PERFORMANCE-BASED MANAGEMENT AND CONDITION PREDICTION OF CIVIL INFRASTRUCTURES

A Thesis Presented

By

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ABSTRACT

Civil infrastructure is the vital element of robust economies. It is crucial to constantly monitor and maintain infrastructure systems as their failure adversely impacts business and network users. Performance-based monitoring of infrastructure provides the most cost-effective infrastructure management solutions. In this study road networks as a subset of infrastructure systems have been analyzed. Pavement management systems consist of elaborate interactions among deterioration and condition prediction models, alternative assessments, and administrative decisions.

Catastrophic events such as storms and floods impose additional costs and maintenance requirements to infrastructure systems. Therefore, condition prediction of pavements in extreme weather events is critical to management system. In this study, a model is proposed which accounts for condition prediction and deterioration in extreme weather events such as floods and snowstorms. Therefore, an accurate deterioration model will be proposed to reduce the risks associated with PMS planning and decisions.

While many studies have been focused on cost-minimizations of treatment strategies, this study provides risk-based evaluation of remaining service life, network quality, and financial consequences of treatment strategies, as well various monitoring frequencies. This study shows that in addition to treatment strategies, the frequency of pavement condition monitoring has significant cost, quality, and serviceability implications. Furthermore, data-driven probabilistic models have been proposed to equip executives with risk-informed decision-making platforms.
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INTRODUCTION

Civil Infrastructure is the network of interconnected systems that serve and support societal and economic consignments. Civil infrastructure encompasses transportation systems (interstate highways, road, bridges, airports, rapid mass transit systems), utilities (pipelines, power, communications), and public facilities (recreation, postal facilities) [41].

Over the past century, United States has made substantial investments on highways, rail systems, ports, canals, water distribution systems, and modern fiber optic systems [40]. Advanced infrastructure networks with satisfactory performance provide a platform for sustainable business growth and global competitive economy, as well as societal advancements.

A practical civil infrastructure also provides resiliency to manmade hazards or natural disasters such as extreme weather events or earthquakes [34]. These events can impair the functionality of all or parts of the network or cause system outage. A well-designed and maintained infrastructure system would be able to compensate for the system outages, preserve primary functionality, or rapidly revive it. On the other hand, deficiency or failure of infrastructure has adverse financial consequences on business and eventually network users.

With the rapid growth of economy and excessive demands, these systems have become more complex in terms of design and maintenance. Consequently, there is an incessant increase in expenses of maintaining the safety and quality of infrastructure systems. Repair and improvement of infrastructure systems exhausts billions of dollars from state, federal, and local governments annually [41]. Furthermore, The American Society of Civil Engineers indicates that Americans spend $54 billion each year in vehicle repairs caused by poor road conditions [41]. Thus, reliable infrastructure health monitoring, maintenance, and management systems are vital for sustainable economic growth, resiliency, and progressive social impacts.
Health monitoring of infrastructures provides time-based information about the infrastructure condition. Performance-based implementation of maintenance strategies corresponding to condition data is significantly more cost-effective [33]. Furthermore, performance-based maintenance of civil infrastructure can decelerate aging, damage accumulation, and therefore significantly improve the service life [33].

Currently, many aging civil infrastructure are still in use despite approaching or even exceeding their primary design life [33]. Thus, it is of great importance to constantly monitor and maintain the condition of operating infrastructure through a performance-based infrastructure management system.

This study is motivated by providing a systematic performance-based infrastructure management system with the capacity of incorporating risks into decision making, and providing accurate deterioration condition prediction. Civil infrastructure transportation systems were chosen as the primary focus of this study.

The transportation system is one of the pivotal foundations of a society [34]. There are more than 4 million miles of public roadways in United States, serving as vital links for carrying goods and people. Based on American Society of Civil Engineers’ (ASCE) report in 2013, roads, are graded D, interpreted as poor. In fact, 32% of major roads’ conditions are classified as poor or mediocre. Such poor conditions have been causing almost one-third of traffic fatalities in the United States. In addition, poor pavement conditions impose high repair and operating costs to the road users. Based on Federal Highway Administration’s estimate, condition and performance improvement of roads requires $170 billion of capital investment [60].

Restoring serviceability of roadways has prominent societal and economic benefits. However, insufficient funding often limits timely repairs and rehabilitation of the pavement. As needs continue to outpace the availability of funding, the proper selection of road maintenance and improvements becomes more crucial [36]. To maximize the benefits and minimize the overall costs of maintaining or preserving the transportation systems, highway administration has provided guidelines for developing pavement management systems as early as the 1970s [37].

Hudson et al. [38] describe a Pavement Management System (PMS) as “...a coordinated set of activities, all directed toward achieving the best value possible for
the available public funds in providing and operating smooth, safe, and economical pavements.”

PMS includes a set of plans, decisions and maintenance actions with the goal of maintaining the road network quality beyond a desirable threshold, minimizing budget expenditures and environmental effects, as well as maximizing network service life [1].

It should be emphasized that PMS decisions should not just focus on cost minimizations and therefore selecting the cheapest alternatives. Yet, an active decision making system is required to propose a compromised solution that offers balance between cost and quality.

To manage road networks in a balanced and cost-effective manner, highway agencies monitor and collect network data including pavement condition and applied treatments. As Figure 1 illustrates PMS elements, these data are further used to enhance PMS decisions. PMS elements are further described in details.
Figure 1 PMS Elements
Performance Measures

Pavement performance is measured as serviceability of a pavement over the desired evaluation period which is obtained by inspection or prediction. Typically, pavement condition is evaluated according to four categories of measurements: roughness, surface distress, structural capacity, and skid resistance. Various indices have been developed to measure pavement performance in terms of one or multiple of these aspects. For example, the International Roughness Index (IRI) is used to characterize the ride quality of a pavement. These four indicators can be combined and presented by an overall condition index, such as the Pavement Condition Index (PCI), which entails information on various pavement distresses [39].

Deterioration Models

Pavement deterioration model is an imperative component of any pavement management system since the future budget and M&R plans would be developed based on the predicted pavement performance measures [60].

Cost-Effectiveness Analysis And Evaluation

There are various methods to estimate life cycle cost and determine the cost-effectiveness. All these methods express the cost-effectiveness by linking some of the important serviceability attributes such as life extension or network quality to long-term costs, over a specific analysis period [13].

Numerous studies have been focused on providing the most cost-effective methodologies for pavement management systems [4, 5, 7, 8, 11, 13]. While each of the suggested methods has been successful to some extent, one major drawback is performing life cycle analysis based on a deterministic approach. Therefore the diversity in input and output of the analysis is not reflected. Deterministic models can cause exclusion of critical and
decision-changing information. Subsequently, they can lead to mistrust in credibility of analysis or what Walls and Smith (1998) [4] perfectly notes as “endless debate over which alternative truly has the lowest life-cycle cost.”

Contrarily, a probabilistic approach can accommodate uncertainties of input variables and generate an entire range of outcomes. This approach can be especially useful when treatment decisions have to be made based on a certain pre-allocated budget [4].

Hence, this study is motivated by providing a probabilistic management platform to account for associated risks and represent the tradeoffs between the performance maximization and life cycle cost minimization. Furthermore, probabilistic models are data-intensive. In order to utilize these models in their full potential, up-to-date data and accurate deterioration models are required. To fulfill this goal, one chapter of this study is allocated to propose an accurate and thorough method for performance based condition prediction including extreme weather events.
1 PROBABILISTIC RISK ANALYSIS AND DECISION MAKING

Probabilistic risk analysis methods are integral components of risk-informed management decisions. These methods are empowering quantitative tools that facilitate assessment and decision-making procedures [35].

Numerous studies have been focused on providing probabilistic risk analysis solutions for different aspects of PMS. Tighe et al. (2001) [15] incorporated pavement material cost and as built pavement thickness as probability based inputs of analysis. Using Monte Carlo simulations, pavement layer cost and total life cycle cost were found. Reigle et al. (2002) [10] considered variability of probabilistic input such as pavement design parameters, performance models, and cost components into LCCA and found cost implications of treatment alternatives, again with Monte Carlo simulations. Salem et al. (2003) [42] evaluated costs of repair alternatives in highway roads by incorporating probabilities of failure of construction/rehabilitation alternatives (failure time) in life-cycle model.

LCCA analyses in formerly mentioned cases are based on estimated deterioration curves. Correspondingly, Monte Carlo simulations are dependent on the existing condition of the pavement, which is an estimate, obtained from deterioration curves. In addition, repair alternatives over the analysis period are hypothetically assigned based on a decision tree or a maintenance panel. Each of these fundamentals adds to the uncertainty of the final evaluation of results.

Therefore, this study is motivated by the substantial need of performing a reliable data-driven analysis.

Additionally, majority of the available studies are focused on financial implications of treatment strategies, and least cost alternative. As mentioned earlier, this study is determined to suggest management options by considering the tradeoffs between cost and
service quality. Hence, this chapter leverages the probabilistic data-driven LCCA to provide PMS solutions based on various outcomes (e.g. cost, remaining service life, network quality) of treatment strategies, as well as pavement monitoring frequency.

1.1 Data and Analysis Scheme

Available data for this study included history of pavement condition and repair activities from 1989 to 2014 in cities of Norwalk, CT and Concord, MA. Reported sections included various functional classes based on traffic distribution: Arterial, Collector, Residential and Local sections. Since applied treatments and time of treatment executions in these functional classes vary, this study was only focused on Arterial sections.

Treatment Type

Activities applied on Arterial sections included Crack Seal, (Thin) Overlay, Mill & Overlay, and Reclaim. These activities were categorized as Preventive (Crack Seal, Thin-Nonstructural Overlay), Rehabilitation (Mill & Overlay) and Emergency (Reclaim). Also, with respect to PCI threshold of implementing mentioned repairs, preventive items performed in lower PCI conditions were categorized as Corrective. Corrective actions are usually performed when sections require maintenances such as rehabilitations, but expenditures limit performing those actions. Therefore, corrective maintenances, which are less costly, are performed to temporarily enhance the pavement condition.

Crack seal and thin hot-mix overlays are the most common preventive actions. Crack seal is applied to prevent the penetration of water and debris into pavement cracks and therefore retard the deterioration process. Since this treatment doesn’t increase the structural capacity of the pavement, its effect lasts only a few years, and further maintenance or repetition is required [12]. Thin hot-mix overlays are also non-structural repairs aiming to enhance the ride-quality, modify surface irregularities, and providing surface friction and drainage [12].
Mill and overlay actions include removing the 1.5 to 3 inches of pavement, and filling a new layer which enhances the structural capacity of the pavement.

