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Network-Level Pavement Performance and Management Study in Connecticut

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Network-Level Pavement Performance and Management Study in Connecticut

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B.S.C.E., University of Connecticut, 2010

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Network-Level Pavement Performance and Management Study in Connecticut

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ABSTRACT

This thesis presents the analysis of asphalt pavement cracking data on the network level in Connecticut. Pavement performance indicators including longitudinal and transverse cracking as well as roughness are investigated with respect to numerous distinct factors that can be grouped into three categories, i.e. climatic-, pavement structure-, and traffic-related. High-quality climatic data was obtained from the national weather stations in Connecticut. Maintenance and construction data was used to determine the pavement age and structure amongst several other factors. Traffic data was acquired from the state records and accumulated traffic loading was estimated for all segments based on their age. High definition pavement images collected by the Automatic Road Analyzer (ARAN) van in 2010 were used to quantify the longitudinal and transverse cracking with respect to their location within the pavement surface. The data was analysed in three different methods. First, a Monte Carlo approach in which all segments are sampled one hundred times for randomized 500 foot sections was done. From this, qualitative and quantitative trends were observed to determine the significance each factor had on the three different types of pavement performance indicators. Second, an artificial neural network was constructed for each of the different performance indicators to see how well the different factors predicted the outcome. Lastly, pavement management analysis was done to understand the budget implications of this dataset under four different management scenarios.
INTRODUCTION

Pavements make up the largest portion of the world’s transportation infrastructure. These pavement networks link towns, states, and even countries together and allow citizens to reach any goods or services which they desire. They are by far the primary choice of mode for transportation, making them a very high priority when it comes to maintaining and preserving the condition of them. This study focuses on maintaining the pavement network in the state of Connecticut by using automated distress surveys.

Flexible pavements consist of two primary ingredients, aggregate and asphalt. Typically flexible pavements have a structure consisting of three to four surfaces: surface course, base course, sub-base course (optional), and existing sub-grade. The surface course is the top layer which comes in direct contact with traffic and serves the vital function of preventing water from seeping and damaging the layers below. Most distresses occur on this surface course and can be caused by numerous events. Primarily these distresses occur because of poor construction issues (subpar compaction during construction), increased traffic loaded, improper mix design, and climate extremes which cause HMA shrinkage, and crack expansion.

In this study, the focus will be on two of the main pavement distresses: longitudinal and transverse cracking, as well as pavement roughness. Longitudinal cracking propagates parallel to the center-line and generally occurs from three main causes: 1) Poor joint construction, 2) Reflective cracks from an underlying layer, or 3) Load related fatigue. Transverse cracking propagates perpendicular to the center-line and occurs because of two main causes: 1) Shrinkage of the asphalt due to extremely cold
temperatures or asphalt binder hardening due to improper grade selection, 2) Reflective cracks from underlying layers. These two distresses are often the first that a pavement structure will experience. Pavement roughness is not technically defined as a pavement distress; it is a measure of the irregularities on the surface layer which affect the quality of ride experienced by the rider. In this study the International Roughness Index (IRI) is used as the roughness measurement. The calculation for IRI is based on a ratio of the suspension motion of the vehicle divided by the distance travelled. IRI is used quite often now because of the simple procedure and calculation of the value, making it a universal value worldwide. The same cannot be said for distress values, since most departments have different acquisition and processing tools for them.

The first part of this study will involve using a Monte Carlo approach on the Connecticut pavement network to determine the factors which are significant for causing longitudinal and transverse cracking. This was done by first collecting data for any potential factors which could be considered probable causes for either transverse or longitudinal cracking. This included acquiring pavement structure data, traffic data, climatic data, and pavement type data. Next, uniform segments were generated which have the same pavement age, pavement type, traffic, and climatic data. In order to assure that quality climatic data was being used, 5.5 mile buffers were created around the 19 quality weather stations in the state and only segments within these buffers were considered in this part of the study to assure climatic quality. For the Monte Carlo approach, all segments were sampled 100 times for random 500 foot sections within these segments. From these sections, distributions with respect to each considered factor were done to see the significance it had on the different pavement performance indicators.
The second part of the study involved the use of artificial neural networks (ANN) to see if it was possible to use the factors acquired to predict the pavement performance indicators. This was done by using the factors as the input matrix, then testing various different network structures to find the highest level of correlation.

Lastly, a modern pavement management system was developed which created performance models at a network-level based on the three pavement performance indicators being discussed. This was done by first, creating a pavement conditioning index using these indicators for the whole network. Next, families were created which had similar characteristics with respect to pavement type, traffic, climate, and structure. For the entire network, 32 different families were created. A decay function was then created to quantify the different rates at which each family is deteriorating. Once this was complete, different treatment options were created and different scenarios were tested to see key differences in pavement management strategies.

OBJECTIVES

This thesis seeks to accomplish the following objectives:

1) Recognize the importance of the different factors on the both types of pavement cracking statistically by utilizing Monte Carlo simulations

2) Use acquired factors to predict pavement performance indicators by means of Artificial Neural Networks.

3) Create a modern pavement management system which uses automated distress data collection methods to predict future decay by creating families and tests different treatment options and management strategies.
BACKGROUND/ LITERATURE REVIEW

Network-Level Pavement Performance studies

In earlier times, having knowledge of an entire pavement network would require a nearly impossible amount of manual distress surveys. The recent advancements in mobile data collection technology have lead to increased departmental uses of automated distress surveys. This automated process allows for a department to obtain distresses as well as other pavement characteristics at a network level.

There have been three main pavement performance values which are captured differently using automated data collection. The first and most simple method, involves driving a van at a constant speed over network roads to calculate and obtain the roughness of the pavement. Based on how the suspension of the vehicle behaves with respect to the road a certain roughness value is calculated and stored at very short increments. Although this value does not give a department any exact distress which may be occurring, it does provide the department with the quality of ride currently being experienced by citizens on the network. This is also one of the most universal measurements currently, since most departments worldwide can use the same technology and get comparable results. The next pavement performance value obtained in an automated fashion is falling weight deflectometer (FWD) data. This method requires the use of a FWD vehicle which contains a load plate and sensors. This method allows departments to back calculate the modulus of elasticity of pavement layers and determine the structural integrity of pavements in the network. This method differs from the others since it gives an idea of how the entire pavement structure is behaving, not just the
surface layer. Combining this method with the others can also help determine which maintenance treatment is best, specifically if reconstruction is necessary. Many states and countries have taken the initiative to collect FWD data for all or certain components of their network [1-4]. Lastly, pavement performance distresses are obtained from still images taken by vans as they pass over the network. This method typically involves using third-party software which calculates certain distresses on the surface layer as prescribed by the department or user. This allows for a department to understand where there are greater densities of distresses on the network. Technologies for capturing these images have increased dramatically in recent years with high resolution and three dimensional images becoming available. These technologies, used with the proper software, will allow departments to have very detailed pavement condition understanding throughout the network. Many researchers have used automated distress surveys to create complex optimization pavement management models [5-7]; however this paper will focus primarily on only generic strategies to test the created database.

In order to decide which treatments to select for these strategies, an in-depth review was done on successful treatments used, as well as cost and lifetime extensions associated with each treatment [8-10]. Only accepted treatments which are done by most states for the pavement performance indicators used in this study were considered. In total, eight different treatment procedures were selected for use in this study. All costs and treatment life extensions are shown in Table 7.

