2020

Data-driven framework for modeling deterioration of pavements in the state of Iowa

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by

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A dissertation submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Civil Engineering (Intelligent Infrastructure Engineering)

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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this dissertation. The Graduate College will ensure this dissertation is globally accessible and will not permit alterations after a degree is conferred.

Iowa State University

Ames, Iowa

2020

DEDICATION

To my beloved parents, Ali and Shahin; who I have not had a chance to visit for more than seven years. To my wonderful sister, Nafiseh; and my brother in law, Vahid; for their unlimited support and unconditional love. Without all of you and your encouragement, endless love, support, and prays of day and night, this dissertation would not have been possible.

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NOMENCLATURE

TAMP	Transportation Asset Management Plan
PMS	Pavement Management System
LSTM	Long Short Term Memory
RNN	Recurrent Neural Network
NN	Neural Network
DM	Deterioration Model
FAA	Federal Aviation Administration
RMSE	Root Mean Square Error
PCC	Portland Cement Concrete
MEPDG	Mechanistic-Empirical Pavement Design Guide
FHWA	Federal Highway Administration

ACKNOWLEDGMENTS

I would like to foremost, express my sincere gratitude to my mentor and major advisor, Dr. Omar Smadi, for his constant support, encouragement, patience, guidance, and friendship in the last five years. Without his patience and guidance, this work would not have been possible.

I would like to thank Dr. Ahmad Alhasan for his help and guidance in the last two years. Besides, I would like to thank my committee members, Dr. Halil Ceylan, Dr. James Alleman, Dr. William Meeker, and Dr. Ashley Buss, for their guidance and support throughout the course of this research.

I would like to express my sincerest appreciation to my best friends Dr. Arash Jamali, Dr. Mohammad Reza Amini, Dr. Sanaz Habibi, and Yasaman Esfandiari, for their unconditional love and support during the worst days of my life.

I also like to acknowledge my colleagues and friends from my internship at Iteris Inc, in particular, Dr. Shayan Khoshmagham and Alicia Yang for their help and support.

In addition, I would also like to thank my friends, Arya Haghighat, Sourosh Mehravar, Saeed Arabi, Bahar Bazargani, Sina Moharamzade, Saba Moeinizade, Saina Shayanjoo, Yazan Abukhalil, Wasama Abdullah, and my colleague at the institute for transportation Dr. Inya Nlenanya for their support and help.

Also, I would like to thank the department faculty and staff for making my time at Iowa State University and Institute for Transportation a wonderful experience.

Last but not least, I would like to express my sincerest appreciation to my lovely family for all their support and unconditional love during the last seven years.

ABSTRACT

Highway networks serve the public by providing access to critical facilities such as hospitals, schools, and markets. Although maintenance and rehabilitation resemble a burden on transportation agencies, postponing required road maintenance can result in even higher direct and indirect costs (Burningham, 2005). Developing a robust and accurate pavement management system (PMS) is the key to supporting decision-makers at local and state highway agencies. One of the most important components of pavement management systems is predicting the deterioration of the network through performance models.

In this research, two major objectives were investigated. In the first part, the process and outcome of deterioration modeling for three different pavement types in the state of Iowa was described. Pavement condition data is collected by the Iowa Department of Transportation (DOT) and stored in a Pavement-Management Information System (PMIS). Typically, the overall pavement condition is quantified using the Pavement Condition Index (PCI), which is a weighted average of indices representing different types of distress, roughness, and deflection. Deterioration models of PCI as a function of time were developed for the different pavement types using two modeling approaches. The first approach is the Long/Short Term Memory (LSTM), a subset of a recurrent neural network. The second approach, used by the Iowa DOT, is developing individual regression models for each section of the different pavement types. A comparison is made between the two approaches to assess the accuracy of each model. The results show that while the individual regression models achieved higher prediction accuracy with respect to asphalt pavements, the LSTM model achieved a higher prediction accuracy over time for concrete and composite pavement types.

In the second part, describes how the accuracy of prediction models can have an effect on the decision-making process in terms of the cost of maintenance and rehabilitation activities. The process is simulating the propagation of the error between the actual and predicted values of pavement performance indicators. Different rate of error was added into the result of prediction models. The results showed a strong correlation between the prediction models' accuracy and the cost of maintenance and rehabilitation activities. Also, increasing the rate of error contribution to the prediction model resulting in a higher benefit reduction rate.

CHAPTER 1. GENERAL INTRODUCTION

Transportation Asset Management Plan

While there are various definitions available for asset management, in general, asset management refers to “making financial investment decisions so that returns are maximized while satisfying risk tolerance and other investor requirements” (Mehairjan, 2017). In transportation, the asset management concept was introduced after the Government Performance and Results Act was passed in 1993 (Abukhalil, 2019). Based on this act, accountability is considered a priority at all levels, and all agencies must provide a clear explanation of their decision-making policy for actions involving public funds (USDOT\FHWA, 2007). All transportation agencies, therefore, must justify and report all maintenance and rehabilitation activities performed on pavements, bridges, traffic signs, culverts, and all other transportation assets.

A Transportation Asset Management Plan (TAMP) is “the strategic and systematic process of operating, maintaining, upgrading, and expanding physical assets effectively throughout their life cycle” (MnDOT, 2016). The US Congress passed the Moving Ahead for Progress Act in the 21st Century as Act MAP-21 in 2012. Based on MAP-21, each state must have a risk-based plan for asset management with respect to infrastructure condition improvement, safety, congestion reduction, and environmental sustainability (Corley-Lay, 2014). Both pavement and bridge assets are prioritized in MAP-21 and highway agencies spend the largest portion of their budget every year to maintain and preserve these two assets.

Although Departments of Transportation (DOTs) spend a great deal of money each year to keep pavement networks in good conditions, based on the 2017 infrastructure report card, America's road GPA is only a D, indicating that US roads are in fair to poor conditions

(American Society of civil Engineers, 2017). The US has had a financial shortcoming in its highway system budget for many years, resulting in a $836 billion backlogs in highway and bridge capital. Since the largest portion of this backlog ($420 billion) is for repairing the highway system, a systematic way to optimize limited funding is needed to maintain and preserve the highway system.

Pavement Management System

A Pavement Management System (PMS) is a systematic process for cost-effectively maintaining and preserving pavement infrastructure. The American Association of State Highway and Transportation Officials (AASHTO) defines PMS as “a set of defined procedures for collecting, analyzing, maintaining, and reporting pavement data to assist the decision-makers in finding optimum strategies for maintaining pavements in serviceable condition over a given period of time for the least cost." (AASHTO, 1993). In the mid-1960s, the concept of PMS was introduced as a decision support tool to help decision-makers engage in required maintenance and rehabilitation activities with a limited budget (Kirbas, 2010). Generally, the most important PMS activities include financial planning, construction, design, pavement evaluation, and maintenance (Falls, 2001).

In PMS, the efficiency of decisions can be improved by evaluating the different outcomes of decisions made at different management levels (George, 2000). A PMS can also reduce the impact of a limited budget by prioritizing maintenance and rehabilitation activities, optimizing the allocation of budgets, and using the most efficient maintenance strategies (TAC, 2016). The following PMS capabilities were identified by AASHTO in 2012 (AASHTO, 2012):

- Evaluating current and future pavement conditions;
- Estimating funding needs required to improve pavement conditions up to a specific level;

- Prioritizing maintenance and rehabilitation activities based on available funds;
- Evaluating the long-term impact on pavement performance while construction practices, design procedures, and material properties change.

In any decision-making and pavement-management system, two levels of administration can be identified: project level and network level (Mbwana, 2001). Determining maintenance and rehabilitation strategies, identifying potential locations requiring treatment, and scheduling maintenance and rehabilitation activities are at the network level. At the project level, detailed maintenance and rehabilitation treatments, and determining the best strategy for maintenance actions can be identified. The different criteria for each decision-making level in PMS are compared in Table 1.

Table 1: Comparison between project and network-level in PMS (Alharbi, 2018)

Decision Level	Decision Makers	Type of Decisions	Range of Assets Considered	Level of Detail	Breadth of Decisions
Network	Asset manager Pavement management engineer District engineer	Treatment recommendations for a multi-year plan Funding needed to achieve performance targets Consequences of different investment strategies	Range of assets in a geographic area	Moderate	Moderate
Project	Design engineer Construction engineer Materials engineer Operations engineer	Maintenance activities for current funding year Pavement rehabilitation thickness design Material type selection Life cycle costing	Specific assets in a particular area	High	Focused

PMS components vary based on available resources and information, including traffic information, pavement condition data, pavement physical inventory features, pavement performance analysis, pavement maintenance prioritization, and investment strategies (Cottrell, 1996). Also, based on a study by Vines, collecting pavement condition data, analyzing the collected data for determining maintenance and rehabilitation activities, and visualizing the output of the analysis for decision-makers are the components of modern PMS (Vines-Cavanaugh, 2017).

Based on the Federal Highway Administration, pavement condition data is a “critical component of any pavement management system.” (Pierce, 2013). Cost of any maintenance and rehabilitation activity relies directly on pavement conditions (Camahan, 1987). As a result of low-quality pavement condition data, the uncertainty in pavement performance prediction will increase (error: the difference between actual and predicted values), and the pavement management system will be affected as a result of wrong predictions (Kulkarni, 1984). Therefore, the quality of pavement condition data is an important factor for having a successful pavement management system. All agencies need to have a Quality Management (QM) in order to collect accurate, complete, and reliable pavement condition data. In general, QM is “an approach to achieving and sustaining high-quality output” (Flynn, 1994). All transportation agencies need to follow the standards and protocols of the American Association of State Highway and Transportation Officials (AASHTO) and the Federal Highway Administration (FHWA) and apply these standards to their preferred method of QM.

Good quality pavement distress data is required for accurately evaluating the condition of pavement sections. In general, pavement condition data can be determined by measuring pavement surface distress, roughness, surface friction, and deflection (Haas, 1994).

The following is a description of each type of pavement condition data:

1. **Pavement Roughness**: pavement roughness refers to pavement surface irregularities that can affect the operating cost of vehicles, driver safety, and ride quality (Islam, 2012). Because it affects road users, roughness is considered one of the most important pavement performance indicators. There are several factors affecting pavement

roughness, including climate factors, traffic loading, drainage type, pavement type, and construction quality (Kargah-Ostadi, 2014). Highway agencies have also widely used the International Roughness Index (IRI) for characterizing pavement roughness as a ride quality (Papagiannakis, 1998).

2. **Pavement surface distress**: There are different types of distresses based on the type of available material such as composite, concrete, and asphalt pavements. Quantification of the severity, type, and size of distress is an effective approach for evaluating pavement condition. Miller and Bellinger in a 2003 AASHTO report identified 16, 15, and 15 types of distress for concrete, asphalt, and composite pavements, respectively. Major distress types in different pavement types are as follows:

    - *Alligator Cracking***:** One of the most significant crack types that can deteriorate asphalt pavements over time is alligator cracks caused by repeated traffic loading. Alligator cracking occurs when the tensile stress is high, and the pavement is carrying loads that the structure cannot sustain (Castell, 2000) (see Figure 1).

Figure 1: Sample of alligator cracking (J.Mrugacz, 2016)

- *Longitudinal Cracking*: Longitudinal cracking appears parallel to the centerlines of pavement sections as a result of the shrinkage of the asphalt layer, poorly constructed joints, improper paver operation, and crack reflection from an underlying layer (Colorado DOT, 2004) (see Figure 2).

Figure 2: Sample of Longitudinal Cracking (Ardani, 2003)

- *Transverse Cracking*: transverse cracking refers to vertical cracks, including reflective cracking and shrinkage cracking, in pavement centerline or laydown direction. The severity level of transverse cracking depends on pavement thickness and base material properties (Zhou, 2010) (see Figure 3).

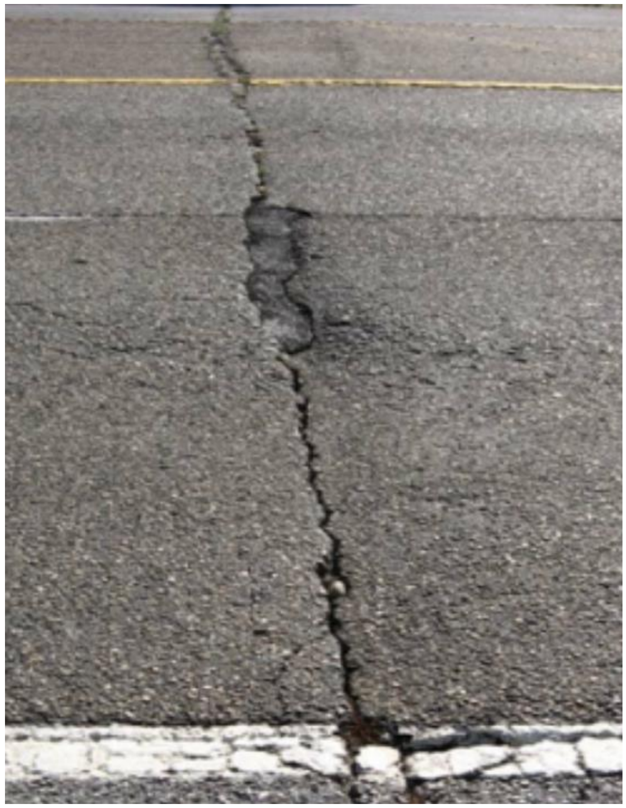

Figure 3: Sample Transverse cracking (Dong, 2013)

- *Rutting*: Rutting is a term describing permanent deformation or consolidation that accumulates in an asphalt pavement surface over time. Rutting occurs because of the movement of the aggregate and binder used in asphalt roads. Rutting severity is affected by temperature variation and traffic loading, impacting subgrade strength (Archilla, 2000) (see Figure 4).

Figure 4: Sample of the rutting (Fussl, 2014)

- *Faulting*: a common distress type in concrete pavement is faulting cracking that results from vertical displacement between subsequent slabs across a joint (Alharbi, 2018). This displacement results in faulting at the transverse joint because of pumping action and lack of base support. Faulting is important because it can have a negative impact on ride quality (Bektas, 2015) (see Figure 5).

Figure 5: Sample of faulting (Iowa Airport Pavement Management System, 2020)

Pavement Condition Rating

Based on subjective ratings of rater experience and ride quality (Attoh-Okine, 2013), Pavement Condition Rating (PCR), was developed in the 1950s by the American Association of State Highway Officials (AASHO). Because the raters' perceptions, riding quality, and vehicle characteristics are subjective, the PCR was not sufficiently accurate to satisfactorily evaluate pavement conditions. As a result of this PCR subjectivity, the Pavement Serviceability Index (PSI), a more objective system, was developed. The PSI was mainly based on rut depth, panel rating, pavement roughness, and cracking (Sun, 2001). The major difference between these two rating systems was that PCR is established on individual observations, while the PSI estimated the physical pavement features using a formula (Fhwa, 2013). Both these rating systems were used by agencies up to 1970s when the Pavement Condition Index (PCI) was developed by the U.S. Army Corps of Engineers based on different types of distresses and severity levels (Shahnazari, 2012). Since that time, state DOTs have used PCI for pavement evaluation. The PCI describes the overall conditions of pavements based on different types of distress, roughness, friction, and deflection (Ceylan, 2014).

Such performance measurement can be used to provide information to pavement engineers (Haas, 1994). PCI has a numerical rating between 0 and 100, with 0 defining the worst and 100 defining the best conditions for pavement segments. Based on the PCI value, decision-makers can also evaluate the functionality of the pavement network, predict the best time for maintenance and rehabilitation activities, and estimate future funding needs (Bektas, 2014). Table 2 is a sample of how the PCI can describe condition categories and general treatment strategies in Los Angeles County.

Table 2: PCI rating (LA county, 2011)

CONDITION CATEGORY	PAVEMENT CONDITION INDEX (PCI)		GENERAL TREATMENT STRATEGY
	Upper Limit	Lower Limit	
Excellent	100	86	Do Nothing/Corrective Maintenance
Good	85	75	Preventative Maintenance
Fair	74	58	Resurface
Poor	57	40	Rehabilitation
Failed	39	0	Reconstruction

Pavement Performance Modeling

A pavement management system could be successful if an accurate performance prediction model describes how pavement conditions change over time (Lytton, 1987). Pavement performance prediction models can effectively optimize maintenance needs and rehabilitation strategies during the pavement service time. Such a prediction model can also help agencies identify maintenance activities that should be undertaken (George, 2000). Figure 6 presents a typical performance curve as a function of time, with the PCI changing over time.

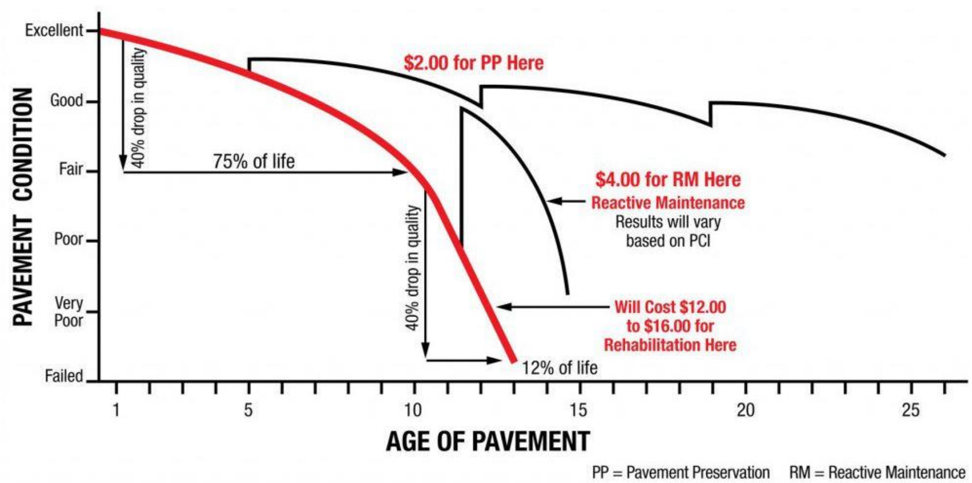

Figure 6: Pavement performance over time (Kumar, 2012)

The figure also represents the impact of maintenance activities on section performance and the importance of optimized pavement preservation in maintaining a high-performance level at a lower cost. A reliable pavement performance prediction model is required to include long-term historical data, all important variables that can have an impact on the response variable, and criteria for evaluating model accuracy (Darter, 1980). Different types of performance models, such as deterministic, probabilistic, neural networks, and knowledge-based (Wolters, 2010) can be used in pavement management to predict the future condition of pavement sections. More detailed information about these performance models is available in the following chapters.

