A METHODOLOGY FOR THE DEVELOPMENT OF PERFORMANCE AND DISTRESS MODELS FOR A PMS USING AUTOMATED DATA

by

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ABSTRACT

MICHAEL JAMES DYE. A methodology for the development of performance and distress models for a PMS using automated data. (Under the direction of DR. DON CHEN)

Automated pavement data collection technologies have gained momentum due to the fact that the automated data have more detail, greater quantity, better quality, and better repeatability. A systematic method of developing performance and distress models; however, is lacking. This study was conducted to address this issue. Maximum Allowable Extent (MAE) values and the Analytical Hierarchy Process (AHP) were used to calculate composite distress and performance indices. Non-linear sigmoidal distress and performance models were then developed. A visual comparison of the automated model curves and the corresponding windshield model curves indicated that the automated models are robust. In addition, trigger points on the North Carolina Department of Transportation (NCDOT) Pavement Management System (PMS) decision tress were determined, which allow NCDOT engineers to select appropriate maintenance actions.

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CHAPTER 1: INTRODUCTION

1.1 Background and Significance

Roadways allow for the transportation of goods and equipment; therefore, it is important to have an established evaluation and maintenance plan for roadways. A common tool used by state highway agencies to evaluate and monitor roadway networks is the Pavement Management System (PMS). A PMS is defined as a set of tools and methods that assist pavement engineers in the decision making process of finding the optimal strategies for evaluating and maintaining pavements to a serviceable condition (Chowdhury, 2010). The PMS concept took root in the United States during the 1970's when state agencies began to understand that performances of the roadways were linked to the maintenance of the pavements (Finn, 1979). PMS has continued to grow ever since its beginning, and received a major upgrade in the 1980's that allowed pavement managers to include decision making techniques as a part of the process for analyzing roadways. This provided the pavement engineers the ability to find the most cost effective alternative for the project (Ferreira et. al., 2002).

Many counties, states, and cities have developed or adapted a PMS to aid in the maintenance of their roadways. This was no different for the state of North Carolina who developed their PMS in 1982 with the passing of the Executive Organization Act of 1971 (Greene, 2011). The state of North Carolina notices that there was a rising need to properly evaluate and maintain the 79,000 miles of roadway pavements throughout the state of

North Carolina, the nation's second largest state-maintained roadways system (Greene, 2011). The North Carolina Department of Transportation (NCDOT) utilizes its PMS to manage data on current roadway conditions which has assisted in the maintenance and the repair of roadway surfaces for an accelerated, efficient process (Mastin, 2011).

There are currently two methods for collecting the distress data, windshield surveys and automated data collection (McQueen and Timm, 2005). Once the distress data have been collected, they are rated through a pavement performance index which reveals the current condition of the pavement.

A windshield survey is a method used by state DOT's to manually collect pavement distress data. In North Carolina, windshield surveys are performed by highly trained personnel who travel at 10-15 mph along predetermined travel paths or along the shoulders of pavement (Kim et. al, 2009). The trained personnel observe distresses on pavements and fill out a standard survey form developed by the NCDOT. Using these forms the personnel make qualitative judgments of pavement performance based on the surface of the roadway for both asphalt concrete and portland cement concrete (Underwood, 2011). The personnel rate the surface of the roadway based on the amount and severity of roadway distresses.

The NCDOT has implemented the automated data collection method as a new tool to their PMS toolbox. This method is performed by using a high speed profiler that is used to collect the distresses from the pavement. The vehicles are equipped with high speed profiling equipment that include state of the art cameras, lasers, and GPS positioning sensors that collect the necessary data (Bertucci, 2009). Previous studies have shown automated data collection can improve data quality, increase safety, and reduce resources (McGhee, 2004).

1.2 Problem Statement

According to the NCDOT High Speed Distress Manual (2011), the NCDOT have started collecting automated data since 2011. The purpose of this research is to establish a methodology for the development of distress and performance models for automated collected data. This research will help NCDOT engineers predict pavement performance, and will ensure that appropriate maintenance action is taken. Currently, performance and distress models used by the NCDOT were developed from windshield collected data. The automated data collection method has shown more consistency among the data verses data collected by windshield surveys (McGhee, 2004). The automated data method records the data numerically, whereas, the windshield method records the data manually. This will lead to different statistical analysis methods to analyze the data, which will lead to different performance and distress models. Therefore, a new set of performance and distress models need to be developed for the automated collected data.

