the interstate highway system (Row et al. 2004), most state highway agencies (SHAs) are shifting their expenditure from new construction to maintenance and rehabilitation of their highway system and they spend a considerable amount of their budgets to collect and monitor the condition of their pavement assets.

Most SHAs are underfunded and hence they need to justify every investment decision made. For example, the National Surface Transportation Policy and Revenue Study Commission recommended increasing spending on preservation, operation, maintenance and upgrade investments by $225 billion to $340 billion annually for the next 50 years while the current expenditure is less than $90 billion annually (Burwell and Puentes 2009). Thus, decisions on what types of treatments should be used and when are highly important to maximize the value of agency's investments and taxpayers' money.

Therefore, SHAs should carefully select a pavement treatment option that is expected to yield the best performance and the highest return on investment. Also, the Federal Highway Administration's (FHWA) initiatives of performance based project delivery and asset management spearheaded by MAP-21 and FAST Acts, have increased the efforts to objectively evaluate the performance of various types of pavement treatments to meet the FHWA's requirements (FHWA 2016). This has created an immediate need for SHAs to analyze their historical pavement condition assessment data to evaluate the effectiveness of maintenance and rehabilitation decisions and conform with the federal requirements. However, the collected historical data is highly underutilized at present due to many technical challenges and data integration issues while the theoretical evaluation process is quite well established. These issues

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seriously hinder the use of historical data to support the agency's pavement management business decisions.

This study uses one DOT's entire historical pavement condition assessment data, pavement treatment contract data, and other data available to demonstrate barriers when a data-driven pavement treatment performance evaluation process is implemented and develop a set of recommendations that DOTs may need to adopt to overcome those barriers and to fully take advantage of expensive data collection efforts.

Literature Review

Many studies evaluated the performance of maintenance and rehabilitation treatments of pavements. These studies use one of the two main sources of data; a) the Long-Term Pavement Performance (LTPP) program database and b) the pavement condition data collected by agencies. The LTPP program, initiated in 1987, represents an important source of pavement performance information (FHWA 2016). The LTPP program has an inventory of material testing; pavement performance monitoring; as well as climate, traffic, maintenance, and rehabilitation data for more than 2,500 test sections located in the United States and Canada (FHWA 2016).

Some of those studies that used the Long-Term Pavement Performance (LTPP) data evaluated the performance of several treatments such as Hot Mix Asphalt (HMA) overlay, slurry seal, chip seal and crack seal (Hall et al. 2002, Wang et al. 2012, Shirazi et al. 2010, Lu and Tolliver 2012, and Dong and Huang 2011). Other studies used the LTPP data to evaluate the performance of microsurfacing and asphalt overlay in Texas (Chen et al. 2003 and Hong et al. 2010). On the other hand, Jahren et al. (1998), Labi and Sinha (2004), Labi et al. (2007), Irfan et al. (2009), Liu et al. (2010), Chen et al. (2009), Ji et al. (2012), and Broughton and Lee (2012) used data

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collected locally at a state level to evaluate the performance of several treatments such as microsurfacing, asphalt overlays, crack seal, and chip seal.

Previous studies also used statistical significance testing to evaluate the performance of several treatments. Labi and Sinha (2004), Labi et al. (2007) and Lu and Tolliver (2012) used one-sided hypothesis test to assess the statistical significance of the estimated performance enhancement at 95% level of confidence. Ji et al. (2012) used the analysis of variance (ANOVA) to compare the Structural Number (SN) and statistical difference of International Roughness Index (IRI) before and after treatment application. However, the aforementioned tests assume a normal distribution of the means of the population which is not necessarily true in some cases. Wang et al (2012) also used the paired t-test to evaluate the effectiveness of pavement treatments by analyzing the IRI measurements between control sections and sections that received specific treatment. On the other hand, Shirazi et al. (2010) recognized the restricting assumptions associated with parametric tests such as paired t-test and used Friedman's test, a non-parametric test, to evaluate treatments performance. However, it should also be noted that quality of the data used in the performance evaluation process is as important as or more important than the statistical methods used. The consistency, precision and accuracy of data collected by highway agencies at the network level are still questionable and more research is needed to assess the quality of the collected data. Also, it should be noted that the aforementioned studies did not carefully examine the existing quality issues associated with the historical data. Those studies may not have faced data quality issues since they used high quality data stored in the LTPP program or collected by agencies for highly monitored control sections.

The main problem with performance evaluation or other infrastructure data analysis processes is not associated with coherency or robustness of the methods employed. It is mainly

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associated with the quality of the input data. Thus, there is an urgent need to analyze the consistency and quality of the collected data and analyze their applicability to support business decisions such as treatment selection or performance evaluation.

The technical challenges and data quality and integration issues have been noticed by several researchers. However, little attention has been given to the effects of those issues on pavement management decisions. Flintsch and McGhee (2009) identified some issues associated with pavement data collection practices. For example, many agencies that have adopted automated and semi-automated data collection methodologies face consistency problems which intensify when the agencies change the equipment used or the service provider.

Quality issues are another source of challenges and barriers to the use of performance data to support pavement management decisions. For example, Salimnejad and Ghariabeh (2012) indicated that pavement condition data was noisy and had too much variability because of the method of data collection. Although 64% of the U.S. highway agencies have formal data collection quality control plan, only 48% of them have a formal quality acceptance plan (Flintsch and McGhee 2009). This indicates that many highway agencies do not have formal quality control or acceptance plans which may adversely affect the quality of the collected data.

Shekharan et al. (2007) evaluated the effects of quality control plan on pavement management systems. The study found out that Virginia DOT significantly increased the accuracy of reporting the existing condition and deficient pavements by 60% and 30% respectively by using a robust quality control plan. Consequently, Virginia DOT saved more than $18 million dollars for the interstate pavement maintenance recommendation (Shekharan et al. 2007). Saliminejad and Ghariabeh (2013) also confirmed that annual budgeting was highly sensitive to errors in pavement condition data.

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The quality of pavement performance data is now under even more scrutiny with the emergence of automated data collection methods, though few studies identified problems and issues associated with historical data-driven pavement performance evaluation. Researchers evaluated those technologies and pointed out to the possible poor quality of data because of several sources of error such as imaging errors, field of view coverage, image quality, technology used, quality of the color contrast, lighting method and processing algorithms (Mcneil and Humplik 1991 and Flintsch and McGhee 2009). Flintsch and McGhee (2009) as well as McQueen and Timm (2005) reported that there was a bias toward detecting high severity cracks when compared to lower severity cracks regardless of the method, automated or manual, of cracking data collection. As for more advanced technologies, such as 3D automated systems, there are also concerns regarding the precision and accuracy of automated systems used to collect pavement condition data (Serigos et al. 2016 and Tsai and Li 2012).

Another type of barrier that hinders the use of historical data is the separate storage of data collected by different business units. For example, Vandervalk-Ostrander et al. (2003) examined the data integration practices of 27 agencies and found out that most agencies were dealing with “disparate data sources in mainframe flat files”. Similarly, Hall (2006) indicated that many agencies were facing challenges and difficulties in integrating their fragmented data while Adams (2008) pointed out that agencies were struggling with data integration issues such as location referencing, disconnected business cycles and inconsistent terminology. Saliminejad and Gharaibeh (2012) found out that the integration of missing maintenance and rehabilitation data with pavement condition data was especially challenging for large pavement networks.

The size of the data used for analyzing the performance of a specific treatment is another barrier, especially for agencies that did not invest resources in extensively monitoring pavement

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sections of interest. For example, the use of the LTPP data in performance evaluation at the national level is beneficial because of the large number of sections stored in the LTPP database. However, using the LTPP data at the state level might not be reliable for some states because of a limited number of test sections. For instance, Iowa has data for only 66 test sections which form a small population especially when those sections are classified into pavement and treatment types. Thus, there is a need to utilize the data collected by DOTs at the state level and to evaluate the performance of pavement treatments. The level of quality control used for the LTPP program is relatively more advanced compared to the level of quality control used by DOTs. For example, the LTPP has a well-developed and documented equipment calibration procedure (Flintsch and McGhee 2009). The LTPP uses a relatively higher percentage of sampling to verify data accuracy such as distress mismatch and misidentification of severity levels (Flintsch and McGhee 2009).

Finally, there is no consensus on which performance indicator should be used to evaluate the performance of pavements. There is a wide range of performance indicators used by researchers to evaluate the performance of different treatments such as IRI, pavement condition rating (PCR), pavement condition index (PCI), and rutting. Some studies used structural performance indicators such the structural number (SN) to evaluate the structural performance after treatment application (Ji et al. 2012). Few studies used individual distresses such as fatigue cracking and transverse cracking for performance evaluation (Hall et al. 2002 and Hong et al. 2010). While many studies used common performance indicators to evaluate the performance of treatments, Liu et al. (2010) used the time between two consecutive treatments or time between treatment application and reconstruction to estimate the service life of thin surface treatments. The methodology adopted by Liu et al. (2010) reflects the DOT’s actual experience on the

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estimation of treatment performance. However, this methodology fails to consider the delay in consecutive treatment application due to funding gaps.

Data-driven Pavement Treatment Performance Evaluation Process

A typical and well-established performance evaluation process of pavement treatments is shown in Figure 3-1. The performance evaluation process is divided into four distinctive steps. First, the historical condition assessment data is spatially integrated with pavement treatment project databases. When these two major databases are spatially integrated, the pavement condition data and the locations of treatment projects are matched so that the initial pavement conditions before a treatment application and the performance of the pavement section after the treatment application can be analyzed. The second step involves categorizing data in the integrated database by several attributes. These attributes can be traffic volumes, pavement design characteristics, treatment characteristics or geotechnical data. This step is important to group similar pavement sections together to statistically analyze the performance of pavement treatments. In step three, the consistency of the pavement condition data after treatment application is evaluated in accordance with a selected method of measuring a treatment's service life along with pavement performance indicators. Finally, in step four, the performance of each pavement treatment is evaluated and performance curves are developed. This study uses the entire historical data obtained from one DOT and follows the four step process described above to identify barriers and challenges that impede implementing a data-driven pavement performance evaluation process.

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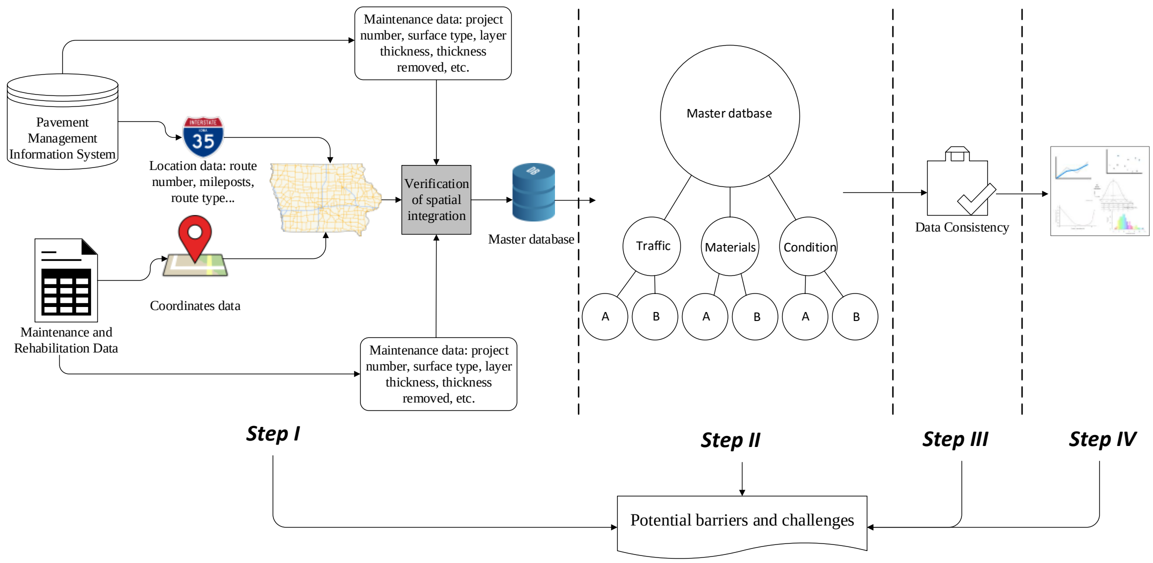

Figure 3-1 Data-driven Pavement Treatment Performance Evaluation Process

Step I: Data Collection and Integration

There are two primary sources of data used. The first is the historical pavement condition data and the second is the pavement treatment contracts data which contains a list of all projects let by the DOT. As for the pavement condition data, the DOT collects rutting and roughness through a vendor that uses a sensor technology. The vendor also takes images and uses image processing algorithms to estimate the cracking data. Afterward, the DOT engineers inspect the image processing results and accept or override the results. The DOT has hired the same vendor to collect the data from 1999 to 2015. The DOT also uses quality control measures throughout the data collection process. Before the data collection process, the vendor collects pavement condition data for eight control sites to calibrate the equipment and validate the results. The calibration of equipment is necessary to collect high quality ride and rutting data. The DOT also checks for data completeness and outliers after data collection. Finally, a time series analysis is done by comparing the current PCI and the previous PCI. When the PCI of the current year is unjustifiably higher than the previous PCI, further inspection is made to find the source(s) of

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error. The condition data is collected every year for half of the state. For example, the pavement condition data for the north west region of the state was collected in 2004, 2006 and 2008 while the pavement condition data for the south east region of the state was collected in 2003, 2005 and 2007.

The project contracts database obtained from the office of contracts contains information about project number, accounting number, project type, project length, and location referencing data. The location for each treatment project is identified using either Geographic Coordinates System (GCS) or Linear Referencing System (LRS) data as well as the location's textual description. The total number of treatment projects let by the DOT from 1999 to 2007 is 1080 projects. It is also worth noting that the last raw condition data available was the 2013 raw condition data. Hence, the evaluation of projects constructed before 2007 was only considered to investigate the long-term performance issues.

The spatial integration of the two databases facilitates an accurate overlay of a treatment project's location and length on the pavement network. The geographic location of each project using a GCS or a LRS has to be used for the spatial integration process. The GCS uses the latitude and longitude data to locate the midpoint of the project while the LRS uses the route number, beginning milepost, and ending milepost to describe the location of the project. The aggregation of distress values is done by using a unique identifier field which indicates that pavement sections share the same properties in terms of traffic and pavement materials. Two barriers are identified in Step I.