Impact of Error in Performance Modeling

All performance prediction models developed by the deterministic, probabilistic, neural network and knowledge-based techniques require accurate data. Frequency of data collection is a major factor that can have an impact on data reliability and error. Generally, the error is the difference between an actual and a predicted value of any physical quantity. There are no simple criteria for determining such errors that can arise out of many causes. Errors are usually categorized as either systematic or random, and it is generally difficult to recognize their sources. Random errors are the “result of irregular causes in which laws of action are unknown or too complex to be investigated, while systematic errors are constant or may vary in some regular way” (Saliminejad, 2013).

Different sources of errors might be present in pavement performance data and consequently, in pavement performance prediction. Since a composite condition index, e.g., the pavement condition index (PCI), includes the measurement of roughness, distresses, rutting, and faulting, and different types of instruments are used to measure these condition indicators instrumental error might be increased. On the other hand, another source of error can be introduced by subjectivity in determining the severity and type of distress. Field and operator conditions are other sources of error that may be introduced. More detailed information about the impact of errors in prediction models and data quality are provided in the following chapters.

The Decision-Making Process in the Pavement Management System

As mentioned earlier, all pavement performance prediction models can help in predicting future pavement conditions and identifying the best treatment strategies. Because each treatment activity is qualified to fix specific distresses, they cannot be assigned randomly. Therefore, a systematic process is needed to assign treatments to specific distresses, resulting in certain conditions. Treatment strategies can be impacted by many factors such as environmental factors, pavement type, pavement condition, roadway class, level of traffic, pavement age, cost of treatment activities, last construction or rehabilitation timing, availability of skilled contractors, availability of quality materials, surface friction, and time of placement (Johnson, 2000).

Consequently, researchers in state DOTs have developed decision trees and matrices for considering as many factors as possible in selecting appropriate treatment strategies. All state DOTs consider some common factors such as pavement type, environmental factor, and traffic condition for treatment selections. However, because some other decision-making factors differ among states, each state DOT has its own methodology for treatment selection. For example, the Michigan DOT (MDOT) finds appropriate treatment strategies using specific thresholds it has established for distress index, remaining service life, international roughness index, rut depth, and riding quality for each pavement type (Abdelaty, 2015). Another example is the Utah DOT, which divides roads into three classes based on AADT and selects treatments using predefined thresholds, and condition indices (Abukhalil, 2019). The South Dakota DOT selects treatments based on the size and severity level of major distresses and decision matrices (Abdelaty, 2015). Figure 7 illustrates an example of a decision tree used as a decision support tool to help identify appropriate treatments.

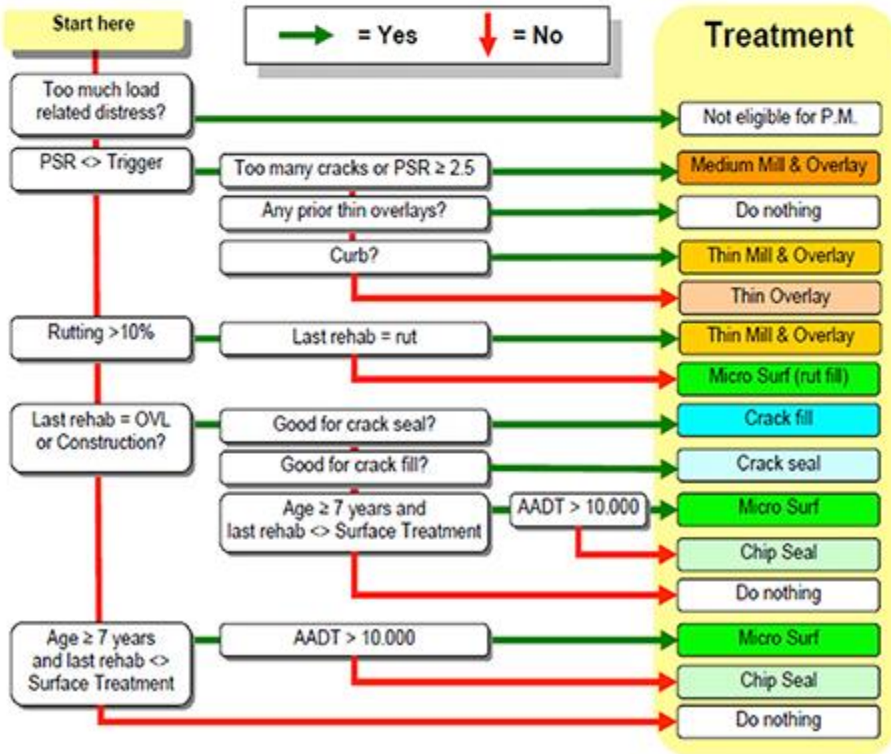

Figure 7: Sample of the pavement preventive maintenance decision tree (Kronick, 2015)

Based on the elements of PMS described above and the effectiveness of each treatment activity, project prioritization at each level of management can be established. Many research studies have developed prioritization techniques such as weighted factors, worst-first, mathematical models, and expert judgment (Ahmed 2017, Dessouky 2016, and Dessouky 2011). As a result of these techniques, a list of maintenance and rehabilitation activities, estimation of funding needs, type, and time of treatment can be identified.

Problem Statement

Highway networks serve the public by providing access to critical facilities such as hospitals, schools, and markets. Although maintenance and rehabilitation resemble a burden on transportation agencies, postponing required road maintenance can result in even higher direct and indirect costs (Burningham, 2005). Developing a robust and accurate pavement management system (PMS) is the key to supporting decision-makers at local and state highway agencies. Despite the fact that many decision-making processes have been well-established, variability in the pavement performance parameters and forecast can have a significant impact on life-cycle cost analysis and consequent robustness of a pavement management system (Haas, 2015).

With advancements in data collection at the network level, pavement performance data can now be collected at a high coverage rate (Smadi, 1999). Because of the spatiotemporal spread of varying pavement-performance datasets, deterministic pavement performance prediction models can be misleading and possibly lead to incorrect decisions with respect to maintenance, rehabilitation, reconstruction, and preservation when performing life-cycle cost analysis. Although there is a large number of deterioration models described in the literature, these models are either oversimplified or too detailed, and therefore increase prediction error. Conversely, because maintenance action is directly related to pavement prediction models, the effect of errors is not negligible. However, little work has been done to investigate the impact of such errors in the decision-making process.

In this research, a new framework by using deep learning approach was developed to increase the prediction accuracy of pavement condition index to make the pavement management system and decision-making process more robust. This framework is suitable for pavement applications because the data is presented in time series with both low observation frequency and high levels of variability. Also, for investigating the effect of error in the decision-making process, the output of the new framework was used to find out how prediction accuracy can have an impact in the cost of maintenance and rehabilitation activities in the pavement management system.

Research Goal and Objectives

The goal of this research is to develop a new framework for pavement deterioration models based on historical pavement condition data. Implementation will include pavement condition data collected from the Iowa pavement management system between 1998 and 2018.

The objectives are as follows:

1. Develop a new framework using a deep-learning approach, specifically the Long Short-Term Memory (LSTM) method, to predict the future condition of composite, asphalt, and concrete pavements.
2. Compare the current method of prediction used in the Iowa DOT with the proposed method in terms of accuracy of prediction.
3. Compare the current method of prediction in the Iowa DOT with the proposed method in terms of impact on decision making, specifically the cost of maintenance and rehabilitation activities.

Organization of the Dissertation

The dissertation contents are divided into four chapters, as follows:

1. Chapter 1 includes a general introduction, background, problem statement, and the research goal and objectives.
2. Chapter 2 describes the process and outcome of deterioration modeling for three different pavement types in the state of Iowa. Deterioration models of PCI as a function of time were developed for the different pavement types using two modeling approaches. The first approach is the Long/Short Term Memory (LSTM), a subset of a recurrent neural network. The second approach, used by the Iowa DOT, is developing individual

regression models for each section of the different pavement types. The results of the proposed framework are compared with the current Iowa DOT method in terms of prediction accuracy.

3. Chapter 3 describes the effect of prediction accuracy in the decision-making process in terms of maintenance costs and rehabilitation activities in different pavement types. The result of the prediction model developed in chapter 2 was used in this chapter. Different scenarios are investigated while adding different rates of error to the predicted values. Iowa DOT decision trees are used to check the effect of the prediction model accuracy in terms of cost of treatments in different pavement types. The results of different scenarios were compared with the base scenario to check whether decreasing or increasing the accuracy of the prediction model can have an effect on the cost of maintenance and rehabilitation or not.
4. Chapter 4, the final chapter, includes general conclusions, recommendations for future research work, and limitations of the study.

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CHAPTER 2. USE OF DEEP LEARNING TO STUDY MODELING DETERIORATION OF PAVEMENTS A CASE STUDY IN IOWA

Modified from a manuscript under review in International journal of pavement engineering

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Abstract

This paper describes the process and outcome of deterioration modeling for three different pavement types in the state of Iowa. Pavement condition data is collected by the Iowa Department of Transportation (DOT) and stored in a Pavement-Management Information System (PMIS). Typically, the overall pavement condition is quantified using the Pavement Condition Index (PCI), which is a weighted average of indices representing different types of distress, roughness, and deflection. Deterioration models of PCI as a function of time were developed for the different pavement types using two modeling approaches. The first approach is the Long/Short Term Memory (LSTM), a subset of a recurrent neural network. The second approach, used by the Iowa DOT, is developing individual regression models for each section of the different pavement types. A comparison is made between the two approaches to assess the accuracy of each model. The results show that while the individual regression models achieved higher prediction accuracy with respect to asphalt pavements, the LSTM model achieved a higher prediction accuracy over time for concrete and composite pavement types.

Keywords: Long/Short Term Memory (LSTM) model, deterioration model, regression model, pavement surface distress, deep learning, prediction accuracy

Introduction

Public agencies use pavement management systems (PMSs) to make objective decisions and conduct activities for maintaining pavements in acceptable conditions at minimal cost (AASHTO, 2012). Since the early 1970s, departments of transportation (DOTs) and other transportation agencies have been implementing and establishing PMSs to match their needs, achieving significant savings and improvement in network conditions (Vasquez, 2011). The Arizona DOT, for example, saved $14 million and $101 million during the first year and the first four years of PMS implementation, respectively (Hassan, 2017). The Colorado Department of Transportation (CDOT) uses PMS to efficiently spend its $740 million annual budget for maintaining and preserving more than 9,100 center-line miles (about 23,000 total lane miles) (Saha, 2017). It appears that there is potential for all such expenses to be more effective if PMS improvements can be developed and implemented.

A major component of any PMS is evaluation and modeling of pavement conditions at the network level. Recently, most states have begun to use automated pavement-condition surveying tools that generate images from remote sensors to collect distress information and report individual distresses through an overall condition index (Ragnoli, 2018). The concept of Pavement Condition Index (PCI), was developed by the U.S. Army Corps of Engineers in 1970 based on different types of distresses and severity levels (Shahnazari, 2012). Since then, most DOTs and related agencies have been using the PCI to evaluate pavement conditions. The PCI provides important information to pavement engineers by describing overall pavement condition based on different types of distress, roughness, and deflection (Ceylan 2014, Haas 2015). The PCI is defined as a numerical rating between 0 and 100, with 0 being the worst condition and 100 the best condition for pavement segments. Based on monitored and modelled PCI values and other important condition indices, decision-makers can evaluate the functionality of pavement networks, predict the best time for maintenance and rehabilitation activities, and estimate future funding needs (Bektas, 2014).

Long and short-term planning of maintenance and rehabilitation activities is the major tool for maximizing proper network conditions at the lowest possible cost and requires accurate and robust deterioration models for pavement networks. A Deterioration Model (DM) predicts future pavement conditions and helps agencies identify the most effective maintenance and rehabilitation activities (George 2000, Lytton 1987), and such planning and optimization become more critical when agencies face budget reduction or are otherwise budget-constrained (Hassan, 2017).

Deterministic, probabilistic, neural network-based, and knowledge-based performance models have been used in pavement management to predict future conditions of pavement sections (Wolters, 2010). Currently, the Iowa Department of Transportation (Iowa DOT) forecasts the future conditions of pavement sections based on individual deterministic regression models for each pavement section. Deterministic models assume that the described process is nonrandom and that observed differences between predicted and measured values are due to random noise in the observation process.

A deterministic model will thus always produce the same output from a given starting condition or initial state. Most deterministic models are based on explicit regression expressions and are categorized into the following three subsets (Li, 1996):

1. ***Empirical Models***: An empirical model, solely based on experimental observations, provides no explanation of the fundamental behavior through constitutive models. These models require large databases for deriving accurate and representative models. Some advantages and disadvantages of empirical methods, based on a study reported by Bulleit and Ylitalo (de Melo, 2000), are:

   Advantages:

   - The mathematical approach for prediction is not complex
   - The relationship between actual and predicted values can be easily described

   Disadvantages:

   - Model sensitivity
   - Restricted to the conditions used to derive the relationships and not useful for extrapolation.

2. ***Mechanistic Models***: Mechanistic models primarily use laboratory testing data and idealized models to mathematically describe fundamental pavement responses like stress, deflection, and strain caused by traffic loading and other surrounding conditions (Mills, 2012). It has been observed over time that sometimes these idealized lab tests and models do not reflect actual conditions in the field and may therefore fail to accurately predict pavement performance. The availability and feasibility of more recent pavement condition assessment tools have resulted in practitioners and agencies avoiding use of mechanistic models (Haas, et al., 1994).

3. ***Mechanistic-Empirical (ME)***: While these models are fundamentally based on mechanistic models, they are calibrated and coupled with the empirical long-term observations from pavement sections under real-life operating conditions. ME models are

more representative of actual conditions, because they consider additional parameters like traffic loading, climate factors, and material properties.

Probabilistic models are another group of pavement performance models, an alternative to deterministic models that do not provide probabilistic distribution of existing values. Markov probabilistic modeling uses samples of probabilistic models, with the transition process represented by a pavement-performance curve (Li, 1996). Using information from the pavement's "before" state, the Markov process predicts the "after" state (George, 2000). The Markov transition method is useful in network-level applications where neither historical data or good regression equations are available, (Shabanpour, 2017). Another advantage of probabilistic models is their use of different distributions for finding expected values of the dependent variable. Also, uncertainty with respect to environmental conditions, material properties, and traffic loading can be captured by these models. The main disadvantage of probabilistic models is that they do not consider the effects of pavement aging on transition probabilities (Shabanpour, 2017).

In addition to Markov models, there are other types of probabilistic models like Bayesian decision models, Bayesian regression models, and semi-Markov models, that generate survivor curves (Golroo, 2012). The greatest advantages of probabilistic models are their capability for capturing uncertainty in the pavement prediction model, and for producing more realistic results than deterministic models.

Over the past few years, Neural Network (NN) applications have received greater attention, and many research studies on the application of NNs in transportation and civil engineering have been published (Adeli 2001, Dougherty 1995, Flood 2008, Flood & Kartam, 1994). Because of their capability for interconnecting neurons between layers, NN applications can often solve complex problems more efficiently than traditional methods (Basheer, 2000). The capabilities of Neural Network models for solving problems from several pavement-engineering categories are as follows (Ceylan, 2014):

- *Classification*: Supervised learning in neural networks can be used to deal with unknown inputs. Neural network models have been used to investigate the classification of pavement distresses from digital images (Nallamothu, 1996). Another research study by Hu (2001) reported using a neural network to detect pavement cracks.
- *Performance Prediction*: Neural Networks have been used in various studies as powerful and versatile computational tools for both determining the performance of existing pavement systems and predicting future conditions. The Pavement Distress Index (PDI), based on surface thickness, pavement age, and traffic level, was predicted using a NN model that outperformed other multiple-linear regressions (Owusu-Ababio, 1998). A back-propagation neural network model was developed by (Lin, 2003) for predicting IRI based on pavement distress.
- *Optimization and maintenance strategies*: Neural networks have been used as computational tools to determine which maintenance and rehabilitation actions should be performed on deteriorated pavement sections, using a hybrid NN and Genetic Algorithm method developed for optimizing maintenance strategy of flexible pavements (Taha, 1995).
- *Distress Prediction*: Neural networks can help pavement engineers predict future distresses, and a multi-layer perceptron back-propagation NN with one hidden

layer has been used to predict future roughness distress in flexible pavements (Huang, 1997).

NNs could be a powerful alternative to traditional techniques that are always limited by normality, linearity, and colinearity assumptions. Two major advantages of using NNs are their ability to model complex and nonlinear large amounts of data, and detect all possible interactions between predictor variables.

It should be mentioned that, because pavement deterioration happens over time, it is important to include the dependency of performance measures on historical data (time) in a prediction model. Accurate time-series prediction is also critical for abnormality detection, resource allocation, and financial planning (Laptev, 2017). Predicting data time-dependency is challenging because such prediction depends on external factors like weather and traffic load (Horne, 2004). Time-series analysis works better with highly-correlated measurements over time, because explanatory variables may fail to explain the correlation mechanisms. On the other hand, in regression analysis the explanatory variables should sufficiently explain the trend, resulting in independent fitting residuals.