Pavement Reclamation takes place when the pavement is structurally obsolete and includes removal and replacement of the entire existing structure [17].

**Treatment Selection**

Available data of implemented repairs had some discrepancies as well. For instance, some monitoring data indicated increase in PCI while no maintenance activities were reported. To compensate for these missing data, PCI threshold of reported treatments was found. Thresholds were obtained from the PCI distribution of sections for each repair type and with respect to mean PCI values. Then, unreported repairs were estimated based on the obtained PCI thresholds. These steps were iterated until convergence was obtained. Figure 1-1 & Figure 1-2 show the results after convergence of iterations.
Figure 1-1: Treatment Strategies in Concord
Figure 1-2 Treatment Strategies in Norwalk
**Cost Data**

Available data included Agency Costs (Dollar Value per Square Yard) for activities in each functional class and for different years of implementation. Due to lack of data, other costs such as User Costs were not included in analysis to avoid uncertainty. For the years that treatment unit cost was not available, a discount rate of 4% was considered to convert the cost to the desired analysis year. This rate was considered based on the information included in datasets.

Once all the repairs and their costs were recognized, analysis could be performed. Following chapters are structured to evaluate the analysis results in terms of treatment strategies and monitoring frequency of road networks.

### 1.2 Framework and Methodology

Some of the most common analyses methods are Life Cycle Cost Analysis (LCCA), Cost-effectiveness Analysis, Equivalent Annual Cost (EAC), and Longevity Cost Index [13].

Cost-effectiveness analysis requires pavement performance curve and formulates effectiveness in terms of the area under the performance curve [13,12]. EAC method provides a deterministic ratio of unit cost per life expectation of treatment [13,12]. Longevity cost index also relates the present treatment cost to life as well as traffic [13,12]. LCCA evaluates the effectiveness of competing treatment strategies by calculating repair costs over an analysis period.

Each of these methods has strengths and drawbacks. For instance, EAC method can generate bias in assigning rating factors, and influence the analysis result [12]. Also, neither of EAC and longevity analyses account for pavement condition. Cost-effectiveness analysis, despite its advantages, does not encompass all distresses and therefore some of the required maintenances are disregarded [13]. Deterministic LCCA suggests the cheapest treatment as the best option regardless of the pavement condition. However, this study has leveraged a data-driven probabilistic approach to compensate for
the deterministic analyses tradeoffs, and account for the involved risks. Finally, LCCA was used as the fundamental analysis method in this study.

**Life Cycle Cost Analysis (LCCA)**

In order to perform LCCA analysis, a certain analysis period and an economic indicator should be defined. In this study Net Present Value (NPV) was chosen as the economic indicator for performing LCCA. Required steps for assigning the analysis period are later described.

**Net Present Value (NPV)**

NPV is the monetary value typically obtained from deducting discounted costs from discounted benefits. However, in this study it is assumed that keeping the road network above a certain threshold would yield similar benefits and therefore NPV is presented in terms of costs. Therefore, in the following analyses, higher NPVs indicate higher costs. Also, it was assumed that initial costs for sections belonging to one functional class were similar. Therefore, NPV was calculated using equation (1-1).

\[
NPV = \sum_{k=1}^{N} \text{Repair Cost}_k \left[ \frac{1}{(1+i)^n} \right]
\]  

(1-1)

Where,

\[ i = \text{Discount rate} \]
\[ n = \text{Year of expenditure} \]

**Analysis Period**

In this study, available sections were constructed at different times. Likewise, reclamation of sections isn’t performed at the same time. Therefore setting an accurate analysis period was substantial for analysis. First, sections were categorized as clusters
with similar survey beginning times. Then, analysis period was performed on each of these clusters. This approach eliminates the effect of different pavement age on LCCA.

Considering the fact that sections had PCIs of 100 at initial surveys, these start times were accounted as construction time and start of analysis period. In addition, end of analysis period was determined based on terminal life of sections in each cluster. Terminal life for each section was defined as when PCI reaches the reclaim threshold. For sections that didn’t experience reclaim during the survey time-span, PCI values were extrapolated to reach reclaim threshold. Extrapolation was based on an exponential decaying curve, fitted into data-points were no repair was implemented. After decay curve was obtained from the last available deterioration data, the curve was used after the last surveyed PCI to find terminal life. Figure 1-3 & Figure 1-4 show this procedure on a sample section in each city. Data of presented figures are presented in Table 1-1 & Table 1-2.

Figure 1-3 Decay Curve Of A Sample Section In Concord
Table 1-1 Sample Section Decay Curve Data In Concord

<table>
<thead>
<tr>
<th>Year</th>
<th>PCI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1993</td>
<td>98</td>
</tr>
<tr>
<td>1997</td>
<td>54</td>
</tr>
<tr>
<td>1998</td>
<td>100</td>
</tr>
<tr>
<td>2002</td>
<td>99</td>
</tr>
<tr>
<td>2005</td>
<td>85</td>
</tr>
<tr>
<td>2010</td>
<td>74</td>
</tr>
<tr>
<td>2014</td>
<td>61</td>
</tr>
</tbody>
</table>

Table 1-2 Sample Section Decay Curve Data In Norwalk

<table>
<thead>
<tr>
<th>Year</th>
<th>PCI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1994</td>
<td>77</td>
</tr>
<tr>
<td>2000</td>
<td>75</td>
</tr>
<tr>
<td>2001</td>
<td>100</td>
</tr>
<tr>
<td>2005</td>
<td>78</td>
</tr>
<tr>
<td>2008</td>
<td>74</td>
</tr>
<tr>
<td>2012</td>
<td>100</td>
</tr>
</tbody>
</table>
Figure 1-4 Decay Curve Of A Sample Section In Norwalk

PCI = 2E+40e-0.044(Year)
$R^2 = 0.92527$
To avoid the uncertainties about repairs and their costs in extrapolated years, analysis end time was set as when the first section in cluster reaches the reclaim threshold. Consequently, any section that had a terminal life after end period of analysis produced a salvage value in its remaining life. Figure 1-5 illustrates the analysis procedure.

**Salvage Value**

Salvage Value for each category was calculated at the time when earliest reclaim had occurred. Therefore, from that time up to the terminal life of the section was considered as remaining life.

When all discounted costs and salvage values were calculated, NPV can be computed.

**Evaluation**

After performing LCCA probabilistic distributions are used to evaluate the analysis. Once the appropriate distributions were assigned to the analysis results, goodness of fits should be examined. In this study, chi-square test was implemented to test the null hypothesis at 5% significance level and evaluate the goodness of fit.

The chi-square test estimates parameters from data to evaluate goodness-of-fit. Chi-square test statistics are obtained by pooling data into bins and calculating the observed and expected counts for the bins. P-value is one of the Chi-square test statistics, which is the probability of obtaining the observed or more extreme sample results under the null
hypothesis. If p-value turns out smaller than the specified significance level, null-hypothesis is rejected at the determined significance level. Chi-square value calculation is represented in equation (1-2).

\[ \chi^2 = \sum_{i=1}^{N} \frac{(O_i - E_i)^2}{E_i} \]  

(1-2)
1.3 Treatment Strategies

1.3.1 Pavement Maintenance Terminology

Treatment strategies are commonly categorized in accordance with AASHTO definitions. The most commonly defined categories include Preventive Maintenance, Pavement Rehabilitation, and Pavement Reconstruction.

AASHTO states preventive maintenance as “the planned strategy of cost-effective treatments to an existing roadway system and its appurtenances that preserves the system, retards future deterioration, and maintains or improves the functional conditions of the system without increasing structural capacity.” It should be noted that treatments are categorized as preventive when applied to preserve the pavement. Same action items applied on a deteriorated pavement are no longer preventive and are categorized as corrective strategies.

AASHTO Highway Subcommittee on Maintenance also defines Pavement Rehabilitation as "structural enhancements that extend the service life of an existing pavement and/or improve its load carrying capacity. Rehabilitation techniques include restoration treatments and structural overlays”. Finally, Pavement Reconstruction is outlined as the complete removal and replacement of the existing structure with either recycled or new materials. Reconstruction is implemented when the pavement fails or becomes functionally obsolete [17].

The efficiency of these treatment strategies varies significantly within the context of their application. Mentioned below are the most common influential factors that lead to choosing one or a group of treatment strategies over another: [12, 16]

- Type and level of distress
- Pavement type and condition
- Load factors including traffic and functional class of the road
- Expected service life of network
Environmental factors such as climate
• Availability of material
• Costs and budget restraints
• Traffic and facility interruption
• Capability of contractors and experience with treatments
• Agency jurisdictions and political issues

Evaluating the success of each treatment strategy is crucial for administration planning and decision-making. Next section describes the most widely used analysis methods for evaluating the cost-effectiveness of treatment strategies.

### 1.3.2 Cost-Effectiveness Analysis And Evaluation

Effectiveness of treatment strategies can be evaluated with various analysis methods. Significant measures of assessing the effectiveness of treatment strategies that are accommodated in different analysis methods are financial consequences, maintained network quality or increased average pavement condition, life extension, and increased area under performance curve comparing to a base alternative which is classically “do nothing” [14].

LCCA is best used for evaluating financial consequences of pavement maintenance strategies over the analysis period, and assessing the competence of each alternative in terms of Net Present Value or other scales [2]. Hence, the remainder of this chapter aims to provide a performance-based analysis of consequences of treatment strategies in terms of cost, remaining service life, and network quality.

### 1.3.3 Financial Consequences Of Treatment Strategies

Numerous studies have analyzed the impacts of treatment strategies on LCCA (Zaniewski et al. 2009; Lamptey et al. 2004; Peshkin et al. 2004;)[8,6,11]. Other Studies also show economic value on implementing rehabilitation strategies once or twice prior to reconstruction [5]. Rajagopal et al. (1990) [7] performed LCCA analysis of three types
of treatments applied at different pavement conditions and found that life cycles are immensely increased when treatments are applied while pavement is experiencing a slow deterioration rate.

In this study, using LCCA, NPVs of different treatment strategies in cities of Concord and Norwalk were obtained. Results are then evaluated based on the distinctions of practices in the two cities. Furthermore, the analysis provides a baseline for evaluating successful strategies based on NPV values.