Barrier 1: Use of different geographic referencing systems

The first barrier is the use of different location referencing systems including GCS and LRS, which causes data fragmentation. The pavement condition data is stored in a Pavement

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Management Information System (PMIS). PMIS systems use LRS to represent pavement segments or links. LRSs are essential to represent the beginning and ending of highway segments. On the other hand, treatments projects are usually geographically referenced using GCS. This creates a data integration problem since the LRS output is a line feature that starts with milepost and ends with a milepost while the GCS output is a point feature located by geographic coordinates. Thus, there is a need to use the geographic coordinates along with the project length to determine the project starting and ending point. The use of two different referencing systems requires extensive efforts to integrate the two databases together. Geoprocessing tools are required to spatially integrate the treatment projects database with the pavement condition data by creating a buffer using the project length to clip the pavement condition data layer. The clipped pavement condition data is then manually cleaned from irrelevant pavement sections. This process is repeated for each year's pavement condition dataset and the final pavement condition data is then exported to aggregate different distress values.

In addition to the use of two different geographic referencing systems, many of the project location coordinates were not accurate. This was evident because many of the projects locations were offset from its known route and manual adjustment were made to snap the project's location to its accurate location.

Barrier 2: Poor or absence of quality control measures for data collection

The second barrier is associated with several data quality issues that resulted in excluding a significant number of the rehabilitation projects from the performance evaluation process. The exclusion of several projects in the analysis was unavoidable because of several reasons including unavailability of performance data, missing information, missing pretreatment condition data, and inconsistent formatting of data. Some locations did not have condition or

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performance data collected at one or more surveying periods. This creates a gap in the available performance data, which hinders the performance evaluation process. Also, for some projects, important pieces of information are recorded such as overlay thickness or milling thickness. Missing pretreatment condition data is another issue. If the pretreatment condition data was not collected, it is challenging to evaluate the post treatment performance. Inconsistent formatting of data was another challenge that was evident and associated with project numbering. Most treatment projects are supposed to be recorded in the pavement management information system (PMIS). However, in many cases, the project number recorded in the PMIS does not match with the project number that is recorded by the office of contracts. For example, an HMA resurfacing project was recorded in the pavement treatment contracts database with project number [STPN-044-4(39)--2J-39] and the same project was recorded in the PMIS as [STPN-44-4(39)--2J-39].

Step II: Pavement Classification

HMA resurfacing, HMA resurfacing with milling, and HMA resurfacing with cold-in-place recycling (CIPR) treatments are the three most frequent rehabilitation treatments by the DOT. Thus, this study uses these three treatment types for performance evaluation. Table 3-1 shows the number of segments and number of projects for each treatment type. In this study, the term “segment” is defined as a stretch of a pavement that shares the same traffic volume, pavement structure and design attributes. The term “project” is defined as the entire treatment application, which may cover multiple segments.

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Table 3-1 Number of segments and projects analyzed

	Pavement type							
Treatment type	AC	PCC	Composite				Number of projects analyzed	Total number of projects
			JPCP(1)	CRC-CTB(2)	JRCP(3)	CRC(4)		
HMA resurfacing	5	51	26	-	-	-	37	193
HMA resurfacing with CIPR	14	-	11	-	-	-	16	25
HMA resurfacing with milling	2	-	24	2	12	5	25	126

(1) AC layer over jointed plain concrete pavement (JPCP)

(2) AC layer over continuous reinforced concrete (CRC) with cement treated base

(3) AC layer over jointed reinforced concrete (JRCP)

(4) AC layer over CRC

Classification of pavement sections by traffic volume is important because traffic loading is an influential factor that affects treatment performances. For example, Labi et al. (2007) found out that traffic was an influential factor on microsurfacing performance. Dong and Huang (2012) also indicated that traffic level was a significant factor on HMA overlay performance. Sites are classified based on traffic loading/equivalent single axle loads (ESALs). Figure 3-2 shows a histogram for the number of segments based on the ESALs for HMA resurfacing on composite pavements. The classification of data is developed by using manual and natural breaks (jenks) classification in order to find naturally occurring data categories (see Figure 3-2). The use of manual and jenks classification minimizes the group variance while maximizing the variance between the groups.

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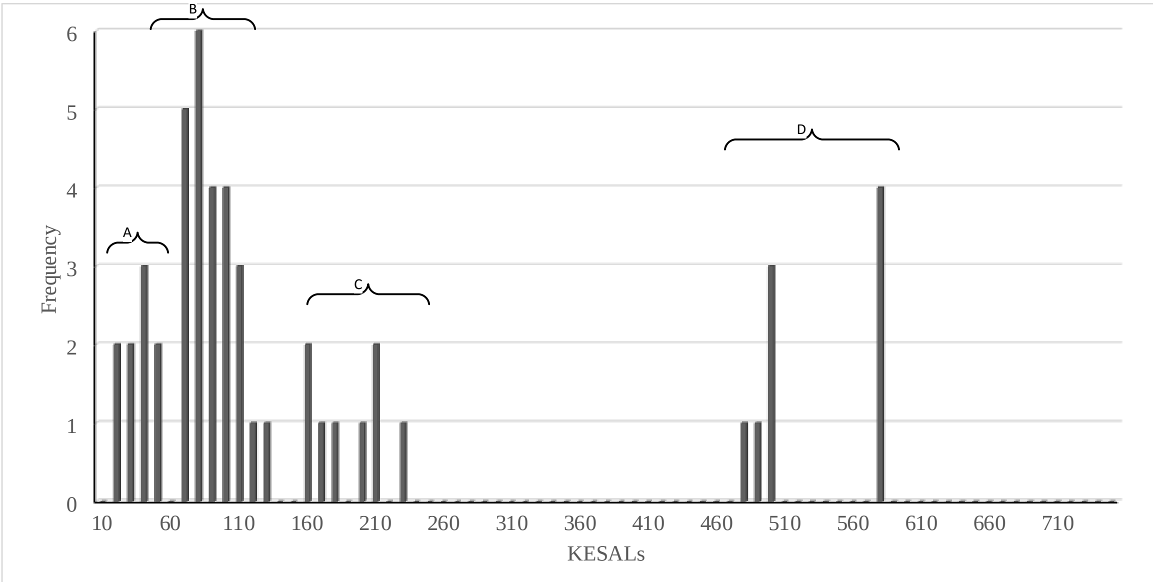

Figure 3-2 Characterization of segments for HMA resurfacing on PCC pavements

Table 3-2 summarizes segment characteristics for each treatment by pavement type. The average pavement thickness, overlay thickness, and milling thickness are calculated for each group. One major barrier was identified in Step 2.

Table 3-2. Characteristics of pavement segments by treatment and pavement type

Pavement type	**Treatments**	**Traffic loadings groups**	**Number of segments in each group**	**Pavement thickness (mm)**	**Overlay thickness (mm)**	**Milling thickness (mm)**
PCC	HMA resurfacing	A, B, C, and D	9, 24, 8, and 9	299, 346, 368, and 330	86, 103, 113, and 92	N/A
Composite-JPCP	HMA resurfacing	A, B, and C	9,14, and 2	383, 401, and 394.5	76, 98.5, and 204	N/A
	HMA resurfacing with milling	A, B, and C	12, 7, and 5	337, 385, and 376	116, 90, and 133	116, 90, and 133
	HMA resurfacing with CIPR	A	11	386	84	N/A
Composite-JRCP	HMA resurfacing	A	12	366	106	97

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	with milling					
AC	HMA resurfacing with CIPR	A	13	296	91	N/A

Barrier 3: Small sample sizes due to characterization of pavement sections

There are several parameters that should be used to group similar pavement segments together such as treatment characteristics, pavement thickness, overlay thickness, traffic volume and subgrade condition. It is challenging to use these parameters simultaneously to group similar segments together, especially because it generates small sizes of samples that share similar characteristics. Using two attributes, traffic loading and pavement type, to group similar segments together resulted in generating small sample sizes. For example, 25 jointed plain concrete pavement segments received HMA resurfacing. Only two of them share high traffic loading (see Table 3-2). Similarly, small sample sizes were generated with respect to HMA resurfacing on jointed plain concrete pavements with high traffic loadings. This barrier is expected to have a broader impact especially when agencies consider multiple attributes or characteristics for grouping similar pavement segments.

Step III: Evaluation of Data Consistency for Performance Evaluation

There are two key factors in evaluating the performance of pavement treatments: a) method of measuring treatment service life and b) pavement performance indicator. In the literature, the estimation of the service life of a pavement treatment, shown in Figure 3-3, is conducted using three different methods; a) time taken for pavement condition to reach a specific threshold value (T_1), b) time taken for post treatment condition reaches the pretreatment condition (T_2), or c) time taken until the application of another maintenance/rehabilitation treatment (T_3). Each one of those three service lives does not have to be less than the other two.

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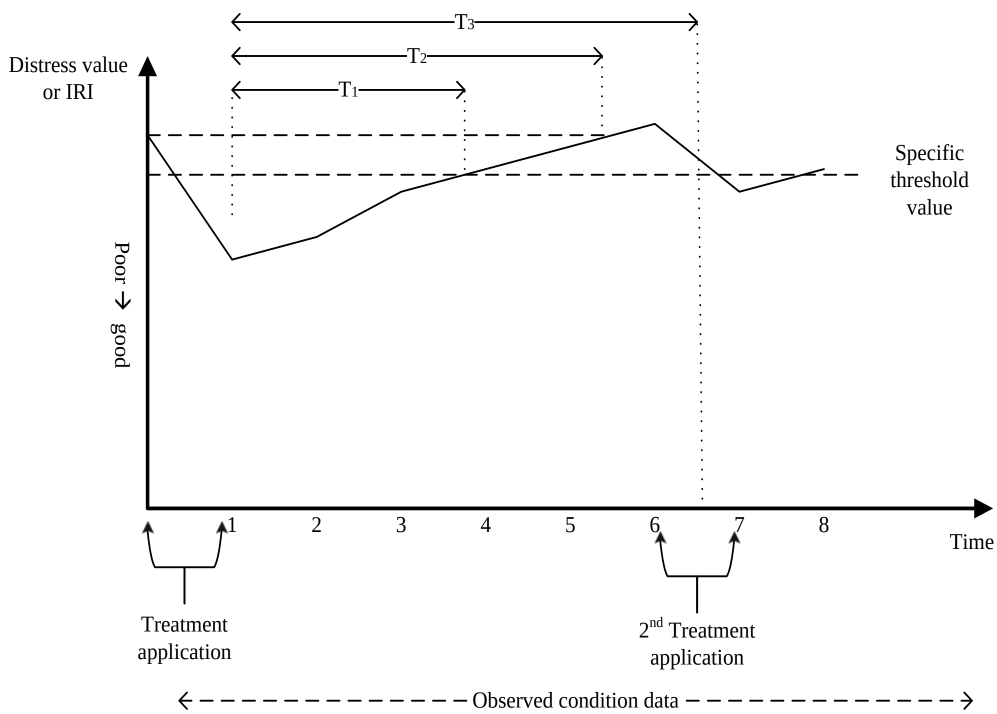

Figure 3-3 Methods for estimating treatment service life

The concept of using a specific performance indicator to measure the service life as part of a treatment performance or effectiveness evaluation is not a new concept (Ping et al. 2010). The concept of service life is simple and easy to communicate with different stakeholders including engineers, administrators, legislators, and general public (Ping et al. 2010). O'Dohorty (2007) proposed the use of service life, measured based on specific threshold, in measuring the performance of the overall network. In terms of performance indicators, Shiyab et al. (2006) determined that effective structural number, IRI and pavement quality index are the best performance indicators to estimate the pavement service life. The pavement quality index is an overall measure that considers the severity and extent levels of several surface distresses. Chou et al. (2008) also used an overall pavement condition measure and used data from Ohio DOT to estimate the service life of pavements.

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In this study, since all three rehabilitation treatments evaluated have asphalt concrete surface, asphalt concrete surface distresses are considered as potential performance indicators. The DOT collects distress condition data including rut depth of wheel paths, alligator cracking, transverse cracking, longitudinal cracking, longitudinal cracking on wheelpath, and IRI for asphalt pavement surfaces. As for cracking data, the DOT classifies cracking distresses into three different levels; low, moderate and high. However, alligator cracking distress is only classified into two severity levels; moderate and high.

As the pavement treatment age increases, pavement condition data over time is expected to show gradual degradation and display typical and natural deterioration patterns as shown in Figure 3-3. Any deviation from this natural deterioration pattern may indicate poor data calibration practices, and/or unrecorded maintenance activities such as localized repairs. Figure 4 shows a clear example of inconsistent deterioration patterns of moderate transverse cracking. The four segments that received HMA with CIPR, shown in Figure 3-4, had a clear performance jump after a treatment application. However, significant and unexplainable performance jumps that were not associated with the treatment application appear in year 5, 7, 9 and 11. For example, segment A shows a decrease in moderate transverse cracking between years five and seven. On the other hand, segment B shows a continuous condition improvement after the treatment application.

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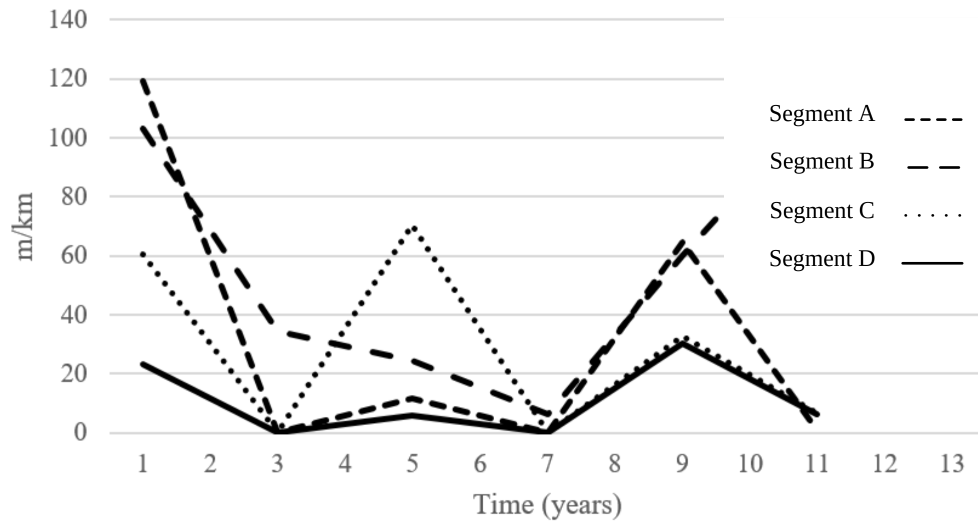

Figure 3-4. Moderate transverse cracking propagation after applying HMA with CIPR

Thus, the consistency of pavement condition data must be evaluated to determine the usability and quality of the data before the pavement performance is evaluated. A pavement segment that exhibits irregular deterioration patterns with abrupt or unexpected performance enhancement is considered to have inconsistent performance. In this study, Equation (3-1) is developed to measure the percentage of data inconsistency.

$$Distress\ Data\ Inconsistency\ Indicator\ (D^2I^2) = \frac{N}{TN} * 100 \ldots \ldots \ldots \ldots \ldots . . (1)$$

Where, N is the number of segment with inconsistent performance and TN is the total number of segment under study.