The first procedure was crack sealing/filling. This is one of the most widely used treatments worldwide because of its low cost and relatively fast application rate. Crack sealing prevents water from seeping through the cracks on the surface layer into the base
layers. Based on a survey addressed to many national agencies [11], it was found that the average treatment life lasted between 2-4 years. However, further research shows that treatment life depends on the current condition of the pavement being applied. Crack sealing pavements which have severe cracking will have a shorter life than crack sealing done on hairline cracking; therefore three different treatment lives were created by combining the surveys with the table created by Hicks [12] which incorporates the current condition of the existing pavement for treatment lives.

Chip sealing and double chip sealing were the next treatments considered. They involve a layer of asphalt followed immediately by a layer of aggregate. This creates a layer to protect the pavement from moisture infiltration. Double chip seals are when an additional layer is created on top of the first. This provides for a smoother riding surface and also creates a much more substantial layer. Double chip seals typically occur in locations with low traffic and poor pavement condition. Typically roads which are going to have chip seal applications have recently had crack sealing done and use this process as a secondary preventative measure. Since this treatment deals with a layer of semi-loose aggregate, it is typically only applied for roads which have ADT traffic volumes less than 5,000.

The next treatment option used in the study is microsurfacing. This process involves the mixture of polymer-modifying asphalt emulsion, water, mineral filler, and other additives spread over the pavement surface [13]. This process began in the 1970’s in Germany, and has been around in the United States since the 1980’s [14]. Its use has picked up significantly because of the flexibility it has in its use; it has no restriction on traffic volume, and only needs one hour to cure before it can handle traffic again.
Thin overlay and thin mill followed by overlays were also considered. These are common pavement maintenance treatment procedures which involve either paving a thin layer of pavement (typically between an inch and 2 inches) above an existing road, or milling to a certain depth and then applying the overlay. It is recommended to mill before overlaying if there is evidence of block cracking, ravelling, or segregation present in the existing pavement [15].

The last two treatments used are for when significant reconstruction of the pavement layer or structure is required. The first of these treatments is cold in-place recycling. This method recycles the existing pavement by milling any depth up to 12 inches of the structure, then mixing it with new binder and compacting using traditional methods. This process is good for the environment since it conserves the need for additional aggregate, and minimizes waste and pollution. The second of these treatments is full reconstruction which involves milling the pavement and reconstructing based on where the structural damage is present.

**Artificial Neural Networks**

Artificial Neural Networks (ANN) have been a useful tool for researchers all over the world for decades, especially for complex datasets for which manual function designs are unfeasible. Pavement researchers specifically have used neural networks because of the complexities involved in computing and predicting: asphalt binder properties, thermal crack detections, as well as for various elements of pavement management on a large scale. In this paper, ANN will be used to predict the three different pavement performance indicators with the numerous factors obtained in the study.
The ability of the neural network to learn from observed data to improve function approximation makes it fairly unique. The attractive abilities of the ANN have drawn much attention to it the past few decades resulting in numerous types, models, training algorithms, etc. A typical ANN structure consists of four primary elements: an input layer, hidden layer, number of neurons, as well as a target layer and is controlled by the training algorithm. Essentially, each neuron will receive a weighted portion of each input element in the layer and attribute a bias towards it creating an input signal. This signal will then be transformed into the output signal by means of a transfer function. There are a vast number of transfer functions which can be applied in this step, however most networks use either linear or sigmoid. This process repeats itself as the network keeps adjusting the weights and bias to meet performance requirements of the network. The standard function for performance in most neural networks is mean squared error (MSE). Depending on the training algorithm used, the network will adjust weights and biases differently to meet performance requirements.

Data Collection and Processing

Due to several data sources with different data formats, a great effort was made to merge different records correctly and to check the quality of the processed data before the analysis. Processed data can be grouped in three main categories, i.e. climatic-, pavement-, and traffic-related.

Climatic data was providing several factors potentially affecting considered pavement segments. In order to obtain detailed yet accurate data, it was decided to query three sources: National Climatic Data Center (NCDC), Quality Controlled Local Climatological Data (QCLCD) and Local Climatological Data (LCD). These services
allows for selection of specific climatic elements from stations around Connecticut. In total, 19 stations across Connecticut were identified with daily weather data going back at least 10 years. The spatial locations of selected weather stations are presented in Figure 1 with the 5.5 mile buffer zones.

Several units within the Connecticut Department of Transportation (ConnDOT) provided pavement-related data. The data is comprised of five main elements: traffic, pavement type and structure, pavement age since last resurfacing project, and pavement cracking data. Average daily traffic (ADT) was obtained as geospatial vector data with respect to state routes. This format allowed for geospatial manipulation of climate and traffic data which was a key step in the initial phase of this study. Age of the top asphalt layer since the last resurfacing project as well as pavement type (flexible vs. composite) was determined by exploring historical maintenance, construction, and project files.

Transverse and longitudinal cracking at 5 meter increment throughout the entire state was collected in 2010 by the Automatic Road ANalyzer (ARAN) van. The van provided a high-quality laser-scan images that were next processed by Wisecrax© software. This software outputs linear meters of transverse and longitudinal cracking with respect to five different zones across the width of the pavement lane: left edge, left wheel path, center, right wheel path, and right edge, to allow for more in depth analysis.
Chapter 1- Monte Carlo Analysis

Segment Selection

As discussed previously, 19 weather stations were considered in this study. In order to ensure the validity of the climatic data, an 8.85 km (5.5 mile) radius was buffered around each weather station, as seen in Figure 1. Next, all segments of state routes that fell within these buffers were exported out and served as the beginning of the database analysis. 2,174 segments were identified at this point which were uniform with respect to annual daily traffic (ADT) and climatic data, and were ranging in length from 15 meters (50 feet) to 8 kilometers (five miles).

FIGURE 1. State road network in Connecticut and 8.85 km (5.5 mile) buffered segments around weather stations

In the next steps, segments were further spited based on the age of top asphalt layer and all segments less than 610 meters (2000 feet) were removed from further analysis to allow for random sampling in the Monte Carlo approach. This process reduced the 2,174 original segments to 947 uniform segments with respect to ADT, age, climatic data, and minimum length. At this point, climatic data and segment ages were used to calculate several weather indices for each segment, including lifetime maximum
and minimum temperature, average lifetime temperature during winter (December/January) and summer (July/August) months, and the number of days below -18°C and above 35°C during lifetime of the segment. This process yielded final 820 segments.