1.3 Purpose and Objectives

The purpose of this research was to develop the distress and performance indices, distress and performance models, and triggers points on the decision trees. The objective of this research was to normalize data, develop distress and performance models, compare automated distress and performance models against windshield distress and performance models, and determine trigger points on the NCDOT PMS decision tress.

1.4 Scope and Limitations

In order to complete the objectives for this project, the researchers needed to clean the data in order to remove outliers, determine the initial distress indices, and compare automated performance curves with the windshield performance curves.

The limitation associated with this project was the models were developed using data collected for North Carolina roadways, and therefore the models might not be applicable to be used in other states. The methodology, however, is flexible enough that any other state DOTs can follow the steps to develop models that will work with roadways.

CHAPTER 2: LITERATURE REVIEW

In order for a PMS to be successful, it must have the ability to accurately predict pavement performance (Lewis et. al, 2013). According to Applied Pavement Technology, pavement prediction models help DOT engineers estimate future pavement conditions; identify the appropriate time for maintenance and rehabilitation action; identify cost effective treatment strategies; estimate statewide pavement goals, objectives, and constraints; and demonstrate the consequences of various pavement investment strategies (2010).

2.1 Windshield Collection Method

The windshield data collection method was the NCDOT's primary method for collecting roadway distress data; and the NCDOT has been using this method since 1982 (Mastin, 2011). The windshield surveys are performed by a team of highly trained personnel who drive vehicles along the right hand lane or along the shoulder of the road, and this is typically done below average highway speeds (Mastin, 2011). The personnel are responsible for determining the condition of the road's surface, as well as to record the current condition of the roadway. This data is recorded on pre-developed survey forms (Sivaneswaran et. al, 2004). An example survey form from the *NCDOT High Speed Distress Manual* can be seen in the Appendix A (Mastin, 2011). The severity rating is based on a rating of none (N), light (L), moderate (M), and severe (S) for each distress; however, the rating of pavement distress is subjected to the personnel's perception (Kim, 2009). The

typical distance covered by a windshield survey crew for one day is between 125-200 miles. This is directly dependent on the weather, number of sections, and the variation in the condition of the roadway (Hartgen, 1983).

The intrinsic problem with the windshield surveys is the quality of the data recorded. Due to the fact that the data is collected by human personnel, the rating of the pavement condition is subjective to the rater. This can lead to the data lacking in credibility, which is a hindrance for a PMS when analyzing the data (Wu, 2001). Another problem with windshield data collection is the ability to repeat the same results between the different raters. This can create variability within the data that can lead to false results when analyzing the data (Mastin, 2011). For example, the windshield collected data has shown that the asphalt rating is recorded more consistently than the data recorded for concrete roadway sections. This has created a large variance between the two types of pavements (Mastin, 2008).

Safety is a concern for the personnel who perform the roadway surveys, as well as, for the travelling motorist (Sivaneswaran et. al, 2004); however, there are no crash test statistics from accidents caused by the windshield surveys. Windshield surveys require a large amount of capital due to the fact that the windshield surveys are heavily labor intensive operations that require staff members for an extensive amount of time (Wu, 2001).

The manually collected data is processed by taking the raw data for each type of distress and determining the deduction value that corresponds to its specific roadway section. The deductions are then combined for each of the distresses to develop a final

performance index for the roadway section. These performance index values are used to determine the appropriate action that is needed for the roadway section.

2.2 Automated Data Collection Method

Automated data is defined as data collected by photography or by the use of non-contact sensor equipment. The data collected for automated distress differs from the data that is collected by windshield surveys in detail, quantity, and quality. The automated data tends to have more detail, greater quantity, better quality, and better repeatability (McGhee, 2004). The automated data is collected using high speed profilers, as seen in Figure 1.