A deep-learning method designed for sequential data is the Recurrent Neural Network (RNN) that has recently received additional attention from researchers primarily because of its capability in learning sequences (Graves 2010, LeCun 2015, Sutskever 2013). RNNs have been widely applied to many time-dependent datasets for use in prediction problems like speech prediction, pattern prediction, economic prediction, and traffic prediction (Busseti 2012, Martens 2011, Wong 2010). Since RNNs are developed to utilize historical data in time-series analysis, inclusion of a regression model that relies on explanatory variables and historical data of the response variable improved the model accuracy. These networks are designated as recurrent because future forecasting depends on both current and previous stages. Several RNN algorithms such as the Long Short Term Memory (LSTM) network have been developed over the past two decades. LSTM was introduced to support modeling and forecasting of long-term data series. The network was developed to overcome the vanishing gradient problem in which algorthims tend to accumulate errors when a long string of observations are added as predictor variables, increasing prediction variability and associated total error. Based on the literature, another RNN network called the Gated Recurrent Unit (GRU) also solved the vanishing gradient problem, but the LSTM outperformed the GRU in many details.

In this study, the LSTM was used for time-dependent prediction of the pavement condition index. This network is suitable for pavement applications because the data is presented in time series with both low observation frequency and high levels of variability. The goal of this study was to develop a new robust deterioration model suitable for long term forecasting, in which the model performance can be objectively evaluated. An LSTM network will utilize historical pavement condition records of the Iowa DOT Pavement Management Information System (PMIS) in the time span between 1998 and 2018. The new time series algorithm, a deep-learning approach specifically developed by LSTM networks, was used to predict future conditions of the three different pavement types. The Keras software package, a high-level neural network API written in Python, was used for generating the LSTM model with a focus on enabling fast experimentation. This package uses a deep-learning open-source library based on the TensorFlow software library. The performance and results of the new algorithm are compared to the current method used by Iowa DOT for deterioration modeling.

Methodology

Figure 8 shows the steps required to be completed in the proposed method, with the individual steps described in detail in the following subsections.

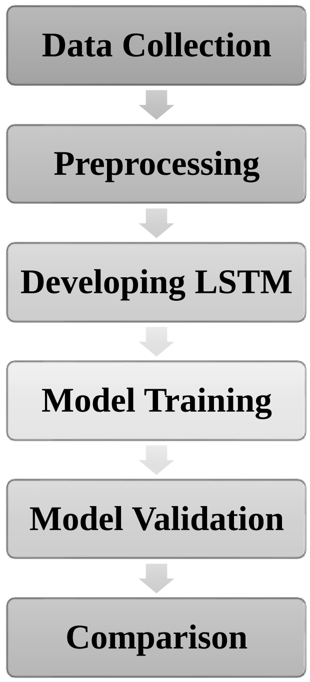

Figure 8: Research Steps

Data

To develop and implement the new framework, historical records of pavement condition data were acquired from the Iowa DOT Pavement Management Information System (PMIS). These data were collected for Iowa’s interstate and primary network since 1997, the year in which the Iowa DOT began collecting automated pavement distress data (Bursanescu, 1997). The data used in this study were acquired between 1998 and 2018, and include information regarding highway system classification, construction and reconstruction dates, unique section identifiers, traffic levels, automated pavement distress data, faulting, and pavement ride quality.

The pavement types included in the study were asphalt concrete (AC), Portland cement concrete (PCC), and composite (COM) pavements.

The pavement distress information collected includes rutting and cracking data such as transverse cracking, longitudinal cracking, alligator cracking, wheel-path cracking, and patching, with low, medium, and high severity levels assigned to cracking data for all pavement types. For AC and COM pavements, rutting was reported as the average rut depth in both wheel paths, and for PCC pavements faulting was estimated using the acquired longitudinal profile. The international roughness index (IRI) was also used to characterize ride quality for all pavement types. Pavement condition data is collected in two-year cycles in which half the network is surveyed every other year. The Iowa DOT spends about $1 million annually on collecting pavement condition data (Bektas, 2014).

In many cases, minor maintenance and rehabilitation records were not available, so the maintenance impact on pavement condition overtime was not modelled in this study. Moreover, segments with PCI values increasing over time were discarded from the analysis because they might be associated with unrecorded maintenance activities. A ten-point PCI increase was arbitrarily considered to be a normal fluctuation due to measurement errors or seasonal impacts. Figure 9 shows the number of different sections for each pavement type, with the descriptive statistics for each pavement type given in Table (3). The total number of data records for all 20 years time frame was comprised of 3,805 AC records, 14,117 COM records, and 13,123 PCC records.

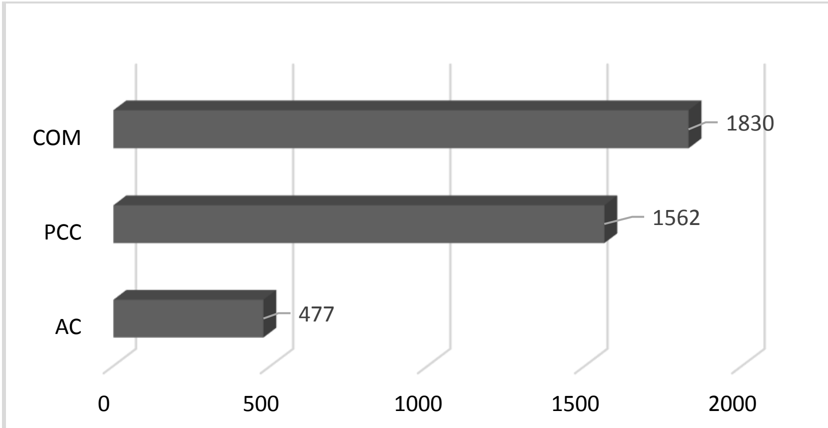

Figure 9: Number of sections in each pavement type

Table 3: Summary statistic of pavement sections (Alharbi, 2018)

Pavement Types	Average Length (Miles)	Minimum Length (Miles)	Maximum Length (Miles)
AC	3.88	0.16	18.61
PCC	2.7	0.05	18.91
COM	2.69	0.05	18.14

Preprocessing

After collecting and arranging the data based on pavement type, condition indices were estimated using the reported condition data. Pavement condition can be summarized using four scaled indices with values ranging from 0 to 100, with 0 corresponding to the worst condition and 100 to the best condition. These indices can then be used to calculate the overall PCI using the same scale for individual indices, resulting in the definition of a global index for comparing different pavement types. In this study, the indices were calculated based on definitions provided in a previous study for the Iowa DOT (Bektas, 2014) and included:

- Riding Index
- Rutting Index (AC and COM Only)
- Cracking Index

- Faulting Index (PCC Only)

In AC and COM pavements, four different cracking sub-indecies were used to calculate the cracking index; these included transverse, longitudinal, alligator, and longitudinal-wheel-path cracking. Only two sub-indecies, transverse and longitudinal cracking, were used to characterize PCC pavements. Three severity levels were used by the Iowa DOT in evaluating pavement distresses, with 1, 1.5, and 2 coefficient values, used for low, medium, and high aggregated severities, respectively. All severity levels were then converted into low severity. Since a maximum value (threshold) corresponds to a deduction of 100 points, a cracking sub-index of 0 was determined for each crack type within pavement type, and all threshold values were extracted from a previous Iowa DOT study (Bektas, 2014). The cracking index values for all three pavement types, based on the coefficient values provided by Iowa DOT experts, were as follows:

$$\begin{aligned}&Cracking\ Index\ (AC\ and\ COM)\\&\quad = 0.2 * (Transverse\ sub\ Index) + 0.1 * (Longitiudinal\ sub\ Index) + 0.3\\&\quad * (Wheel - path\ sub\ Index) + 0.4 * (Alligator\ sub\ Index)\end{aligned}$$

$$\begin{aligned}&Cracking\ Index\ (PCC)\\&\quad = 0.6 * (Transverse\ sub\ Index) + 0.4 * (Longitiudinal\ sub\ Index)\end{aligned}$$

The International Roughness Index (IRI) is the most commonly used ride-quality index. The Riding Index used in this study was based on the IRI acquired by the Iowa DOT and expressed on a scale of 100. IRI values below 0.5m/km were taken as a perfect 100, while values above 4.0m/km were taken as 0 on the index scale. Other values between 0.5 and 4 m/km were calculated using linear interpolation.

Rutting is defined as the permanent total deformation or consolidation accumulated in an asphalt pavement surface wheel path. The rutting index from this study used rut depths available in the PMIS database, and, based on previous research, a threshold value of 12 mm corresponded to 0 on the rutting Index scale of 100, and values below 12 mm were applied as corresponding deductions.

Faulting is defined as the difference in slab elevation across a joint or crack occuring due to differential vertical displacement between two sides. Similar to the rutting index for AC pavements, the faulting index is expressed on a scale of 100, with the faulting value equal to or greater than 12 mm set to 0 and the faulting value equal to zero set to 100 on the index scale (Bektas, 2014).

After calculating all cracking, riding, rutting, and faulting indecies for AC, COM, and PCC pavements, a weighted average formula was used to calculate the PCI values. The current formulae for calculating the PCI for AC, COM, and PCC pavements are as follows (Bektas, 2014):

$$PCI\ (PCC) = 0.4 * (Cracking\ Index) + 0.4 * (Riding\ Index) + 0.2 * (Faulting\ Index)$$

$$PCI\ (AC) = 0.4 * (Cracking\ Index) + 0.4 * (Riding\ Index) + 0.2 * (Rutting\ Index)$$

$$PCI\ (COM) = 0.4 * (Cracking\ Index) + 0.4 * (Riding\ Index) + 0.2 * (Rutting\ Index)$$

Based on PCI values, the Iowa DOT classifies pavement condition for the interstate highway system as good, with a PCI value between 76-100, fair, with a PCI value between 51 and 75, and poor, with a PCI value between 0 and 50. Based on these classifications, approximately 91% and 79% of the interstate highway system and the non-interstate highway system in the state of Iowa was categorized as good condition pavement up to the end of 2017 (Iowa DOT Transportation Asset Management Plan, 2018).

Developing the Long Short Term Memory (LSTM) Deterioration Model

To predict the future condition of individual pavement sections a modified RNN algorithm called LSTM was used in this research. While in conventional feed-forward neural networks, all observations are considered independent, the models in RNN consider the effects of previous observations and therefore account for the correlation between consecutive observations. It is worth mentioning that RNNs can work properly only with short term dependencies, and for making an accurate prediction with an RNN, having information from previous stages is mandatory. In fact, an RNN fails when too many inputs from historical observations are used. Observations added as predictor variables will increase variability in the predictions and the total error, a phenomenon referred to as the vanishing gradient effect. Generally, in feed-forward neural networks, the multiplication of errors from previous layers, rate of learning, and input for a layer define the updating weight for the following layer. As a result of several multiplications of the small value of activation-function derivatives (Sigmoid, Tanh, ReLU), the gradient approaches zero, increasing training complexity and causing information loss within the training layers. To overcome this limitation, LSTM was proposed as a modified version of traditional RNNs while taking advantage of the effectiveness of RNN methods.

The information in LSTMs flows through a cell states mechanism in which LSTMs can selectively either forget or remember information based on its impact on model performance (Chris Olah, 2015). Figure 10 is a schematic of the repeating module in an RNN that goes through three major steps.

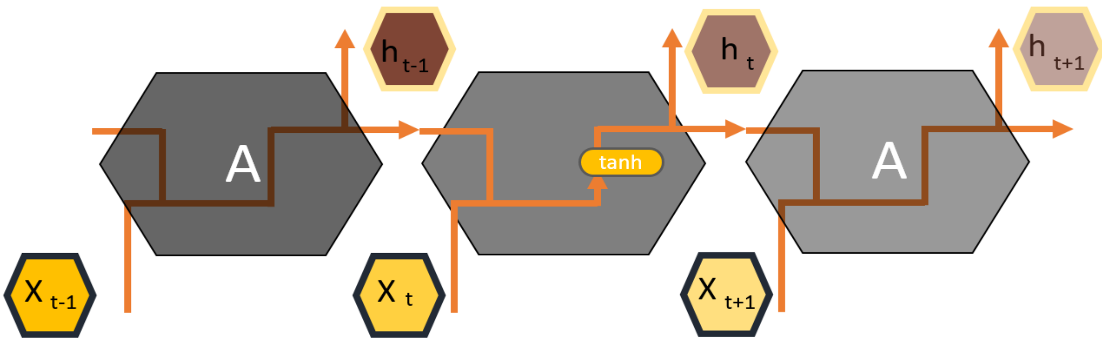

Figure 10: Schematic of Repeating Module in RNN (Chris Olah, 2015)

In the first step, the LSTM passes the output from the previous time step $(t-1)$ to the forget gate, where it is classified using the sigmoidal function shown in Equation 1 either as significant information passed to the next step in the training or insignificant information dropped from the training model.

$$Ft = \sigma(Wf[h(t-1), Xt]) + bf \quad (1)$$

where Ft represents the forget gate, σ is the Sigmoid function, Wf represents the weight for the forget gate neurons, $h(t-1)$ is the output of a previous LSTM block at time$(t-1)$, Xt represents the input at the current time step, and bf represents biases for the forget gate.

In the second step, the LSTM decides what new information should be stored in the cell state by identifying values requiring updating by the Sigmoidal function and the vector of new candidate values created by the Tanh function that could be added to the next state. These two functions are shown in Equations 2 and 3:

$$It = \sigma(Wi[h(t-1), Xt] + bi \quad (2)$$

$$C't = tanh(Wc[h(t-1), Xt] + bc \quad (3)$$

where It represents the input gate, Wi represents the weight for respective gate neurons, Xt represents the input at the current time step, and $C't$ represents the candidate for cell state at time step (t).

By combining information from the previous cell and the input gate from the current time step, the information for the later step will be updated. Equation 4 represents how information is filtered from the forget gate layer combined with new information from the current time step. Other Sigmoid and Tanh functions help the LSTM cell decide what information should be taken as output. Equations 5 and 6 represent the Sigmoidal and Tanh functions in the last step:

$$Ct = Ft * C(t-1) + It * C't \tag{4}$$

$$Ot = \sigma(Wo[h(t-1), Xt] + bo \tag{5}$$

$$ht = Ot * tanh(Ct) \tag{6}$$

where Ct is a cell state (memory) at time step (t), Ot represents the output gate, and ht represents the output of the LSTM block at time step (t).

Model Training

For the learning process in the LSTM algorithm, the dataset corresponding to PCC and COM pavements is divided into training (70%) and validation (30%) sets. Because the number of records in AC pavements was less than that of the two other pavement types, the database was divided into training (80%) and validation (20%) sets for AC pavements. The training dataset was used for developing the model and conducting the learning process, while the validation dataset was used for checking the accuracy of the model.

Validation

Model validation is performed to confirm that the output of the statistical model is acceptable with respect to the collected data (actual data). In order to evaluate any machine learning model, it is necessary to test the model with data not used in the training set. In this study, a Train_Test split approach was used for Cross-Validation (CV), a validation technique that checks the effectiveness of the machine-learning model. After performing model training on 70% of the database (the training dataset), the validation dataset was used as a test sample to validate model performance.

Comparison

The LSTM model performance was compared with the sigmoidal and exponential functions used by Iowa DOT to fit deterioration models for individual sections. The accuracy of each model with respect to riding, cracking, and rutting in AC and COM pavement types, and riding, cracking, and faulting in PCC pavement types were compared for both models.

Result and Discussion

In the following sections, the application of each modeling approach in the databases of the three different pavement types is described and the results are presented and discussed. The overall results from both models are presented in Table 4, with the actual value of each index compared with the predicted value of the same index from the LSTM and Iowa DOT regression models.

The Iowa DOT has an individual regression model for each individual section with specific factors for predicting the future condition of the pavements based on age. While the sigmoidal transformation functions were applied to cracking, rutting, and faulting indices, the exponential function was used to fit the riding index. Based on the actual and predicted values of each index, the PCI value was calculated for each pavement type. Figures (11-13) present the comparisons between actual PCI value and predicted PCI value for each pavement type in the DOT and LSTM models.