Based on Figure 1-6 (a) in analysis of Concord, when NPV is limited to small values, preventive maintenances provide the highest probability of meeting the budget criteria. Also, as shown by Figure 1-6 (b) implementing preventive activities yield the lowest costs during the analysis period, at any given risk. LCCA in concord indicates that implementing corrective repairs is costly. Corrective repairs do not enhance the structural capacity. Consequently, while crack seals and thin overlays as preventive strategies performed at high PCIs are cost-effective, same action items executed as corrective alternatives at lower PCIs do not eliminate the need of rehabilitation.
Figure 1-6. Financial Consequences of Treatment Strategies in Concord
Table 1-3 shows the summary of the distributions for each treatment strategy.

### Table 1-3 Financial Consequences of Treatment Strategies, Concord

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Preventive</th>
<th>P&amp;R</th>
<th>P&amp;C&amp;R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sections</td>
<td>36</td>
<td>30</td>
<td>17</td>
</tr>
<tr>
<td>Distribution</td>
<td>Lognormal</td>
<td>Lognormal</td>
<td>Lognormal</td>
</tr>
<tr>
<td>Mean</td>
<td>2.01</td>
<td>7.15</td>
<td>9.36</td>
</tr>
<tr>
<td>Variance</td>
<td>8.00</td>
<td>2.58</td>
<td>9.84</td>
</tr>
<tr>
<td>$\mu$</td>
<td>0.15</td>
<td>1.94</td>
<td>2.18</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>1.04</td>
<td>0.22</td>
<td>0.33</td>
</tr>
<tr>
<td>Goodness of Fit: P-Value</td>
<td>0.14</td>
<td>0.37</td>
<td>0.31</td>
</tr>
<tr>
<td>$\chi^2$</td>
<td>6.91</td>
<td>0.81</td>
<td>1.04</td>
</tr>
</tbody>
</table>

Similar analysis in Norwalk reveals that Preventive and Rehabilitations costs are slightly close. This is due to the fact that the only implemented preventive action has been thin overlay. See Figure 1-7. It is required to note that unit costs of repair in Norwalk were higher than Concord.

Figure 1-7 also demonstrates that Preventive measures are the most cost-effective options for any taken risk.
Figure 1-7 Financial Consequences of Treatment Strategies, Norwalk
Life cycle analysis in Norwalk also shows that for about 60% of the times, combined Preventive and Rehabilitation (P&R) activities were more costly than joint Corrective and Rehabilitation (C&R) practice. This is due to the fact that P&R actions were implemented more frequently than C&R actions. See Figure 1-8 for details of this analysis.

- There have been sections, which only received rehabilitation treatments without any preventive or corrective actions. It is found that rehabilitations joint with corrective or preventive measures are more expensive. However, the effect of life
extension will be discussed in next section to evaluate the effectiveness from other perspectives.

Table 1-4 provides a summary of distribution of treatment strategies costs in Norwalk.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Preventive</th>
<th>P&amp;R</th>
<th>C&amp;R</th>
<th>Rehabilitation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sections</td>
<td>29</td>
<td>38</td>
<td>30</td>
<td>32</td>
</tr>
<tr>
<td>Distribution</td>
<td>Lognormal</td>
<td>Lognormal</td>
<td>Lognormal</td>
<td>Lognormal</td>
</tr>
<tr>
<td>Mean</td>
<td>9.57</td>
<td>18.37</td>
<td>15.55</td>
<td>10.16</td>
</tr>
<tr>
<td>Variance</td>
<td>16.55</td>
<td>87.87</td>
<td>14.42</td>
<td>10.20</td>
</tr>
<tr>
<td>( \mu )</td>
<td>2.18</td>
<td>2.79</td>
<td>2.71</td>
<td>2.27</td>
</tr>
<tr>
<td>( \sigma )</td>
<td>0.41</td>
<td>0.48</td>
<td>0.24</td>
<td>0.31</td>
</tr>
<tr>
<td>Goodness of Fit: P-Value</td>
<td>0.13</td>
<td>0.62</td>
<td>0.56</td>
<td>0.17</td>
</tr>
<tr>
<td>( \chi^2 )</td>
<td>4.11</td>
<td>0.96</td>
<td>5.86</td>
<td>3.54</td>
</tr>
</tbody>
</table>

Equation (1-1) can be used for probability density function of Lognormal distribution:

\[
y = f(x | \mu, \sigma) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{(\ln x - \mu)^2}{2\sigma^2}}
\]

Where,

\( \mu = \text{Log mean} \)

\( \sigma = \text{Log standard deviation} \)
1.3.4 Effect Of Treatment Strategies On Remaining Service Life

Remaining service life is one of the important factors of measuring effectiveness of treatment strategies. Preventive maintenances applied before drastic distresses, decelerate the deterioration and extend the serviceability of pavements. However, These maintenances are non-structural and do not increase the structural integrity of the pavements. On the other hand, Rehabilitations are applied when pavements are already distressed. Due to this fact, despite the structural solidification provided by rehabilitations, deterioration rate will be still ascending. Studies have shown that preventive maintenances are associated with extending pavement life per unit investment [14].

As explained earlier in the basis of analysis, remaining service life of sections with various treatment strategies was calculated comparing to the baseline section that first reaches its terminal life during analysis period. Results of these analyses in Concord and Norwalk are subsequently discussed.
Figure 1-9 Effect Of Treatment Strategies On Remaining Service Life (RSL), Concord

Figure 1-9 (b) indicates that about 70% of the times combination of rehabilitations with preventive or corrective actions provides longer remaining service life comparing to preventive actions in City of Concord. This is due to the fact that rehabilitations are structural repairs and significantly enhance the remaining service life whereas crack seals, despite keeping distresses at a low level, do not improve structural capacity.

However, further analysis in city of Norwalk substantiates that preventive actions when performed as thin-overlay, can be the most effective strategy in extending remaining service life. Distribution details of Concord analysis are provided in Table 1-5.
Table 1-5 Effect Of Treatment Strategies On Remaining Service Life (RSL), Concord

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Preventive</th>
<th>P&amp;R</th>
<th>P&amp;C&amp;R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sections</td>
<td>36</td>
<td>22</td>
<td>12</td>
</tr>
<tr>
<td>Distribution</td>
<td>Extreme value</td>
<td>Extreme value</td>
<td>Extreme Value</td>
</tr>
<tr>
<td>Mean</td>
<td>23.53</td>
<td>26.43</td>
<td>26.75</td>
</tr>
<tr>
<td>Variance</td>
<td>93.88</td>
<td>18.66</td>
<td>12.34</td>
</tr>
<tr>
<td>Location Parameter (µ)</td>
<td>27.89</td>
<td>28.37</td>
<td>28.33</td>
</tr>
<tr>
<td>Scale Parameter (σ)</td>
<td>7.55</td>
<td>3.37</td>
<td>2.74</td>
</tr>
<tr>
<td>Goodness of Fit: P-Value</td>
<td>0.11</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>$\chi^2$</td>
<td>2.46</td>
<td>0.02</td>
<td>0.07</td>
</tr>
</tbody>
</table>

As shown in Figure 1-10, preventive strategies in city of Norwalk result in higher life extensions at any given risk. Analysis in Norwalk also declares that joint implementation of preventive and rehabilitation strategies, has very similar consequences to combined corrective and rehabilitations. However, since preventive actions are executed when pavements are not severely distressed as opposed to corrective measures, RSL of P&R actions is slightly longer than C&R strategies.

Figure 1-10 (a) shows that when expected life criterion is set to be higher than 25 years, preventive measures have the highest probability of satisfying the RSL condition.

In analysis of P&R and P&C&R activities in Norwalk, despite not rejecting the null-hypothesis as if data follows Extreme value distribution, due to low number of available sections in each bin (less than 5), p-value was not calculated. However, obtained chi-square values that indicate the difference between observations and estimations were small and therefore substantiated fitted distributions. See Table 1-5.
Figure 1-10 Effect Of Treatment Strategies On Remaining Service Life (RSL), Norwalk
Table 1-6 Effect Of Treatment Strategies On Remaining Service Life (RSL), Norwalk

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Preventive</th>
<th>P+R</th>
<th>C+R</th>
<th>Rehabilitation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sections</td>
<td>31</td>
<td>38</td>
<td>30</td>
<td>33</td>
</tr>
<tr>
<td>Distribution</td>
<td>Extreme value</td>
<td>Extreme value</td>
<td>Extreme value</td>
<td>Extreme value</td>
</tr>
<tr>
<td>Mean</td>
<td>27.57</td>
<td>24.09</td>
<td>23.38</td>
<td>21.27</td>
</tr>
<tr>
<td>Variance</td>
<td>29.81</td>
<td>58.00</td>
<td>63.73</td>
<td>93.10</td>
</tr>
<tr>
<td>Location Parameter (µ)</td>
<td>20.03</td>
<td>27.51</td>
<td>26.976</td>
<td>25.61</td>
</tr>
<tr>
<td>Scale Parameter (σ)</td>
<td>4.26</td>
<td>5.94</td>
<td>6.22</td>
<td>7.52</td>
</tr>
<tr>
<td>Goodness of Fit: P-Value</td>
<td>0.2147</td>
<td>0.1079</td>
<td>0.0609</td>
<td>0.1803</td>
</tr>
<tr>
<td>$\chi^2$</td>
<td>1.5397</td>
<td>2.5846</td>
<td>3.512</td>
<td>1.7955</td>
</tr>
</tbody>
</table>

Equation can be used to obtain extreme value probability distribution for each strategy.

$$y = f(x | \mu, \sigma) = \sigma^{-1} \exp \left( \frac{x - \mu}{\sigma} \right) \exp \left( -\exp \left( \frac{x - \mu}{\sigma} \right) \right)$$  \hspace{1cm} (1-2)

Where,

$\mu =$ Location Parameter

$\sigma =$ Scale Parameter
Lastly difference of practice in two cities, leads to the following conclusions:

- Analysis of RSL in two cities shows different effectiveness of treatment strategies. This is due to the fact that preventive strategies in Norwalk included only thin-overlay, while Concord has practiced both thin-overlay and crack seal.

- The fact that crack seals are temporarily non-structural treatments substantiates the difference in effectiveness of preventive strategies. It can be distilled from the analysis that thin-overlays are more effective than crack seals in terms of life extension of roads.