FIGURE 1: High speed profiler (International Cybernetics, 2014)

The high speed profiler vehicles are equipped with state of the art cameras, lasers, and GPS positioning sensors (Bertucci, 2009). When compared to manual survey methods the automated survey methods can collect more data, with improved quality, while increasing safety, and with minimal resources (McGhee, 2004). The profilers can vary in make or model of vehicles, and the profilers do not require a DOT identification to be

mounted on the vehicle. This is because private vendors are often used to collect the data. The data is recorded as the vehicle travels in the most right hand lane while the profiler records the condition of the roadway. The most right hand lane was been deemed the travel lane by the NCDOT. The automated collection method severity rating is based on a rating of none (N), light (L), moderate (M), and severe (S) for each distress. This is for asphalt concrete and the portland cement concrete.

The automated method has achieved breakthroughs in PMS by implementing some of the latest technology available. Since the 1980's, video imagery has been used by state DOTs as a tool for pavement management. Video imagery is the act of recording the roadway surface through means of video tape while the profiler records the data when the vehicle is driven down the roadways. The information is then analyzed frame by frame against a reference measurement (Baker et. al, 1987). The problem with video is its inability to record 3D data. Video imagery cannot discern between all distresses in the pavement caused by load and non-load-related sources (Sun, 2011). Digital cameras were also implemented as the technology increased. The digital cameras used have a high resolution to ensure that high quality photographs are taken. According to Wang (2002), high resolution digital cameras can capture cracks on the roadway surface with a width that is less than two millimeters. However, perhaps the greatest breakthrough in technology came from the implementation of lasers. These lasers recently have become quite popular in PMS because of their ability to produce 3D data. Lasers overcome the problems that occur with the limitation of 2D data recording systems by being able to differentiate between pavement distresses and debris on the roadway surface (Sun, 2011). The lasers work by using a triangulation technique, which is where a signal is sent out that measures

the vertical distance to the pavement surface at several points (Al-Quadi, 1992). The implementation of new advances in computer data processing gives the NCDOT engineers the ability to process real time data as the high speed profilers collect the images (Wang, 2002). With the advancement of laser technology, data can be collected at highway speeds; the data captured by these lasers can be recorded at 1 inch intervals or less (McGhee, 2004).

However, the automated data method has not yet been perfected, as there are still minor issues that can occur after the data is collected. Since private vendors can hold state PMS contracts to collect the data, there can be slight differences in the way the data is processed through their developed algorithms. This can lead to slight variations between different vendor's distress ratings.

Certain distresses are challenging for the automated collection to gather and process. The Wyoming Department of Transportation (WDOT) stated that they it is challenging for patching and bleeding to be fully handled by the automated process (McGhee, 2004). Shadows also make it difficult to distinguishing distresses in shadowy areas. This can affect the extent and severity of the distresses on the roadways. There are also problems with identifying fixes to different pavement treatments such as chip-sealed, tined, and sealed crack surfaces. However, with the introduction of 3D data collection capabilities researchers are optimistic that these problems can be solved (McGhee, 2004). The differences between the windshield surveys and the automated surveys can be seen in Table 1.

TABLE 1: Windshield data compared to automated data

Windshield Survey Data		Automated Data	
Type of Data:	Categorical	Type of Data:	Quantitative
Benefits:	Well known process, personnel trained, collects data, and established decision trees	Benefits:	Quicker data collection, consistent data collection, and safer for personnel
Issues:	Variability between raters, safety issues, and a time consuming process	Issues:	Variability in interpretation of the data cleaning by the independent contractor, identifying all distress types
Processing:	Converts categorical data into quantitative data to determine pavement distress levels	Processing:	Uses quantitate data to determine pavement distress levels
Procedure:	Uses MAE values to determine a PCR value	Procedure:	This study will develop a methodology for the procedure

2.3 Types of Distress

Pavement distress is used by the NCDOT to develop the Pavement Condition Rating (PCR) values which are used to make pavement management, maintenance, rehabilitation estimations (Mastin, 2011). The PCR values are a point based deduction matrix that removes points depending on the distresses on the roadway, for more information on PCR values refer to Section 2.4. The data for pavement distresses can be collected through the manual or automated collection methods. The distresses that were collected for this study can be seen in Table 2; as well as a description of the distress

severity levels, units, and description are in the remaining portion of this section. The units

for the distresses in Table 2 are the NCDOT's method of recording the distresses.