**Monte Carlo Approach and Randomized Sections Selection**

Monte Carlo approach was employed on 820 uniform segments. In this process, each segment was randomly sampled 100 times and each sampling produced 152 meter (500 feet) section for further analysis. In the sampling process, the uniform distribution was used, i.e. each location within a segment had equal chance of being selected. After each section was created, the cracking data for that section was extracted from the database and saved in the 2D table together with other factors. Finally, in order to facilitate robust and semi-automated analysis, all data was stored in a three-dimensional (3-D) array: 133 columns stored various indices of considered factors and variables, 820 rows corresponded to different sections and 100 depth-layers was produced from the Monte Carlo process. All data processing and analysis on the final 3-D array with 11 millions entries was conducted using MATLAB® environment. The entire process is displayed in the flowchart presented in Figure 2.
FIGURE 2. Flow chart of data pre-processing

It should be mentioned here that all factors considered in this study were binned to allow for the categorical statistical analysis. The factors and their corresponding levels (bins) are shown in Table 1.
TABLE 1. Categorical binning of factors

<table>
<thead>
<tr>
<th>Factor</th>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pavement type</td>
<td>Asphalt</td>
<td>Concrete</td>
<td>Composite N/A</td>
</tr>
<tr>
<td>Accumulated traffic</td>
<td>&lt;.05*10^6</td>
<td>&gt;.05<em>10^6, &lt;.35</em>10^6</td>
<td>&gt;.35*10^6</td>
</tr>
<tr>
<td>Truck traffic</td>
<td>Low</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td>Pavement thickness</td>
<td>&lt;10&quot;</td>
<td>&gt;10&quot;, &lt;14&quot;</td>
<td>&gt;14&quot;</td>
</tr>
<tr>
<td>HMA thickness</td>
<td>&lt;3&quot;</td>
<td>&gt;3&quot;, &lt;6&quot;</td>
<td>&gt;6&quot;</td>
</tr>
<tr>
<td>Total base thickness</td>
<td>&lt;10&quot;</td>
<td>&gt;10&quot;, &lt;15&quot;</td>
<td>&gt;15&quot;</td>
</tr>
<tr>
<td>Base thickness</td>
<td>&lt;6&quot;</td>
<td>&gt;6&quot;, &lt;9&quot;</td>
<td>&gt;9&quot;</td>
</tr>
<tr>
<td>Long. cracking</td>
<td>&lt;.05 m/m²</td>
<td>&gt;.05, &lt;.15 m/m²</td>
<td>&gt;.15 m/m²</td>
</tr>
<tr>
<td>Trans. cracking</td>
<td>&lt;.02 m/m²</td>
<td>&gt;.02, &lt;.05 m/m²</td>
<td>&gt;.05 m/m²</td>
</tr>
<tr>
<td>ARAN filming month</td>
<td>April-July</td>
<td>August-October</td>
<td>November-December</td>
</tr>
<tr>
<td>Soil type</td>
<td>G</td>
<td>P</td>
<td>N/A</td>
</tr>
<tr>
<td>Max temperature</td>
<td>&lt;36.1°C</td>
<td>&gt;36.1°C, &lt;38.3°C</td>
<td>&gt;38.3°C</td>
</tr>
<tr>
<td>Days over 35°C</td>
<td>&lt;5</td>
<td>&gt;5, &lt;15</td>
<td>&gt;15</td>
</tr>
<tr>
<td>Min temperature</td>
<td>&gt;-20.5°C</td>
<td>&lt;-20.5°C, &gt;-23.3°C</td>
<td>&lt;-23.3°C</td>
</tr>
<tr>
<td>Days under -18.0°C</td>
<td>&lt;4</td>
<td>&gt;4, &lt;10</td>
<td>&gt;10</td>
</tr>
<tr>
<td>Avg. Winter temp.</td>
<td>&gt;-5.5°C</td>
<td>&gt;-7.2°C, &lt;-5.5°C</td>
<td>&lt;-7.2°C</td>
</tr>
<tr>
<td>Avg. Summer temp.</td>
<td>&lt;27.2°C</td>
<td>&gt;27.2°C, &lt;28.3°C</td>
<td>&gt;28.3°C</td>
</tr>
</tbody>
</table>

**Data Analysis**

Due to the page limit, only the linear trends between the cracking data and various factors are presented in this manuscript. While the linear trends are not necessary the most accurate and appropriate for all relationships, it was assumed that Monte Carlo distributions of slope and intercept coefficients will produce statistically valid outcomes. The data analysis is spitted into two parts: first, general results are discussed which show overall trends and observations. Next, more detailed results are discussed, which also includes a summary table with the significance of different factors on both cracking types with respect to pavement age.

**General Analysis**

In order to check the data quality as well as robustness of applied data processing, general analysis produced several figures with expected trends between pavement
cracking and pavement age as well as crack location. The general trends for both longitudinal and transverse cracking vs. pavement age are shown in Figure 3. One can notice that both cracking types in fact increase with time, more significantly for longitudinal than transverse cracking. The densities of cracking in meters over squared meter of a pavement (m/m²) were calculated by dividing the total linear cracking detected by Wisecrax© by the area of the section. A more in depth analysis of longitudinal cracking is presented in Figure 4, where densities are split by the location. It can be observed that longitudinal cracking is higher in the wheel paths than on the ends or in the center which could be expected since longitudinal cracking should accumulate faster and to greater extend in the wheel paths due to the repeated traffic loadings.

![Figure 3. Scatter plot of longitudinal and transverse cracking with respect to age of top HMA layer](image)

In Figure 4, the notches on the bars indicate the statistical difference between different locations. For example, notches for the left edge and left wheel-path do not overlap and it can determined that they are statistically different with a 95% confidence interval. On the other hand, there is also no significant difference between the right edge
and the right wheel-path but one should notice a greater density range in the right wheel-path than in any other location.

**FIGURE 4.** Boxplot of longitudinal cracking density with respect to pavement location.

**Detailed Results**

There were three main steps employed in order to evaluate the effect of different factors on cracking. First, linear trends were created for all Monte Carlo cases. The slopes and intercepts for each case were stored in a table. Next, histograms and corresponding normal distribution fits were created from these slopes and intercepts to evaluate the differences between different factor levels. Lastly, two separate t-tests were run to determine if, 1) the factor in general was significant for the specific pavement cracking, and 2) there was statistical difference between different levels of the same factor.

Figure 5 shows a linear trend from one layer of the 3-D array (i.e. one Monte Carlo run over all segments) for age vs. transverse cracking factored by ‘Avg. Winter Temperature’. It can be seen from this figure that the average winter temperature has a significant impact on transverse cracking as pavement age progresses. Sections that exceeded an average winter temperature of -5.5°C had much less significant slope than sections which fell below -5.5°F.
A typical analysis step comprised a loop over the depth of 3-D array and calculating linear trend slopes for each section with respect to the two (or three) levels of the categorical factor (like one case shown in Figure 5). Figure 6 shows an example of such a loop for pavement age vs. transverse cracking density with respect to ‘Avg. Winter Temperature’. It is evident by observing the Figure 6 that there is a significant difference in slopes between the three different levels of this factor.

**FIGURE 5.** Single run for age vs. transverse cracking factored by ‘Avg. Winter Temperature’

**FIGURE 6.** Pavement age vs. transverse cracking with respect to three levels of ‘Avg. Winter Temperature’
The most powerful feature of Monte Carlo approach used in this study is the ability of preparing distributions of slope and intercepts coefficients calculated from the linear trends shown in Figure 6. Figure 7 shows the histograms of slope coefficients from Figure 6 and corresponding normal distribution fits for each level of the ‘Avg. Winter Temperature’ factor. One can observed that different levels of that factor remain significantly different for all Monte Carlo cases.

**FIGURE 7.** Pavement age vs. transverse cracking normal distributions of slopes with respect to three levels of ‘Avg. Winter Temperature’

**Example of factor analysis: ‘Pavement type’**

Pavement type was found to be a significant factor for both cracking types when analyzed either against age and accumulated traffic. Figure 8 shows the distribution plots of slope coefficients for age versus both types of pavement cracking grouped by the pavement type.
It is evident from Figure 8 that the type of pavement played a significant role in case of longitudinal cracking. Sections with full-depth asphalt pavements had twice the slope than composite pavements. On the other hand, pavement type played rather a minimal role for transverse cracking. Although the distributions are slightly set apart, the slopes are far less distinct that those for longitudinal cracking.