1.3.6 Effect Of Treatment Strategies On Network Quality

As mentioned earlier, preventive maintenance is applied when pavements are at incipient stages of distress. Zaniewski et al. [16] remarks this issue by stating, “Treatments must be applied in time to preserve the pavement’s structure. Treating distressed pavements is not preventive maintenance”. These declarations substantiate that preventive maintenances lead to higher pavement qualities. Whereas allowing pavement condition to reach rehabilitation thresholds, means pavement experiences lower qualities during its service life. In addition, studies also show that preventive maintenances yield higher pavement qualities at lower costs [16].
Therefore, this part of analysis is focused on effect of treatment strategies on average maintained PCI of the network, as well as the worst experienced pavement conditions due to each strategy.

Average and minimum maintained PCI in Concord are shown in Figure 1-11 and Figure 1-12. As expected, preventive strategies provide the highest average PCI at any given risk. It is notable that in this well-maintained network (in terms of PCI), about 44% of the network is maintained with preventive strategies. Analysis of the worst network quality (minimum PCI) is even more sensitive to treatment strategies. Concord analysis reveals that treatment strategies can change worst PCI values by 25%. In fact, at any given risk, worst condition of preventive measures is 25% higher than worst condition of combined preventive, corrective and rehabilitation strategy. Detailed results are further provided.

Table 1-7 Effect Of Treatment Strategies on Average Network Quality (PCI), Concord

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Preventive</th>
<th>P+R</th>
<th>PCR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sections</td>
<td>36</td>
<td>30</td>
<td>17</td>
</tr>
<tr>
<td>Distribution</td>
<td>Extreme Value</td>
<td>Extreme Value</td>
<td>Extreme Value</td>
</tr>
<tr>
<td>Mean</td>
<td>87.62</td>
<td>86.25</td>
<td>81.94</td>
</tr>
<tr>
<td>Variance</td>
<td>16.65</td>
<td>12.896</td>
<td>13.99</td>
</tr>
<tr>
<td>Location</td>
<td>89.46</td>
<td>87.86</td>
<td>83.62</td>
</tr>
<tr>
<td>Parameter (μ)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scale</td>
<td>3.18</td>
<td>2.8</td>
<td>2.915</td>
</tr>
<tr>
<td>Parameter (σ)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Goodness of Fit: P-Value</td>
<td>0.5566</td>
<td>0.5578</td>
<td>0.8678</td>
</tr>
<tr>
<td>χ²</td>
<td>0.1719</td>
<td>2.0709</td>
<td>0.2836</td>
</tr>
</tbody>
</table>
Table 1-8 Effect Of Treatment Strategies on Minimum Network Quality (PCI), Concord

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Preventive</th>
<th>P+R</th>
<th>PCR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sections</td>
<td>36</td>
<td>30</td>
<td>17</td>
</tr>
<tr>
<td>Distribution</td>
<td>Extreme value</td>
<td>Extreme value</td>
<td>Extreme value</td>
</tr>
<tr>
<td>Mean</td>
<td>76.06</td>
<td>68.91</td>
<td>54.10</td>
</tr>
<tr>
<td>Variance</td>
<td>70.67</td>
<td>107.95</td>
<td>77.99</td>
</tr>
<tr>
<td>Location Parameter (µ)</td>
<td>79.84</td>
<td>73.59</td>
<td>58.07</td>
</tr>
<tr>
<td>Scale Parameter (σ)</td>
<td>6.55</td>
<td>8.1</td>
<td>6.88</td>
</tr>
<tr>
<td>Goodness of Fit: P-Value</td>
<td>0.4436</td>
<td>0.1263</td>
<td>0.4009</td>
</tr>
<tr>
<td>$\chi^2$</td>
<td>8.93</td>
<td>2.3371</td>
<td>4.037</td>
</tr>
</tbody>
</table>

Very similar to analysis in Concord, analysis in Norwalk also indicates that preventive measures provide the highest average and minimum network quality at any given risk. Furthermore, the analysis indicates that sections treated with preventive and rehabilitation strategies, experience higher average and minimum PCIs comparing to sections maintained with combined preventive, corrective and rehabilitation measures. This substantiates the claim that roads experience lower average and minimum quality over the analysis period when maintained with corrective strategies.
Figure 1-11 Average Network Quality (PCI) Of Treatment Strategies, Concord
Figure 1-12 Minimum Network quality (PCI) of treatment strategies, Concord
Figure 1-13 Average Network Quality Of Treatment Strategies (PCI), Norwalk
Figure 1-14 Minimum Network quality (PCI) of treatment strategies, Norwalk
Table 1-9 Effect Of Treatment Strategies on Average Network Quality (PCI), Norwalk

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Preventive</th>
<th>P+R</th>
<th>C+R</th>
<th>Rehabilitation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sections</td>
<td>31</td>
<td>38</td>
<td>30</td>
<td>33</td>
</tr>
<tr>
<td>Distribution</td>
<td>Extreme Value</td>
<td>Extreme Value</td>
<td>Extreme Value</td>
<td>Extreme Value</td>
</tr>
<tr>
<td>Mean</td>
<td>87.46</td>
<td>85.24</td>
<td>75.82</td>
<td>82.64</td>
</tr>
<tr>
<td>Variance</td>
<td>12.57</td>
<td>10.51</td>
<td>43.329</td>
<td>22.63</td>
</tr>
<tr>
<td>Location Parameter (µ)</td>
<td>89.05</td>
<td>86.69</td>
<td>78.79</td>
<td>84.78</td>
</tr>
<tr>
<td>Scale Parameter (σ)</td>
<td>2.76</td>
<td>2.53</td>
<td>5.13</td>
<td>3.71</td>
</tr>
<tr>
<td>Goodness of Fit: P-Value</td>
<td>0.8468</td>
<td>0.7728</td>
<td>0.1015</td>
<td>0.3544</td>
</tr>
<tr>
<td>$\chi^2$</td>
<td>1.3847</td>
<td>1.7981</td>
<td>2.682</td>
<td>3.2522</td>
</tr>
</tbody>
</table>

Table 1-10 Effect Of Treatment Strategies on Minimum Network Quality (PCI), Norwalk

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Preventive</th>
<th>P+R</th>
<th>C+R</th>
<th>Rehabilitation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sections</td>
<td>31</td>
<td>38</td>
<td>30</td>
<td>33</td>
</tr>
<tr>
<td>Distribution</td>
<td>Extreme Value</td>
<td>Extreme Value</td>
<td>Extreme Value</td>
<td>Extreme Value</td>
</tr>
<tr>
<td>Mean</td>
<td>76.15</td>
<td>70.55</td>
<td>49.96</td>
<td>65.388</td>
</tr>
<tr>
<td>Variance</td>
<td>15.93</td>
<td>27.55</td>
<td>332.365</td>
<td>50.835</td>
</tr>
<tr>
<td>Location Parameter (µ)</td>
<td>77.94</td>
<td>72.92</td>
<td>58.166</td>
<td>68.5977</td>
</tr>
<tr>
<td>Scale Parameter (σ)</td>
<td>3.11</td>
<td>4.09</td>
<td>14.216</td>
<td>5.559</td>
</tr>
<tr>
<td>Goodness of Fit: P-Value</td>
<td>0.4217</td>
<td>0.415</td>
<td>0.1827</td>
<td>0.5606</td>
</tr>
<tr>
<td>$\chi^2$</td>
<td>2.8111</td>
<td>1.7587</td>
<td>1.7757</td>
<td>2.0572</td>
</tr>
</tbody>
</table>
1.4 Monitoring Frequency

Monitoring of the network provides invaluable data that if utilized, can significantly improve performance prediction and PMS decisions. Few studies have accentuated the importance of a reliable up-to-date database. Smith et al. (2005) [5] mentions that an improved database is substantial for estimation of rehabilitation performance. Haider et al. (2011) [3] studied the impact of monitoring frequency on PMS decisions. The results indicated that when data had a noticeable variability over time (i.e., rutting data), monitoring interval had a prominent effect on performance prediction and consequently influenced PMS decisions.

Finally, monitoring frequency drastically impacts the identification of pre-distress conditions or existing distresses. These identifications consequently affect the entire PMS decision-making process in the realms of performance prediction models and priorities in assigning treatment strategies. Therefore, the remainder of this chapter is focused on identifying the impact of monitoring frequency on overall life cycle cost, remaining service life, and network quality.

1.4.1 Cost-Effectiveness Of Monitoring Frequency

Monitoring frequency has complicated implications on cost. On one hand, there are costs associated with frequent inspection of roads in terms of time and resources. On the other hand, shorter monitoring intervals provide more reliable assessment of road conditions, which lead to cost-effective decisions. While only a few studies have focused on monitoring frequency, Haider et al. (2011) [3] addressed this issue by mentioning the effect of monitoring frequency on identifying project boundaries, timings, optimum treatment strategies, and their outcomes on cost-effectiveness.

In this study, after performing LCCA analysis on all arterial sections of the network, NPV values were categorized based on the inspection frequency of each section. Distributions of financial consequences of monitoring frequencies in terms of NPV ($$/SY) in Concord in are shown in Figure 1-15. Results of similar analysis in Norwalk are presented in Figure 1-16.
Analysis in Concord Figure 1-15(a) shows that when budget is limited to lower values, 3-year monitoring frequency has higher probability of meeting the budget criterion as opposed to 4-year monitoring intervals. Figure 1-15 (b) also indicates that at any given risk, cost of 3-year monitoring frequency is lower than that of 4-years.