Table 3 shows the D^2I^2 for each performance indicator based on this criterion. The D^2I^2 is a measure that ranges from 0% to 100%, where 0% represents excellent consistency and 100% presents perfect inconsistency. Three ranges are proposed based on the D^2I^2score; a) high

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consistency with the D^2I^2 score of 0% to 30%, b) moderate consistency with the D^2I^2 score of 30% to 50% , and low consistency with the D^2I^2 score greater than 50%.

Table 3-3. Percentages of segments exhibiting inconsistent deterioration patterns

Distress type		Pavement Type					
		PCC (HMA resurfacing)	Composite-JPCP			Composite-JRCP (Milling)	AC (CIPR)
			Resurfacing	Milling	CIPR		
Alligator cracking	M[1]	28%	19%	25%	46%	13%	61.50%
	H[2]	4%	0%	8%	9%	13%	23.10%
	Agg[3]	28%	19%	28%	36%	13%	46%
Transverse cracking	L[4]	46%	27%	50%	36%	33%	38.50%
	M	84%	85%	33%	55%	88%	84.60%
	H	50%	69%	8%	55%	58%	69.20%
	Agg	44%	27%	50%	54%	29%	31%
Longitudinal cracking	L	40%	27%	25%	27.30%	25%	61.50%
	M	76%	65%	25%	63.60%	67%	76.90%
	H	62%	58%	25%	54.50%	54%	69.20%
	Agg	38%	38%	25%	18%	17%	46%
Longitudinal wheelpath cracking	L	46%	27%	25%	36.40%	33%	46.20%
	M	68%	62%	33%	54.50%	54%	76.90%
	H	28%	42%	8%	36.40%	50%	76.90%
	Agg	54%	35%	25%	27%	25%	54%
Rutting		36%	31%	13%	14%	29%	39%
Roughness		28%	19%	8%	18%	17%	19%

Based on the analysis of the pavement condition data, the deterioration patterns of moderate and high alligator cracking were consistent. In fact, alligator cracking had the least percentage of segments of inconsistent deterioration patterns. Also, the short- and long-term performance of segments was excellent as the level of extent of alligator cracking was very low i.e., zero or almost zero m^2/km.

In terms of transverse, longitudinal, and longitudinal on wheelpath cracking, the majority of segments exhibited inconsistent deterioration pattern. For instance, 84 percent of PCC

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pavement segments that received HMA resurfacing treatment had inconsistent pavement deterioration pattern in terms of moderate transverse cracking. The majority of segments also exhibited inconsistent deterioration patterns in terms of moderate severity distresses. However, it is important to note that the extent level of cracking can be inconsistent to some degree. This mainly occurs because of the deterioration process of pavements. Some of the low severity cracks transform into moderate or high severity cracks over time. Similarly, some of the moderate severity cracks transform into high severity cracks. As such, the aggregated value of cracks by the severity level should have a consistent deterioration pattern. However, many segments exhibited inconsistent deterioration patterns even in terms of aggregated value of cracks (see Table 3-3).

The analysis of pavement performance at the distress level reveals fundamental drawback when collective condition measures such as the PCI are used. The method of calculation of collective condition indexes include aggregating several distress values together to generate an overall measure of the pavement condition. Thus, the PCI might not be sensitive to errors at the distress level. For example, a measurement error in a low severity distress type may not make a major effect on the overall index. Moreover, these errors may result in overestimating or underestimating the extent level of several distress types. With the absence of tight quality control measures related to collecting individual distress data, the calculation of a collective measure such as the PCI is subjected to numerous combinations of errors. On the worst case scenario, underestimated and overestimated extent and severity level of several distress types may cancel out their effect and there could be tens of errors combination that undermine the integrity and reliability of collective measures such as PCI.

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Barrier 4: Inconsistent long-term performance data

The inconsistent pattern of condition data is a serious problem that may cause poor and unreliable estimation of the treatment service life. The high D^2I^2 values in Table 3-3 are strong evidence that many sections actually have inconsistent and unexplainable performance data at the distress level and this is one of the most significant barriers to developing performance curves of pavement treatments and determining the service lives of the treatments.

Barrier 5: Selection of a representative performance indicator(s)

Ultimately, the performance of a pavement treatment should be evaluated by using each individual performance indicator, which will help SHAs make accurate maintenance and rehabilitation decision in the future. This is essential for project level decision makers as they need to analyze the pavement condition to apply the right maintenance/rehabilitation treatment. As such, each distress type should be considered as a performance indicator and an average service life for pavements should be estimated from that perspective. However, there is no general consensus on which performance indicators should be used to estimate a treatment's service life. Additionally, since each pavement distress would trigger a different maintenance and rehabilitation strategy, an overall measure such as PCI would not be suitable for project level decision making. For example, Illinois DOT does not recommend fog seal or sand seal treatment to address rutting depth less than 0.5 inches while recommends microsurfacing to address such condition (Illinois DOT 2010). Similarly, a treatment selection decision-support system developed for Iowa local agencies shows that the existing distress type and its severity and extent level determine the appropriate treatment strategy (Abdelaty et al. 2015). For example, low or moderate severity longitudinal cracking can be sealed or filled, however, major maintenance or rehabilitation treatments are more suitable to address high severity longitudinal cracking. As

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such, choosing one or more performance indicators might not provide the complete picture of the treatment performance.

Barrier 6: methodology to estimate pavement service lives

Similar to barrier 5, there is no consensus on which method should be used to measure the service life of a pavement treatment. Different methods would result in different service lives and consequently, different effectiveness and economic value of each maintenance and rehabilitation treatment. Figure 3-5 shows the rutting data for a composite pavement segment that received HMA resurfacing treatment. The treatment was applied in 2005 and performance data were collected in 2004, 2006, 2008, and 2012. The estimated service lives for that specific treatment can be drastically different based on the method used to measure the service life. For example, the estimated service life can reach 13 years (T_1) when a specific threshold value is set by the agency. In this illustrative example, an arbitrary threshold value is selected based on the one DOT failure threshold values (Bektas et al. 2015). It is worth mentioning that the Iowa DOT uses 12 mm as failure threshold value for rutting. Additionally, future pavement deterioration was extrapolated based on the past observed performance. The second service life is estimated to be approximately seven years and is calculated based on the time taken so that the pavement reverts to its pretreatment condition. This illustrative example shows how the method used to estimate treatment service life could be different.

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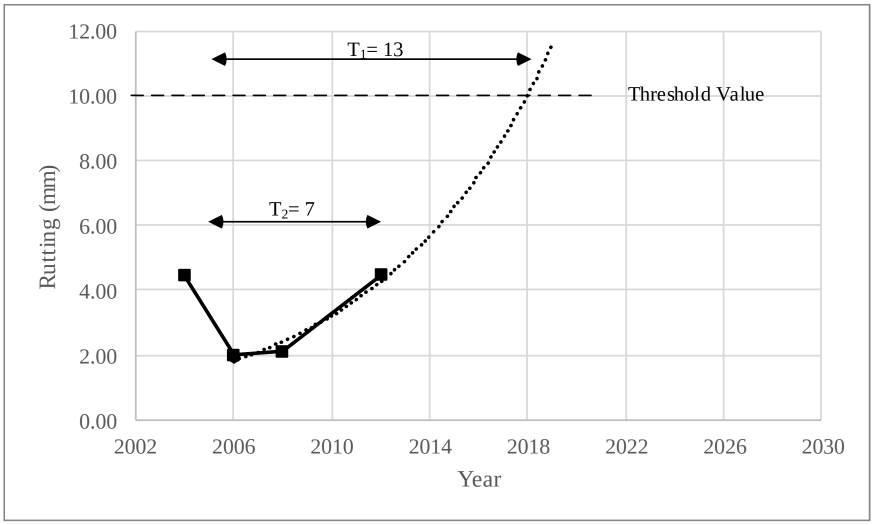

Figure 3-5 Estimation of treatment service life using different methodologies

Similarly, Figure 3-6 shows the estimation of service life for HMA resurfacing applied to a composite pavement section. The time taken by that specific section to revert to its pretreatment condition is approximately 10 years. On the hand, it is found that another treatment was applied between 2011 and 2012. Thus, the treatment service life based on the latter case is estimated to be 6.5 years.

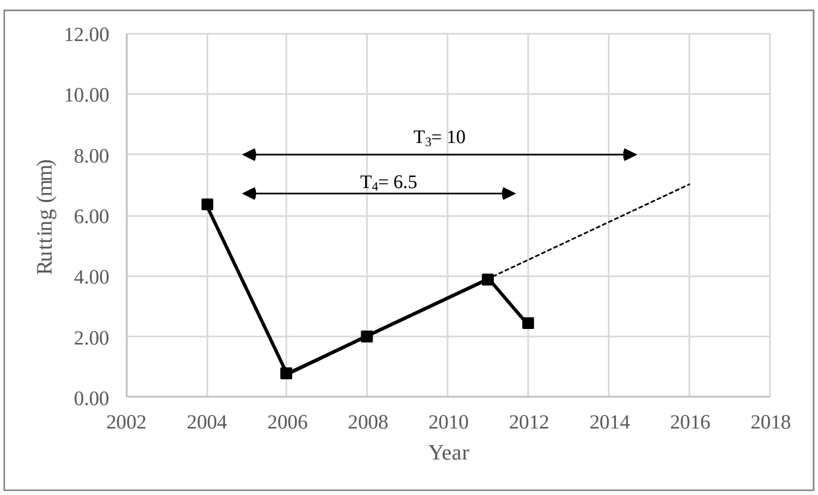

Figure 3-6 Estimation of treatment service life using different methodologies

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Barrier 7: Poor documentation of maintenance and performance data

This barrier might be the root cause of barrier 5. With interviews with the DOT engineers and review of current practices, the following factors were identified as potential reasons behind irregular patterns; a) no documentation or poor documentation of in-house maintenance activities, b) recording sealed cracks as low severity cracks, c) crack transformation from one type to another, and d) error in distress identification, measurement, and recording. The DOT performs in-house maintenance activities such as crack sealing/filling which are not recorded in terms of its location and quantity. Also, sealed cracks are recorded as low severity cracks and hence the pattern of crack deterioration gets irregular. In some cases, cracks transform from one type to another because of misidentification or deterioration. For example, Kim et al. (2010) reported that longitudinal cracking might change to alligator cracking between survey periods. However, with current data, it is not possible to quantify the amount of distress transformation.

Step IV: Treatment Performance Evaluation

In this study, a treatment's service life is measured with respect to the time lapsed until the pavement reaches its pre-treatment condition. Also, the service life is terminated when another maintenance or rehabilitation treatment is applied.

Two statistical significance tests are conducted to investigate whether the posttreatment condition is significantly higher than the pretreatment condition at the end of the observed service years. The first test is a paired t-test while the other test is a distribution free non-parametric Wilcoxon singed rank test. Tables 3-4 and 3-5 show the test results for each treatment type and the average service life in terms of ride quality and rutting because of their consistent performance over time (see Table 3-3). It is worth mentioning that the number of records is different from the number of segments analyzed because rutting and ride quality are collected for

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both the left and right wheelpaths. According to the results of significance tests, the IRI and rutting values after treatment application are significantly better than those values before treatment application. Generally, the estimated service lives for each treatment differ based on the performance indicator used. This means that different maintenance and rehabilitation strategies could be triggered based on the pavement performance. For example, it is more probable that agencies need to address rutting problems before ride quality issues based on the service lives summarized in Tables 3-4 and 3-5. By addressing specific distresses in timely manner, agencies would maximize their return on maintenance and rehabilitation investments. Accordingly, it is important to incorporate all the performance indicators in the performance evaluation process and integrate the results with pavement management systems.

Table 3-4. Significance testing using IRI data

Pavement Type	Treatment Type	Number of records	t-test Test statistic (p-value)	Wilcoxon signed rank test Test statistic (p-value)	Minimum, average and maximum service life
PCC	HMA resurfacing	100	(1.15×10^{-34})	(6.2×10^{-18})	(3, 6.6 ,9)
Composite with JPCP	HMA resurfacing	49	(2.08×10^{-15})	(1.3×10^{-8})	(5, 7.6, 12)
	HMA resurfacing with milling	48	(4.15×10^{-16})	(4.72×10^{-9})	(5, 6.6, 9)
	HMA resurfacing with CIPR	20	(3.29×10^{-11})	(8.86×10^{-5})	(3, 4.8, 7)
Composite with JRCP	HMA resurfacing with milling	24	(4.75×10^{-5})	(0.0014)	(5, 5.3, 7)

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AC	HMA resurfacing with CIPR	26	(1.07×10^{-12})	(3.78×10^{-6})	(7, 8.9, 13)

Table 3-5. Significance testing using rutting data

Pavement Type	Treatment Type	Number of records	t-test Test statistic (p-value)	Wilcoxon signed rank test Test statistic (p-value)	Minimum, average and maximum service life
Composite with JPCP	HMA resurfacing	49	(7.66×10^{-10})	(4.34×10^{-8})	(3, 6.7, 12)
Composite with JPCP Composite with JRCP	HMA resurfacing with milling	48	(3.20×10^{-10})	(1.63×10^{-9})	(3, 6.1, 9)
	HMA resurfacing with CIPR	19	(1.36×10^{-5})	(1.32×10^{-4})	(1, 3.4, 7)
	HMA resurfacing with milling	24	(9.36×10^{-9})	(2.59×10^{-5})	(5, 5.3, 7)
AC	HMA resurfacing with CIPR	26	(9.27×10^{-8})	(8.29×10^{-6})	(1, 6.5, 9)

Recommendations to Change

The analysis of the historical data identified seven major barriers that seriously impede the immediate implementation of a data-driven treatment performance evaluation process. This section discusses major recommendations to SHAs in order to fully utilize the collected data and improve the data collection and management practices.