Table 4: Summary statistic of each model on the test dataset

			Actual mean	Predicted mean	Actual standard deviation	Predicted standard deviation	R-square
PCC	DOT	*PCI*	58.06	68.63	23.18	19.14	0.44
		Crack	79.62	83.02	23.83	17.56	0.26
		Fault	61.27	99.74	20.04	0.21	-3.68
		Ride	34.89	38.69	39.55	37.82	0.66
	LSTM	*PCI*	58.06	54.13	23.18	21.12	0.70
		Crack	79.62	67.67	23.83	20.95	-0.26
		Fault	61.27	62.78	20.04	14.30	0.62
		Ride	34.89	36.27	39.55	40.48	0.86
COM	DOT	*PCI*	68.71	78.66	19.61	17.9	0.11
		Crack	62.91	78.08	19.74	15.75	-0.05
		Rut	60.44	98.36	17.35	0.57	-4.7
		Ride	78.64	74.51	32.41	34.35	-0.02
	LSTM	*PCI*	68.71	72.48	19.61	17.55	0.50
		Crack	62.91	66.01	19.74	16.88	0.39
		Rut	60.44	61.92	17.35	15.35	0.19
		Ride	78.64	84.23	32.41	29.03	0.43
AC	DOT	*PCI*	71.02	82.95	19.58	17.73	0.31
		Crack	64.11	80.88	24.52	16.02	0.15
		Rut	64.05	98.42	15.14	0.47	-5.11
		Ride	81.51	77.29	29.83	33.73	0.55
	LSTM	*PCI*	71.02	72.89	19.58	17.36	0.61
		Crack	64.11	67.08	24.52	21.78	0.35
		Rut	64.05	63.74	15.14	12.33	0.19
		Ride	81.51	83.28	29.83	27.65	0.61

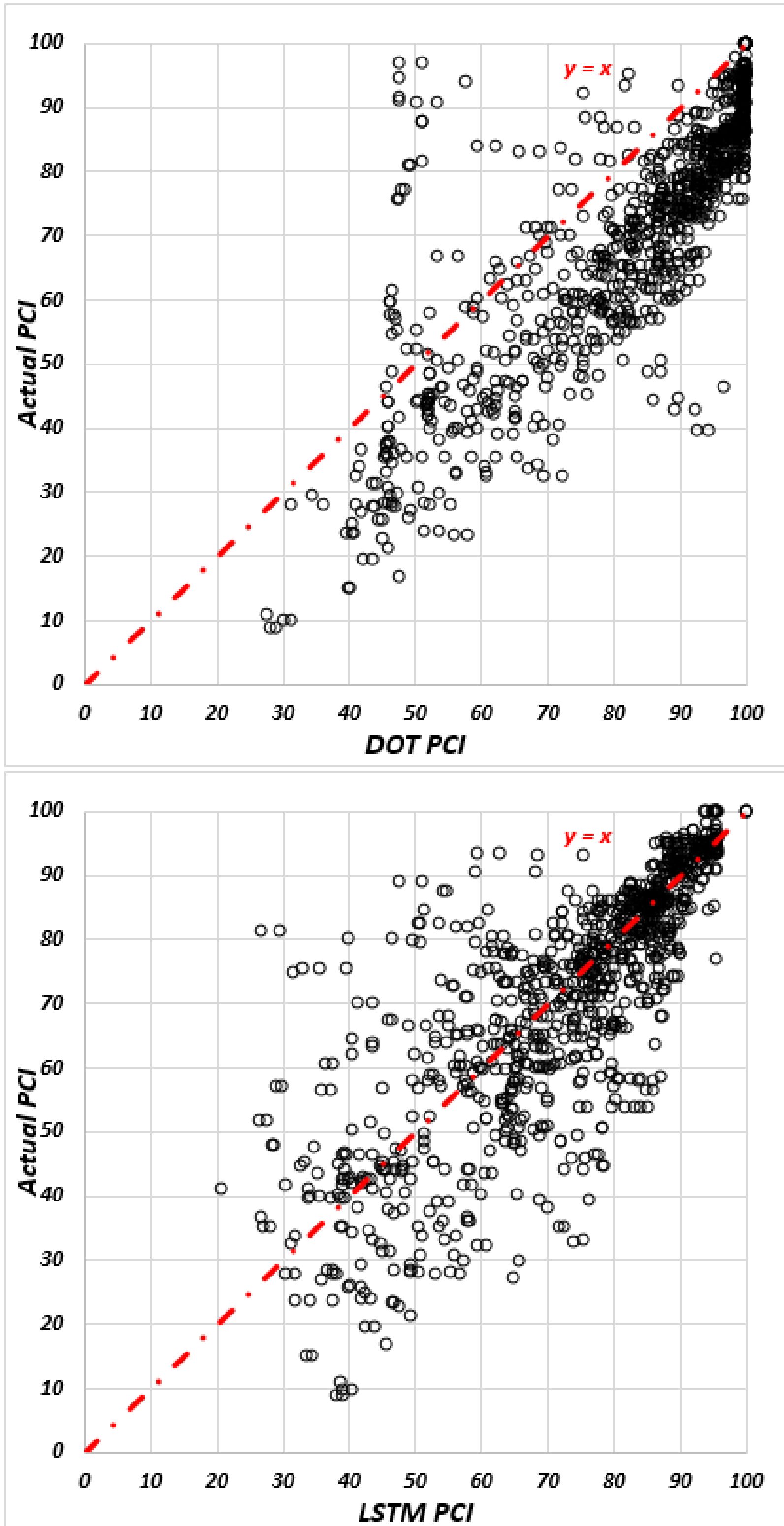

Figure 11: The Actual PCI over Predicted PCI in AC sections for DOT and LSTM models respectively

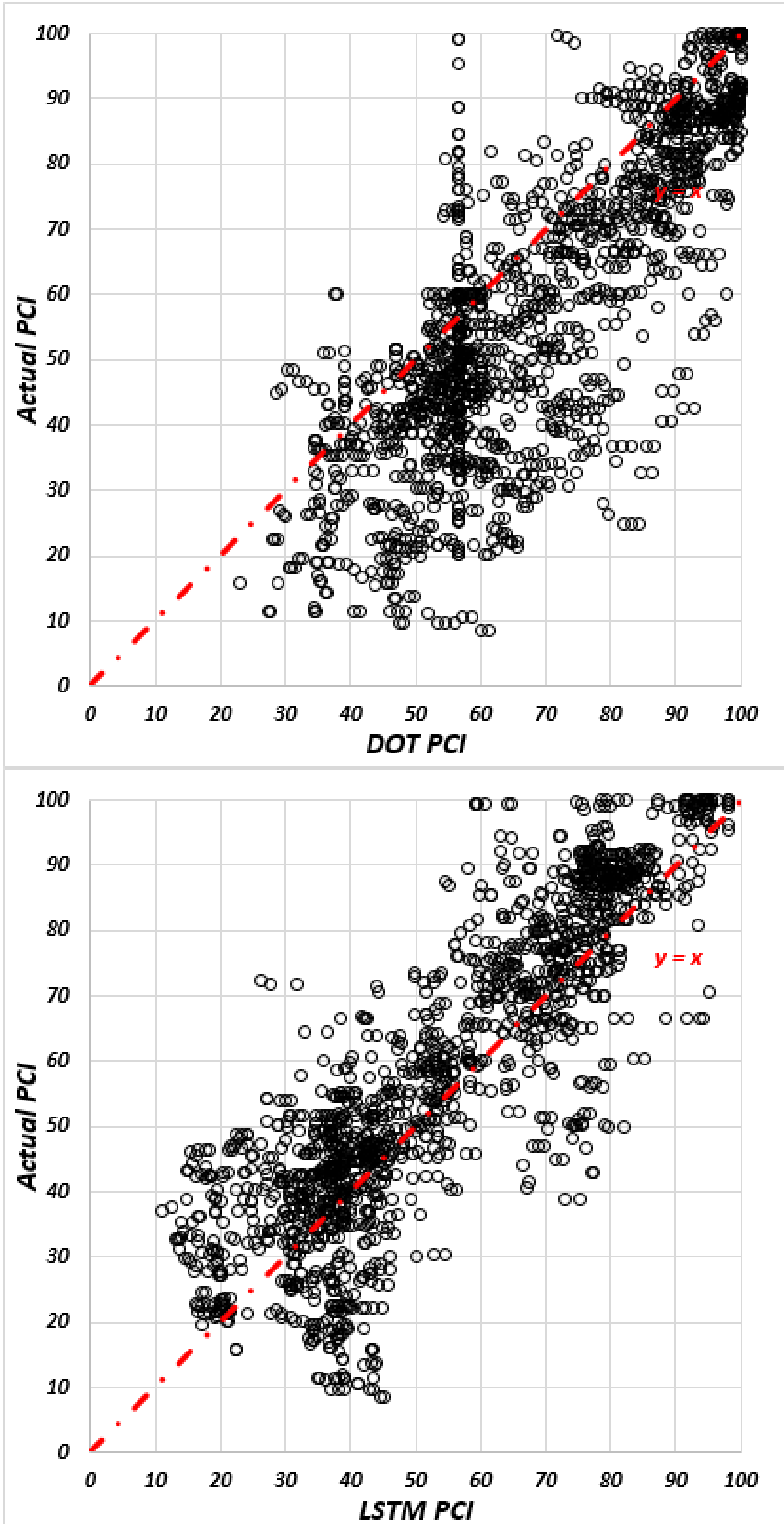

Figure 12: The Actual PCI over Predicted PCI in COM sections for DOT and LSTM models respectively

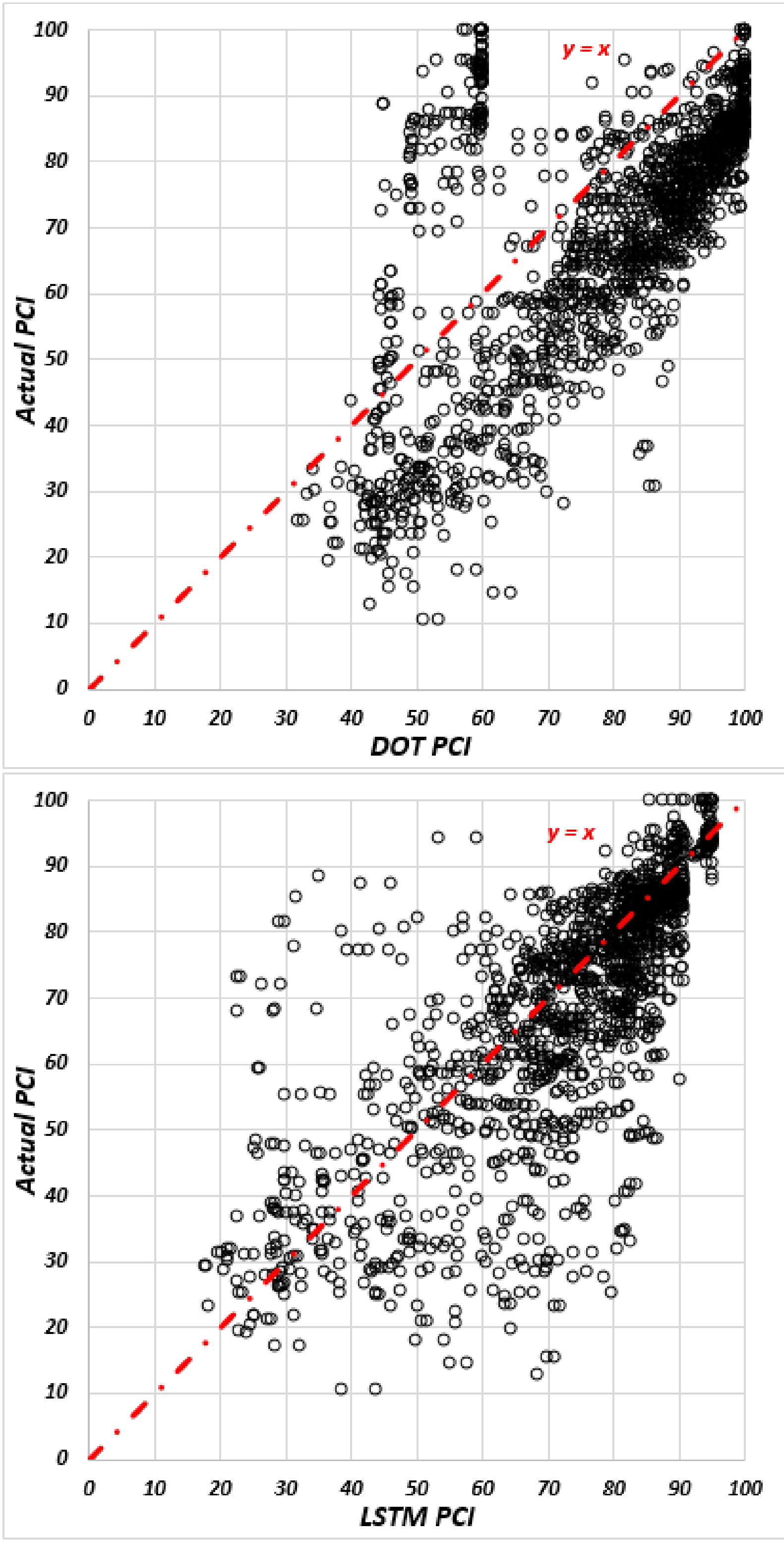

Figure 13: The Actual PCI over Predicted PCI in PCC sections for DOT and LSTM models respectively

It should be noted that the evaluations of the regression models are restricted to the residuals between the fitted functions and the actual readings, although the LSTM evaluation was based on its ability to predict full performance curves not included during the training stage. For validating the prediction results of the individual regression models and comparing the results of the current Iowa DOT method with LSTM models, 50 AC, 80 PCC, and 80 COM sections were tested. The results were compared with the actual value of each index.

The comparison included models developed for AC, COM, and PCC pavements. R-square and Standard Error of Estimate (SEE) were considered to evaluate the accuracy of the models. The R-square and SEE functions are shown in equation 7 and 8:

$$R^2 = 1 - \left(\frac{SSres}{SStot}\right) = 1 - \left(\frac{(\sum_i (Y_i - \hat{Y}_i)^2)}{\sum_i (Y_i - \overline{Y_i})^2}\right) \tag{7}$$

$$SEE = \sqrt{\sum (Y_i - \dot{Y}_i)/N} \tag{8}$$

Where Y_i is the actual value, $\widehat{Y}_i$ is the predicted value, $\overline{Y_i}$ is the average of actual values, and N represents the number of observation.

The results for AC pavements showing that the LSTM model got higher prediction accuracy, compared to the individual DOT regression models. The R-square values in the LSTM models were 0.61 for the riding index, 0.19 for the rutting index, 0.35 for the cracking index, and 0.61 for the PCI. This is while the values for the DOT models were 0.55, -5.11, 0.15, and 0.31, respectively. It is worth mentioning, that, R-square is defined as the proportion of variance explained by the fit, if the fit is actually worse than just fitting a horizontal line, then R-square is negative. Also the result of SEEs for both models indicates that the LSTM model got less standard error of estimate, compared to DOT models. The SEE values in the LSTM models were 18.66 for the riding index, 19.74 for cracking index, 13.58 for rutting index, and 12.18 for the

PCI. This is while the values for the DOT models were 20.08, 22.57, 37.40, and 16.17, respectively.

Also The results for COM pavements showing that the LSTM model got higher prediction accuracy. The R-square values were 0.43 for the riding index, 0.19 for the rutting index, 0.39 for the cracking index, and 0.50 for the PCI in LSTM models, while the corresponding values for the DOT models were -0.02, -4.7, -0.05, and 0.11, respectively. Also SEE metrics for both models indicates that the LSTM model got less standard error of estimate, compared to DOT models. The SEE values in the LSTM models were 24.5 for the riding index, 15.29 for cracking index, 15.57 for rutting index, and 13.78 for the PCI. This is while the values for the DOT models were 32.7, 19.72, 41.48, and 18.46, respectively.

Also, the LSTM model outperformed DOT's regression models with respect to PCC pavements. Fluctuations in the PCC database due to maintenance activities were less than the two other pavement types. The R-square values were 0.86 for the riding index, 0.62 for the rutting index, -0.26 for the cracking index, and 0.70 for the PCI in LSTM models, and the corresponding values in the DOT models were 0.66, -3.68, 0.26, and 0.44, respectively. Also the result of SEEs for both models indicates that the LSTM model got less standard error of estimate, compared to DOT models. The SEE values in the LSTM models were 14.71 for the riding index, 26.83 for cracking index, 12.4 for faulting index, and 12.51 for the PCI. This is while the values for the DOT models were 22.96, 20.37, 43.35, and 17.21, respectively.

Figures (14-16) also reflect the effect of age on the prediction residuals for each model in both the short and long term duration. These results show that the errors will more significantly widen and fluctuate after the first five years of pavement age for all three pavement types. Residuals can generally be either positive or negative; however consistent differences between the predicted and observed values to one side of the prediction model is referred to as bias, and the variability in the mean observed value of these residuals is referred to as variance. Bias can be formally defined as the expected value of the model residuals, as shown in Equation 9.

$$Bias = E[\hat{y} - y] \approx \frac{1}{N}\sum_{i=1}^{N} \epsilon \qquad (9)$$

Where $\hat{y}$ is the predicted value, y is the observed value, and ϵ is the model residual $\epsilon = \hat{y} - y$.

As can be seen in Figures (14-16), the DOT regression models show a consistently higher bias as the average line deviates from the zero value. To check whether the bias of the DOT regression model was significantly higher or lower than the LSTM model bias a hypothesis test was performed to calculate the regression and LSTM models average absolute residual values. To determine the possibly unequal residual variance between the models, the Kolmogorov-Smirnov test, a non-parametric test that allows for testing with unequal variances, was performed. Results showed that the regression model had a significantly higher bias with a negative value, meaning that the regression model will consistently overestimate the index values and result in less conservative predictions. The means of the residual of the PCI for the LSTM and DOT models were (3.93, -10.57) for PCC, (-1.87, -11.93) for AC, and (-3.77, -9.94) for COM pavement types. Even though the variance of the residuals increased in the LSTM over time, the mean of the residual in the LSTM model was still less than that of the regression models. The solid black line and dotted blue line in the figures show how the mean errors changed over time.