Similar conclusion can be extracted from the analysis in Norwalk based on Figure 1-16. When budget is limited to smaller values, 3-year, 4-year, and 5-year monitoring intervals have coordinately higher to lower probabilities of meeting the expenditure limit. Also, based on Figure 1-16(b), for any acceptable risk, 3-year monitoring frequency results in lowest and 5-year in highest NPV values. Details of distributions are subsequently presented.
Figure 1-15 Financial Consequences (NPV $$/SY) Of Monitoring Frequency, Concord
Table 1-11 Financial Consequences (NPV $$/SY) Of Monitoring Frequency, Concord

<table>
<thead>
<tr>
<th>Monitoring Frequency</th>
<th>3Yrs</th>
<th>4Yrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sections</td>
<td>62</td>
<td>39</td>
</tr>
<tr>
<td>Distribution</td>
<td>Lognormal</td>
<td>Log-Logistic</td>
</tr>
<tr>
<td>Mean</td>
<td>28.68</td>
<td>37.13</td>
</tr>
<tr>
<td>Variance</td>
<td>3793.38</td>
<td>inf</td>
</tr>
<tr>
<td>Location Parameter (μ)</td>
<td>2.49</td>
<td>2.93</td>
</tr>
<tr>
<td>Scale Parameter (σ)</td>
<td>1.31</td>
<td>0.5998</td>
</tr>
<tr>
<td>Goodness of Fit: P-Value</td>
<td>0.0694</td>
<td>0.0811</td>
</tr>
<tr>
<td>χ²</td>
<td>3.296</td>
<td>3.0419</td>
</tr>
</tbody>
</table>

Table 1-12 Financial Consequences (NPV $$/SY) Of Monitoring Frequency, Norwalk

<table>
<thead>
<tr>
<th>Monitoring Frequency</th>
<th>3Yrs</th>
<th>4Yrs</th>
<th>5Yrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sections</td>
<td>30</td>
<td>70</td>
<td>39</td>
</tr>
<tr>
<td>Distribution</td>
<td>Lognormal</td>
<td>Lognormal</td>
<td>Lognormal</td>
</tr>
<tr>
<td>Mean</td>
<td>38.01</td>
<td>42.11</td>
<td>46.49</td>
</tr>
<tr>
<td>Variance</td>
<td>1799.64</td>
<td>1353.68</td>
<td>984.33</td>
</tr>
<tr>
<td>Location Parameter (μ)</td>
<td>3.23</td>
<td>3.46</td>
<td>3.65</td>
</tr>
<tr>
<td>Scale Parameter (σ)</td>
<td>0.8994</td>
<td>0.75</td>
<td>0.612</td>
</tr>
<tr>
<td>Goodness of Fit: P-Value</td>
<td>0.6343</td>
<td>0.3</td>
<td>0.0988</td>
</tr>
<tr>
<td>χ²</td>
<td>2.5581</td>
<td>3.6638</td>
<td>2.7249</td>
</tr>
</tbody>
</table>
Figure 1-16 Financial Consequences (NPV $$/SY) Of Monitoring Frequency, Norwalk
1.4.2 Effect of Monitoring Frequency on Remaining Service life

As mentioned earlier, monitoring frequency impacts the performance prediction, distress identification, treatment strategies, PMS decisions, and therefore service life of the network. Smith et al. [5] in FHWA report of 2005 from Arizona Department of Transportation recommends biennial analyses for more accurate performance prediction and estimations of pavement life.

In this sub-chapter of life cycle analysis, remaining service life comparing to the base road segment that reaches its terminal life was calculated, and categorized for each monitoring frequency to obtain probability distributions. Consequences of monitoring frequencies on Remaining Service Life (RSL) in cities of Concord and Norwalk are accordingly presented in Figure 1-17 and Figure 1-18.

In analysis of Concord network, Figure 1-17 indicates that for any given risk, 3-year monitoring interval provides higher RSL comparing to 4-year inspections.

Similar analysis in Norwalk’s network indicates that while 3-year and 4-year monitoring frequencies are close in results, yet at any given risk, 3-year inspection frequency results in the highest and 5-year frequency in lowest values of remaining service life.

It is required to note that due to lack of data points in Concord for 4-year monitoring interval, p-value could not be calculated for RSL. However, since the null-hypothesis was not rejected and the calculated chi-square value was 7.5%, extreme value distribution was considered appropriate for this category of data.
Figure 1-17 Remaining Service Life (RSL) Of Monitoring Frequencies, Concord
**Table 1-13 Remaining Service Life (RSL) Of Monitoring Frequencies, Concord**

<table>
<thead>
<tr>
<th>Monitoring Frequency</th>
<th>3Yrs</th>
<th>4Yrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sections</td>
<td>47</td>
<td>21</td>
</tr>
<tr>
<td>Distribution</td>
<td>Extreme Value</td>
<td>Extreme Value</td>
</tr>
<tr>
<td>Mean</td>
<td>19.90</td>
<td>10.13</td>
</tr>
<tr>
<td>Variance</td>
<td>140.00</td>
<td>313.503</td>
</tr>
<tr>
<td>Location Parameter (μ)</td>
<td>25.22</td>
<td>18.10</td>
</tr>
<tr>
<td>Scale Parameter (σ)</td>
<td>9.225</td>
<td>13.805</td>
</tr>
<tr>
<td>Goodness of Fit: P-Value</td>
<td>0.0824</td>
<td>--</td>
</tr>
<tr>
<td>χ²</td>
<td>3.0161</td>
<td>0.0751</td>
</tr>
</tbody>
</table>

**Table 1-14 Remaining Service Life (RSL) Of Monitoring Frequencies, Norwalk**

<table>
<thead>
<tr>
<th>Monitoring Frequency</th>
<th>3Yrs</th>
<th>4Yrs</th>
<th>5Yrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sections</td>
<td>31</td>
<td>70</td>
<td>40</td>
</tr>
<tr>
<td>Distribution</td>
<td>Extreme Value</td>
<td>Extreme Value</td>
<td>Extreme Value</td>
</tr>
<tr>
<td>Mean</td>
<td>24.99</td>
<td>24.42</td>
<td>22.46</td>
</tr>
<tr>
<td>Variance</td>
<td>50.43</td>
<td>47.66</td>
<td>83.79</td>
</tr>
<tr>
<td>Location Parameter (μ)</td>
<td>28.1865</td>
<td>27.53</td>
<td>26.5771</td>
</tr>
<tr>
<td>Scale Parameter (σ)</td>
<td>5.537</td>
<td>5.38</td>
<td>7.1369</td>
</tr>
<tr>
<td>Goodness of Fit: P-Value</td>
<td>0.1908</td>
<td>0.266</td>
<td>0.1482</td>
</tr>
<tr>
<td>χ²</td>
<td>1.7113</td>
<td>3.9581</td>
<td>2.0902</td>
</tr>
</tbody>
</table>
Figure 1-18 Remaining Service Life (RSL) Of Monitoring Frequencies, Norwalk
1.4.3 Effect of Monitoring Frequency on Network Quality

Monitoring frequency can affect network quality on different levels of PMS. These aspects include identification of distresses, planning for appropriate maintenance strategies, and implementation of planned treatments. Each of these phases directly impacts the network quality.

Studies have shown that when inspections are performed more frequently, higher rates of distress growth is captured [3]. McGhee et al. [18] emphasizes the necessity of monitoring distress quantities on a year-to-year basis. Furthermore, pavement segments that require repairs have lower chances of being captured when monitoring intervals are longer. The other shortcoming of less frequent monitoring is that when section is recognized for treatment, the distress might already be severe. Therefore, the repair would be more costly, the remaining service life would be shorter, and the road section experiences poorer qualities before being repaired.

This part of the analysis is focused on consequences of monitoring intervals on average and minimum experienced PCI of Concord and Norwalk Network.

As shown by Figure 1-19, 3-year and 4-year monitoring intervals have close consequences in terms of average maintained condition. Yet, it is still evident that for any taken risk, average PCI of 3-year monitoring intervals are slightly higher than 4-year frequency.

However, analysis of minimum PCI in Concord, as presented in Figure 1-20, indicates that about 70% of the times, 3-year monitoring frequency has higher probabilities of satisfying the minimum PCI criterion comparing to 4-year inspection frequency.

Similar analysis in Norwalk indicates that average maintained PCI of monitoring frequencies are slightly close while longer frequencies have lower average PCIs at any given risk. See Figure 1-21.

Further analysis of minimum PCI in Norwalk in Figure 1-22 indicates more significant impact of monitoring frequency. 80% of the times, 5-year monitoring frequency results in 20% lower PCI values. Details of the distributions are accordingly provided in Table 1-15 to Table 1-18.
Figure 1-19 Average Network Quality (PCI) Of Monitoring Frequencies, Concord
Figure 1-20 Minimum Network Quality (PCI) Of Monitoring Frequencies, Concord
Table 1-15 Average Network Quality (PCI) Of Monitoring Frequencies, Concord

<table>
<thead>
<tr>
<th>Monitoring Frequency</th>
<th>3Yrs</th>
<th>4Yrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sections</td>
<td>78</td>
<td>21</td>
</tr>
<tr>
<td>Distribution</td>
<td>Extreme value</td>
<td>Extreme value</td>
</tr>
<tr>
<td>Mean</td>
<td>85.83</td>
<td>85.38</td>
</tr>
<tr>
<td>Variance</td>
<td>20.30</td>
<td>25.08</td>
</tr>
<tr>
<td>Location Parameter (μ)</td>
<td>87.86</td>
<td>87.63</td>
</tr>
<tr>
<td>Scale Parameter (σ)</td>
<td>3.51</td>
<td>3.9</td>
</tr>
<tr>
<td>Goodness of Fit: P-Value</td>
<td>0.8959</td>
<td>0.8692</td>
</tr>
<tr>
<td>χ²</td>
<td>1.09</td>
<td>1.2539</td>
</tr>
</tbody>
</table>

Table 1-16 Minimum Network Quality (PCI) Of Monitoring Frequencies, Concord

<table>
<thead>
<tr>
<th>Monitoring Frequency</th>
<th>3Yrs</th>
<th>4Yrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sections</td>
<td>78</td>
<td>21</td>
</tr>
<tr>
<td>Distribution</td>
<td>Extreme value</td>
<td>Lognormal</td>
</tr>
<tr>
<td>Mean</td>
<td>66.47</td>
<td>68.78</td>
</tr>
<tr>
<td>Variance</td>
<td>179.89</td>
<td>414.00</td>
</tr>
<tr>
<td>Location Parameter (μ)</td>
<td>72.51</td>
<td>4.19</td>
</tr>
<tr>
<td>Scale Parameter (σ)</td>
<td>10.46</td>
<td>0.29</td>
</tr>
<tr>
<td>Goodness of Fit: P-Value</td>
<td>0.5991</td>
<td>0.1843</td>
</tr>
<tr>
<td>χ²</td>
<td>1.8732</td>
<td>1.7627</td>
</tr>
</tbody>
</table>
Table 1-17 Average Network Quality (PCI) Of Monitoring Frequencies, Norwalk