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Recommendation to Change for barrier 1: First, the locations of pavement treatment projects need to be recorded accurately. Since many projects had inaccurate latitude and longitude data, it is recommended collecting multiple points with latitudes and longitudes within a narrow proximity of the project specified location. This will allow the agency to quickly detect and discard inaccurate location data. Second, a standard location identification system must be used throughout the different offices of the agency. A GCS based system is recommended since it is compatible with most geo-location based systems.

Recommendation to Change for barrier 2: There is a need to develop stricter quality control measures and standards for collecting pavement condition data and recording maintenance and rehabilitation data. For example, some data points show unrealistic rutting or IRI values, which indicates an evident error in measurement. The unexpected variation in crack deterioration patterns indicates the possibility of crack severity misidentification, inconsistency in severity level identification, or human error. SHAs may change the threshold values in determining the different levels of distress such as low, moderate and high. In such cases, previous historical data should be adjusted to meet the new definitions. Also, it is recommended to run the time series check on the historical data at the distress level to detect any errors or distress misidentification.

Recommendation to Change for barrier 3: SHAs should collect pavement condition data for treated pavement segments more frequently. Additionally, the agencies should establish a long-term plan on tracking the performance of treated segments to ensure that historical data can be used to establish a data-driven performance evaluation. This would drastically increase the number of observed segments, which may facilitate the adoption of advanced statistical and analytical methods.

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Recommendation to Change for barrier 4: The inconsistent deterioration patterns of pavement distresses over time are often the result of primarily poor recording practices of in-house maintenance activities. SHAs must establish a formal practice to collect location data for each maintenance activity. The use of GPS enabled tablet PCs is common and is a cost-effective means for the purpose. Since the DOT records sealed cracks as low severity cracks, it is recommended recording sealed cracks separately or recording the percent of sealed cracks. Also, it is recommended recording the purpose of patching in a separate field such as “addressing high severity alligator cracking” or “utility cut”. When collecting and storing data, the agencies need to consider the needed and possible uses of data to minimize the existing data issues and fragmentation. Also, the current practices of aggregating raw pavement condition data to form longer segments should be revised. For example, the agencies collect rutting and IRI data for left and right wheelpaths and then calculate the average to represent the rut depth or IRI value. However, there is no justification regarding the use of the average or the maximum wheelpath values. Agencies accumulate the pavement cracking data as long as the pavement segment shares the same geometric and material attributes. This could yield long segments, ten miles or more, which heavily misrepresents the existing condition especially if the distresses were not evenly distributed along the pavement segment.

Recommendation to Change for barriers 5 and 6: The performance evaluation process should be done by considering the different failure perspectives. Using one collective measure such as the PCI to measure the pavement performance could be misleading since each individual distress could yield a different performance or service life. For example, a PCI may not be a good indicator if a pavement needs a crack sealing or microsurfacing. As such, evaluating the pavement performance at the distress level would be more informative and accurate.

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Additionally, the performance evaluation process and other decision-making processes should be integrated. For example, agency-wide consensus among different business units on what performance indicators should be used and how to estimate the service life should be made to achieve a true and effective data-driven decision making/support system.

Recommendation to Change for barrier 7: Maintenance and rehabilitation data should also include key pieces of information that are needed for pavement performance analysis. For instance, HMA resurfacing with CIPR should include the percentage of recycled material. Other overlay projects should include inputs that affect the performance of pavement such as binder content, binder type, and air void percentage. Moreover, basic project information such as overlay thickness and milling thickness should be recorded appropriately using consistent terms. Some different technical terms were used alternatively referring to the same process. For example, milling and scarification are two different terms used in the PMIS but they refer to the same process which is surface removal. There is a need to develop data exchange quality management guidelines to ensure that data can be exchanged and integrated easily between different business units. While terminology consistency issue is found to be a persistent problem, data formatting is another major issue especially when the data is shared between two or more business units. For example, maintenance project numbers are in different formats in each database. Thus, using the project number as a common identifier is challenging and inefficient.

Because of the identified barriers associated with the distinctive steps of the performance evaluation process, the utilization of the collected data has not been fully achieved. As such, the use of collected data for performance evaluation or budgeting requires significant manual interventions. This creates an urgent need to improve highway agencies' data collection, storage, and management practices to achieve the highest return on their investments.

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Summary and Conclusions

SHAs invest a significant amount of budget annually to collect pavement condition assessment data digitally. The ultimate goal of this data collection effort is to better understand the performance of pavements under different operating conditions and assist SHAs in making cost-effective decision for future pavement management decisions. However, many old practices in SHAs pose serious threats and work as barriers to integrating data for scientifically evaluating the performance of pavement. This study identified technical and integration issues when an SHA implements a data-driven pavement performance evaluation process. A GIS-based data integration framework is used to spatially integrate the pavement management data and rehabilitation project's data. Several barriers are identified at different stages of the performance evaluation process. The majority of those barriers are related to data quality, consistency and exchange standards. These exchange standards should facilitate data integration between different offices and business units. Because of these barriers, agencies are not likely to achieve the satisfactory return of their data collection investments.

Moreover, the adoption of a robust data-driven pavement performance evaluation will be a challenging task given the existing barriers. Recommendations to the identified seven barriers. Utilization of collected data can be significantly improved by recording missing data such as in-house maintenance projects. Moreover, developing stricter quality control measures and data exchange standards will significantly facilitate the analysis of data to support various pavement management decisions.

As for future research, there is a need to improve the data utilization protocols and quality control standards used by highway agencies. This entails an urgent need to analyze the current data management and exchange practices to overcome the heterogeneity of databases. There is a

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need to develop a new method to represent the pavement condition to overcome the limitations associated with other indexes such as the PCI. Finally, a critical assessment of the drawbacks of the current technological advancements such as image processing algorithms and imaging/sensor technologies used to detect cracking data should be done to overcome the current limitations.

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CHAPTER 4: DYNAMIC MULTIDIMENSIONAL PAVEMENT DELINEATION APPROACH

Abstract

Over the past decades, highway agencies have used automated as well as semi-automated data collection method such as laser scanning and ultrasonic waves, resulting in the collection of an enormous amount of high-density pavement condition data. Most highway agencies are now able to quantify the level of extent and severity of different distresses even for extremely short length of pavement sections. A scientific and dynamic method to aggregate those small pavement sections into reasonable size segments plays an important role in implementing several pavement management tasks. For example, accurately representing the overall pavement network performance and making practical maintenance and rehabilitation decisions require an accurate presentation of pavement condition data. This paper proposes a new segmentation method for pavement sections that finds homogenous segments by considering multiple pavement distresses using the affinity propagation clustering technique. The affinity propagation clustering technique finds the similarity between data points in a multidimensional space. A case study was conducted using pavement condition data in Iowa to illustrate the capabilities and applications of the proposed segmentation framework. The results of the case study showed that agencies have the ability to evaluate the accuracy of the delineated segments by changing the delineation parameters including the minimum segment length. The proposed algorithm is expected to significantly enhance many pavement management applications such as deterioration modeling and maintenance programming.

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Introduction

State Highway Agencies (SHAs) across the United States are now able to collect a large amount of pavement condition information because of the advanced technological data collection methods. The majority of SHAs collect pavement performance data, which encompass measurements of the international roughness index (IRI) and rut depth using electronic sensing devices that utilize laser, acoustic, and infrared technologies (McGhee 2004). These agencies also use imaging technologies and automated image processing techniques to estimate the levels of severity and extent of surface distresses. For instance, the Iowa Department of Transportation (DOT) collects pavement distress data for every 52 feet of half of its network (5,630 miles) annually which results in more than half a million records of pavement condition data. Similarly, the Oklahoma DOT collects 800,000 pavement data records annually for approximately 8,000 miles (Calvarese 2007) while the Texas DOT collects pavement condition data every 0.1 mile (Texas DOT 2013). California Department of Transportation collects ground-penetrating radar (GPR) data for its entire 50,000 lane-mile state highway network (Zhao et al. 2013). These massive condition surveying efforts by SHAs result in high-density data that accurately describes the pavement condition.

This high-density raw data is used to support a variety of decision-making applications. However, the raw data must be processed and delineated in order to determine reasonable lengths of homogenous pavement segments. The delineation process of pavement sections should consider a variety of attributes including the existing distresses, pavement type, maintenance history, and traffic volume. Additionally, the delineation method should be adaptable to accommodate the agency’s needs. For example, agencies may need to delineate the pavement condition data at very short segments to find localized deteriorated sections and apply

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appropriate pavement treatments such as patching or partial depth repairs. Thus, a dynamic pavement condition delineation algorithm that allows agencies to control the attributes used to find similar segments would be beneficial for pavement management applications and enhance their effectiveness.

Furthermore, an effective pavement management system should be able to support a variety of decision making systems and data analytics applications including pavement maintenance performance evaluation, pavement deterioration model development, and budgeting. For instance, the performance of a maintenance or rehabilitation treatment depends on the pavement condition prior to treatment application. Thus, finding homogenous segments that share relatively uniform pavement condition will help agencies evaluate the effectiveness of different treatments accurately. Similarly, the process of developing pavement deterioration models can be significantly enhanced by tracking the pavement performance of homogenous sections.

The main objective of this study is to develop a pavement condition data delineation methodology that can dynamically detect homogenous pavement segments and accurately represent pavement performance. To illustrate the utility, data was collected from the Iowa DOT and a case study was conducted to test the proposed methodology and possible future implications.

Literature Review

The cumulative difference approach (CDA), developed by the American Association of State Highway and Transportation Officials (AASHTO), is one of the earliest methods used for delineating pavement condition data (AASHTO 1993). The CDA finds statistically homogeneous segments based on the pavement condition/distress data such as deflection, skid

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resistance, and severities of various pavement distresses, etc. Figure 4-1 shows the CDA approach based on an ideal assumption of a continuous and constant distress value (ri). The segment length is represented on the x-axis using different intervals specified at (xi). Figure 4-1(a) illustrates the actual pavement distress value over pavement length. Figure 4-1(b) represents the cumulative area, which is determined by integrating each individual pavement response rate over the interval limits. Finally, Figure 4-1(c) shows the difference in cumulative area values between the actual and the average area, which represents the fundamental concept used to determine uniform and homogeneous segments (AASHTO 1993).

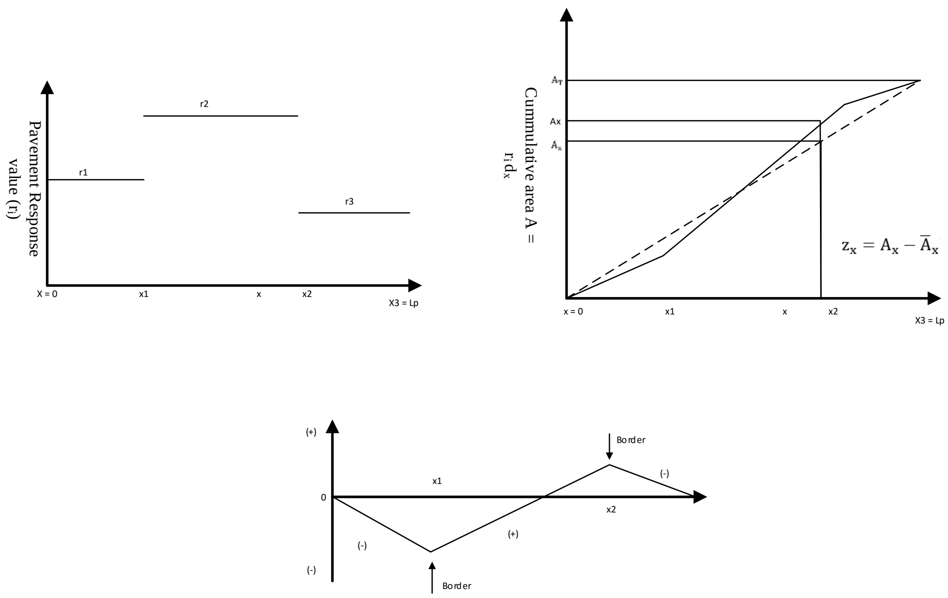

Figure 4-1. CDA approach (AASHTO 1993)

Since the pavement condition data are collected as point measurement, the numerical difference between pavement responses (i.e., conditions) is calculated using equation 4-1:

$$z_x = \sum_{i=1}^{n} a_i - \frac{\sum_{i=1}^{n} a_i}{L_p} \sum_{i=1}^{n} X_i \dots\dots\dots\dots\dots\dots\dots\dots\dots (1)$$

Where a_i is calculated using equation 4-2:

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$$a_i = \frac{(r_{i-1} + r_i) \times x_i}{2} \dots\dots\dots\dots\dots\dots\dots\dots\dots.(2)$$

Where n is the n^{th} pavement response measurement, r_i is the pavement response value of the i^{th} measurement, and L_p is the total segment length.

Many studies identified the limitations of the CDA approach and developed new delineation algorithms to overcome the limitations. For instance, Divinsky et al. (1997), Misra and Das (2004), and El Gendy and Shalaby (2004) identified some limitations associated with the CDA method in finding homogeneous segments. First, the CDA fails to identify more than one homogeneous segment with different average response levels because the method only considers the absolute slope change in magnitudes. Second, the CDA method cannot identify the same homogenous segments when elevating the distress value by a fixed value. Third, the CDA method does not provide the decision maker with the flexibility to choose the number of homogenous segments. Finally, the delineated segments are significantly influenced by the overall average of the pavement distress values. Based on the limitations of the CDA approach, several studies proposed new delineation methods. Table 4-1 summarizes those methods and performance indicators used to identify homogeneous pavement segments.