TABLE 2: Pavement distresses

Distress	Units
Alligator	Square Feet
Patching	Square Feet
Delamination	Square Feet
Rutting	Average Length in Inches
Bleeding	Square Feet
Transverse Cracking	Linear Feet
Non-Wheel Path Longitudinal Cracking	Linear Feet
Longitudinal Lane Join Cracking	Linear Feet
Raveling	Square Feet

2.3.1 Alligator Cracking

Alligator cracking occurs in areas subjected to repetitive wheel loads; for rating

purposes they are only found in the wheel path. Alligator cracking typically starts as

longitudinal cracking within the wheel path which develops into a series of interconnected

cracks having an "alligator hide" pattern (Mastin, 2011). Alligator cracking is measured in

square feet. Low severity alligator cracking is defined as a single sealed or unsealed

longitudinal crack in the wheel path or an area of cracks with no or few interconnecting

cracks with no spalling; these cracks are less than 0.125 inch in width. Moderate severity

for alligator cracking is defined as an area of interconnecting cracks that forms an alligator

pattern and may have some slight spalling; these cracks are generally 0.25 inch wide. High

severity alligator cracking is defined as an area that consist of moderately or severely

spalled cracks forming an alligator pattern; these cracks are generally greater than 0.325 inch wide (Mastin, 2011).

2.3.2 Patching Wheel Path

Patching is an area of a pavement surface that has been removed and replaced or where additional material has been placed on the pavement surface to cover cracking or other distresses. There are two types of patching that are recorded, the patching that is within the wheel path and patching that is not in the wheel path. Wheel path and non-wheel path patching is counted separately and is measured in square feet. Patching does not have severity levels associated with the distress, but only an amount of patching is recorded (Mastin, 2011).

2.3.3 Delamination

Delamination is an area of pavement that is missing due to the loss of adhesion between the surface and the under-laying layers. Traditionally delamination is only one layer thick and is usually associated with the surface course. Delamination is recorded in square foot and does not have severity levels associated with the distress; it is recorded in the amount of delamination that occurs (Mastin, 2011).

2.3.4 Rutting

Rutting is a longitudinal surface depression in the wheel path. Rutting data is collected using 3D laser sensors which provide a cross section of the pavement surface. A minimum of a dozen points are required to calculate the rut depths; rutting is measured in vertical inches. Rutting receives no severity rating when the vertical deformation is less than 0.25 inch; a low severity rating when the vertical deformation is between 0.25 inch to 0.5 inch; a moderate severity rating when the vertical deformation is between 0.5 inch to.1

inch; high severity rating when the vertical deformation is greater than 1 inch (Mastin, 2011).

2.3.5 Bleeding

Bleeding is the presence of too much liquid bituminous material on the pavement surface. The result is the surface having a shiny, glass-like, or reflective surface, and it may also be tacky to the touch. This is more noticeable in warm weather and is usually found within the wheel paths. Bleeding is recorded in square feet. There are only two severity levels for bleeding, low severity and high severity. The bleeding distress receives a low severity rating when the pavement surface is discolored compared to the surrounding asphalt which is caused by excessive liquid asphalt. Bleeding receives a high severity rating when excessive liquid asphalt gives the pavement surface a shiny appearance which can cause tire marks to be evident in warm weather (Mastin, 2011).

2.3.6 Transverse Cracking

Transverse cracking occurs when random cracks run primarily across the roadway surface, but not over the joints in the jointed concrete pavement that resides underneath and is recorded in linear feet (Mastin, 2011). A low severity transverse crack is defined as a sealed crack in good condition or an unsealed crack with a width less than 0.25 inch; moderate severity cracking applies to any unsealed cracks that range between 0.25 inch to 0.5 inch or any crack that is adjacent to transverse cracking with 5-10 feet, sealed or unsealed; high severity rating applies to any unsealed crack that is greater than 0.5 inch in its width and any crack that is within 5 feet, sealed or unsealed. It is important to note that the severity of transverse cracking is defined by the highest level of severity within roadway section being evaluated (Mastin, 2011).