T-test analysis

The distributions shown in Figures 7 and 8 represent only a small portion of the analysis conducted on each of the seventeen factors. In order to summarize the influence of different factors, Table 2 was created. This table uses one- and two-sample t-tests at 99% level and shows the effect that each categorical factor had on both cracking types considered in this study.
TABLE 2. T-test results on factors with respect to pavement age.

### Longitudinal Cracking Density vs Age grouped by: 

<table>
<thead>
<tr>
<th>Factor</th>
<th>C1</th>
<th>C2</th>
<th>C3-Min</th>
<th>C3-Max</th>
<th>Slope Importance</th>
<th>C4-Min</th>
<th>C4-Max</th>
<th>Intercept Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max Temps</td>
<td>1</td>
<td>1</td>
<td>0.022341</td>
<td>0.0458</td>
<td>1.8</td>
<td>0.03291</td>
<td>0.16807</td>
<td>1.5</td>
</tr>
<tr>
<td>Average Summer Temp</td>
<td>1</td>
<td>1</td>
<td>0.022892</td>
<td>0.04525</td>
<td>1.8</td>
<td>-0.00745</td>
<td>0.17629</td>
<td>1.6</td>
</tr>
<tr>
<td>Average Winter Temp</td>
<td>1</td>
<td>1</td>
<td>0.013619</td>
<td>0.04201</td>
<td>1.7</td>
<td>-0.04693</td>
<td>0.24991</td>
<td>2.3</td>
</tr>
<tr>
<td>Min Temps</td>
<td>1</td>
<td>1</td>
<td>0.02329</td>
<td>0.03725</td>
<td>1.5</td>
<td>-0.01619</td>
<td>0.14003</td>
<td>1.3</td>
</tr>
<tr>
<td>Months Filmed</td>
<td>1</td>
<td>1</td>
<td>0.042429</td>
<td>0.03601</td>
<td>1.4</td>
<td>0.10595</td>
<td>0.16259</td>
<td>1.5</td>
</tr>
<tr>
<td>Pavement Thickness</td>
<td>1</td>
<td>1</td>
<td>0.02589</td>
<td>0.03542</td>
<td>1.4</td>
<td>0.09421</td>
<td>0.1224</td>
<td>1.1</td>
</tr>
<tr>
<td>Base thickness</td>
<td>1</td>
<td>1</td>
<td>0.02589</td>
<td>0.03542</td>
<td>1.4</td>
<td>0.07797</td>
<td>0.11617</td>
<td>1.1</td>
</tr>
<tr>
<td>HMA Thickness</td>
<td>1</td>
<td>1</td>
<td>0.016107</td>
<td>0.03402</td>
<td>1.8</td>
<td>-0.00745</td>
<td>0.20334</td>
<td>1.9</td>
</tr>
<tr>
<td>Family Trucks</td>
<td>1</td>
<td>1</td>
<td>0.01597</td>
<td>0.03393</td>
<td>1.4</td>
<td>0.07842</td>
<td>0.20161</td>
<td>1.8</td>
</tr>
<tr>
<td># Days &lt;0°F</td>
<td>1</td>
<td>1</td>
<td>0.0189</td>
<td>0.03357</td>
<td>1.4</td>
<td>0.02632</td>
<td>0.16392</td>
<td>1.5</td>
</tr>
<tr>
<td># Days &gt;95°F</td>
<td>1</td>
<td>1</td>
<td>0.012514</td>
<td>0.03287</td>
<td>1.8</td>
<td>-0.01767</td>
<td>0.30771</td>
<td>2.8</td>
</tr>
<tr>
<td>Pavement Type</td>
<td>1</td>
<td>1</td>
<td>0.016613</td>
<td>0.03182</td>
<td>1.3</td>
<td>0.02632</td>
<td>0.19813</td>
<td>1.8</td>
</tr>
<tr>
<td>Pavement Soils</td>
<td>1</td>
<td>1</td>
<td>0.012928</td>
<td>0.02887</td>
<td>1.2</td>
<td>0.07794</td>
<td>0.17699</td>
<td>1.6</td>
</tr>
<tr>
<td>Total Base Thickness</td>
<td>1</td>
<td>1</td>
<td>0.01928</td>
<td>0.02506</td>
<td>1.0</td>
<td>0.11499</td>
<td>0.16441</td>
<td>1.5</td>
</tr>
</tbody>
</table>

### Transverse Cracking Density vs Age grouped by: 

<table>
<thead>
<tr>
<th>Factor</th>
<th>C1</th>
<th>C2</th>
<th>C3-Min</th>
<th>C3-Max</th>
<th>Slope Importance</th>
<th>C4-Min</th>
<th>C4-Max</th>
<th>Intercept Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max Temps</td>
<td>1</td>
<td>1</td>
<td>0.005633</td>
<td>0.02033</td>
<td>2.4</td>
<td>-0.06530</td>
<td>0.04168</td>
<td>1.5</td>
</tr>
<tr>
<td>HMA Thickness</td>
<td>1</td>
<td>1</td>
<td>0.005586</td>
<td>0.01732</td>
<td>2.1</td>
<td>-0.03241</td>
<td>0.04510</td>
<td>1.7</td>
</tr>
<tr>
<td>Accumulative Traffic</td>
<td>1</td>
<td>1</td>
<td>0.002623</td>
<td>0.01721</td>
<td>2.0</td>
<td>-0.02509</td>
<td>0.03599</td>
<td>1.3</td>
</tr>
<tr>
<td>Months Filmed</td>
<td>1</td>
<td>1</td>
<td>0.003526</td>
<td>0.01558</td>
<td>1.9</td>
<td>0.01103</td>
<td>0.04795</td>
<td>1.8</td>
</tr>
<tr>
<td>Base thickness</td>
<td>0</td>
<td>1</td>
<td>0.006733</td>
<td>0.01362</td>
<td>1.6</td>
<td>-0.01515</td>
<td>0.02958</td>
<td>1.1</td>
</tr>
<tr>
<td>Average Winter Temp</td>
<td>1</td>
<td>1</td>
<td>0.0013829</td>
<td>0.01362</td>
<td>1.6</td>
<td>-0.02976</td>
<td>0.07487</td>
<td>2.8</td>
</tr>
<tr>
<td>Average Summer Temp</td>
<td>1</td>
<td>1</td>
<td>0.009482</td>
<td>0.01261</td>
<td>1.5</td>
<td>0.00632</td>
<td>0.03404</td>
<td>1.3</td>
</tr>
<tr>
<td># Days &lt;0°F</td>
<td>1</td>
<td>1</td>
<td>0.0018834</td>
<td>0.01191</td>
<td>1.4</td>
<td>-0.00015</td>
<td>0.04961</td>
<td>1.7</td>
</tr>
<tr>
<td># Days &gt;95°F</td>
<td>1</td>
<td>1</td>
<td>0.0014152</td>
<td>0.01157</td>
<td>1.4</td>
<td>-0.01595</td>
<td>0.06434</td>
<td>2.4</td>
</tr>
<tr>
<td>Min Temps</td>
<td>1</td>
<td>1</td>
<td>0.0041452</td>
<td>0.01119</td>
<td>1.3</td>
<td>0.00292</td>
<td>0.16099</td>
<td>6.0</td>
</tr>
<tr>
<td>Family Trucks</td>
<td>1</td>
<td>1</td>
<td>0.0037893</td>
<td>0.01001</td>
<td>1.2</td>
<td>0.01199</td>
<td>0.03219</td>
<td>1.2</td>
</tr>
<tr>
<td>Total Base Thickness</td>
<td>1</td>
<td>1</td>
<td>0.0071345</td>
<td>0.00936</td>
<td>1.1</td>
<td>0.00955</td>
<td>0.03955</td>
<td>1.5</td>
</tr>
<tr>
<td>Pavement Thickness</td>
<td>1</td>
<td>1</td>
<td>0.0071658</td>
<td>0.00912</td>
<td>1.1</td>
<td>0.0041763</td>
<td>0.02697</td>
<td>1.0</td>
</tr>
<tr>
<td>Pavement Type</td>
<td>1</td>
<td>1</td>
<td>0.0013829</td>
<td>0.00860</td>
<td>1.0</td>
<td>0.01598</td>
<td>0.07487</td>
<td>2.8</td>
</tr>
<tr>
<td>Pavement Soils</td>
<td>1</td>
<td>1</td>
<td>0.0013829</td>
<td>0.00839</td>
<td>1.0</td>
<td>0.01895</td>
<td>0.07487</td>
<td>2.8</td>
</tr>
</tbody>
</table>