<table>
<thead>
<tr>
<th>Monitoring Frequency</th>
<th>3Yrs</th>
<th>4Yrs</th>
<th>5Yrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sections</td>
<td>31</td>
<td>70</td>
<td>40</td>
</tr>
<tr>
<td>Distribution</td>
<td>Extreme value</td>
<td>Extreme value</td>
<td>Extreme Value</td>
</tr>
<tr>
<td>Mean</td>
<td>82.0029</td>
<td>81.87</td>
<td>80.82</td>
</tr>
<tr>
<td>Variance</td>
<td>43.79</td>
<td>41.18</td>
<td>49.1482</td>
</tr>
<tr>
<td>Location Parameter (μ)</td>
<td>84.98</td>
<td>84.76</td>
<td>83.98</td>
</tr>
<tr>
<td>Scale Parameter (σ)</td>
<td>5.16</td>
<td>5.0036</td>
<td>5.466</td>
</tr>
<tr>
<td>Goodness of Fit: P-Value</td>
<td>0.583</td>
<td>0.8252</td>
<td>0.6106</td>
</tr>
<tr>
<td>χ²</td>
<td>5.6838</td>
<td>0.9008</td>
<td>1.82</td>
</tr>
</tbody>
</table>

Table 1-18 Minimum Network Quality (PCI) Of Monitoring Frequencies, Norwalk

<table>
<thead>
<tr>
<th>Monitoring Frequency</th>
<th>3Yrs</th>
<th>4Yrs</th>
<th>5Yrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sections</td>
<td>60</td>
<td>50</td>
<td>44</td>
</tr>
<tr>
<td>Distribution</td>
<td>Extreme value</td>
<td>Extreme value</td>
<td>Extreme Value</td>
</tr>
<tr>
<td>Mean</td>
<td>65.63</td>
<td>65.25</td>
<td>56.45</td>
</tr>
<tr>
<td>Variance</td>
<td>121.776</td>
<td>97.04</td>
<td>470.17</td>
</tr>
<tr>
<td>Location Parameter (μ)</td>
<td>70.595</td>
<td>69.68</td>
<td>66.21</td>
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<tr>
<td>Scale Parameter (σ)</td>
<td>8.604</td>
<td>7.68</td>
<td>16.906</td>
</tr>
<tr>
<td>Goodness of Fit: P-Value</td>
<td>0.2907</td>
<td>0.7423</td>
<td>0.1184</td>
</tr>
<tr>
<td>χ²</td>
<td>2.4708</td>
<td>1.2447</td>
<td>4.2677</td>
</tr>
</tbody>
</table>
Figure 1-21 Average Network Quality (PCI) Of Monitoring Frequencies, Norwalk
(a) Probability Density Function Of Minimum PCIs

(b) Cumulative Probability Of Minimum PCIs

Figure 1-22 Minimum Network Quality (PCI) Of Monitoring Frequencies, Norwalk
1.4.4 Application of Risk-based approach in management decisions

To demonstrate the application of risk-based analyses previously discussed, this sub-chapter provides a few examples of pavement management system targets and suggested solutions. Considering the network of Concord, three various scenarios are presented:

<table>
<thead>
<tr>
<th>Target 1:</th>
</tr>
</thead>
<tbody>
<tr>
<td>✓ Road Condition  ( \geq 70 )</td>
</tr>
<tr>
<td>✓ Cost  ( \leq 8($)$/SY$)</td>
</tr>
<tr>
<td>✓ Risk  ( \leq 20% )</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Outcomes (20% Risk)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preventive Treatment</td>
</tr>
<tr>
<td>Monitoring Freq. 3 Years</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Treatment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preventive</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Suggestions</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th>RSL</th>
<th>Cost ($$/SY)</th>
<th>PCI</th>
</tr>
</thead>
<tbody>
<tr>
<td>11-30</td>
<td>3-37</td>
<td>58-78</td>
</tr>
</tbody>
</table>

Figure 1-23 PMS Solution Case-1
As illustrated in Figure 1-23 appropriate treatment strategies and required monitoring frequencies are proposed based on network management goals. Preventive strategy is recognized as the treatment option, which satisfies all the required criteria. Consequently, this maintenance option along with other limits set, results in 17 to 32 years of service life. On the other hand, 3-year monitoring frequency sets some limits on targets. For the assigned 20% acceptable risk, cost and PCI requirements may not be met. According to Figure 1-23 cost and PCI can vary such that they may or may not satisfy the limits. Detailed steps for suggestions of Case-1 are further illustrated in Figure 1-24 to Figure 1-29.

Figure 1-24 Treatment Suggestion To Meet Budget Limit At 20% Risk
Figure 1-25 Treatment Suggestion To Meet PCI Limit At 20% Risk

Figure 1-26 Outcome Of Treatment Suggestion On RSL At 20% Risk
Figure 1-27 Monitoring Frequency Outcome On RSL At 20% Risk

Figure 1-28 Monitoring Frequency Outcome On Cost At 20% Risk
Figure 1-29 Monitoring Frequency Outcome On PCI At 20% Risk
Target 2:

- ✅ Road Condition $\geq 75$
- ✅ Cost $\leq 8 \text{ ($$/SY)}$
- ✅ RSL $\geq 30 \text{ Years}$

<table>
<thead>
<tr>
<th>Suggestion</th>
<th>Outcomes</th>
<th>Monitor Frequency</th>
<th>Cost Risk</th>
<th>PCI Risk</th>
<th>RSL Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Preventive</td>
<td>5%</td>
<td>35%</td>
<td>75%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>P&amp;R</td>
<td>20%</td>
<td>75%</td>
<td>90%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>P&amp;C&amp;R</td>
<td>65%</td>
<td>100%</td>
<td>95%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 1-30 PMS Solution Case-2
Figure 1-30 demonstrates a different perspective where goals are set based on condition, cost, and service life. In this case, various treatment strategies and monitoring frequencies can be implemented with different risk factors. Also, risk factor for each criterion is different as presented in outcomes. Decision makers can then decide based on the level of risk acceptance.

| ✓ Target 3:          |  |
|----------------------|  |
| ✓ Road Condition     | ≥ 75 |
| ✓ Risk               | ≤ 30% |
| ✓ RSL                | ≥ 20 Years |

| ✓ Target 3:          |  |
|----------------------|  |
| Suggestion           | Outcomes         |
| Treatment            | Expected Cost    |
| Preventive           | 0.75-2($$/SY)    |

| ✓ Target 3:          |  |
|----------------------|  |
| Suggestion           | Outcomes         |
| Monitoring Frequency | Expected Cost    |
|                      | PCI Risk         |
|                      | RSL Risk         |
| 3 Years              | 5-22 ($$/SY)     |
|                      | 70%              |
|                      | 40%              |

Figure 1-31 PMS Solution Case-3
Last case (Figure 1-31) illustrates a situation where cost will be determined based on accepted risk, road quality, and service life. Preventive maintenance was able to satisfy the PMS limits with the suggested cost. 3-year monitoring frequency on the other hand, satisfies PCI and RSL limits at higher risks than initial target. However, possible cost range of 3-year monitoring frequency is proposed based on the initial 30% risk.
1.5 Chapter Summary And Conclusions

This chapter was determined to suggest risk-informed management solutions by reflecting the tradeoffs between cost and service quality. Probabilistic data-driven LCCA was leveraged to provide outcomes of various treatment strategies and pavement monitoring frequency alternatives in terms of cost, remaining service life, and network quality. The major contributions and findings of this study are summarized bellow:

- When NPV is limited to small values, preventive maintenances provide the highest probability of meeting the budget criteria.

- Implementing preventive activities yield the lowest costs during the analysis period, at any given risk.

- Executing corrective repairs is costly. Corrective repairs do not enhance the structural capacity. Consequently, while crack seals and thin overlays as preventive strategies performed at high PCIs are cost-effective, same action items executed as corrective alternatives at lower PCIs do not eliminate the need of rehabilitation.

- Rehabilitations are structural repairs and significantly enhance the remaining service life. Whereas crack seals, despite keeping distresses at a low level, do not improve structural capacity and therefore service life. However, further analysis in city of Norwalk substantiates that preventive actions when performed as thin overlay, can be the most effective strategy in extending remaining service life.
Briefly, difference of practice in two cities, leads to the following conclusions in terms of RSL:

- Analysis of RSL in two cities shows different effectiveness of treatment strategies. This is due to the fact that preventive strategies in Norwalk included only thin-overlay, while Concord has practiced both thin-overlay and crack seal.

- The fact that crack seals are temporarily non-structural treatments substantiates the reason for difference in effectiveness of preventive strategies. It can be distilled from the analysis that thin-overlays are more effective than crack seals in terms of life extension of roads.

- Preventive strategies provide the highest average PCI at any given risk.

- Analysis of the worst network quality (minimum PCI) is more sensitive to treatment strategies and monitoring frequencies comparing to average PCI.

- Concord analysis reveals that treatment strategies can change worst PCI values by 25%. In fact, at any given risk, worst condition of preventive measures is 25% higher than worst condition of combined preventive, corrective and rehabilitation strategies.

- When budget is limited, 3-year monitoring frequency has higher probability of meeting the budget criterion as opposed to 4-year monitoring intervals.

- 3-year, 4-year, and 5-year monitoring intervals have coordinately higher to lower probabilities of meeting the expenditure limit.
- For any given risk, 3-year monitoring interval provides higher RSL comparing to 4-year and 5-year inspections.

- Longer monitoring frequencies have lower average PCIs at any given risk.

- In 80% of the conditions, 5-year monitoring frequency results in 20% lower minimum PCI values.