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Table 4-1. Methods and performance indicators used to identify homogenous pavement segments

Study	Methods	Response variable
Divinsky et al. (1997)	CDA	Roughness
Ping et al. (1999)	CDA and significance testing	Rut depth
Kenedy et al. (2000)	CDA and significance testing	Roughness
Cuhadar et al. (2002)	Wavelet transform	Generic
Misra and Das (2004)	Classification analysis and regression trees (CART)	Roughness
El Gendy and Shalaby (2004)	Statistical quality control charts-Absolute difference approach	Generic
Thomas (2005)	Bayesian Algorithm	Roughness
Tejeda et al. (2008)	Accumulated sum (CUSUM)	Skid resistance
Yang et al. (2009)	Fuzzy c-mean clustering	Pavement condition rating
D'Apuzzo and Nicolosi (2012)	Cumulative sum or difference, Bayesian algorithm, LCPC (Labortoire Central des Ponts et Chasussees)	Skid resistance

Divinsky et al (1997) modified the CDA approach to delineate pavement condition data using the IRI as a response variable. They modified the CDA approach to include the calculation of the response value standard deviation to delineate pavement condition data to consider the scatter characteristics of the response values. Although the modified CDA approach overcame one of the major weaknesses of the CDA approach, it failed to account for considering the variability of other response values. Similarly, Ping et al. (1999) combined the CDA method with statistical significance testing (t-test) to identify homogenous pavement segments based on the rut depth using data gathered by Florida DOT. The proposed methodology uses two constraints to delineate rutting values. The first constraint considers achieving a minimum segment length for practicality reasons. The second constraint addresses joining adjacent

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segments by minimizing the mean rut depth. The study found out that the sum of squared error values increased when the minimum segment length was higher than 0.06 mile or when the rut depth measurements between adjacent segments were very disperse. The approach implemented by Ping et al. (1999) did not consider extreme values of rut depth in segmentation. Kennedy et al. (2000) also combined the CDA approach and paired t-test significance testing to identify homogenous segments using IRI as response values.

On the other hand, some studies developed new algorithms to delineate pavement condition data to fully replace the use of the CDA approach. Cuhadar et al. (2002) argued that the CDA approach is not effective because of the "noise-like ripples" of the observed data, which are averaged to find homogenous segments. Thus, they developed a wavelet transform that was well concentrated in time and frequency to automatically delineate the pavement condition data. The wavelet transform approach was found to have high performance for automatic segmentation. The algorithm detects singularities of the smooth waveform and mark them as border points.

Misra and Das (2004) developed a segmentation approach that attempted to overcome the limitations of the CDA using classification analysis and regression trees (CART). The first step of the approach was to divide the dataset into several subsets by minimizing the value of the mean and the mean squared error of the pavement IRI values. The algorithm keeps dividing the dataset to subsets until the minimum segment length is achieved. The proposed methodology also joined adjacent segments based on statistical similarity. El Gendy and Shalaby (2004) also developed a segmentation approach using the quality control charts which considered the variance of the pavement response instead of the average to reduce the response variability within the aggregated pavement sections. The control chart approach defines the upper and lower

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limits based on a sample standard deviation. The lower and upper limits are used to determine homogenous segments by keeping the pavement distress value between the limits. When the pavement distress values are beyond the limits, the segment border resets and a new segment is determined. However, the lower and upper limit can change based on the initial sample selection and response value.

Thomas (2005) developed an automated road segmentation model using a Bayesian algorithm. The algorithm uses a long series of transformed measurements and returns the series into partitioned homogenous segments. Box-Cox transformation was utilized to transform the IRI measurement before analysis to bring the returned segments to the model assumption of normally distributed observations. Change points in the long series of data were determined using the posterior mode. However, the proposed algorithm fails to practically determine additional segment break points after the first break point is determined. As a result, a heuristic part is integrated with the algorithm to place initial change points in a sequential way based on the road construction history. Cafiso and Di Graziano (2012) also proposed a new methodology that finds change-points that can be used to detect homogenous segments. These change-points are determined based on minimizing the sum of the squared errors with respect to the original pavement response data.

Tejeda et al. (2008) developed a procedure for specifically delineating skid resistance data to potentially facilitate road safety management. The procedure uses the leverage method to find outlier skid resistance data. Then, the accumulated sum (CUSUM) method is used to delineate the skid resistance data. The CUSUM method is used to find a point that divides two segments with different means. Finally, the procedure groups adjacent segments using the Student's t-test of mean equities at 95% confidence level. However, the delineation results will

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be affected based on the choice of the CUSUM starting point along the pavement sections. An algorithm developed by Yang et al. (2009) spatially clusters pavement segments to determine pavement preservation project boundaries. The algorithm uses fuzzy c-mean clustering method to minimize the variation in each cluster of pavement segments. Pavement condition rating, an overall pavement condition measure that considers several surface distresses, is used as the response variable in the proposed algorithm. The algorithm also considers hard natural boundaries such as bridges, roadway characteristics and so forth. The study also recommended using the detailed segment-level distress to increase the accuracy of the segmentation process. Similarly, Saliminejad and Gharaibeh (2016) used a clustering algorithm to find homogenous pavement segments based on their deterioration pattern which is represented by an overall condition index. The clustering algorithm is based on using an unskewed probability distribution to estimate how close the data point to each other within the cluster. Zhao et al. (2013) used GPR data to developed a segmentation algorithm that delineated pavement sections based on surface type, layer thickness and base type. Zhang and Flintsch (2013) proposed an algorithm that segments pavement sections based on the deflection measurements for pavement maintenance purposes. The algorithm used wavelet transform to de-noise the deflection measurements. Furthermore, the algorithm utilized CART algorithm and t-test to locate peak measurements and test statistical significance between segments. The minimum segment length used by Zhao et al. (2013) was 100 meters (328 feet) while the minimum segment length used by Zhang and Flintsch (2013) was 150 meters (492 feet).

Based on the analysis of the existing literature, many studies concluded that the CDA approach is obsolete and there is a need to replace with a method that can accommodate the high density pavement condition data. Additionally, all of the previous attempts to delineate pavement

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condition data has failed to consider multiple existing pavement distresses. This study proposes an efficient and dynamic pavement segmentation algorithm that aggregates pavement section at the distress level.

Dynamic Delineation Framework

The proposed delineation framework, illustrated in Figure 4-2, is divided into three steps. The first step of the segmentation framework aims to detect hard boundaries set by different attributes such as pavement characteristics or traffic volume. Hard boundaries are determined by the pavement geometry, pavement design, or other existing structure. For example, the start and end points of these segments consider the existing barriers such as bridges or traffic intersections. These attributes are historically defined and stored in the agency's pavement management information system. The output of the first step is a database that contains a list of pavement segments that are truncated based on the existing hard boundaries. While some agencies (e.g., Iowa DOT) consider the maintenance history as a hard boundary, it is not necessary that the construction history constraint would yield homogenous pavement segments.

The second step aims to summarize the raw pavement condition data to form pavement segments that have a specified minimum segment length. Finally, the affinity propagation algorithm is used to find longer homogenous segments. Further details on these steps are discussed below. For the rest of this study, the term "section" is operationalized as the raw data collected by agencies (e.g., shortest unit of pavements) whereas the term "segment" refers to a pavement that consists of multiple pavement sections.

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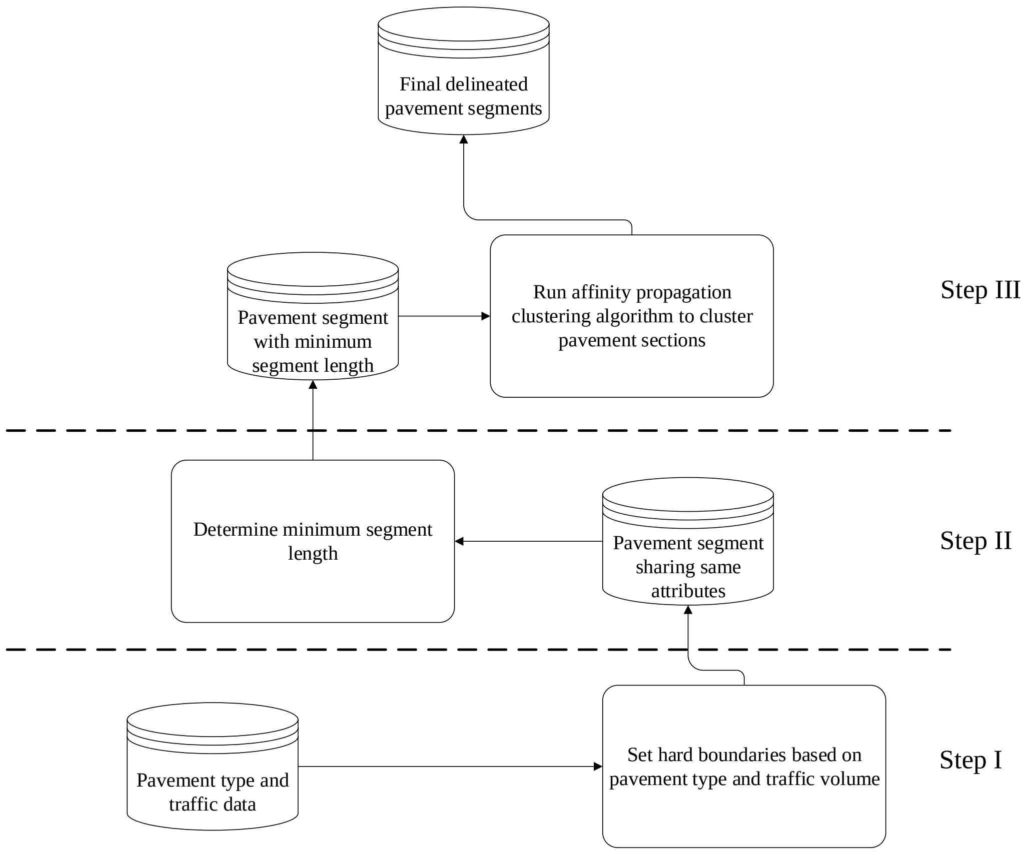

Figure 4-2. Dynamic segmentation framework

Step 1: Setting Hard Boundaries

Information stored in agencies' pavement management information systems is used to determine the start and end mileposts of pavement segments. Highway agencies often set these hard boundaries by assigning a unique key identifier to pavement segments. For example, the Iowa DOT assigns a unique identifier called "Original Key" to pavement segments that share the same attributes (e.g., pavement design, maintenance history, and traffic volume).

In this study, a special type of data structure called "Ordered Dictionary" is used to store the pavement condition data based on identified hard boundaries. An Ordered dictionary is similar to a database that is used to map attributes to keys. In this context, the key used in the dictionary is the original key and the attributes associated with each original key are the pavement condition data (see Figure 4-3). For implementation purposes, ordered dictionaries are

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used because they keep the order of its records after data processing. This is an important feature for this data structure to keep the order of pavement sections after data processing to ensure the geometric continuity of pavement sections.

Index

Section$_1$ attributes

Data Dictionary = {**Original Key 1**: [Attribute$_{1,1}$, Attribute$_{1,2}$,….,Attribute$_{1,i}$], [Attribute$_{2,1}$, Attribute$_{2,2}$,….,Attribute$_{2,i}$],…..[Attribute$_{n,1}$, Attribute$_{n,2}$,….,Attribute$_{n,i}$],
Original Key 2: [Attribute$_{1,1}$, Attribute$_{1,2}$,….,Attribute$_{1,i}$], [Attribute$_{2,1}$, Attribute$_{2,2}$,….,Attribute$_{2,i}$],…..[Attribute$_{n,1}$, Attribute$_{n,2}$,….,Attribute$_{n,i}$],
….,
Original Key N[[Attribute$_{1,1}$, Attribute$_{1,2}$,….,Attribute$_{1,i}$], [Attribute$_{2,1}$, Attribute$_{2,2}$,….,Attribute$_{2,i}$],…..[Attribute$_{n,1}$, Attribute$_{n,2}$,….,Attribute$_{n,i}$]}

Section$_n$ attributes

Attributes for N sections

Figure 4-3. Data structure for pavement condition data

Step 2: Determining Minimum Segment Length

From the literature review, there is no consensus on a minimum segment length. In fact, short segments help agencies determine locally distressed sections, which will trigger local treatments such as patching, or partial depth repairs. On the other hand, longer segments are considered more practical for maintenance planning and overall condition reporting. As such, the proposed delineation algorithm provides the flexibility to determine the minimum segment length. The algorithm uses the moving window average and cumulative sum to summarize the pavement condition data to create longer segments that meet the minimum segment length requirement. The width of the moving window is set by the user/agency which provides the flexibility to run different types of analyses including the effect of minimum segment length on condition representation and maintenance programming. Figure 4-4 shows an example of the moving window summary concept. In this example, the width of the window is 'n'. The summary of the resulted segment is calculated as shown in Figure 4-4.

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Cracking data

Data Dictionary = {**Original Key 1**: $[RUT_{1,1}, IRI_{1,2},\ldots,Crack\ X_{1,i}]$,
$[RUT_{2,1}, IRI_{2,2},\ldots,Crack\ X_{2,i}]$, → $\left[\sum_{i=1,1}^{n}\frac{RUT_{i,1}}{n}, \sum_{i=1,1}^{n}\frac{IRI_{i,1}}{n},\ldots, \sum_{i=1,1}^{n}\frac{Crack\ X_{i,1}}{Segment\ Length}\right]$
$[RUT_{3,1}, IRI_{3,2},\ldots,Crack\ X_{3,i}]$,
$[RUT_{4,1}, IRI_{4,2},\ldots,Crack\ X_{4,i}]$,
$[RUT_{5,1}, IRI_{5,2},\ldots,Crack\ X_{5,i}]$,
$[RUT_{6,1}, IRI_{6,2},\ldots,Crack\ X_{6,i}]$,
$[RUT_{7,1}, IRI_{7,2},\ldots,Crack\ X_{7,i}]$,
$[RUT_{8,1}, IRI_{8,2},\ldots,Crack\ X_{8,i}]$,
$[RUT_{9,1}, IRI_{9,2},\ldots,Crack\ X_{9,i}]$,
$[RUT_{10,1}, IRI_{10,2},\ldots,Crack\ X_{10,i}]$,
.
.
.
.
$[RUT_{n,1}, IRI_{n,2},\ldots,Crack\ X_{n,i}]$….}

Figure 4-4. Moving window to determine the minimum segment length

Step 3: Delineating Pavement Sections Using Affinity Propagation

In this step, the affinity propagation algorithm is used to determine similar pavement segments the segments that were summarized in step 2. The affinity propagation method was developed by Frey and Dueck (2007). It finds representative data points "exemplars" and their clusters by exchanging recursive real-valued messages between data points (Frey and Dueck 2007). The magnitude of each message indicates the resemblance of one pavement section has for selecting another pavement section as its exemplar. This clustering algorithm uses the Euclidean distance to measure the similarity between potential exemplars and data points. Unlike other clustering techniques that randomly choose initial subset of data points to find a good solution, affinity propagation considers all data points as potential exemplars (Frey and Dueck 2007). Affinity propagation also clusters the data points in N dimensional space where N represents the number of attributes or features.