Two columns with different null hypotheses were prepared for each factor: C1 tests the null hypothesis that the slope of any level was equal to 0, whereas C2 hypothesized that the slope of any level within each factor was the same. In columns C1 and C2, a one (1) implies that there is statistical evidence to reject the corresponding null hypothesis. Columns C3 and C4 show the average slope and intercept determined for this factor from lowest (min) and highest (max) distributions respectively. C3 gives a better understanding of the contribution of a given factor to the accumulation of a particular cracking over the years. Intercept values provide valuable information on the initial
accumulation of cracking. Finally, the *importance* columns for both slopes and intercepts present normalized values with respect to the smallest observed values.
CHAPTER 2 – ARTIFICIAL NEURAL NETWORK ANALYSIS

Construction of Neural Network

In this paper, a back-propagation feed forward network was used. Back-propagation was used since it deals relatively well with nonlinear differentiable transfer functions. Specifically, the Levenburg-Marquardt back-propagation algorithm was used since it is faster than the typical conjugate gradient methods and more precise than simple Quasi-Newton algorithms. The Levensburg-Marquardt (L-M) algorithm first came about in 1963 when Marquardt created an algorithm called the ‘maximum neighborhood’ method which was an optimum interpolation between the gradient method and the Taylor series method. This same algorithm was then incorporated into the back-propagation algorithm in 1994 by Hayes who also discussed the efficiency the algorithm trained with along with the high level of precision observed in comparison to other optimization algorithms. Essentially, the L-M algorithm, shown below, has a variable mu which determines whether Newton’s method is being used, or the tradition gradient descent. When mu is zero, than the algorithm is simply Newton’s method, however when mu is large it becomes a gradient descent. The emphasis when using the L-M algorithm in neural networks is to decrease the value of mu after each successful iteration in attempt to shift to Newton’s method.

\[ x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \]

Where,
- \( J \) = Jacobian matrix (first derivative of network errors in terms of weights)
- \( \mu \) = mu, discussed above
- \( J^T J \) = Hessian matrix (second derivative of network errors in terms of weights)
Three different ANNs were constructed and trained for each of the different pavement performance indicators. The parameters used in this study are shown in Table 3. For each case, data was split into three different sections dedicated to training, validating, and testing the network. These subsets are needed so that the network can meet performance requirements, validate that the network is properly fitting the data, and to independently test the network on untrained data. There was no need to assign certain sections to specific subsets, so random sections were assigned to subsets. The percentage breakdown for the training, validating, and testing was 70%, 15%, and 15% respectively. Other percentage breakdowns were considered for the networks; however the 70/15/15 breakdown performed modestly better since the majority of the focus should be on training the network for complex datasets.
TABLE 3- ANN Parameters, inputs that have asterisks (*) were input into the network as categorical values based on binning from Table 1.

<table>
<thead>
<tr>
<th>Inputs</th>
<th>Transverse Cracking</th>
<th>Longitudinal Cracking</th>
<th>IRI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1) Age</td>
<td>2) Average Winter Temp.*</td>
<td>3) Average Summer Temp.*</td>
<td>1) Age</td>
</tr>
<tr>
<td>4) # Days &lt;0°F*</td>
<td>5) # Days &gt;95°F*</td>
<td>6) Absolute Min. Temp*</td>
<td>2) Average Winter Temp.*</td>
</tr>
<tr>
<td>7) Absolute Max Temp*</td>
<td>8) ARAN months filmed*</td>
<td>9) Base Thickness*</td>
<td>3) Average Summer Temp.*</td>
</tr>
<tr>
<td>10) Total Pavement Thickness*</td>
<td>11) Accumulative Traffic*</td>
<td>12) Pavement Type*</td>
<td>4) # Days &lt;0°F*</td>
</tr>
<tr>
<td>13) Pavement Soils*</td>
<td></td>
<td></td>
<td>5) # Days &gt;95°F*</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number of outputs</th>
<th>1</th>
<th>1</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of hidden layers</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Number of neurons/layer</td>
<td>500</td>
<td>250</td>
<td>250</td>
</tr>
</tbody>
</table>

**Results**

It was unknown how each performance indicator would behave with the given factors so assuming a set number of neurons without an experimental procedure could result in underachieving correlation. The ideal number of neurons to use in the hidden layer was determined by running the ANN with different neurons for each case to see where the best correlation was made. Since the network randomly divided the subgroups
randomly, each network was run three times at each trial of neurons to avoid any outlying results. Figure 9 shows the plot of the $R^2$-value with respect to how many neurons were used for each pavement performance indicator. Each value shown was the highest correlation obtained in the three trials. It can be seen from this figure that each performance indicator reacted to the factors differently within the network. Both longitudinal cracking and IRI has best results at 250 neurons, whereas transverse cracking was predicted best using 500 neurons.

![Figure 9: Correlation results based on different neurons used.](image)

It can be seen in Figure 9 that very worthy correlation values were achieved from the factors provided. Figures 10, 11, and 12 show the training, validation, testing, and overall correlations of the measured pavement performance indicator with the neural network predicted values. The greatest correlation came from transverse cracking (Figure 10), which was expected given the in depth factors which were provided from detailed climatic data. Longitudinal cracking had a very good correlation as well, but IRI managed a $R^2$ value of only .8755. This can be attributed to the fact that many factors
were not directly associated with the IRI pavement predictor as much as they were with the cracking indicators.

FIGURE 10- Transverse Cracking Neural Network Results
FIGURE 11 - Longitudinal Cracking Neural Network Results

FIGURE 12 - IRI Neural Network Results
To further investigate importance that each factor had in predicting each pavement performance indicator, average weights/hidden neuron layer were calculated. Table 4 below shows a conditionally formatted table of these results. This table shows that for IRI, the three most distinguished factors were age, and both transverse and longitudinal cracking. This makes logical sense considering that IRI is measured in roughness experienced by the van while driving which should be, and was directly related to the amount of cracking on the pavement. For both cracking performance indicators age, the month in which the ARAN van filmed the route and pavement type stood out as distinct factors. All three of these factors can be a vital role in the cracking detected, especially considering the software used may be sensitive to the time the van filmed the route. It was also positive to see that the most important factor in predicting transverse cracking was average winter temperature since this is a known cause for transverse cracking to occur.