Lastly, to pinpoint the tradeoffs between costs and service quality, benefit to cost indicators are obtained from mean-value of provided distributions. These indicators are scaled ratios between average PCI and cost, minimum PCI and cost, and RSL and cost.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Concord</th>
<th>Norwalk</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Preventive</td>
<td>P+R</td>
</tr>
<tr>
<td>RSL/Cost</td>
<td>1</td>
<td>0.32</td>
</tr>
<tr>
<td>Avg PCI/Cost</td>
<td>1</td>
<td>0.28</td>
</tr>
<tr>
<td>Min PCI/Cost</td>
<td>1</td>
<td>0.25</td>
</tr>
</tbody>
</table>
Table 1-20 Benefit To Cost Ratios Of Monitoring Frequencies

<table>
<thead>
<tr>
<th>Monitoring Frequency</th>
<th>Concord</th>
<th>Norwalk</th>
<th>Concord</th>
<th>Norwalk</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3Yrs</td>
<td>4Yrs</td>
<td>3Yrs</td>
<td>4Yrs</td>
</tr>
<tr>
<td>RSL/Cost</td>
<td>1</td>
<td>0.39</td>
<td>1</td>
<td>0.88</td>
</tr>
<tr>
<td>Avg PCI/Cost</td>
<td>1</td>
<td>0.77</td>
<td>1</td>
<td>0.90</td>
</tr>
<tr>
<td>Min PCI/Cost</td>
<td>1</td>
<td>0.80</td>
<td>1</td>
<td>0.90</td>
</tr>
</tbody>
</table>

Figure 1-32 Benefit To Cost Ratios Of Treatment Strategies (Table 1-19)
Figure 1-33 Benefit To Cost Ratios Of Monitoring Frequencies (Table 1-20)
2 PERFORMANCE BASED CONDITION PREDICTION

Effective execution of PMS planning and project prioritization, in addition to comprehensive up-to-date data and associated risks, drastically depends on the accuracy of future deterioration prediction.

Prediction of pavement deterioration influences many PMS components such as determining the rehabilitation time, corresponding treatment alternatives for future years and selecting the most effective maintenance and rehabilitation (M&R) alternatives [20]. Condition of pavements during and at the end of investment time span significantly affects budget allocation and prioritization decisions. Therefore, a precise deterioration model is vital to the success of such immense investment plans.

Lastly, a solid deterioration model will not only helps road controlling authorities in cost-effective scheduling of maintenance activities and budget allocations, but it can also be employed for the design of pavement structures. Consequently, these models can be utilized for evaluation of different design, maintenance, and rehabilitation strategies based on geographical regions, estimated volumes of traffic and other factors [21].

There are numerous factors that affect the accuracy of deterioration models. Many efforts have been taken to consider the most influential parameters and provide precise performance models. In this chapter, first, an overview of influential parameters and widely used models are presented. Despite all the success, there are still some factors such as extreme weather events that are overlooked in deterioration models. Therefore, this chapter aims to provide one of the most cutting edge and inclusive performance based models for condition prediction.
2.1 General Influencing Parameters On Pavement Performance

Interactions between climate, vehicles and the road result in deformation and deterioration of pavements. Prediction of this behavior is complicated. While deterioration models for rigid pavements have had a decent performance, because of the high viscoelastic characteristic of the asphalt, current deterioration models for flexible pavements have had limited success so far.

Pavement infrastructure deterioration is caused by aggregated impact of traffic loads, environmental conditions, and other contributors. The behavior of pavement under these factors depends on the characteristics of its structure (materials and thickness of each pavement layer), the quality of its construction, and the subgrade (bearing capacity and presence of water) [22]. Each factor causes certain distresses on the pavement. Understanding factors that lead to deterioration of roads help infrastructure managers to refine their construction and maintenance specifications.

Load: Cracking and rutting caused by pavement bending under traffic loads are two of the most prominent forms of distresses. Tire pressure produced by vehicles in the radius of loaded area induces tensile stress on the pavement, lateral shear in the surface and vertical stress at the subgrade, which gradually deteriorate the pavement [23].

Material Properties: Severity of distresses and the pace of their formation are heavily influenced by material properties of the pavement. Strength and bearing capacity, gradation, modules of elasticity and resilience of the materials used in construction determine pavements endurance under load and climate fluctuations [24].

Construction Quality: Freitas et al. [25] shows that construction quality influences the two significant factors in initiation of top-down cracking: voids and aggregate gradations caused. Construction quality also determines the initial pavement condition, which has an impact on the pace that pavement failures occur.

Environmental Conditions: Climate oscillations, precipitation and freeze/thaw cycles are the primary causes of some dominant distresses such as longitudinal and transversal cracks [26].
• **Temperature:** Temperature fluctuations are followed by tensile and compressive stress in pavement, which initiates thermal cracking. Smith et al [27] shows a correlation between pavement deterioration and temperature where surge in temperature facilitates rutting and cracking in the pavement.

• **Precipitation:** Studies on pavement performance evaluations show that other than formation of longitudinal and alligator cracks, roughness of the road also worsens with a boost in precipitation.

• **Freeze/thaw cycles:** In cold regions, water penetrated into the pavement layers freezes in the winter. Thaw of these ice particles during spring causes deformation in pavement layers and triggers fatigue cracking [28].

The effects of traffic loads and environmental factors on pavement condition prediction have been widely studied [28, 29, 30, 31]. Majority of prediction models, regardless of the applied approach for prediction, have considered to some extent similar factors.

### 2.2 Condition Prediction/Deterioration Modeling Of Pavements

Depending on how aging of the pavement is simulated, road deterioration models can be categorized into three main classes of Empirical, Probabilistic, and Mechanistic-Empirical. Following section explains the basis of these models, their drawbacks and finally, the proposed methodology.

• Empirical prediction models are typically simple performance models that are obtained from fitting curves to historic performance data. The Highway development and Management Tool (HDM-4) is an example of these models that is widely used for condition prediction and strategic planning of pavements at
The proposed roughness deterioration model by HDM-4 is developed based on structural damage to the pavement and change in roughness due to cracking, rutting, potholing, and environment. This model requires extensive information on the road network to perform well. Additionally, it needs to be calibrated for different regions.

- Probabilistic models are typically based on the Markov chain process and work with transition probability matrices to account for the probability of pavement condition transitioning from one state to another. MicroPAVER is one of the widely used tools, which applies this model [45]. While this model is able to overcome the stochastic characteristics of influential factors on deterioration, there are some limitations. Establishment of these probability matrices can be costly and time-consuming as historic data or opinions of expert engineers are required. Furthermore, applicability of the transition matrix is limited to only several widely spaced categories typically classified by traffic volume, pavement structure and climate regions [43]. In addition, time independent stochastic process of Markov chains, implies that rate of deterioration does not depend on time [46]. However, many studies have demonstrated that deterioration accelerates as age of the pavement grows [47].

- Mechanistic-empirical models are based on constitutive laws between mechanical characteristics of pavements and external factors. In these models, mechanical characteristics of pavements such as stress-strain relationships are associated with external elements like traffic loads. Eventually, future pavement condition is projected using statistical models. National Cooperative Highway Research Program (NCHRP) has included this type of performance prediction model in the 2002 mechanistic-empirical design guidelines [48].

While these studies have modeled natural deterioration with some level of success, most have neglected the aggravating effect of extreme weather events.
Aftermaths of events such as hurricane Sandy in New York and New Jersey and hurricane Katrina in New Orleans [49] emphasize the importance of considering extreme weather events in performance prediction of pavements. Moreover, a study after the 2006/2007 Denver, Colorado snowstorms indicated 16% decline in road conditions [50]. Poor pavement conditions are caused by shear failure, weakening of the subgrade, cracking, and worsening the severity of existing cracks as a result of extreme weather events.

Fundamentally, severe floods increase the subgrade’s moisture content and drastically damage the surface layer. Snowstorms also increase pavement roughness by inducing thermal cracks and causing uneven frost heaves. In addition, heavy loads of snow, which sometimes remains on pavements for months, and heavy loads applied by snow removal vehicles further damage the pavements [51,52].

In this study, efforts have been taken to quantify the effects of extreme weather events on performance of flexible pavements. Next sections are structured based on data collection, quantification of extreme events, and development of a regression-based model for performance prediction in extreme conditions.

2.3 Data & Methodology

In order to conduct a data driven approach for development of a performance prediction model, pavement condition and extreme weather events data had to be collected.

Performance data were obtained from the Long Term Pavement Performance (LTPP) database [53], which contains pavement performance data of over 2,400 pavement sections throughout the United States and Canada. In addition to performance, traffic and climatic data were gathered from 8 states of New York, Louisiana, Oregon, Colorado, New Jersey, Illinois, Ohio, and Florida for an analysis period of 18 years (1996 to 2013). These states were selected since they encompass the most inclusive datasets and were specifically affected by significant extreme weather events.
Discussions here are focused on using the IRI as the performance measurement of pavement sections. Typically obtained from longitudinal road profiles, ASTM defines IRI as “a quantitative estimate of a pavement property defined as roughness using longitudinal profile measures.”[56] IRI is widely used for evaluating and managing highways since the early 1980s.

Extreme weather events data were obtained from the National Oceanic and Atmospheric Administration (NOAA) database [54]. In order to quantify the magnitude of floods and snowstorms, duration and the reported depth of snow and flooded water were acquired.

One challenge was to match the LTPP sections corresponding to the county-based extreme weather events data obtained from NOAA. To make the datasets of two different references consistent, pavement sections and climate regions were categorized based on their counties.

In addition, some sections in the LTPP database had insufficient data for two of the parameters used in the proposed model: Structural Number and Equivalent Single Axle Load (ESAL). Missing structural numbers were estimated based on the pavement type, information of layers thicknesses, subgrade moduli, and available structural number of the adjacent sections with similar characteristics recorded in the LTPP database. Absent ESAL values were estimated based on traffic counts, number of lanes, and vehicle axle loads [55].

Performance surveys and models provide natural deterioration information in annual format. On the other hand, events taking place in zones prone to extreme climate conditions have a high frequency of occurrence and an instantaneous nature. Therefore, to effectively capture the effect of events occurring between surveys, a monthly accurate analysis was required. For that purpose, annual climate and traffic reports of LTPP were converted into monthly format data.

Lastly, a natural deterioration model was required to capture and quantify the effect of extreme events. At many cases, multiple extreme events occurred between two measurements of IRIs. Based on the reports of depth, duration, and property damage, less
significant events were filtered out and data points with only one major extreme event between surveyed IRIs were attained. Data collection procedure is illustrated in Figure 2-1.

Figure 2-1 Data Collection Procedure
Proposed model consists of two parts: A natural deterioration model, and a deterioration model due to extreme weather events. The first part has been adopted and the latter has been developed based on the collected data described earlier.