The method outperforms other clustering methods in many aspects. For example, the number of clusters does not have to be specified before the algorithm initiation. However, the affinity propagation does require the user to specify a cluster generation preference (*pr-value*), which is a value that specifies how preferable each point to be an exemplar. More exemplars or

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clusters will emerge by increasing *pr-value* and vice versa. The affinity propagation also outperforms other techniques such as the k-means clustering and the expectation minimization algorithm since they rely on random sampling to identify the initial clusters that may result in poor solutions. Additionally, the affinity propagation clustering technique has an advantage over the hierarchical agglomerative clustering and spectral clustering since they rely on pairwise grouping. Thus, all points within a cluster do not have to be similar to a single center as because of the method of clustering (Frey and Dueck 2007).

Implementation

In order to implement the proposed delineation algorithm, a script was developed using Python programming language. Throughout the implementation process, the script uses a variety of functions that help with the processing of the pavement condition data, which is stored in arrays and dictionaries. Thus, the script uses the "NumPy" package for scientific computing (Walt et al. 2011). The NumPy package provides powerful tools and functions that can process n-dimensional array objects. Furthermore, the script uses the "scikit-learn" package for machine learning applications (Pedragosa et al. 2011). The scikit-learn package contains efficient tools for data mining and analysis which enables the integration of the affinity propagation algorithm in the proposed delineation method. The script takes the input data from a geodatabase file type that contain the raw pavement condition data and other information such as latitude and longitude, original keys, pavement types and so forth. Geodatabase files store both spatial and non-spatial data. Figure 4-5 shows the pseudo code of the proposed algorithm.

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```
Specify the geodatabase file containing raw pavement condition data
Create empty array to store pavement condition data and other pertinent data
Populate the empty array with features from the geodatabase file
Average the rut depth and IRI values for the left and right wheelpaths
Replace the left and right wheelpaths measurements with average measurements

Create a Normalization function:
    calculate the standard deviation (stdv) of feature records
    calculate the average (avg) of feature records
    if values of all feature records equal to zero;
        override the standard deviation value to be (1)
    Else
        calculate the normalized value as (feature record - avg) / stdv

Create a Summarize function:
    define segment length
    number of arrays = m
     m = total number of data points/number of data points in the specified segment length
    create an m-number of empty arrays that will contain the summarized data
    calculate average rut depth and IRI values based on the specified segment length
    calculate the cumulative sum of cracking data based on the specified segment length
    if the m is not a whole number;
        create an array with length (k), k = remainder of m
    stack the m-number arrays

Define user arguments:
    define file name and path
    define output file name
    define segment length
    define affinity propagation parameters (e.g., clustering preference value, max number of iterations...)

Store the input data in an Ordered Dictionary data structure
Create an empty Ordered Dictionary data for cluster labels