**TABLE 4 - Average weight/hidden neuron layer for each pavement performance indicator.**

<table>
<thead>
<tr>
<th></th>
<th>IRI</th>
<th>Longitudinal Cracking</th>
<th>Transverse Cracking</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>0.996004474</td>
<td>0.858775693</td>
<td>0.497387672</td>
</tr>
<tr>
<td>Average Winter Temp.</td>
<td>0.618114471</td>
<td>0.704468552</td>
<td>0.521853483</td>
</tr>
<tr>
<td>Average Summer Temp.</td>
<td>0.652775049</td>
<td>0.748266776</td>
<td>0.495540876</td>
</tr>
<tr>
<td># Days &lt;0°F</td>
<td>0.57703021</td>
<td>0.674811021</td>
<td>0.486865</td>
</tr>
<tr>
<td># Days &gt;95°F</td>
<td>0.61516048</td>
<td>0.66009739</td>
<td>0.495411675</td>
</tr>
<tr>
<td>Absolute Min. Temp.</td>
<td>0.648345077</td>
<td>0.674355294</td>
<td>0.489583687</td>
</tr>
<tr>
<td>Absolute Max Temp.</td>
<td>0.614746641</td>
<td>0.704812181</td>
<td>0.490359725</td>
</tr>
<tr>
<td>ARAN months filmed</td>
<td>0.642315561</td>
<td>0.779362636</td>
<td>0.502667364</td>
</tr>
<tr>
<td>Base Thickness</td>
<td>0.744878897</td>
<td>0.66131494</td>
<td>0.488483503</td>
</tr>
<tr>
<td>Total Pavement Thick.</td>
<td>0.800212158</td>
<td>0.583948614</td>
<td>0.491391238</td>
</tr>
<tr>
<td>Accumulative Traffic</td>
<td>0.632173789</td>
<td>0.631916477</td>
<td>0.483230922</td>
</tr>
<tr>
<td>Pavement Type</td>
<td>0.61306238</td>
<td>0.766639251</td>
<td>0.499844653</td>
</tr>
<tr>
<td>Pavement Soils</td>
<td>0.558415441</td>
<td>0.61454095</td>
<td>0.480107877</td>
</tr>
<tr>
<td>Transverse Cracking</td>
<td>1.0797677723</td>
<td>0.61454095</td>
<td>0.480107877</td>
</tr>
<tr>
<td>Longitudinal Cracking</td>
<td>1.059983405</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
CHAPTER 3 – PAVEMENT MANAGEMENT SYSTEM

Creating Management System

Pavement management systems (PMS) are processes which involve planning and executing maintenance of an entire network of pavement aimed to minimize budget while maximizing pavement life. These systems typically begin by having an understanding of what the current pavement conditions are throughout the network. Next they assign a specific priority to the repair of pavements depending on numerous variables ranging from traffic volumes to citizen complaints. The typical approach to maintaining a network is to keep as many roads as possible above fair condition, while minimizing the number of roads in poor condition.

In order to create a pavement management system, the network needs to be well defined and organized. All segments in this chapter are initially split into uniform sections based on similar characteristics on pavement type, total thickness, and traffic volumes resulting in 13,505 segments which cover a length of 3,281 miles of state roads. Much like the previous chapters, only segments from the newer ARAN van will be used for quality control and all segments which are less than 500 feet were eliminated. A total of 5,581 segments were eliminated totalling 1,380 miles for segments which had been filmed by Van 7, and 3,854 segments totally 135 miles were eliminated for being less than 500 feet. This left the usable dataset to be 4,070 segments totally 1,760 miles, or 54% of the entire state network. Figure 13 below shows a spatial representation of which segments were used in the study, and which segments were eliminated.
Next, a weighted surface interpolation was done to interpolate weather indices from surrounding weather stations to each individual segment. This was done by locating the three closest weather stations to the segment’s midpoint and interpolating the index value from all three, giving the closest weather station the most weight. The same weather indices were used from Monte Carlo Analysis chapter. Two overall climatic indices were created, one to assess how cold of a climate the segment experience and one for hot. Table 5 below shows the indices used with regard to both indices.

**TABLE 5- Index ranges used for interpolating cold and hot climate regions**

<table>
<thead>
<tr>
<th>Cold Climate</th>
<th>Hot Climate</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Index</strong></td>
<td><strong>Level 1</strong></td>
</tr>
<tr>
<td>Absolute Min Temp.</td>
<td>&gt;-5°F</td>
</tr>
<tr>
<td># Days &lt;0°F</td>
<td>&lt;4</td>
</tr>
<tr>
<td>Avg. Winter Temp.</td>
<td>&gt;22°F</td>
</tr>
</tbody>
</table>
After a surface interpolation was done for all six of these indices for each segment, an average was done for three cold climate indices and three hot climate indices. All indices have been arranged so that the higher the level is, the more significantly the region is considered cold or hot. Therefore, after averaging all three indices, the higher values represent segments which have more extreme conditions. A histogram was done for both hot and cold climate averages for all segments and two groups were created to distinguish segments. Figures 14a and 14b show these two categorical groupings for both cold and hot climates spatially in Connecticut. This analysis shows that there are two primary climatic regions. The western part of the state experiences less cold weather and more hot weather, whereas the central part of the state experiences colder and less hot climates. This may not be necessary applicable to a single index, but is for the three averaged indices considered in this study.
Computing Pavement Condition

The first step for any PMS is to construct a way to index the condition of all pavements within the network. In this case, a pavement condition index (PCI) was created based off of the three pavement performance indicators used in the study: longitudinal and transverse cracking and IRI. For both longitudinal and transverse cracking, ASTM D6433-10 was used to calculate the number of deduct points to use based on cracking density in meters using the medium severity case. Since IRI is not a distress and therefore not listed in the ASTM D6433-10 standard, deduct points were computed using a correlation from a study done connecting PCI with IRI [16]. Once deduct points were computed for all three indicators, they were summed and plugged into the ASTM D6433-10 total deduct point chart with n=3, which outputs a PCI deduction value based on the number of different distresses used. This was done for all segments. Figure 15 shows a histogram of the PCI for all segments considered in this network:
In order to fully assure that the pavement condition index system is valid, random segments at the high and low end of the spectrum were inspected using Digital Highway software. All segments which were randomly examined proved to be rated correctly. Figures 16a and 16b below show pavement images from segments were received the highest and lowest PCI ratings. Figures 16a comes from Route 124 between Mile marker 5.07 and 5.19 which received the worst PCI rating in the network. Figure 16b comes from Route 2 between Mile marker 4.26 and 4.37. The clear distinction between the two segments on opposing sides of the PCI spectrum shows the success of the rating system.
Categorical Family Grouping

All segments were categorized into families which share similar attributes to create a more in depth management system. Since each segment will deteriorate differently over time, this step is done to create a different decay coefficient for each family type. 32 families were created throughout the entire network based on five attributes. Table 6 below shows how the 32 families were categorically created. Interpolated climatic index averages were used for both cold and hot climates as discussed previously and shown in Table 5.