### 2.3.1 Natural Deterioration Model

To choose an appropriate natural deterioration model based on the availability of data, some of the widely used models were studied. In a study conducted by Jackson et al. [28], multivariate regression analysis was implemented on LTPP data test sections classified as SPS-1, SPS-8, GPS-1, GPS-2, and GPS-6 to propose flexible pavement performance models. Effects of environmental factors such as freeze cycles and deep frost penetration, on pavement performance have been considered in this study. A deterioration model predicting roughness of flexible pavements was proposed as the following:

\[
\ln(\Delta \text{IRI+1}) = \text{Age}(4.5\text{FI} + 1.78\text{CI} + 1.09\text{FTC} + 2.4\text{PRECIP} + \frac{5.39\log(\text{ESAL})}{\text{SN}}) \tag{2-1}
\]

Where:

- \(\Delta \text{IRI}\) : Change in International Roughness Index
- \(\text{Age}\) : Pavement Age
- \(\text{FI}\) : Freezing Index (Degree-days when air temperatures are below and above zero degrees Celsius)
- \(\text{CI}\) : Cooling Index (Temperature relation to the relative humidity and discomfort)
- \(\text{FTC}\) : Freeze-thaw Cycles
This model has leveraged the comprehensive LTPP performance data and predicted the accumulation of roughness with time with a root mean square error (RSME) of 0.17. Therefore, this model was chosen as the basic approach for quantifying the effect of extreme events.

### 2.3.2 Quantification Of Impact Factor

As mentioned earlier, performance data from LTPP and extreme weather events data from NOAA are not necessarily synchronized. Quantifying the impact of extreme weather events needs prediction of performance data to the month the event has occurred. Natural deterioration model proposed by Jackson et al [28], presented in equation (2-1) was used to carry this prediction.

Consequently, IRI recorded before an extreme weather event was forward-projected to the time of the event by natural deterioration model. Then, the IRI value recorded after the event was backward-projected to the time of the event. Difference between the forward-projected and the backward-projected IRI values is the additional deterioration caused by the extreme event occurred in between. The explained methodology is illustrated in Figure 2-2.
Figure 2-3 shows the analysis implemented on a section in Colorado from 1996 to 2013. Points marked with upside triangles represent surveyed IRI values recorded in LTPP database. Natural deterioration, which is backward and forward projected between measured IRIs at the time of extreme weather event occurrence, is presented with the blue-filled prediction line.

Also, measurements of IRIs are connected to each other with the dash line to illustrate the difference between predicted and surveyed IRI values. June 2011 (Month 187) is an example of extreme event occurrence as reported with 1 (ft) of flooding in 1 hour; the predicted IRI value for that month is 1.213 (m/km) while the actual measurement in less than 2 months later indicates an IRI value of 1.46 (m/km).
Difference between the measured and predicted values indicates the impact of the flood in this specific case. On another note, maintenance actions can also be observed in this plot. Month 125 is an example of maintenance action where the predicted IRI value is 1.33 (m/km) and the survey indicates decrease in IRI.

![Image](image)

**Figure 2-3 Impact Of Extreme Events And Maintenance Actions On Measured And Predicted IRI Values**

### 2.3.3 Deterioration In Extreme Conditions

Applying the described methodology, 75 data points were quantified which were impacted by only one flood or snowstorm in the 1996 to 2013 period. Depth and duration of the extreme events were chosen as indicators of events’ magnitudes. After observing the high correlation of traffic (ESAL) and pavement roughness (IRI) with the quantified impact values, these factors were also considered as possible predictors. Deciding what algorithm to use depends heavily on the application and what is expected from the fusion system. Pattern recognition, artificial intelligence and regression are some common
fusion techniques. Here, an algorithm that is adept at variable selection is required as one might conclude that not all of these parameters are necessary to predict IRI scores.

Consequently, the high correlation between the predictors and the deterioration rates led to employing a statistical regression model. Another reason for considering regression is the limited number of data points, as regression could deal better with them than machine learning techniques such as Neural Networks [58].

Regression is a statistical tool for exploring relationships between variables that are related in a nondeterministic manner. Proposed model in this study is Stepwise Regression. Stepwise regression enters and removes variables one at a time to see whether it improves the model. Usually, this takes the form of a sequence of F-tests, but other techniques such as t-tests, adjusted R-square, Bayesian information criterion, or false discovery rate are also possible [59]. Finally, obtained correlations are presented in Table 2-1.

Table 2-1 Correlation Of Predictors With Percentage Increase In IRI Due To The Extreme Event

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Correlation with %ΔIRI for Snow Storms</th>
<th>Correlation with %ΔIRI for Floods</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial IRI</td>
<td>72%</td>
<td>84%</td>
</tr>
<tr>
<td>ESAL</td>
<td>16%</td>
<td>37%</td>
</tr>
<tr>
<td>Event Depth</td>
<td>5%</td>
<td>9%</td>
</tr>
<tr>
<td>Event Duration</td>
<td>2%</td>
<td>13%</td>
</tr>
</tbody>
</table>

A well-suited regression model for the application here should be able to select a subset of the possible combinations of predictors in Table 2-1. By implementing stepwise regression, the size of the regression coefficients has been penalized. Stepwise Regression works with entering and removing variables one at a time and removes insignificant variables at each step [57]. Figure 2-4 illustrates the stepwise regression process.
Accordingly, Significance at the confidence interval of 95% has been calculated using F-tests in Equation (2-2).

\[
r^2_{y|x_1,...,x_{p-1}} = \frac{SSE_{p-1} - SSE_p}{SSE_{p-1}}
\]

\[
= \frac{SSE_{(x_1,...,x_{p-1})} - SSE_{(x_1,...,x_p)}}{SSE_{(x_1,...,x_{p-1})}}
\]

Where:

- \( r \): Total variation in y that is accounted for by a regression on x
- \( SSE_p \): Error sum of squares in step p (on variables \( x_1, ..., x_p \))
Stepwise regression was implemented separately on two sets of the acquired data: sections impact by Floods, sections impacted by Snow Storms. For Snow Storms, 29 out of the 42 available sections were entered into the fusion model for training at the confident interval of 95%, which rendered the model in Equation (2-3).

\[
\%\Delta IRI_S = 5.09 - 2.5NIRI + 1.7NDepth - 1.74NDuration + 0.706ESAL \times Duration
\]

(2-3)

Where:

- \%\Delta IRI_S: Percentage of change in IRI due to the snowstorm
- NIRI: Normalized IRI of the section before the snow storm
- NDepth: Normalized Depth of the snow storm
- NDuration: Normalized Duration of the snow storm
- ESAL: Equivalent Single Axle Load (derived from traffic)
- Duration: Duration of the snow storm

Testing this model on the remaining 13 sections had 93% correlation with the reference impact values, as shown in Figure 2-5.
Similar to what was discussed above, equation (2-4) was rendered after training on 28 sections affected by a single flood.

\[
\% \Delta IRI_F = -4.47 + 0.48 IRI \text{-} 0.23 \text{Depth} - 0.57 \text{Duration} - 26.49 \text{NESAL} - 0.49 \text{Depth} \times IRI
\]  

(2-4)

Where:

- \( \% \Delta IRI_F \): Percentage of change in IRI due to Floods
- \( IRI \): IRI of the section before the flood
- \( \text{Depth} \): Depth of the flood
- \( \text{Duration} \): Duration of the flood
- \( \text{NESAL} \): Normalized Equivalent Single Axle Load (derived from traffic)

The remaining sections were used for testing, which indicated 91% correlation with the reference impact values Figure 2-6.
2.3.4 Final Deterioration Model

The final deterioration model, which considers both natural causes and occurrences of floods and snowstorms, is provided in Equation (2-5).

\[ \Delta \text{IRI} = \Delta \text{IRI}_{\text{Natural}} + \Delta \text{IRI}_{\text{Snowstorm}} + \Delta \text{IRI}_{\text{Flood}} \]  

(2-5)

Where:

\( \Delta \text{IRI} \): Overall change in IRI
\( \Delta \text{IRI}_{\text{Natural}} \): Change in IRI due to natural causes, Equation (2-1)
\( \Delta \text{IRI}_{\text{Snowstorm}} \): Change in IRI due to a single snowstorm, Equation (2-3)
\( \Delta \text{IRI}_{\text{Flood}} \): Change in IRI due to a single flood, Equation (2-4)
2.4 Conclusions

Pavement deterioration modeling is a vital element of pavement management systems. In this chapter, a pavement deterioration model was developed using data from eight states over eighteen years. This model considers the effect of traffic loads, climate conditions, and occurrence of the extreme weather events. Performance and traffic load data were collected from the Long Term Pavement Performance (LTPP) database. National Oceanic and Atmospheric Administration (NOAA) reports for extreme weather events were used to quantify the magnitude of floods and snowstorms. For deterioration due to natural causes, a mechanistic empirical model suggested by LTPP was adopted. A stepwise regression approach was undertaken to quantify the effect of the extreme weather events in terms of percentage of change in International Roughness Index (IRI). Predicted conditions based on the model rendered more than 90% correlation with the actual conditions surveyed after extreme events.
SUMMARY AND OUTLOOK

Infrastructure management systems are essential for a robust and competitive economy. Considering the uncertainties and risks associated with pavement management systems, this study provides an accurate deterioration model to project future pavement condition impacted by extreme weather events. The model was developed using data from eight states over eighteen years, and reflected the effect of traffic loads, climate conditions, duration, and depth of extreme weather events such as floods and snowstorms. A stepwise regression approach was undertaken to quantify the effect of the extreme weather events in terms of percentage of change in International Roughness Index (IRI). Predicted conditions based on the model rendered more than 90% correlation with the actual conditions surveyed after extreme events.

Furthermore, probabilistic data-driven LCCA was leveraged to provide outcomes of various treatment strategies and pavement monitoring frequency alternatives in terms of cost, remaining service life, and network quality. Risk-informed management solutions were proposed by implicating the tradeoffs between cost, quality and serviceability. Associated risks are modeled so administrators can rank their priorities and customize their decision-making platforms based on the tolerable risk level. Findings indicated that preventive strategies are capable of meeting limited budgets, significantly elevating pavement condition, and providing high remaining service life. It was also found that shorter monitoring intervals result in lower costs, as well as higher road qualities and remaining service lives.

Yet, there are opportunities for improving the presented work. Use of more data, or simulation can determine the optimum monitoring frequency interval rather than suggestions based on currently available data. Using sensor systems for pavement monitoring, suggestions for treatment strategies can be crafted specifically based on distress type rather than general PCI value for the entire section. Also, considering the frequency of implemented treatments would significantly improve the results. In addition, integrating the extreme event deterioration modeling and risk-based LCCA into one single operating platform, would provide a strong tool for pavement management systems.
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