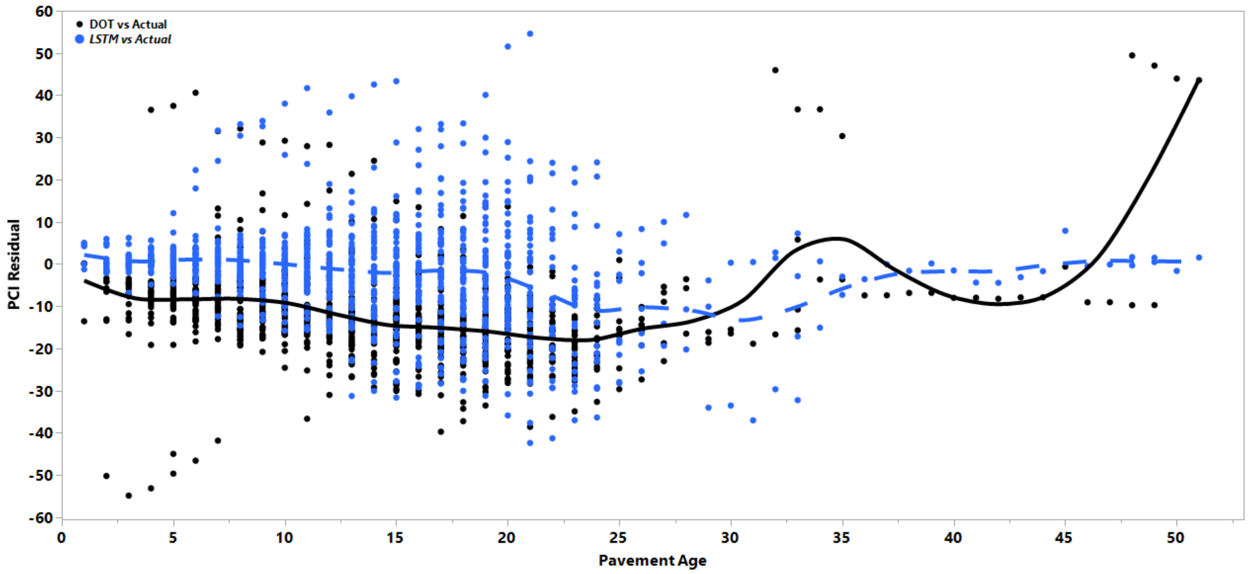

Figure 14: PCI Residual vs Age in AC pavements

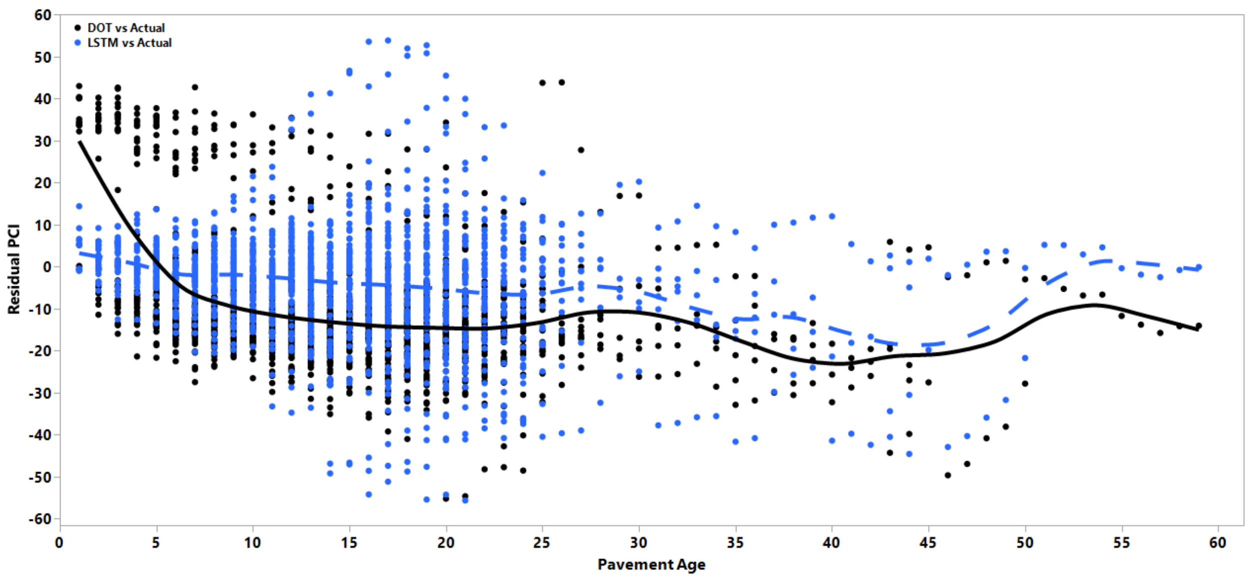

Figure 15: PCI Residual vs Age in COM pavements

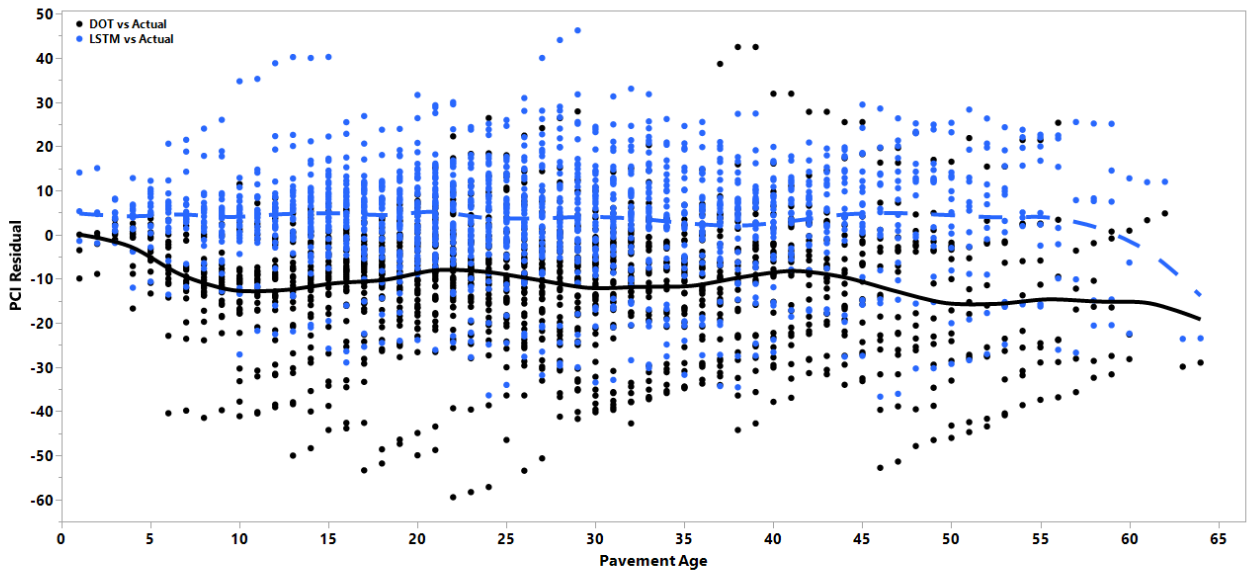

Figure 16: PCI Residual vs Age in PCC pavements

Conclusion

The deterioration models of the historical pavement condition data for the state of Iowa were developed using an LSTM approach. The proposed model and current method in Iowa DOT were compared to investigate the model accuracy. The comparison between the developed model and the individual regression models used by the Iowa DOT from the three different pavement types indicates that prediction accuracy in the LSTM model is higher than individual regression models.

The LSTM achieved a higher PCI prediction accuracy than the individual regression models in all three pavement types. A hypothesis analysis of mean was conducted for the PCI residual in both techniques and the results exhibit less LSTM bias than that of individual regression models.

Overall, each of these two methods has its own advantages and disadvantages. The equation of the individual regression models requires an annual update, and each section will exhibit a new year-by-year behavior, making the prediction process more complex. The LSTM is only one more consistent model compatible for all sections using a training process. The LSTM approach was sensitive to the data fluctuation resulting from unrecorded maintenance activities. While the evaluation of the regression models was restricted to residuals between the fitted functions and the actual readings, the evaluation for the LSTM was based on its ability to predict full performance curves not included during the training stage.

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CHAPTER 3. HOW PREDICTION ACCURACY CAN AFFECT THE DECISION-MAKING PROCESS IN PAVEMENT MANAGEMENT SYSTEMS

Modified from a manuscript under review in International journal of pavement research and technology

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Abstract

One of the most important components of pavement management systems is predicting the deterioration of the network through performance models. The accuracy of the prediction model is important for prioritizing maintenance action. This paper describes how the accuracy of prediction models can have an effect on the decision-making process in terms of the cost of maintenance and rehabilitation activities. The process is simulating the propagation of the error between the actual and predicted values of pavement performance indicators. Different rate of error was added into the result of prediction models. The results showed a strong correlation between the prediction models' accuracy and the cost of maintenance and rehabilitation activities. Also, increasing the rate of error contribution to the prediction model resulting in a higher benefit reduction rate.

Keywords: Prediction accuracy, pavement management system, decision-making, maintenance assignment, benefit optimization

Introduction

With an ageing transportation network, highway agencies are finding it challenging to maintain their deteriorating assets in good condition. Given the limited budget to maintain the network, departments of transportation (DOTs) need to efficiently manage their assets to satisfy network-level goals.

The Transportation Asset Management Plan (TAMP) is "the strategic and systematic process of operating, maintaining, upgrading, and expanding physical assets effectively throughout their life cycle" (MnDOT, 2016). In 2012, the US Congress passed the Moving Ahead for Progress in the 21st Century Act (MAP-21), which requires each state DOT to present a risk-based asset management plan to maintain and improve their infrastructure condition (Corley-Lay, 2014). MAP-21 requires evaluating the pavement condition of highways through its infrastructure conditions criteria. Another legislation, known as Fixing America's Surface Transportation (FAST), also passed in 2015 to support performance-based asset management methods. Pavement and bridge assets are prioritized in both acts, and highway agencies spend the biggest portion of their budget on maintaining and preserving these two assets every year.

Although Departments of Transportation (DOTs) are actively maintaining their transportation assets, the 2017 infrastructure report card shows that US roads are in a fair to poor condition with a D GPA (American Society of Civil Engineers, 2017). The biggest problem that keeps the US roads in a fair to poor condition is that the US has had a financial shortcoming in its highway system for many years. As a result of this shortcoming, the US has $836 billion backlogs in highway and bridge capital. The biggest portion of this backlog ($420 billion) is for repairing the highway system. So, a systematic way to optimize this limited funding is needed to maintain and preserve the highway system.

To achieve the TAMP goals, the Pavement Management System (PMS) presents a support tool to derive objective decisions to keep the pavements in an acceptable condition at a minimum cost (AASHTO, 2012). Significant savings and improvement were observed in the network condition since the 1970s when DOTs established and implemented their own PMSs to match their needs (Vasquez 2011, Smadi 2004). Arizona DOT uses PMS for maintenance action in a 7400-mile network of highways and recognizing the minimum funding required to implement the maintenance program (Golabi, 2019). Also, they saved $101 million in the first four years of implementation of PMS (Hassan, 2017). A comprehensive PMS involves collecting data, inspecting the road network, predicting network deterioration through performance models, and optimizing maintenance and rehabilitation activities over the planning horizon.

The decision levels in PMS are categorized into the project level, network level, and administrative level. Figure 17 shows the hierarchical decision level in the pavement management system (Li, 2005).

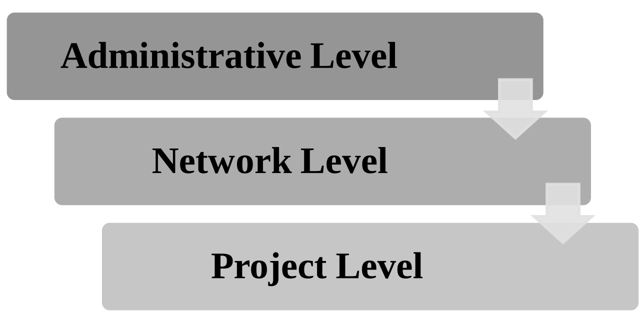


Figure 17: PMSs decision levels

Funds are allocated to different transportation asset categories at the administrative level. The goals of network-level management are normally related to the budget process. These goals include identifying the maintenance, rehabilitation, and reconstruction needs, determining the funding needs, forecasting the impact of various funding options in the future, and prioritizing the maintenance activities for the selected funding option. In case of a limited budget, network-level management selects sections based on criteria such as the least cost first, the worst section first, and the highest benefit-cost ratio. At the project level, detailed maintenance and rehabilitation treatments and the best strategy for maintenance actions will be identified. Pavement condition evaluation is necessary for making an efficient decision at each of these decision levels.

Evaluating and modeling of pavement conditions is a major part of all PMSs. Nowadays, almost all state DOTs are using automated surveying tools to evaluate pavement conditions. The data collection covers pavement distress data such as transverse cracking, longitudinal cracking, alligator cracking, wheel-path cracking, patching, and surface friction. To summarize the pavement condition, the U.S Army Corps of Engineering developed the Pavement Condition Index (PCI) in the 1970s. The index represents a weighted average of sub-indices, reflecting the severity levels of different distress types (Shahnazari, 2012). Since then, PCI has been widely used to represent the pavement condition (Haas, 1994). PCI has a numerical value between 0 and 100, where 0 defines the worst and 100 defines the best condition for pavement segments. Also, based on the value of PCI, decision-makers can evaluate the functionality of the pavement network, predict the best time for any maintenance and rehabilitation activities, and estimate future funding needs (Bektas, 2014).

These activities need to be prioritized in order to minimize the cost of maintenance activities and maximize the life cycle of the network (Donev, 2018). To reach this goal, a robust and accurate deterioration model is needed. Maintenance optimization is sensitive to deterioration models that describe the change in pavement condition over time (Lytton, 1987). By reducing the error in deterioration models, agencies can obtain significant budget savings through timely intervention and accurate planning (Madanat, 1993). The pavement management system could be successful if an accurate deterioration model optimizes the maintenance and rehabilitation strategies during the pavement service time. Also, deterioration models can help agencies identify what maintenance activities are needed (George, 2000). Long-term and short-term planning that become possible with deterioration models is even more critical when highway agencies have a shortcoming in funding (Hassan, 2017).

There are different types of deterioration models used in the pavement management system to help decision-makers predict the future condition of pavement sections. Wolters and Zimmerman categorized these models in probabilistic, deterministic, knowledge-based, and neural networks (Wolters, 2010). The deterministic model is a system in which no randomness is involved in the development of the future states of the system. Structural performance, function performance, primary responses, and damage models are all included in deterministic models. The base of the most deterministic models is regression. Also, deterministic models can be broken into empirical models, mechanistic models, and mechanistic-empirical models (Li, 1996).

Probabilistic models predict the future condition of pavements by giving a transition matrix with which the pavement would fall into a particular condition state, describing the possible pavement conditions of the random process. Neural Network (NN) models have got more attention in the past few years between researchers because of their capability to interconnect neurons between layers. NN applications can solve complex problems in a more efficient way than traditional methods (Basheer, 2000). These problems can be in different categories of pavement engineering, based on research conducted by Ceylan in 2014 (Ceylan, 2014). Deterioration models attempt to fit time series data with low observation frequency and high levels of variability, which can be properly captured using Recurrent Neural Networks

(RNN). In the past few years, many different RNN algorithms have been developed by researchers, including the Long Short Term Memory (LSTM), introduced to allow for modeling and forecasting long term data series.

All these DMs are designed to predict the future condition of pavement sections so that maintenance and rehabilitation activities can be planned. Each activity is suitable for specific distress and decision-makers cannot apply one treatment to all types of distresses. Because each pavement section can have more than one distress type and each distress type has its own treatment solution, state DOTs have defined their own decision trees for applying specific treatments to specific road sections with specific conditions. Nevertheless, all state DOTs have some mutual factors for selecting these treatments, such as the traffic condition, environmental factors, and pavement type. The treatment selection process is different in each state based on their pavement condition evaluation process. Some state DOTs use optimization routines for treatment assignment and some others use threshold value for assigning the treatment strategies.

In order to maximize the effectiveness of treatments, treatment effectiveness needs to be defined. There are different definitions available, such as extending the life of the pavement by treatments, improving the pavement deterioration curve by treatment, and the service life of the treatments. In general, however, treatment effectiveness is how well a treatment works during the pavement age so that the need for another treatment is eliminated. The right treatments can not only improve the pavement condition but also decrease the rate of deterioration of the pavement sections.

The uncertainties in pavement performance prediction produce errors which are classified into random and systematic errors. These type of errors can be due to human involvement (such as errors happening during data entry, data preprocessing, and visual rating) or be technology errors (such as those that come from the instrument). Random errors are the "result of irregular causes in which laws of action are unknown or too complex to be investigated. However, systematic errors are constant or may vary in some regular way" (Saliminejad, 2013). Saliminejad and Gharibeh have proven that even acceptable ranges of systematic and random errors could have an impact on the output of the PMS and average annual budget. Based on a study by Haider and Chatti, unbiased sampling can reduce the rate of systematic errors; however, increasing the sample size can reduce the rate of random errors (Haider, 2011). In PMS, positive error in condition data (overestimating the condition index and underestimating distress) is less effective than the negative error (underestimating the condition index and overestimation of distress).

Different sources of errors might be introduced in pavement performance data and consequently, in pavement performance prediction. A composite condition index (for instance, the pavement condition index (PCI)) includes the measurement of roughness, distress, rutting, and faulting. The instrumental error might increase because of using different types of instruments to measure these condition indicators. On the other hand, another source of error can be introduced due to the subjectivity in the determination of severity and type of distresses. Also, another source of error may be introduced due to field and operator conditions. Because the maintenance actions in each state DOT is directly related to pavement prediction models, the effect of errors is not negligible. However, little work has been done to investigate the impact of errors in the decision-making process.

In this research, the result of the pavement prediction model (LSTM model), already developed in a previous study is used (Hosseini, 2020). LSTM is used for time-dependent prediction of the pavement condition index. The goal of this study is to investigate the effect of prediction accuracy in the decision-making process in terms of maintenance costs and rehabilitation activities in different pavement types. Historical pavement condition data of the Iowa DOT Pavement Management Information System (PMIS) between 1998 to 2018 were used for developing the prediction model. Different scenarios are investigated while adding different rates of error to the predicted values. Iowa DOT decision trees are used to check the effect of the prediction model accuracy in terms of cost of treatments in different pavement types. The results of different scenarios were compared with the base scenario to check whether decreasing or increasing the accuracy of the prediction model can have an effect on the cost of maintenance and rehabilitation or not.

Methodology

Figure 18 represents the steps involved in completing this research study. Each individual step is described in detail in the following subsections.