**TABLE 6- Categorical binning of families**

<table>
<thead>
<tr>
<th>Level</th>
<th>Cold Climate Index Avg.</th>
<th>Hot Climate Index Avg.</th>
<th>Traffic Volume</th>
<th>Pavement Thickness</th>
<th>Pavement Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1</td>
<td>&lt;1.75</td>
<td>&lt;1.75</td>
<td>&lt;80,000 ADT</td>
<td>&lt;12”</td>
<td>Flexible</td>
</tr>
<tr>
<td>Level 2</td>
<td>&gt;1.75</td>
<td>&gt;1.75</td>
<td>&gt;80,000 ADT</td>
<td>&gt;12”</td>
<td>Composite</td>
</tr>
</tbody>
</table>

After assigning each segment to a family, plots of pavement age vs. PCI were created. The following exponential decay function was created to fit all families:
\[ PCI = 100 \times e^{-\frac{age}{\alpha}} \]

Where:

\( \alpha \) = decay parameter varying for each family.

Figure 17 below shows two of the families which have contrasting decaying coefficient values. The family on the left consists of flexible pavement with average climate with high traffic volume and thick pavement and has the least significant decay parameter value of all families with \( \alpha = 54.28 \). The family on the right has a cold climate with low traffic and thickness on composite pavement had has the most significant decay parameter value all families with \( \alpha = 17.41 \).

![FIGURE 17- Sample family decay function plots](image)

**Pavement Management Approach & Implementation**

The management approach used in this paper is to bring all pavements which are marginally below a certain PCI threshold above it, and let pavements which are well below this threshold decay until they reach a reconstruction level in which case they are treated. This is a sensible modern day approach since many departments have budgetary constraints. If the entire budget is spent attempting to fix the poor condition roads, only a
handful of roads will be fixed and all the pavements which are in fair condition now deteriorate more. This typically leads to an increase of poor condition roads over time and puts the department in a significant budgetary conflict.

The treatments used in the thesis are common maintenance procedures used in all departments across the nation. As discussed earlier, the life expectancy of the treatments depends on two primary characteristics: condition of the pavement being treated, and traffic volume. The life extension for treatments is split based on the pavement condition being good, fair, or poor. The values obtained for life expectancy and cost per mile for a 30 foot width were based off of literature review and are shown in Table 7 below. Since the pavement will deteriorate at a faster rate after each treatment is applied, a reduction value was created for each treatment.

**TABLE 7- Pavement treatments with associated costs**

<table>
<thead>
<tr>
<th>Treatment</th>
<th>L.E. Good</th>
<th>L.E. Fair</th>
<th>L.E. Poor</th>
<th>Cost/mile</th>
<th>Alpha Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crack Seal/Fill</td>
<td>2 to 7 Years</td>
<td>2 to 5 Years</td>
<td>1 to 4 Years</td>
<td>$13,200</td>
<td>-3</td>
</tr>
<tr>
<td>Chip Seal</td>
<td>6 to 10 Years</td>
<td>4 to 6 Years</td>
<td>2 to 4 Years</td>
<td>$30,800</td>
<td>-2</td>
</tr>
<tr>
<td>Double Chip Seal</td>
<td>7 to 12 Years</td>
<td>5 to 7 Years</td>
<td>3 to 5 Years</td>
<td>$48,400</td>
<td>-1</td>
</tr>
<tr>
<td>Microsurfacing</td>
<td>7 to 12 Years</td>
<td>5 to 7 Years</td>
<td>3 to 6 Years</td>
<td>$52,800</td>
<td>-1</td>
</tr>
<tr>
<td>Thin Overlay</td>
<td>8 to 11 Years</td>
<td>6 to 9 Years</td>
<td>3 to 7 Years</td>
<td>$61,600</td>
<td>-1</td>
</tr>
<tr>
<td>Thin Mill/Overlay</td>
<td>10 to 13 Years</td>
<td>9 to 11 Years</td>
<td>8 to 10 Years</td>
<td>$74,800</td>
<td>-.5</td>
</tr>
<tr>
<td>Cold In Place Recycling</td>
<td>PCI to 85</td>
<td>PCI to 82.5</td>
<td>PCI to 80</td>
<td>$96,800</td>
<td>-.5</td>
</tr>
<tr>
<td>Reconstruction</td>
<td>PCI to 92.5</td>
<td>PCI to 90</td>
<td>PCI to 87.5</td>
<td>$110,000</td>
<td>-.5</td>
</tr>
</tbody>
</table>
In order to simplify the maintenance approach for such a large network, six treatment sequences were created based on common practices and treatment constraints. Each segment was assigned to a specific treatment sequence based on current PCI and traffic volume. Table 8 displays the six different treatments along with their selection constraints using the numbers assigned to each treatment option in Table 7.

**TABLE 8- Six Treatment Sequences Considered**

<table>
<thead>
<tr>
<th>Sequence</th>
<th>Step 1</th>
<th>Step 2</th>
<th>Step 3</th>
<th>Starting Triggers</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Crack Seal/Fill</td>
<td>Chip Seal</td>
<td>Thin Overlay</td>
<td>At Threshold Value</td>
</tr>
<tr>
<td>2</td>
<td>Crack Seal/Fill</td>
<td>Double Chip Seal</td>
<td>Thin Overlay</td>
<td>At Threshold Value</td>
</tr>
<tr>
<td>3</td>
<td>Crack Seal/Fill</td>
<td>Microsurfacing</td>
<td>Thin Overlay</td>
<td>At Threshold Value</td>
</tr>
<tr>
<td>4</td>
<td>Thin Mill/Overlay</td>
<td>Crack Seal/Fill</td>
<td>Microsurfacing</td>
<td>At Threshold Value -5</td>
</tr>
<tr>
<td>5</td>
<td>Cold In Place Recycling</td>
<td>Crack Seal/Fill</td>
<td>Microsurfacing</td>
<td>At Threshold Value -20</td>
</tr>
<tr>
<td>6</td>
<td>Reconstruction</td>
<td>Crack Seal/Fill</td>
<td>Microsurfacing</td>
<td>At Threshold Value -20</td>
</tr>
</tbody>
</table>

In order to determine which sequence to use, both PCI and traffic were used as primary decision makers, as shown in the flowchart in Figure 18.

![FIGURE 18-Sequence decision flowchart](image-url)
Pavement Management Scenarios

Four different management scenarios were used in this thesis to observe changes in pavement condition over time, as well as associated costs. The four scenarios were: 1) do nothing, 2) keep the PCI threshold above 60, 3) keep the PCI threshold above 70, and 4) keep the PCI threshold above 80. These scenarios were used to determine the advantages and disadvantages of keeping the pavement condition of the network at a high level and obtaining the most significant lifetime extensions from the treatments. All four scenarios were tested for a simulation period of 20 years. Since all treatments are not done exactly the same in the field, it is improper to assign a definite value for the lifetime extensions for each treatment, therefore a random normal lifetime extension was created each time for each treatment within the ranges for good, fair, and poor conditions.

Scenario#1- Do nothing

This scenario was done initially to assess what would happen if nothing was done to the roads for the next 20 years. This is a management approach for considering the worst case scenario and the resulting outcomes to both the pavement condition as well as the overall costs. In order to observe the changing pavement condition over time three categories of condition were created:

1) Good condition, which represents pavements which have a PCI above 70
2) Fair condition, which represent pavements between PCI 50 and 70
3) Poor condition, which represent pavements which are below PCI 50.
Figure 19 below shows the change in pavement condition for the next 20 years under scenario #1.

This figure shows the dramatic decline in pavement condition which would occur with no treatments for the next 20 years. Nearly all segments would be in poor condition and require the most significant, and costly treatment. For this scenario, treatments were selected based solely on PCI and ADT of segments after 20 years of simulation. Nearly all segments needed to be reconstructed and were assigned to either Cold in Place Recycling or Reconstruction.