for key in the Ordered Dictionary data:
    summarize data points as specified by user
    normalize pavement condition data
    implement the affinity propagation algorithm
    generate a list of cluster labels
    store the cluster labels in the ordered dictionary
    append the cluster labels to the original condition data
Exit
```

Figure 4-5. Python script pseudo code

The algorithm imports data from ArcGIS, a commercial geographic information software application, in a geodatabase file format. Using array-processing functions, the pavement condition data is organized and processed. Two functions are created including a "*normalize*" function and a "*summarize*" function. The normalize function calculates the z-score for each distress value. While the summarize function aggregates the pavement condition data for a specific length as specified by the user. The user is required to assign the minimum segment length to be used in the summarize function. Additionally, the user is required to assign the affinity propagation input parameters such as the clustering *pr-value* and minimum segment length. Afterward, data clustering for each original key is implemented using the affinity propagation algorithm. The output of the affinity propagation is a cluster label for each record, which is then stored in ordered dictionary and appended to the original pavement condition data.

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Case Study

In order to test and show the capabilities of the proposed delineation algorithm, a case study was conducted using the data collected by the Iowa DOT that is collected every 52 feet. For every section, the DOT collects the location data including geographic location, beginning milepost and ending milepost. Additionally, the Iowa DOT collects faulting, rut depth, IRI, longitudinal cracking, longitudinal cracking on wheelpath, transverse cracking and alligator cracking. It is worth mentioning that the Iowa DOT collects IRI measurement and rut depth for both the left and right wheelpaths.

In this case study, 237.24 miles or 24,089 pavement sections, of I-35 were selected as input data. A total of 108 original keys were found which means that there are 108 segments in the 237.24 miles that share different pavement or traffic characteristics. The minimum, average and maximum segment lengths were 0.5, 2.2, and 14.0 miles respectively. Four different pavement types including Portland cement concrete (PCC), Asphalt concrete (AC), composite on continuous reinforced concrete, and composite with jointed plain concrete were identified in this study. Figure 4-6 shows the location of the selected pavement segments for the case study implementation.

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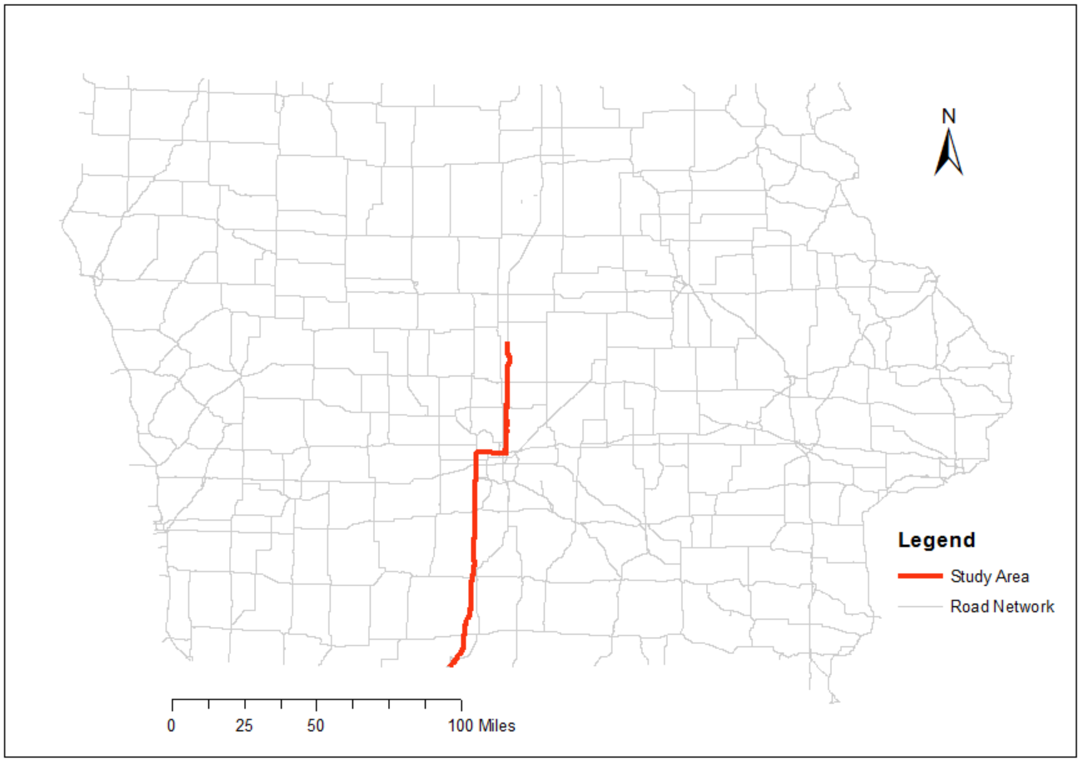

Figure 4-6. Case study location

The proposed segmentation algorithm was applied to the data collected. Several iterations were conducted by changing the minimum segment length and the preference for generating high or low number of clusters. A total of 15 iterations were conducted including five different minimum segment lengths including 0.01, 0.05, 0.1, 0.15, and 0.2 miles. For each minimum segment length, the proposed algorithm is applied three times by changing the preference of generating low or high number of clusters. The pr-values were -50, -100, and -200 which correspond to high, moderate and low preference of cluster generation. The pr-values were determined based on several other iterations to examine the number of clusters generated by changing the preference value. It was found that reducing the preference value beyond the -200 limit yielded only one cluster per dataset. On the other hand, increasing the preference value over the -50 limit would yield too many clusters which generates a numerous number of segments

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having the specified minimum segment length. Table 4-2 shows the number of segments, lengths, and percentage of data reduction for each iteration. The percentage of data reduction was measured by dividing the number of segments emerged from running the algorithm by the total number of pavement sections (24,089). It is observed that the percentage of data reduction and the average segment length increase by increasing the minimum segment length of the preference or cluster generation.

Table 4-2. Percentage of Data Reduction

Minimum segment length (mile)	*Pr-value*	Number of segments	Average and maximum segment lengths	Percentage of data reduction
0.01	Low	2704	0.09, 2.92	88.8%
	Moderate	3689	0.06, 1.99	84.7%
	High	4252	0.06, 0.89	82.3%
0.05	Low	337	0.7, 8.53	98.6%
	Moderate	873	0.27, 3.28	96.4%
	High	1702	0.14, 1.95	92.9%
0.1	Low	130	1.82, 12.31	99.5%
	Moderate	306	0.78. 4.44	98.7%
	High	628	0.38, 3.28	97.4%
0.15	Low	111	2.14, 13.90	99.5%
	Moderate	178	1.33, 8.53	99.3%
	High	351	0.68, 4.28	98.5%
0.2	Low	109	2.18, 13.85	99.5%
	Moderate	146	1.62, 13.85	99.3%
	High	272	0.87, 5.32	98.8%

For each iteration, the pavement condition index (PCI) and ride quality index (RQI) were calculated for each segment according to the Iowa DOT procedures (Bektas et al. 2014). The PCI is an indication of the overall pavement condition whereas the RQI represents the ride quality. First, pavement surface distresses are aggregated according to the pavement type.

For each cracking type, three levels of severity are collected including low, moderate and high. The crack severities were aggregated using the coefficients of 1, 1.5, and 2 for low,

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moderate and high severities respectively. After aggregating crack severities, a crack index (CI) for each crack type was calculated according to the pavement type. The value of each index is from 0 to 100 where 100 represents excellent condition and 0 represents poor condition. The Iowa DOT uses a failure threshold value for each index and then uses deduction to proportionally calculate the CI. For PCC pavements, the threshold values for the transverse cracking and longitudinal cracking indexes are 241.4 count/mile (150 count/km) and 1320 ft/mile (250 m/km) respectively. For AC pavements, the threshold values for the transverse cracking, longitudinal cracking, longitudinal cracking on wheel path, and alligator cracking are 482.8 count/mile (300 count/km), 2640 ft/mile (500 m/km), 2640 ft/mile (500m/km), and 6235.2 ft2/mile (360 m2/km) respectively. For composite pavements, the threshold values for transverse cracking and longitudinal cracking indexes are 804.67 count/mile (500 count/km) and 2640 ft/mile (500 m/km) respectively. The CIs for PCC, AC and composite pavements were calculated according to equations 4-1 to 4-3 respectively:

$$CI_{PCC} = 0.6 * TCI + 0.4 * LCI \qquad (1)$$

$$CI_{AC} = 0.2 * TCI + 0.1 * LCI + 0.3 * LWCI + 0.4 * ACI \qquad (2)$$

$$CI_{Composite} = 0.65 * TCI + 0.35 * LCI \qquad (3)$$

Where TCI is the transverse cracking index, LCI is the longitudinal cracking index, LWCI is the longitudinal cracking on wheel path cracking index and ACI is the alligator cracking index.

The Iowa DOT then calculates rutting, ride quality, and faulting performance indicators that are used to estimate the PCI according to the pavement type. The rutting index (RI) is derived from the rut depth, which is the depression on the wheel path in asphalt pavements. The

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failure threshold value is 0.47 inches (12 mm) and corresponds to a RI of 0. The RQI is similarly derived from the IRI measurements. IRI measurements less than or equal 31.68 in/mile (0.5 m/km) corresponds a perfect RQI of 100 while IRI measurements greater than or equal 253.44 in/mile (4 m/km) corresponds to poor RQI of 0. Faulting index (FI) is derived based on the faulting values which are the vertical displacements between neighboring slabs in PCC pavements. A vertical displacement of 0.47 inches (12 mm) corresponds to a 0 index.

Based on the aforementioned indexes, the PCIs were calculated according to the Iowa DOT practice as shown in Equations 4-4 and 4-5:

$$PCI_{PCC} = 0.4 * RQI + 0.2 * CI_{PCC} + 0.4 * FI \qquad (4)$$

$$PCI_{AC,Composite} = 0.4 * RQI + 0.2 * RI + 0.4 * CI_{AC,composite} \qquad (5)$$

For each iteration, pavement condition indexes were calculated for all segments. Additionally, the PCIs of pavement sections and delineated segments were also calculated. By comparing the pavement condition indexes or distresses of the delineated segments to the pavement sections, agencies can estimate how accurate the delineated segments represent the original pavement condition.

In order to evaluate the accuracy of condition representation, the study developed two methods to measure the accuracy of the delineated segments when compared to the raw pavement condition data. The first method evaluates the pavement condition representation at the distress level while the second method evaluates the condition representation using the overall condition indicators including the PCI and RQI. Thus, the first method looks at the absolute error for each pavement distress according to the pavement type. The sum absolute error is calculated according to Equation 4-6:

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$$Sum\ Absolute\ Error = \sum_{i=1}^{N}\sum_{k=1}^{M}|RS_{i,k} - RD_{i,k}| \qquad (6)$$

Where N is the number of sections, M is the number of distresses under consideration, RS is the normalized response value of a specific distress of a segment, and RD is the normalized response value of a specific distress of a pavement section. The normalization or standardization of the distress values was conducted by calculating the z-score for each distress value. This provides a consistent method to compare different distress values to each other since they were represented in different units or methods. Figure 4-7 shows an example of the absolute error, before normalization, of rut depth between the delineated segment and the raw pavement condition data. In this example, the delineated segment receives the average value of the pavement section's rut depth.

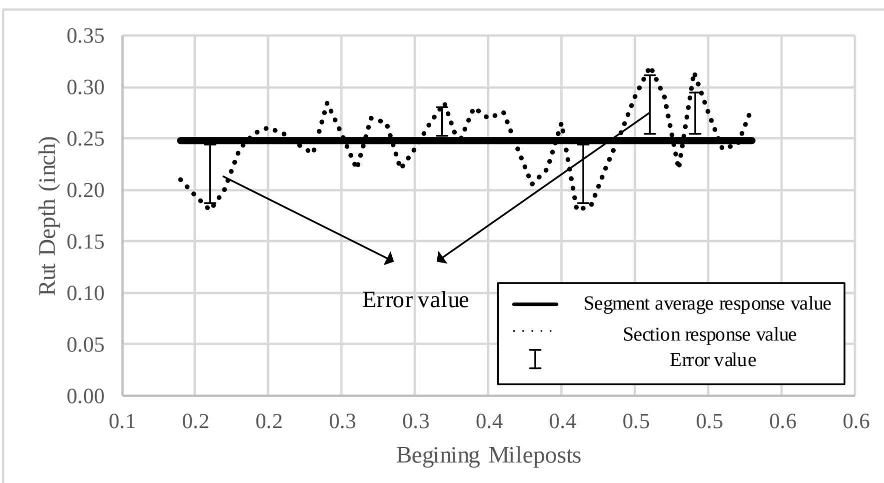

Figure 4-7. Error estimation between delineated segments and original distress values

The sum of the absolute error is used as an accuracy measure. The higher the absolute error, the higher the deviation of the summarized data or delineated segments from the raw pavement condition data. Figure 4-8 shows the relationship between the sum of absolute error and the percentage of data reduction where an exponential relationship between the percentage

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of data reduction and the absolute error was observed. The sum absolute error increases drastically when the percentage of data reduction goes above 97%.

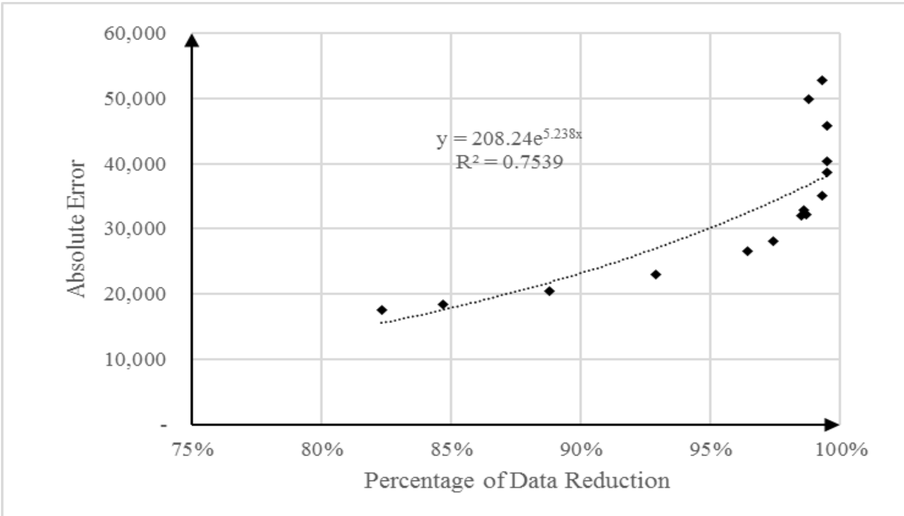

Figure 4-8. Relationship between the sum of the absolute error and percentage of data reduction

The second method aims at assessing the overall pavement condition representation accuracy by comparing the PCI and RQI distributions of pavement sections to the PCI and RQI distributions of the delineated segments. Figure 4-9 shows the PCI values versus the percentage of segments of the raw condition data and the delineated segments that emerged from each iteration when setting the minimum segment length to 0.1 miles. It is observed from Figure 9 that there are some variations in condition representation. For example, the percentage of pavement sections that had a PCI between 35 and 40 was approximately 6%. However, this percentage escalated to 16%, 10% and 8% according to the preference of generating few, moderate, and many clusters respectively. One important aspect of that example is that agencies need to accurately determine the percentage of segments with poor condition to estimate the funding needed for rehabilitation projects. For example, the percentage of pavement sections with PCI of

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40 or less is 10%. When delineating pavement segments with a minimum segment length of 0.1 miles, this percentage was from 18% to 12% according to the clustering generation preference.

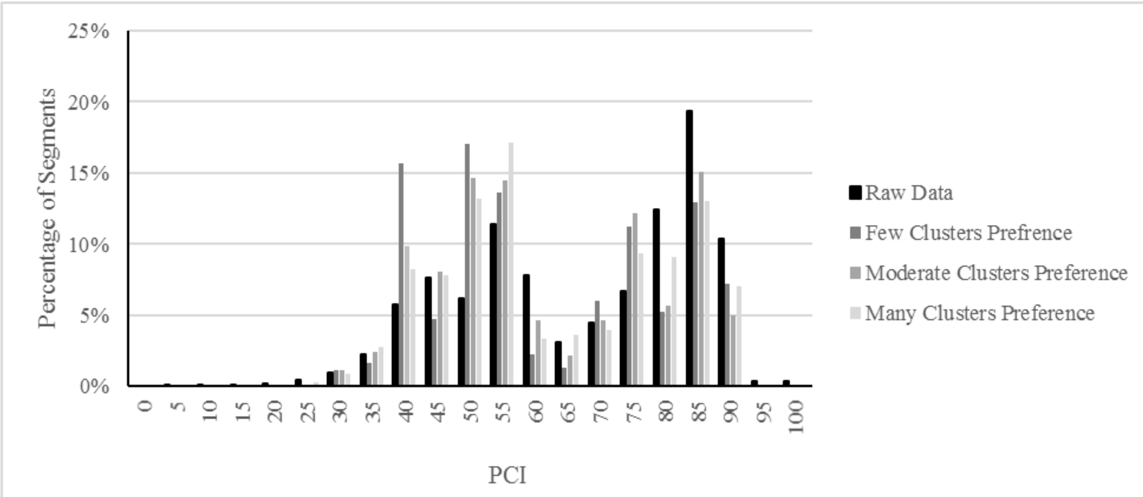

Figure 4-9. PCI distributions for pavement sections and delineated segments

Similarly, Figure 10 shows the RQI distributions for pavement sections and the delineated segments versus the percentage of sections when the minimum length is set to 0.1 miles. In the case shown in Figure 4-10, the proposed segmentation method resulted in underestimating the percentage of delineated segments with high ride quality (i.e., RQI greater than 85). Simultaneously, the percentage of pavement segments with RQI between 70 and 80 were overestimated.

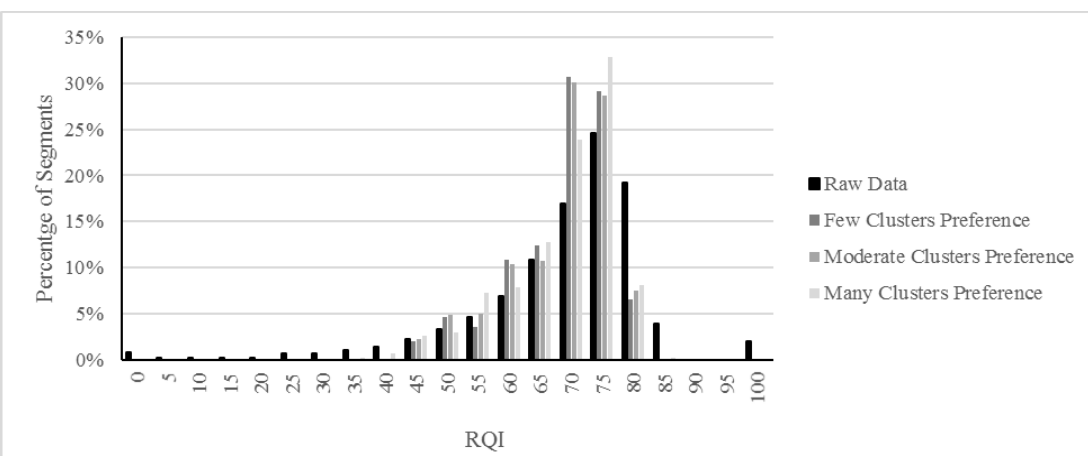

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Figure 4-10. PCI distributions for pavement sections and delineated segments