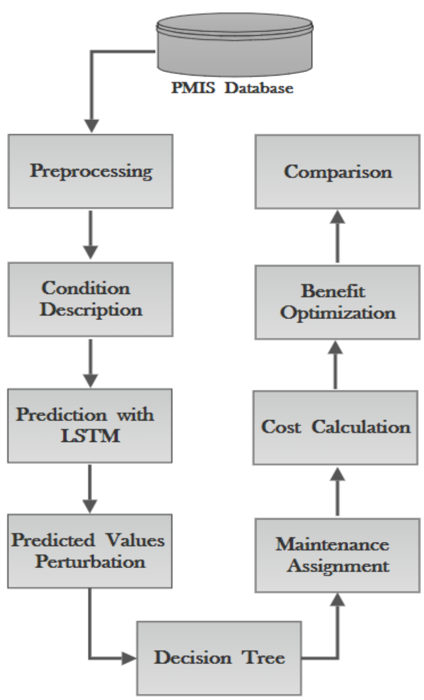


Figure 18: Research Steps

Data

Information regarding the highway system, including construction history, section identification, maintenance history, pavement age, traffic loading, and pavement distresses are available in the Iowa DOT PMIS database and was used to develop the prediction model in the previous study (Hosseini, 2020). The condition data of pavement sections from 1998 through 2018 was used for model development purposes. The data collection covered pavement distresses data such a transverse cracking, longitudinal cracking, alligator cracking, wheel-path cracking, patching, and surface friction. Three severity levels are assigned to distresses data: low, medium, and high, for all pavement types. Rutting depth for asphalt and composite pavements and faulting for concrete pavements have also been collected. The international roughness index (IRI) was used to characterize ride quality for all pavement types. The Iowa DOT spends about $1 million annually on collecting pavement condition data (Bektas, 2014).

The pavement types included in the study were asphalt concrete (AC), Portland cement concrete (PCC), and composite (COM) pavements. For training the prediction model, 477 AC sections, 1562 PCC sections, and 1830 COM sections were used. The lengths of these sections were varied between 0.05 to 18 miles, making a large impact on treatment costs.

Preprocessing

After the data collection process, condition indices were estimated using the reported condition data. In the current database, different types of units are used for each distress type. Since the PCI is based on a scale of 100, individual indices and sub-indices were also estimated on a scale of 100 in order to make comparison easier. In this study, four individual indexes are used for AC, COM, and PCC pavements:

- Riding Index
- Rutting Index

- Cracking Index
- Faulting Index

The overall PCI is the combination of riding, rutting, and cracking indices for AC and COM pavements and riding, cracking, and faulting indices for PCC pavements. The weights for individual indexes were determined in a previous study for Iowa DOT by Bektas and Smadi (Bektas, 2014). Moreover, all indexes are derived based on the proposed approach in the same study.

1. Cracking Index

Four different sub-indexes were used to calculate the cracking index in AC and COM pavements based on transverse cracking, longitudinal cracking, alligator cracking, and longitudinal-wheel-path cracking. For PCC pavements, transverse cracking and longitudinal cracking were established as sub-indexes. Three severity levels were evaluated for pavement distresses by the Iowa DOT: low, medium, and high. The coefficients of 1, 1.5, and 2 are the low, medium, and high aggregated severities, respectively, and convert all severity levels into low severity (Bektas, 2014). A maximum value (threshold), corresponds to a deduction of 100 points. Therefore, a cracking sub-index of 0, was determined for each crack type within pavement type. Table 5 describes the threshold values for each sub-index in different pavement types.

Table 5: Threshold value for different sub-indexes (Bektas, 2014)

Sub-Index	PCC pavements	ACC pavements
Transverse Cracking (count/km)	150	300
Longitudinal Cracking (m/km)	250	500

Wheel-path Cracking (m/km)	N/A	500
Alligator Cracking (m^2/km)	N/A	360

The cracking index is the combination of weighted sub-indexes; these weights are determined based on expert opinion at the Iowa DOT. Table 6 shows the weight of each sub-index for calculating the cracking index.

Table 6: Weight of each sub-index for calculating the cracking index (Bektas, 2014)

Sub-Index	**PCC weight (%)**	**AC weight (%)**
Transverse Crack	60	20
Longitudinal Crack	40	10
Wheel-path Crack	0	30
Alligator Crack	0	40

The cracking indexes for AC, COM, and PCC pavements, based on the coefficient values provided by Iowa DOT experts are as follows:

$$Cracking\ Index\ (AC\ and\ COM)$$
$$= 0.2 * (Transverse\ sub\ Index) + 0.1 * (Longitiudinal\ sub\ Index)$$
$$+ 0.3 * (Wheel - path\ sub\ Index) + 0.4 * (Alligator\ sub\ Index$$

$$Cracking\ Index\ (PCC)$$
$$= 0.6 * (Transverse\ sub\ Index) + 0.4 * (Longitiudinal\ sub\ Index)$$

2. Riding Index

The International Roughness Index (IRI) is the roughness index most commonly obtained from measured longitudinal road profiles. The Riding Index in this study is based on the IRI measurements, as expressed on a scale of 100. IRI values below 0.5m/km are taken as a perfect 100, whereas, the values above 4.0m/km are 0 on the index scale; any other value between 0.5 and 4 m/km was calculated with interpolation (Bektas, 2014).

3. Rutting Index

Rutting is a term for when permanent deformation or consolidation accumulates in an asphalt pavement surface over time. Rutting occurs because the aggregate and binder in asphalt roads can move. A threshold value of 12 mm was set to 0 on a rutting Index scale of 100, and the values below 12 mm were applied as deductions correspondingly based on previous research (Bektas, 2014).

4. Faulting Index

Faulting is a difference in elevation across a joint or crack; usually, the approach slab is higher than the leave slab due to pumping. Similar to rutting index in AC pavements, a threshold value of 12 mm was set to 0 on the index scale of 100 based on previous research (Bektas, 2014).

5. Calculating Pavement Condition Index (PCI)

After calculating all cracking, riding, rutting, and faulting indexes for AC and PCC pavements, the Iowa DOT uses the formula obtained from pure regression analysis to combine all these indexes and come up with a pavement condition index to describe the current condition of the pavements. The current formula for calculating the PCI for AC and PCC pavements are as follows (Bektas, 2014):

$$PCI\ (PCC) = 0.4 * (Cracking\ Index) + 0.4 * (Riding\ Index) + 0.2 * (Faulting\ Index)$$

$$PCI\ (AC) = 0.4 * (Cracking\ Index) + 0.4 * (Riding\ Index) + 0.2 * (Rutting\ Index)$$

$$PCI\ (COM) = 0.4 * (Cracking\ Index) + 0.4 * (Riding\ Index) + 0.2 * (Rutting\ Index)$$

Based on the PCI values, Iowa DOT classifies pavement condition for the interstate highway system as *good*, where PCI is between 76-100; *fair*, where PCI is between 51-75; and *poor*, for sections with PCI between 0-50. Based on the Iowa DOT classification, approximately 91% and 79% of the interstate highway system and non-intestate highway system in the state of Iowa was categorized as being in a good condition pavement till the end of 2017 (Iowa DOT Transportation Asset Management Plan, 2018).

Condition Description

After gathering and processing all the information from the last step, performance indicators needed for decision making were defined. Each pavement type has its own performance indicator, different for AC, COM and PCC. In this study, the cracking, riding, rutting, and PCI for AC and COM pavements are identified as performance indicators. But the cracking, riding, faulting, and PCI in PCC were used as a performance indicator. Highway agencies are using these performance measurements for selecting maintenance activities to expand the life of pavements and improve pavement conditions.

Prediction with LSTM

The LSTM, which is an RNN algorithm, was used to predict the future condition of individual pavement sections of the three different pavement types. The LSTM algorithm in this study was previously developed by the author in another study (Hosseini, 2020). The database was divided into a training dataset and a validation dataset. The training dataset was used for the learning process and developing the model. The validation dataset was used to validate that the model works well. Because the AC pavement type had a lower number of records compared to the other two pavement types, 80% of the records were used for training the model and (20%) for validating the model. In PCC and COM pavement types, these numbers are (70%) for training and (30%) for validating the model.

Model validation confirmed that the output of the statistical model was acceptable with respect to the collected data. For evaluating any machine learning models, it is necessary to test some data which was not used in the training process. The Train_Test split approach was used for Cross-Validation (CV), a validation technique that checks the effectiveness of the machine learning model. After performing the model training on 70% of the database (training dataset), the validation dataset was used as a test sample to validate the model performance. The prediction for all three pavement types was conducted for 20 years with the developed model. For AC, PCC and COM pavement types, 50, 80, and 80 sample sections were used for prediction purposes, respectively.

Perturbation of the predicted values

Figure 19 illustrates the developed process for perturbating of predicted values. The process starts with;

- Calculating the error which is the difference between the actual and predicted values of the performance indicators (ride index, rut index, crack index, and fault index)
- Estimating the standard deviation (σ) of the errors calculated in the first step for all test sections
- Generating the normally distributed random numbers with respect to the standard deviation and mean zero
- Updating the performance indicators by adding the generated random numbers (positive or negative) to increase the sparsness of the point around the fitted model
- Calculating the PCI based on the new performance indicators values

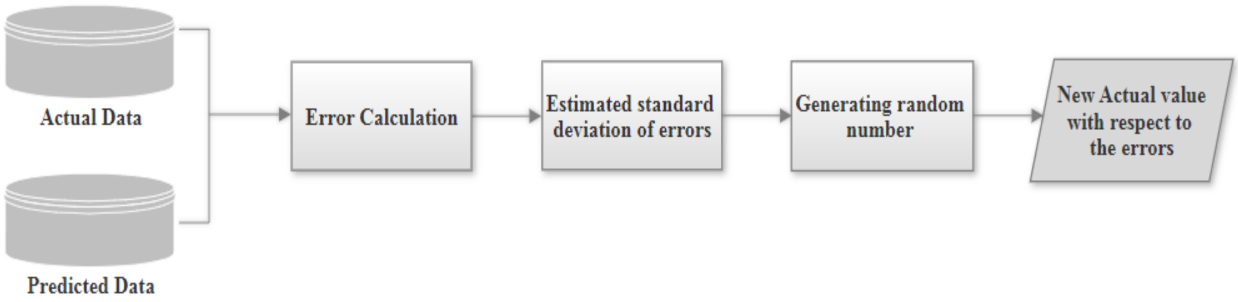
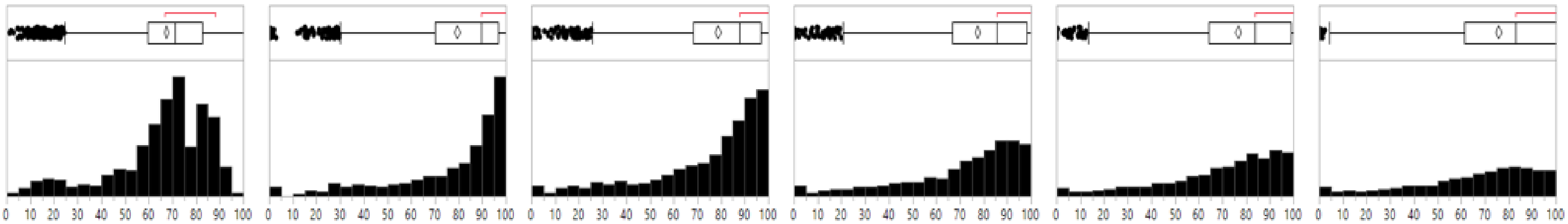


Figure 19: Noise generation process

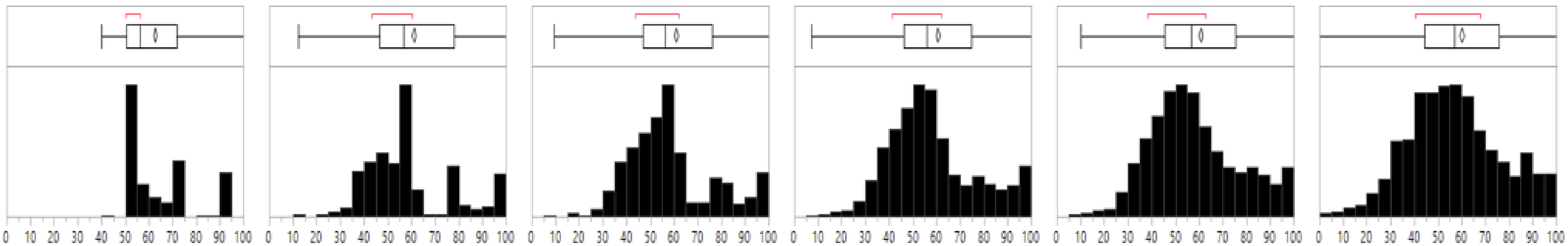
Five different scenarios were assumed from the minimum error rate to the maximum error rate to investigate the effect of increasing the error on the decision-making process:

- ***Scenario 1***: 10% error rate added to the performance indicators
- ***Scenario 2***: 30% error rate added to the performance indicators
- ***Scenario 3***: 50% error rate added to the performance indicators
- ***Scenario 4***: 70% error rate added to the performance indicators
- ***Scenario 5***: 90% error rate added to the performance indicators

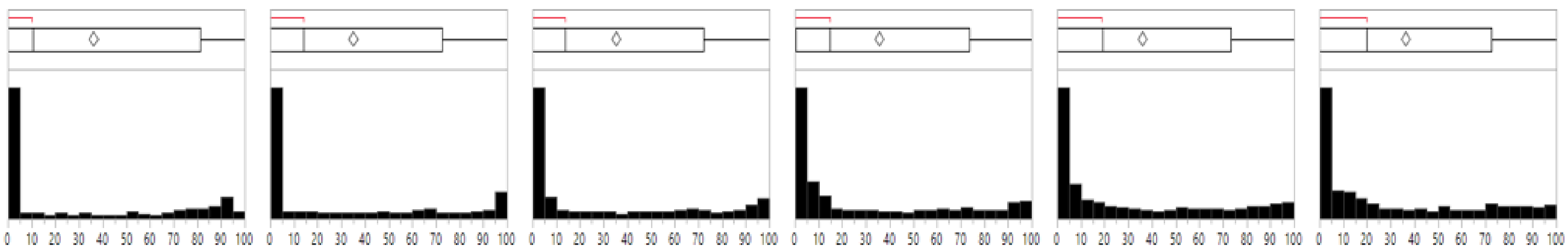
As a result of adding different error rates in AC pavements, the errors have the potential to increase or decrease the PCI in a range of [-3, 3], [-8, 8], [-12, 12], [-19, 19], [-25, 25] in scenarios 1 to 5, respectively. These numbers for COM pavements are [-3, 3], [-11, 11], [-15, 15], [-25, 25], [-33, 33] in scenarios 1 to 5, respectively. Also in PCC pavements, the PCI changed in a range of [-2, 2], [-7, 7], [-13, 13], [-20, 20], [-25, 25] in scenarios 1 to 5, respectively. Figures (20-22) show the distribution of the performance indicators for each pavement type, PCC, AC, and COM respectively for the base and 5 different error scenarios. Figure 23 shows the resulting PCI distribution for the three pavement types.



Distribution of cracking index after adding different error rate in PCC pavements

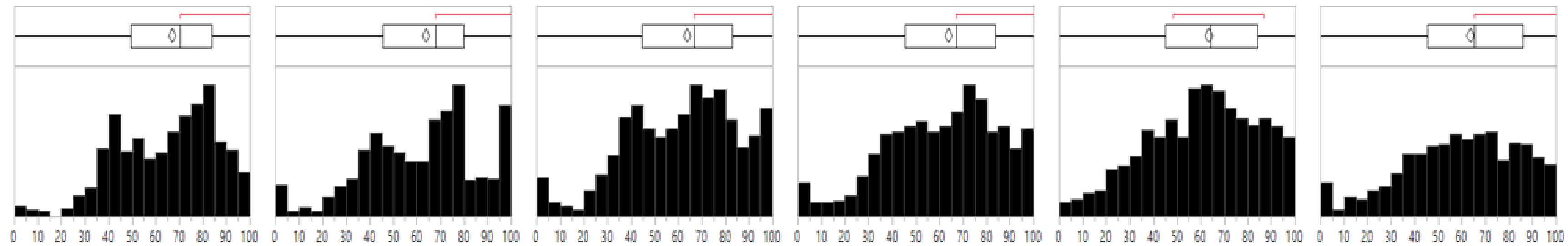


Distribution of faulting index after adding different error rate in PCC pavements