**Scenario#2- Keep PCI threshold above 60**

The next scenario was to simulate the next 20 years by keeping the PCI threshold above a value of 60. This was done by plugging 60 into the constraint equations in table 8 and assigned specific treatment scenarios for each segment in the network. Once treatment scenarios were assigned, the simulation began for 20 years and once the PCI
fell below 60, the next step in the sequence was triggered. Figure 20 below shows a sample plot of a segment in the network which falls under sequence three.

![Sample Segment Treatment Sequence](image)

**FIGURE 20- Sample Segment Treatment Sequence**

The estimated cost was calculated depending on the simulation year in which the treatment occurs to incorporate the future cost correctly. This was done for all segments and the total estimate cost for maintaining the network at the level was calculated. Next, the pavement condition throughout the simulation period was observed after incorporating the treatments done each year. Figure 21 below shows the pavement condition over time for this scenario using the same condition grouping of good, fair, and poor as discussed in the previous scenario. The vast improvement between this scenario and the previous is evident with only minimal segments achieving a poor condition over time and most maintaining at least fair condition.
Scenario#3 - Keep PCI threshold above 70

The next scenario was to keep the PCI threshold above 70. The biggest difference between this scenario and the previous of keeping PCI above 60 is the improvement of lifetime extension of treatments, as well as less significant alpha value reductions. Since the PCI threshold is bumped up to 70, the treatments will occur on pavements which are considered to be in good condition. For this scenario good condition lifetime extensions from table 7 were used. Also, the alpha value reductions shown in table 7 were cut in half assuming that the decay rate will not increase as much when treating on good condition pavement. Figure 22 shows the pavement condition for this scenario. There is a noticeable increase in the number of good condition segments, primarily because this scenario segments which fall under a good condition to get treated the following year.
Scenario#4- Keep PCI threshold above 80

The last scenario done was to analyze how keeping the PCI above 80 would affect the price and condition of the network. Although the reality of keeping the condition of a network as large as the one being considered at a level this high is unlikely due to limitations in resources, it is done to see the affects. This scenario also uses the lifetime extensions in the good column of table 7, however uses an increased mean with a more confined standard deviation when taking random normal values to assure values are selected in the higher side of the range. It can be seen in Figure 23 that the condition of the network when simulated for 20 years consists of nearly all good condition segments. There are also no poor condition segments, unlike in scenario #3 where there were a few.
Pavement Management Cost Analysis

In order to fully assess the different scenarios, a cost analysis must be done to put valuation with respect to the pavement condition. It can be seen from the previous section that clearly a department would prefer to use scenario #4 to keep the PCI threshold high and the network in good condition, but in order to do so much be able to afford the cost. For each scenario presented in the previous section the cost of the treatments was recorded based on the year in which they occurred. The current inflation rate of 2.7% was used to adjust the cost to future years. Figure 24 shows the comparison in yearly cost for the scenarios 2, 3, and 4. Scenario 1 was not included in this figure because it only has a single cost at year 20.
Initially the highest costs are associated with Scenario #4, since most segments in the network need to be initially treated to go above the PCI threshold of 80. Afterwards however, the costs associated with this scenario outperform both Scenario #2 and 3 since the extension of the treatments last longer and the number of treatments required decrease. Scenario #3 also follows a similar trend to but a much lesser extent. Although the initial costs are much higher than Scenario #2, it doesn’t provide reduced costs later on in simulation years like Scenario #4 does. However, since it maintains a higher level of condition than Scenario #1, it should still be considered a better alternative. Unlike the others, Scenario #1 starts off with very low costs for treatments, since most segments are above this threshold and waiting to trigger for their first treatment. However, since the life extension for the treatments is less the other scenarios, the demand for more treatments occurs at a higher frequency resulting in higher costs as the simulation periods increases.
To further investigate the lifetime costs, a comparison was done to evaluate the differences between the net present value (NPV) costs for all four scenarios, shown in Figure 25. Scenario #1 has the most expensive NPV associated with it since the pavement decays and the most expensive treatments are required after 20 years. Scenarios 2, 3, and 4 all have fairly similar values, however there is an appealing trend showing a decrease in cost when a higher PCI threshold is used. This is primarily due to longer life extensions which may end up avoiding the later and more expensive steps in the treatment sequences.
CONCLUSIONS

The first Chapter evaluated the influence of thirteen distinct factors and their levels on the pavement cracking at a network level. Comprehensive pre-processing and multiple checks were performed in order to produce a good quality data for the analysis. One hundred Monte Carlo random simulations were conducted for each segment to ensure that outcomes are statistically valid and unbiased. While each factor can be analyzed separately in details and two such examples were shown, two t-tests were conducted to evaluate all factors in the same fashion. These t-tests evaluated if a factor was significant itself as well as if different levels of the same factor were statistically different. The results showed that all but two factors tested were significant for both t-tests at the 99% level. This implies that nearly each factor considered in this study has some impact on pavement cracking, and also behaves differently at different levels. It should be noted here that many factors have very small but still statistically significant slope that cannot be neglected. This chapter shows the power of using network level analysis on pavement performance data. The ability to run distresses against numerous factors allows for a more complex dissection of the pavement performance. Trends and other observations made in this study are limited to Connecticut conditions and are not necessary valid elsewhere.

In Chapter 2, the dataset of factors obtained were used for training and predicting pavement performance indicators using Artificial Neural Networks. Three different networks were created for each different pavement performance indicator. It was found that the networks created demonstrated a high level of correlation between the measured and predicted values, more so for the cracking indicators compared to IRI. Weights per
hidden neuron layer were then averaged to further understand the importance of each factor within the each network. The following conclusions were made:

1) Transverse and Longitudinal Cracking were both predicted with high levels of correlation, IRI demonstrated a good correlation but not as good as the other indicators.

2) It was found that age, the months that the van filmed the route, and pavement type were controlling factors for predicting cracking indicators.

3) Average winter temperature was the most significant factor in predicting transverse cracking

Chapter 3 focuses on developing a pavement management system for flexible and composite pavements in the Connecticut road network. For the purpose of quality assurance, segments from the older imaging system were removed since the crack detection differed significantly from the newer system. Segments which were less than 500 feet were also eliminated to avoid segments which would not qualify as potential projects at a network level. Climatic data was created by weighted surface interpolation from the segment’s midpoint to the three nearest high quality weather stations. All segments were grouped into families sharing similar attributes and a decay equation was fitted for each family. Six different pavement management sequences were considered and each of them contained three steps of different surface treatments. Four different scenarios were tested for a simulation period of 20 years to monitor cost and pavement conditions over time. In each simulation iteration, a stochastic approach was used to establish life extensions of the treatments. Based on the results, the following observations can be made:
1) Scenario #1 for doing nothing for 20 years shows the importance in maintaining road networks frequently, as nearly all segments in the network deteriorated to poor condition in this time. The cost associated with repairing the network after nothing was done after 20 years far surpassed the other scenarios.

2) Scenario #2 had low costs initially since many segments were above the PCI threshold of 60. However the life extension of treatments was lower since the treatments were being done on fair condition pavements and resulted in more frequent repairs and higher costs than both Scenario #3 and Scenario #4.

3) Both Scenario #3 and Scenario #4 kept the condition of the network at remarkable high levels; however, the cost analysis supported the use of Scenario #4. If a highway department has enough capital and resources to support the high initial costs and extensive workload of these scenarios, they would be rewarded with longer treatment extensions, less frequent applications, and less cost in future years.
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