As such, it is important to measure the overall condition distribution variations between the pavement sections and the delineated segments. Figures 11 to 13 show the difference between the PCI values of the pavement sections and the delineated pavement segments for each clustering preference at the three minimum segment lengths. The difference between the actual PCI of the pavement sections and the delineated segments increased when the PCI is greater than 40 and less than 90 points. By increasing the minimum segment length, the difference between the PCI distribution of the raw pavement condition data and the PCI distribution of the delineated segments increased.

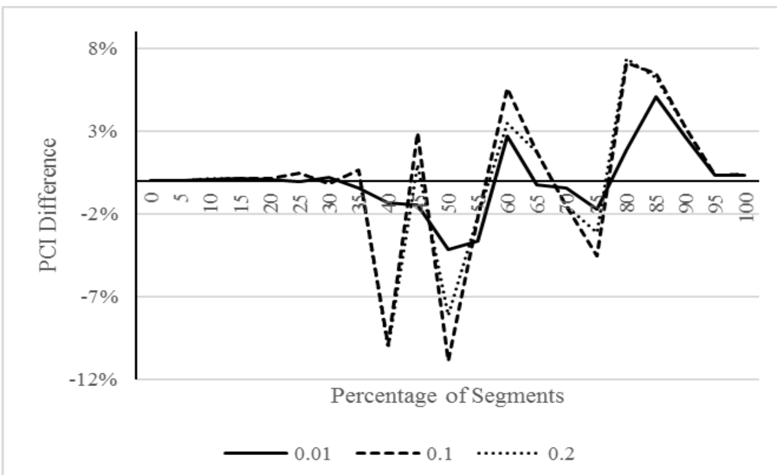

Figure 4-11. Variation in PCI distributions associated with few clustering preference

As expected, the accuracy of the condition representation increased by increasing the preference to generate more clusters. This is also measured by calculating the area under the curves in Figures 4-11 to 4-13. For example, when setting the minimum segment length to 0.2 miles, the area under the curves were 2.02, 1.88, and 1.79 for few, moderate and many clustering generation preferences respectively. This means that setting the clustering algorithm to generate more clusters will increase the overall accuracy of the pavement condition representation.

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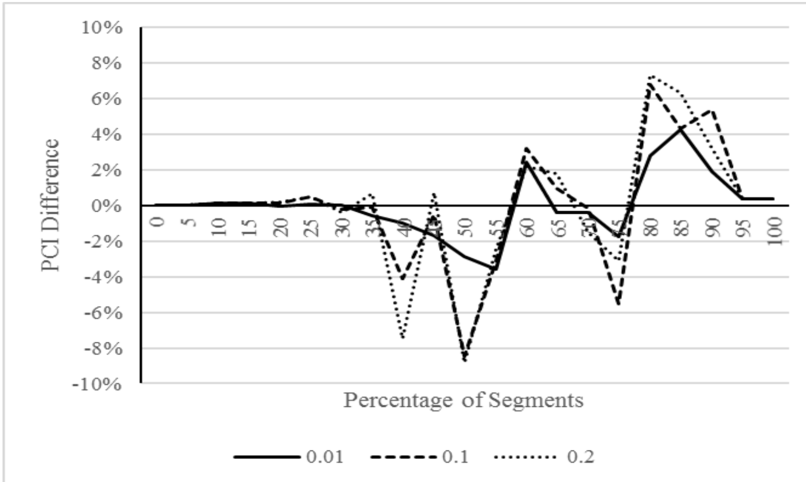

Figure 4-12. Variation in PCI distributions associated with moderate clustering preference

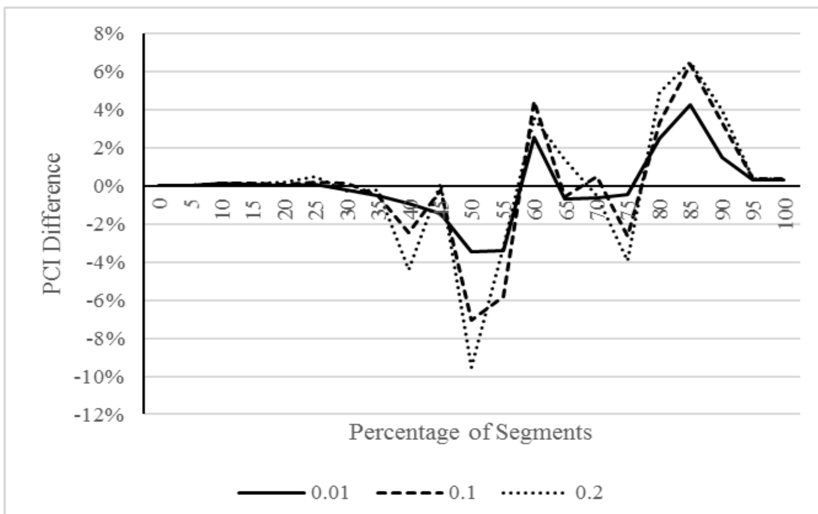

Figure 4-13. Variation in PCI distributions associated with many clustering preference

Similarly, the overall accuracy of representing the segments' ride quality was assessed by comparing the RQI distribution of the pavement sections to the RQI distribution of the delineated segments. Figures 4-14 to 4-16 show the RQI differences at few, moderate and high cluster generation preferences. By calculating the area under the curves, it is observed that the level of accuracy of representing the ride quality increased by decreasing the clustering generation preference. However, the level of accuracy decreased by increasing the minimum segment length requirement.

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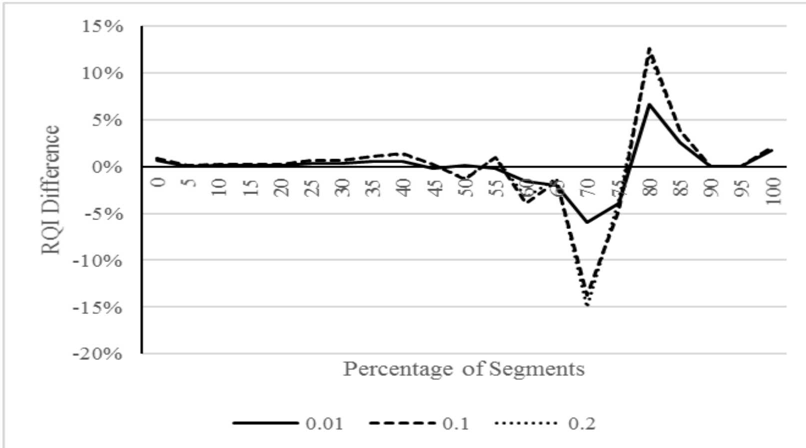

Figure 4-14. Variation in RQI distributions associated with few clustering preference

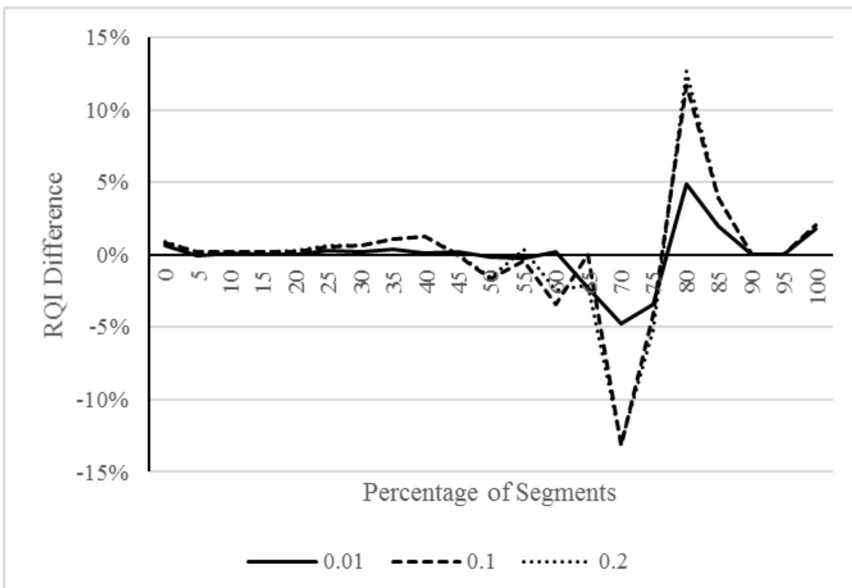

Figure 4-15. Variation in RQI distributions associated with moderate clustering preference

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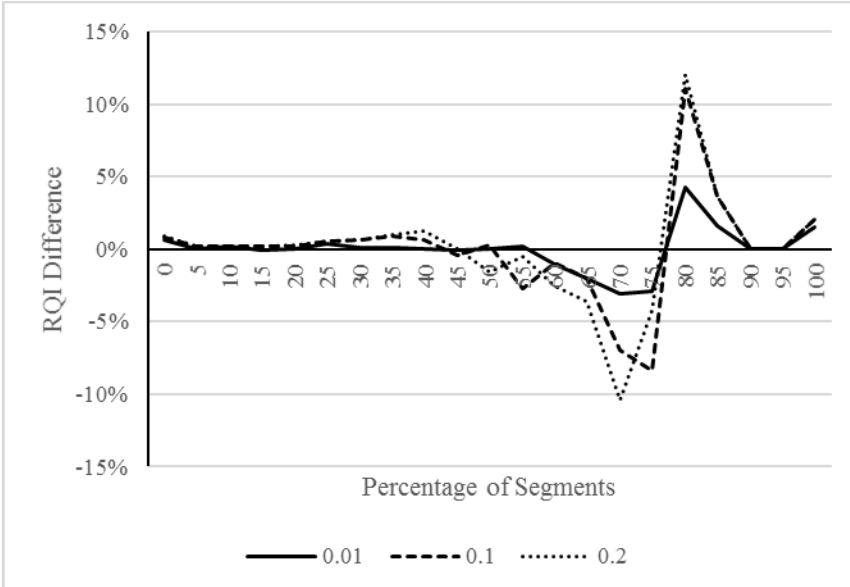

Figure 4-16. Variation in RQI distributions associated with many clustering preference

Additionally, the proposed segmentation algorithm showed that it accurately represents the overall ride quality of the segments when the RQI was less than 65 regardless of the minimum segment length requirement or the number of clusters generation preference.

Pavement Condition Data Visualization

The delineated segments are plotted in ArcMap 10.3, GIS software application, by using a Python script that converts a series of points to polylines. This conversion was conducted by utilizing the start and end geographic coordinates for each pavement section. A unique ID was also assigned to each delineated segment based on the cluster label generated by the affinity propagation algorithm. Based on the unique IDs, the start and end geographic coordinates were determined for each delineated segment. Furthermore, points along the polyline were used to plot the geometry of the polylines. The python script uses the unique ID and geographic coordinates as input parameters to produce maps containing polylines that are also associated to a table of attributes that contains the PCI, RQI, and CI data. One important benefit of using the proposed algorithm is presented by creating symbolized maps of the delineated segments. The symbolized

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maps allow agencies to capture the pavement condition at detailed level according to the delineation algorithm preferences. Figure 4-17 shows nine symbolized maps of the delineated segments when the minimum segment length was 0.2 miles for low, moderate and high clustering preferences. Figure 4-17 is divided into three parts; a) symbology of delineated segments using the PCI, b) symbology of delineated segments using the CI, and c) symbology of delineated segments using the RQI. Based on the maps illustrated in Figure 4-17, agencies can detect heavily deteriorated segments at high clustering generation preferences. Furthermore, agencies can detect segments with good condition that may be suitable candidate for preservation or minor maintenance strategies. Agencies can also detect segments that share the same design attributes and traffic characteristics but deteriorated at a different and unexpected rate. Figure 4-17 shows three examples of the aforementioned applications by magnifying three different locations of the study area. The first example, Figure 4-17(a), shows that the proposed algorithm can detect overall heavily deteriorated segments by increasing the clustering generation preference. In the second example, Figure 4-17(b), the algorithm differentiates between segments with poor and good condition when using the CI to symbolize the pavement segments. Similarly, the algorithm is able to differentiate between segments with different ride quality conditions (See Figure 4-17(c)).

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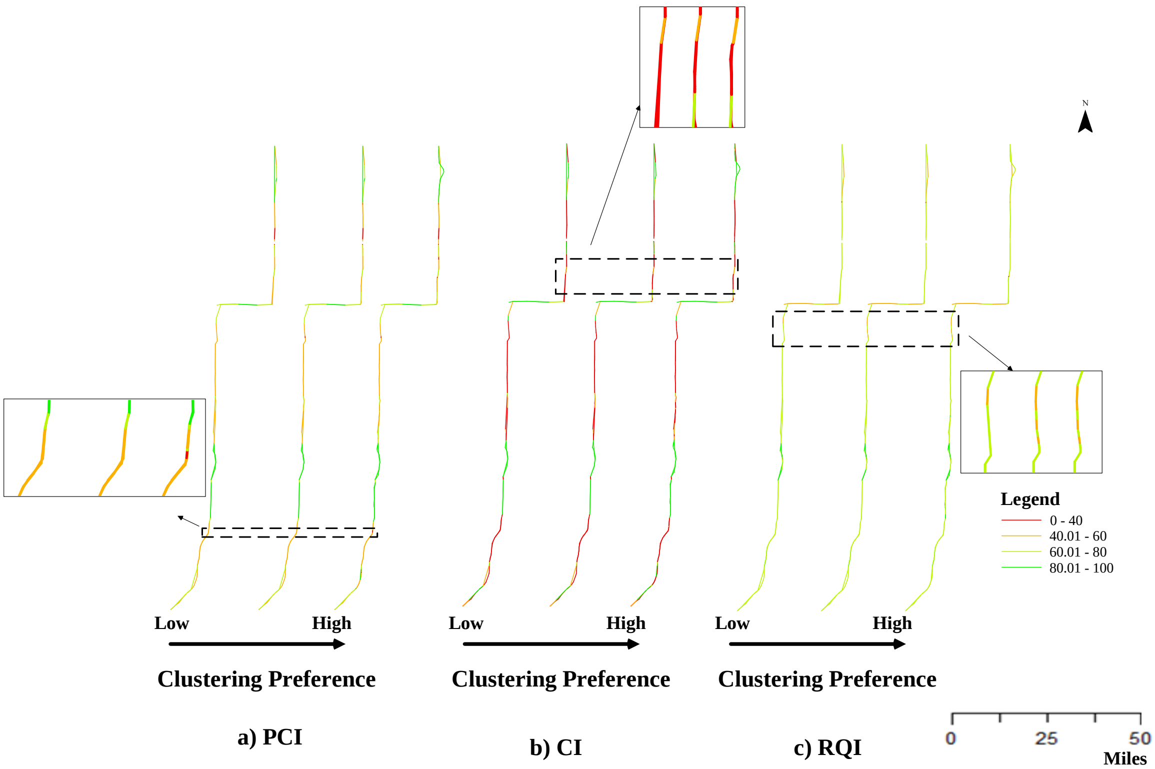

Figure 4-17. Pavement condition data visualization of delineated segments

Summary and Conclusion

This study presents a pavement delineation algorithm that allows agencies to control the minimum segment length and the preference to generate high or low number of delineated segments. Additionally, the algorithm presents an important advantage over the other delineation techniques by considering multiple distresses when finding homogenous segments. The proposed technique also utilizes a powerful clustering algorithm, affinity propagation, which takes less time to find the most representative clusters compared to other clustering algorithms. The study also automated the proposed algorithm by using a Python script that takes the raw pavement condition data collected by agencies to generate delineated segments.

A case study using 237 miles of pavement condition data collected in Iowa was conducted to show the capabilities of the proposed algorithm. Several iterations were conducted

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that considered changing the minimum segment length and preference to generate low or high number of clusters. The results of the case study showed that increasing the minimum segment length and reducing the preference to generate more clusters will generally result in high percentage of data reduction associated with high level of inaccuracy of condition data representation. It is also observed that relationship between the percentage of data reduction and level of accuracy of pavement condition representation follows an exponential relationship. The exponential relationship provides evidence that there is a break point where the benefit of reducing the pavement condition data is unjustifiable and may provide misleading pavement condition representation. The misrepresentation of the pavement condition data can also impose serious implications on the agency decision making processes and the agency's ability to accurately predict the future condition and program maintenance and rehabilitation strategies.

The proposed algorithm in this study offers a foundation to revise many infrastructure asset management application and theories. For example, modeling the deterioration of pavement segments can be significantly enhanced by using the proposed delineation algorithm to find homogeneous pavement segments. Based on the results of the case study, pavement sections that share the similar traffic volume and design attributes have showed different overall condition. As such, this study can be expanded in the future to present a significant leap in understanding and accurate modeling of pavement deterioration. Additionally, the proposed algorithm can benefit agencies by accurately determining the right maintenance and rehabilitation strategies.

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CONSOLIDATED CONCLUSIONS

Highway agencies have been collecting a massive amount of digital data from their daily business processes. However, the digital data collected is significantly underutilized in terms of supporting a variety of decision-making systems. This study used historical data to enhance the LCCA practices adopted by a wide range of agencies. Additionally, the study identified the barriers and challenges faced by agencies in developing a data-driven performance evaluation process. Finally, the study developed a dynamic pavement delineation algorithm that aims to aggregate the raw pavement condition data to form longer homogenous pavement segments.

The first paper presented a cost classification framework that differentiates between pavement cost items and non-pavement cost items to improve the LCCA practices. The cost classification framework was developed based on a rigorous analysis of approximately 100 rehabilitation projects cost data. The results of the analysis were incorporated with a stochastic LCCA to evaluate the effect of including non-pavement cost items on investment decisions. The stochastic LCCA was performed by utilizing a Monte Carlo simulation model. The results of the stochastic LCCA showed that agencies may select uneconomic decisions because of the inclusion of non-pavement cost items in the pavement life-cycle costs. Furthermore, the study showed that assuming non-pavement cost items are insignificant when compared to the pavement cost items is invalid.

The second paper identified seven major barriers and challenges associated with the utilization of historical pavement condition data to evaluate the performance of pavement treatments. These barriers and challenges were identified at each step of a typical data-driven performance evaluation process including:

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- Use of different geographic referencing systems
- Poor or absence of quality control measures for data collection
- Small sample sizes due to characterization of pavement sections
- Inconsistent long-term performance data
- Selection of a representative performance indicator(s)
- Selecting a methodology to estimate pavement service lives
- Poor documentation of maintenance and performance data

Furthermore, the study proposed a data consistency indicator that measures the consistency of any performance indicator over time. This indicator provides a scientific mean to agencies in the process of selecting an appropriate performance indicator to analyze pavement performance. The study also paves the way toward adopting and implementing a data-driven performance evaluation process by developing a set of recommendations to change the current practices.

In the third paper, a dynamic pavement delineation algorithm was developed to aggregate the raw pavement condition data to form longer and homogenous pavement segment that can be used for several pavement management applications. The proposed algorithm overcomes the limitations of the other existing delineation methods by segmenting the pavement sections at the distress level. Additionally, the proposed algorithm provides agencies with the flexibility of choosing the minimum segment length. The algorithm also uses a powerful data clustering technique called the affinity propagation. A Python script was developed in order to implement and automate the proposed algorithm. Using the developed Python script, the algorithm was used to delineate approximately 237 miles of raw condition data. Additionally, the flexibility feature of the algorithm was used by conducting fifteen iterations. For each iteration, the minimum

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segment length and clustering generation preference were changed to test their effects on the overall condition representation. Based on the analysis of the results, it was found that the relationship between data reduction and error in condition representation is exponential. This means that the error in representing the pavement condition due to the pavement delineation process increased drastically at higher rates of data reduction. This study provided an efficient and powerful tool that can be used by agencies to dynamically delineate their pavement condition data based on their needs.

Overall, this study developed a variety of methodologies that aims to improve the use of digital data by transportation agencies. Ultimately, the results of this study will help transportation agencies adopt data-driven and evidence-based decision making systems.

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