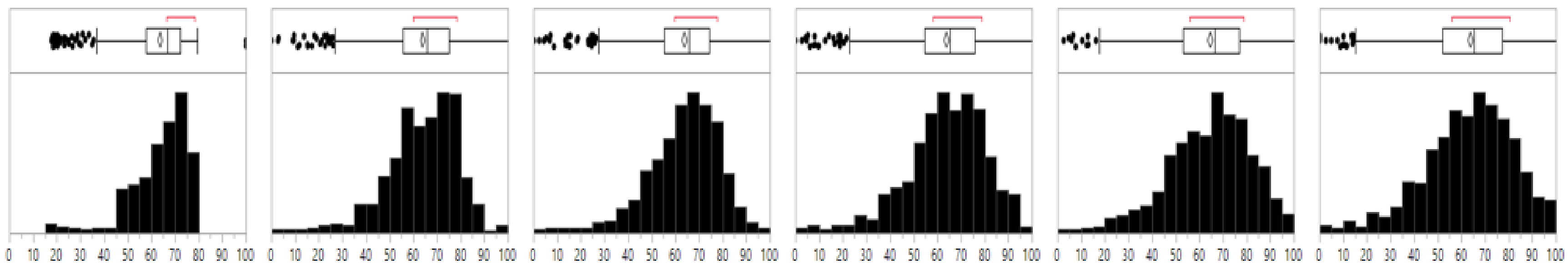


Distribution of riding index after adding different error rate in PCC pavements

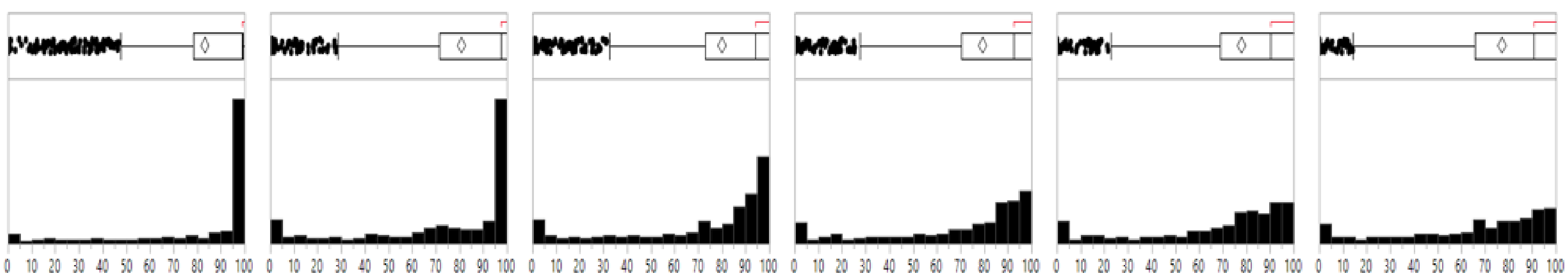
Figure 20: Distribution of individual indexes in PCC pavement type after applying the different rate of errors (Base Scenario, 10, 30, 50, 70, and 90% rate of error, left to right)



Distribution of cracking index after adding different error rate in AC pavements

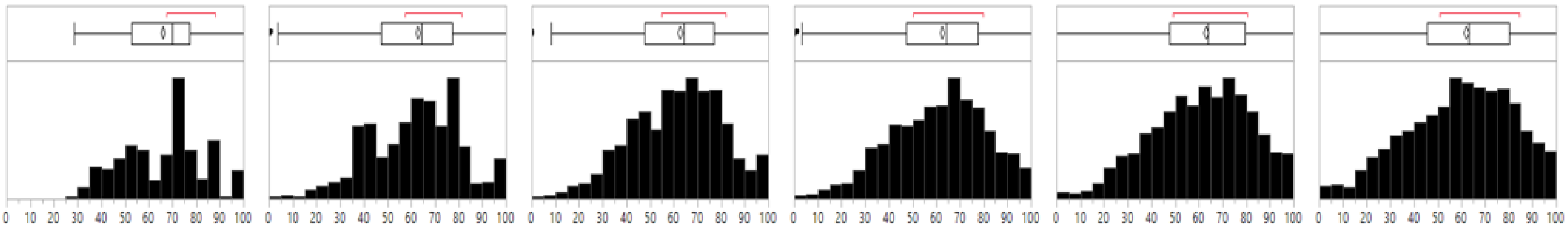


Distribution of rutting index after adding different error rate in AC pavements

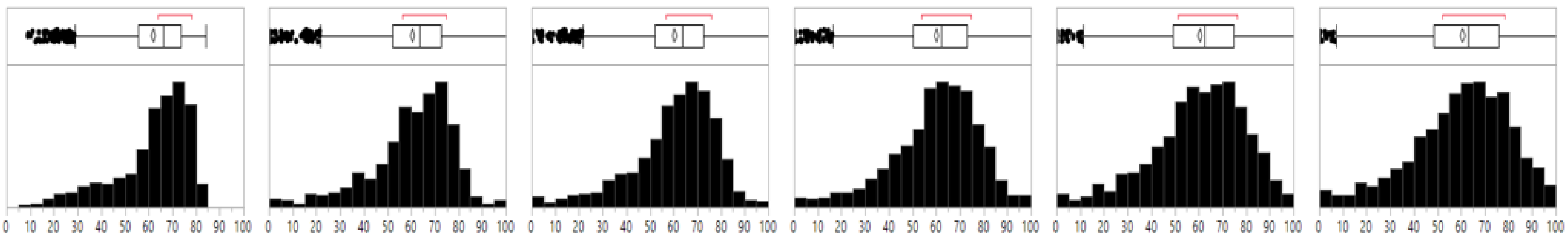


Distribution of riding index after adding different error rate in AC pavements

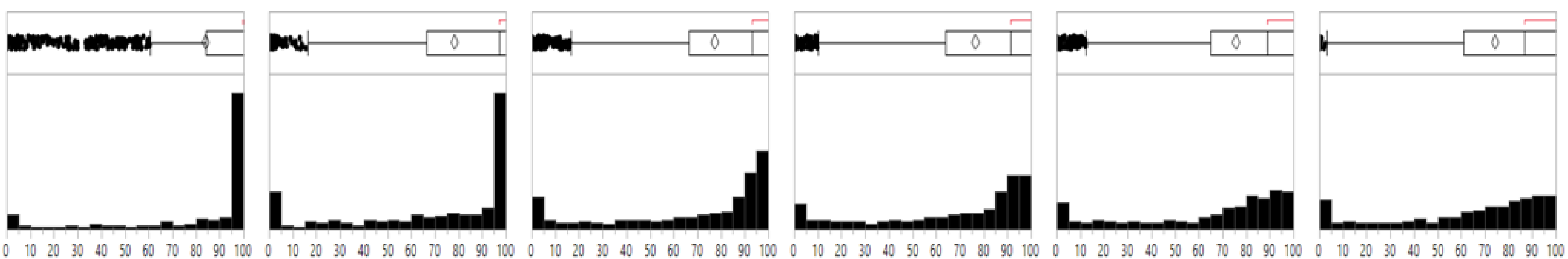
Figure 21: Distribution of individual indexes in AC pavement type after applying the different rate of errors (Base Scenario, 10, 30, 50, 70, and 90% rate of error, left to right)



Distribution of cracking index after adding different error rate in COM pavements

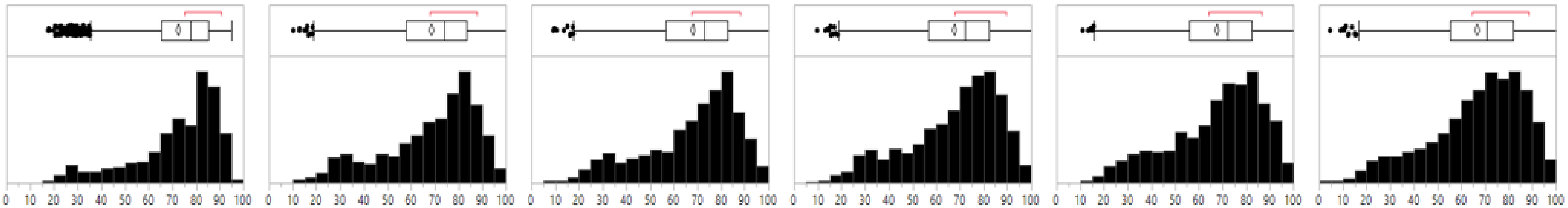


Distribution of rutting index after adding different error rate in COM pavements

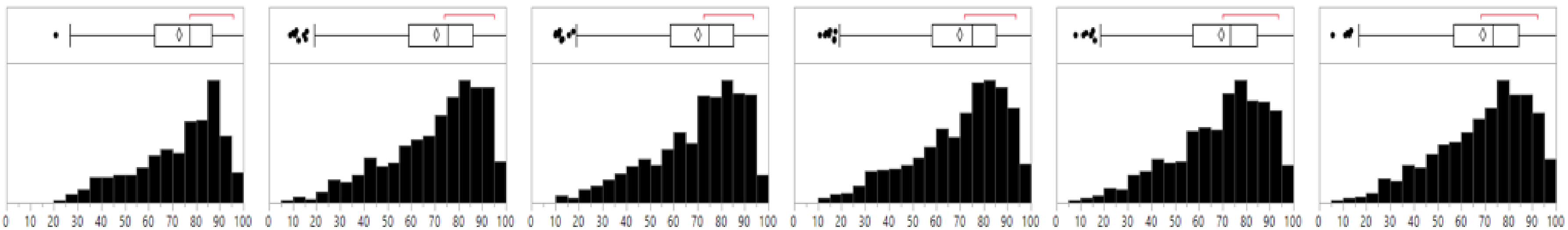


Distribution of riding index after adding different error rate in COM pavements

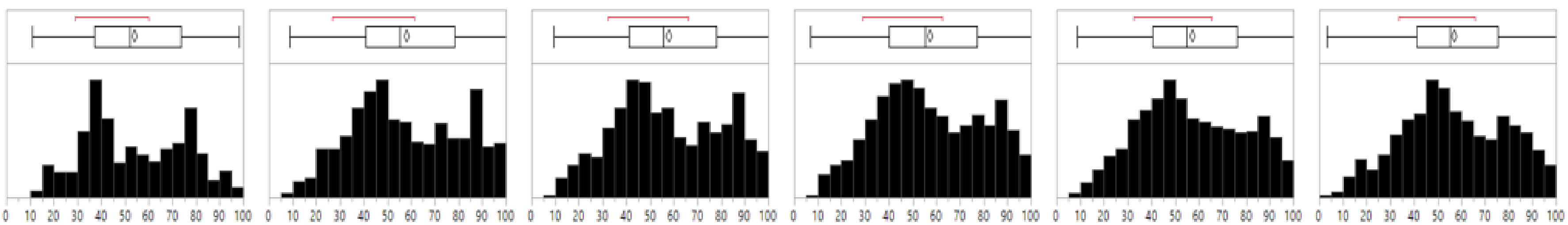
Figure 22: Distribution of individual indexes in COM pavement type after applying the different rate of errors (Base Scenario, 10, 30, 50, 70, and 90% rate of error, left to right)



Distribution of PCI after adding different error rate in COM pavements



Distribution of PCI after adding different error rate in AC pavements



Distribution of PCI after adding different error rate in PCC pavements

Figure 23: Distribution of PCI in different pavement types after applying the different rate of errors (Base Scenario, 10, 30, 50, 70, and 90% rate of error, left to right)

As can be seen from Figure 23, the PCI distribution remains almost similar for different error rates in all three pavement types since the errors are applied to the individual performance indicators and the PCI is calculated based on these new values. Figures (24-26) show the PCI values for the base and 5 error scenarios for the three pavement types (PCC, AC, and COM).

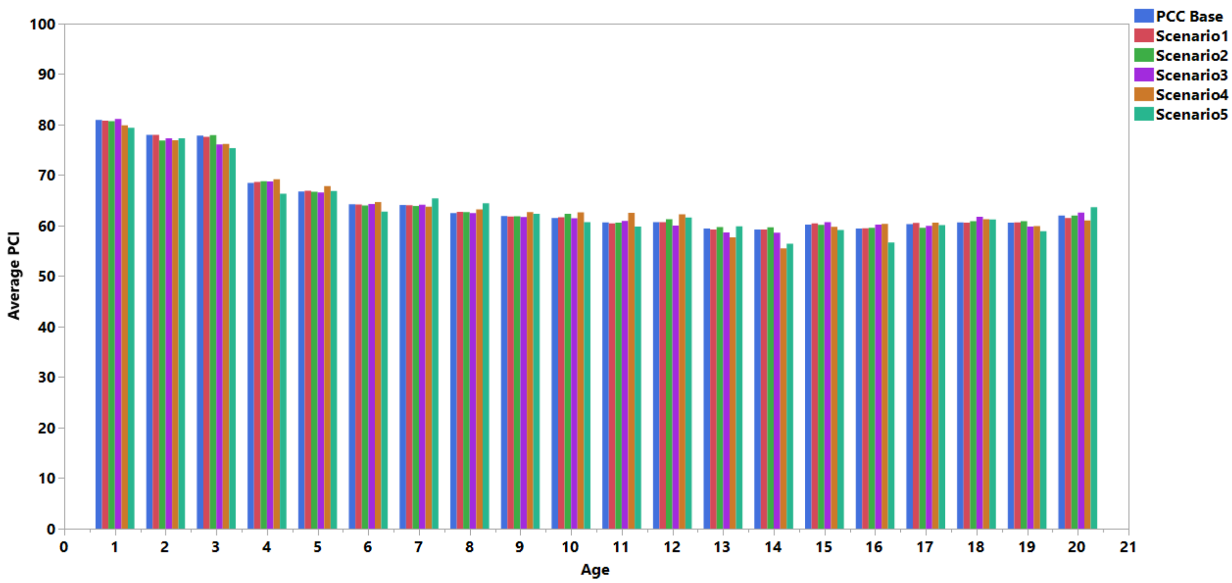


Figure 24: Weighted average PCI for PCC pavements vs pavement age

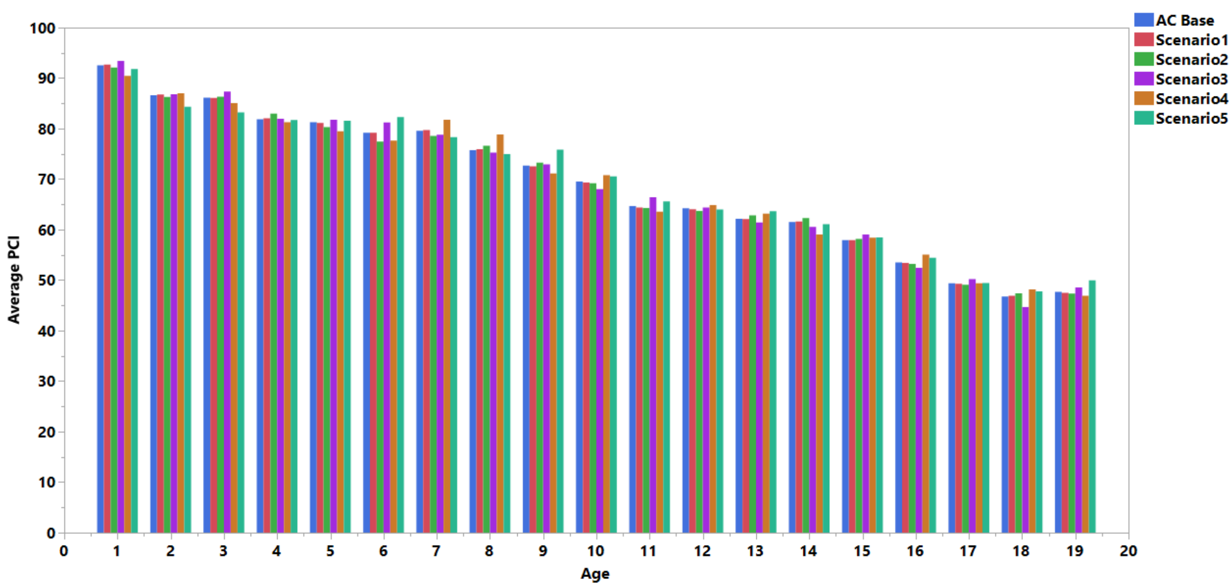


Figure 25: Weighted average PCI for AC pavements vs pavement age

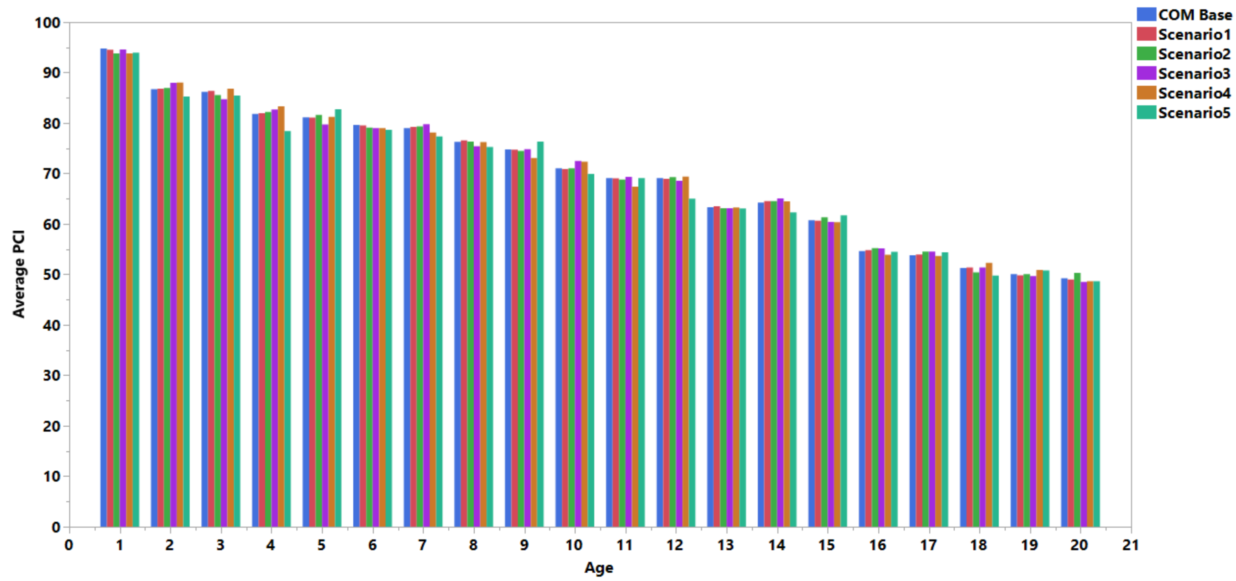


Figure 26: Weighted average PCI for COM pavements vs pavement age

Decision tree and maintenance assignment

Each state DOT has its own decision tree to assign treatment actions: if the condition of the pavement is acceptable, then no action is needed; otherwise, treatment is assigned based on the decision trees. For this study, this is achieved by adopting existing decision trees and matrices developed by the Iowa DOT. Because each pavement type has its own performance indicator, different decision trees are available based on pavement types. Table 7 shows the decision tree for AC and COM pavements and Table 8 shows the decision trees for PCC pavements.

Table 7: Modified Iowa DOT decision matrix for AC and COM pavements

K	PCI	Cracking Index	Riding Index	Rutting Index	Treatment
1	>50 and <80	>40	>=40	<50	Thin Surface treatment
2	>20 and <50	>40	>=40		Functional rehabilitation
				>=50	
3	>20 and <50	<40	<40	>50	Minor Structural
4	>20 and <50	<40		>50	Major Structural
5	<=20				Reconstruction
6	Otherwise				Do nothing

Table 8: Modified Iowa DOT decision matrix for PCC pavements

K	PCI	Cracking Index	Riding Index	Faulting Index	Treatment
1	>20		>40 and <=60		Diamond Grinding
				>=50	
2	>20		<=40		Functional rehabilitation
3	>20		0		Minor Structural
4	>20	>40			Major Structural
5	<=20				Reconstruction
6	Otherwise				Do nothing

It is worth mentioning that the PCI is not the only factor for assigning the treatment actions as can be seen from the decision trees. It is possible to have different treatment assignments for sections with similar PCI values when the other performance indicators are different (Cracking, Riding, Rutting, and Faulting indeces).

Cost calculation

Based on the condition of the pavement section and the treatment assignment from the decision tree, the cost of maintenance can be calculated. Iowa DOT has its own unit cost for each treatment action. Table 5 shows the unit cost for each treatment action based on mile lane units.

Table 9: Cost of Treatments (Mile-Lane)

Asset type	Treatment	Unit cost
Pavement	Thin surface treatment	$25,000/ mile-lane
	Diamond grinding	$30,000/ mile-lane
	Functional rehabilitation	$220,000/ mile-lane
	Minor structural	$240,000/ mile-lane (Primary) $380,000/ mile-lane (Interstate)
	Major structural	$400,000/ mile-lane (Primary) $550,000/ mile-lane (Interstate)
	Reconstruction	$600,000/ mile-lane (Primary) $750,000/ mile-lane (Interstate)

Optimization

The selection process in this study is based on maximizing (optimizing) the total benefit acquired from the different treatments applied to the sections that are given a limited budget. Several definitions of benefit can be found in the literature; however, one of the widely used definitions is the area between the deterioration curve without treatment activity and the expected deterioration curve after treatment, as depicted in Figure 21-23.

Based on the decision trees and performance indicators affected by different error rates, the treatment activities were identified for each test section. As a result of the selected treatment activities, the cost of treatments for each section was calculated based on the Iowa DOT unit cost, mile-lane. Each treatment activity can extend the life of pavements by increasing the PCI. Tables 10 and 11 show the proposed reset values on performance curves for the different pavement types as recommended by the Iowa DOT. Reset values represent the increase in PCI values attributed to each treatment.

Table 10: Reset Values for PCC pavements

Treatment	**PCI**
Diamond Griding	+20 (improve)
Functional Rehabilitation	80
Minor Structural	90
Major Structural	95
Reconstruction	100

Table 11: Reset Values for AC and COM pavements

Treatment	**PCI**
Thin Surface	+20 (improve)
Functional Rehabilitation	80
Minor Structural	90
Major Structural	95
Reconstruction	100

After increasing the PCI for each section based on the reset values, the total benefit for each section was calculated. For determining the total benefit, the area under deterioration without treatments needs to be calculated first, as shown in equation 1. Figure 21 illustrates the pavement deterioration curve without applying the treatment.

$$\text{Area1} = \int_a^b f(x)dx \qquad (1)$$

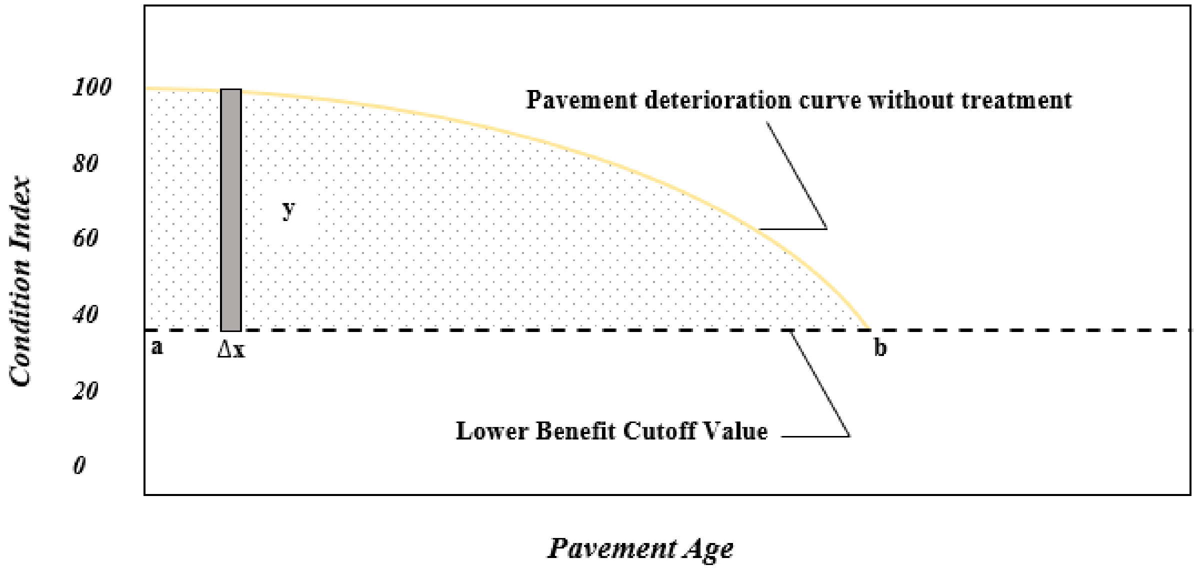


Figure 27: Deterioration curve without treatment

In the next step, both areas under the with-treatment and the without-treatment curves need to be calculated, as shown in equation 2. Figure 22 illustrates the area under both deterioration curves.

Area2 = $\int_a^b f(x)dx + \int_b^c f(x)dx$ (2)

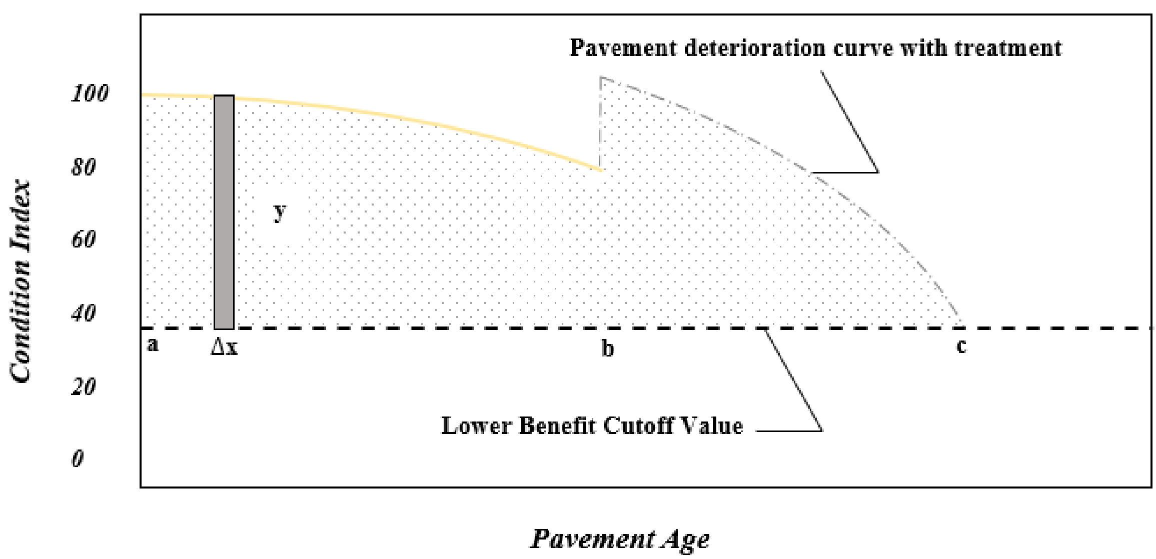


Figure 28: Deterioration curve with treatment

Then, the total benefit is the difference between the areas resulting from equation 1 and equation 2, as shown below in equation 3 and figure 23:

Total Benefit = Area1 – Area2 (3)

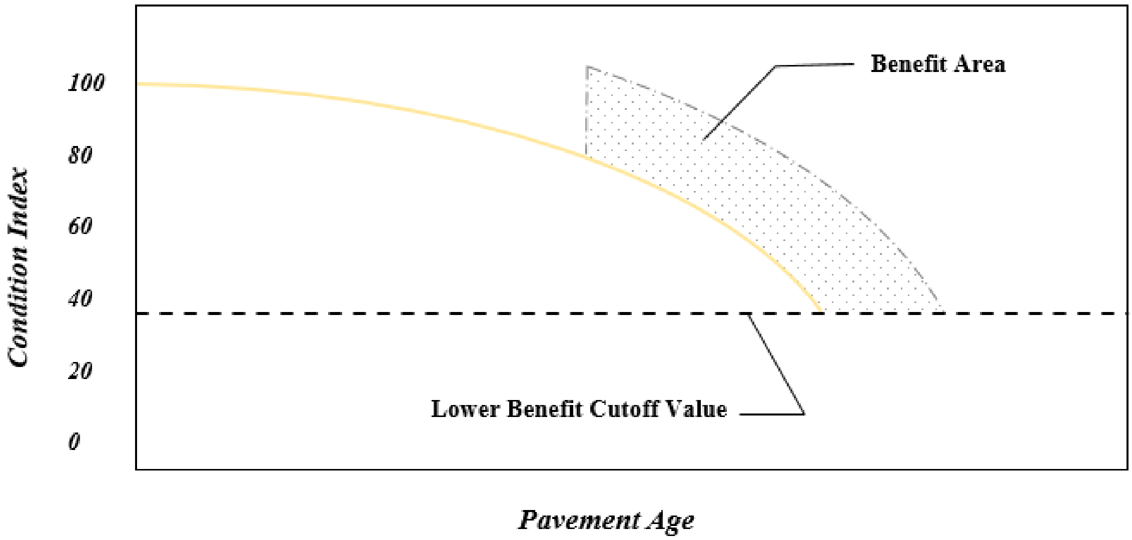


Figure 29: Total Benefit Area

Optimization is done to maximize the total benefit when the budget is limited and is less than the actual total cost. This analysis showed the effect of increasing the error on the benefit. The optimization part was conducted in Microsoft Office Solver in the following steps:

- As mentioned earlier, five different scenarios based on a different amount of error contribution to the prediction model were investigated to see how an increase in error rate can change the decision-making process.
- The total benefit for each scenario was calculated for each pavement type for each test section, as described above.
- The total cost of treatments for each scenario was calculated for each test section based on decision trees and the unit costs.

- The limited budget, which is 15% less than the total cost is assumed as an available budget
- By increasing the error contribution, the total cost (need) for maintenance actions increased, the available budget stayed constant, and Solver optimized these conditions to maximize the total benefit.

The following section describes the outcomes from the optimization part and also the effect of increasing error contribution on the prediction model in terms of cost and benefit.

Results and Discussion

This section describes the results of simulating the contribution of error in the prediction model developed by LSTM. The overall outcomes from different error rates are presented in Tables 8 and 9. Five different scenarios were conducted which show the impact of an error increase on the cost and benefit. All scenarios were compared with the base scenario in which no error is applied to the prediction model.

Table 12: Cost of treatments over 20 years for five different scenarios (in a million dollars)

Cost	Base Scenario	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
AC	$54.071	$62.929	$75.210	$91.734	$101.879	$92.958
COM	$53.891	$90.714	$76.044	$114.129	$103.085	$155.484
PCC	$74.402	$74.948	$78.611	$90.138	$88.531	$107.774

Table 13: Rate of benefit reduction with different amount of error contribution

Benefit	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
AC	%2	%3	%5	%5	%8
COM	%4	%4	%10	%9	%22
PCC	%6	%6	%8	%11	%20

Based on the reported results, the base scenario has the minimum maintenance cost in all three pavement types. The results showed that the higher the error rate, the more money was needed for maintaining the pavement network. This result is based on the fact that when the prediction model cannot predict properly, some sections will have unnecessary maintenance. Also, maintaining some sections in need of urgent maintenance were delayed; as a result of which, the treatment action would change, and more expensive treatments would be needed for these sections. Table 8, which shows the results of the needed cost for different scenarios, is based on the predicted value of 50 AC, 80 COM, and 80 PCC sections with different lengths in 20 years.

Also, results showed that an increase in the error rate could reduce the benefit when agencies face a budget reduction or limitation. As a result of a higher benefit reduction rate, the overall pavement network condition could be worse. In all pavement types for the first scenario, where minimum error contribution was applied to the predicted value, a minimum rate of benefit reduction was observed. The more error added to the predicted values, the higher the percentage of benefit reduction.

Conclusion

The results of the pavement prediction model developed with LSTM were used in this study. To investigate the effect of increasing the error on the decision-making process, five different scenarios were assumed from the minimum error rate to the maximum error rate. The scenarios were investigated by adding different rates of error (%10, %30, %50, %70, and %90) to the predicted values of performance indicators. The PCI was calculated based on the modified performance indicators with different error rates. The Iowa DOT decision trees were used to check the effect of the prediction model accuracy on the cost of treatments in different pavement types.

The results from the different scenarios were compared to check whether decreasing or increasing the accuracy of the prediction model can have an effect on the cost of maintenance. Also, all five scenarios were compared with the original output of the prediction model as a base scenario in terms of cost and benefit. Based on the reported results, increasing the rate of error has a significant correlation with the cost of maintenance activities, and agencies need to improve the prediction accuracy of their current models to prevent spending unnecessary costs. The more error was added to the prediction model, the higher the cost of maintenance needed for maintaining the pavement network. The base scenario has the minimum cost compared to the other five scenarios. Also, increasing the rate of error into the prediction model can increase the rate of benefit reduction and consequently worsen the pavement network condition.

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CHAPTER 4. GENERAL CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH WORK

A pavement prediction performance model is necessary at the network level for assigning the available funding to any maintenance and rehabilitation activities, and at the project level for determining the best strategies. The objective of this study was to develop a new framework using the LSTM approach to predict the future condition of composite, asphalt, and concrete pavements. Also, for the Iowa DOT, the effect of prediction accuracy was investigated in terms of the cost and benefit of maintenance and rehabilitation activities on test sections in the state of Iowa.

The deterioration models of the historical pavement condition data for the state of Iowa were developed using an LSTM approach. The proposed model and current method in Iowa DOT were compared to investigate the model accuracy. Validation of the models indicated that the LSTM model predictions were generally close to the actual values of the riding, rutting, faulting, and cracking indices, as well as PCI. The comparison between the developed model and the individual regression models used by the Iowa DOT from the three different pavement types indicates that the LSTM model achieved a higher prediction accuracy than the Iowa DOT individual regression models. A hypothesis analysis of mean was conducted for the PCI residual in both techniques, and the results exhibited less LSTM bias than those of individual regression models.

Each of these two methods has their own advantages and disadvantages. The equation of the individual regression models requires an annual update, and each section will exhibit a new year-by-year behaviour, changes the prediction process more complex. The LSTM provides one more consistent model compatible for all sections using a training process. The LSTM approach was sensitive to the data fluctuation resulting from unrecorded maintenance activities. While the evaluation of the regression models was restricted to residuals between the fitted functions and the actual readings, the evaluation of the LSTM was based on its ability to predict full performance curves not included during the training stage.

The results of the pavement prediction model developed with LSTM were used to investigate the effect of increasing the error on the decision-making process. Five different scenarios were assumed from the minimum error rate to the maximum error rate. The scenarios were investigated by adding different rates of error (10%, 30%, 50%, 70%, and 90%) to the predicted values of performance indicators. The PCI was calculated based on the modified performance indicators with different error rates. The Iowa DOT decision trees were used to check the effect of the prediction model accuracy on the cost of treatments in different pavement types.

The results of different scenarios were compared to check whether decreasing or increasing the accuracy of the prediction model can have an effect on the cost of maintenance. Also, all five scenarios were compared with the original output of the prediction model as a base scenario in terms of cost and benefit. Based on the reported results, increasing the rate of error has a significant correlation with the cost of maintenance activities, and agencies need to improve the prediction accuracy of their current models to prevent errors in calculating cost. The more error was added to the prediction model, the higher the cost of maintenance needed for maintaining the pavement network. The base scenario has the minimum cost compared to the other five scenarios. Also, increasing the rate of error into the prediction model can increase the rate of benefit reduction and consequently worsen the pavement network condition.

Overall, an LSTM model can be a decision support tool that can help state DOTs for resource allocation and maintenance activities in the pavement management system. Also, the importance of prediction accuracy was proven, which can encourage agencies to work on this aspect of pavement prediction models in each pavement management system.

This research had some limitations as follows:

1. In many cases in the PMIS database, minor maintenance and rehabilitation records were not available; so, the impact of maintenance on pavement condition overtime was not modelled in this study.
2. Segments with PCI values increasing over time were discarded from the analysis because they might be associated with unrecorded maintenance activities. So, the training process did not cover the entire database.
3. Because in the LSTM algorithm, the dependent and independent variables are the same and prediction is time-dependent, external factors such as weather information cannot be involved in the condition prediction.
4. The inconsistency and missing value in the PMIS database were observed, which can decrease the accuracy of prediction in the time-dependent algorithm such as LSTM.
5. The impact of section structure and design are not included in the model.

In this research, some of the assumed variability captured but not necessarily the overall uncertainty in predictions, so, future work might address the uncertainty levels in predictions and the contributing components. Also, in this research prediction conducted based on univariate LSTM model, future work might address multivariate LSTM model, that can capture the impact of each index into the PCI. Also, historical weather data could be another variable that can involve in the multivariate LSTM prediction model for future research work.