2.3.7 Non-Wheel Path Longitudinal Cracking

Non-wheel path (NWP) longitudinal cracking is when there are cracks that run parallel with the center of the roadway. However, it is important to note that only cracking outside the wheel path meets the NWP requirement of longitudinal cracking. Cracking fitting this description is commonly found on the inside of the wheel path and is known as low severity alligator cracking (Mastin, 2011). NWP longitudinal cracking is recorded in linear feet and the minimum length counted is 1 foot. There are only two severity levels for NWP longitudinal cracking, low severity and high severity. NWP longitudinal crack receives a low severity rating when the crack seal is in good condition and the width cannot be estimated or when the crack is unsealed but is less than 0.25 inch in width. A NWP longitudinal crack receives a high severity rating when the crack is unsealed or when the crack is adjacent to other cracking (Mastin, 2011).

2.3.8 Longitudinal Lane Joint Cracking

Longitudinal lane joint cracking occurs when the joint is able to be penetrated by water. There are two distress levels for longitudinal lane joint cracking, low severity and high severity (Mastin, 2011). Longitudinal lane join cracking receives a low severity rating when the sealant is in good condition and the width cannot be estimated or when the joint is unsealed. A longitudinal lane joint cracking receives a high severity rating when the paving is cracked with severe spalling or adjacent cracking (Mastin, 2011).

2.3.9 Raveling

Raveling is the result of the roadway surface layer dislodging aggregate particles or loss of asphalt binder. This distress is more prevalent with chip seal or slurry surfaces than with plant mix surface. Raveling is a sign of hardening or poor application of asphalt binder

(Mastin, 2011). The raveling distress receives a low severity rating when aggregate loss within the pavement lanes is minimal and the stripping is beginning to be detected and some aggregate is starting to wear away. Pavement Interactive (2007) describe stripping as the displacement of the asphalt binder from the aggregates when the hydrophobic aggregate has been introduced to water. The raveling distress receives a moderate severity rating when stripping becomes evident, or where there are small areas less than one square foot, where strips of aggregate are broken away. A raveling distress receives a high severity rating when the stripping becomes very evident, and aggregate accumulation begins to propose a problem along the shoulders of the roadway and large areas or greater than one square foot, of the aggregate is stripped away (Mastin, 2011).

2.4 Pavement Condition Rating (PCR)

To properly determine the condition of the roadway pavements, a PMS must have the ability to produce a repeatable rating system (Shahin, 1994). One indicator pavement engineers can use to determine roadway condition is Pavement Condition Rating (PCR). This is an index that helps PMS engineers have a repeatable rating system to evaluate roadway condition.

The PCR rating system is a point based deduction matrix that removes points depending upon the amount of distresses on the roadway. The PCR matrix starts with a value of 100 for a perfect roadway without any distress. Deduction values are assigned for each distress based on the severity levels and the frequency of the distress. The PCR rating can be seen in Equation 1 (Reza et. al, 2005). It is important to note that not all distresses are weighted the same. This is because some distresses like alligator cracking, transverse

cracking, and rutting have a greater impact to the pavement deterioration than other distresses.

$$PCR = 100 - \text{Sum of Deductions} \qquad \qquad EQ\,(1)$$

The NCDOT uses the PCR as the dependent variable for the distress and performance models. It is important to understand that not all DOTs use PCR as the performance index for evaluating pavement performance. For example, performance indices that are used by other DOTs are: pavement quality index (PQI), international roughness index (IRI), pavement condition index (PCI), overall pavement index (OPI), ride quality index (RQI), present serviceability rating (PSR), and overall combined index (OCI). This is not an exhaustive list of performance indices use by other DOTs, and the performance index vary from state to state (Reza et. al., 2005).

2.5 Regression Analysis

Regression analysis is a statistical tool that gives the user the ability to measure the difference between two given phenomena (Dizikes, 2012). Regression analysis testing is performed to establish a link between the performance index and the effective age of the roadway surface. In this research, regression analysis was used to reveal a relationship between the performance of the roadway surface and the age of the pavement.

The first step in developing a regression curve is to determine if the data supports a section model or a family model. A section model applies to a specific pavement section, whereas, a family model represents a group of pavement with similar surface type, underlying pavement layers and traffic volumes (Lewis et. all, 2013). Since the NCDOT

currently uses family models for the windshield data, it was determined that family models would be acceptable for the automated data.

The second step was to develop a regression model that predicts only a single performance index based on the age of the pavement. There are two types of deterministic regression forms that could be used to model the performance curves: the linear and the non-linear equations (Lewis et. all, 2013). Linear regression is the simpler of the two and can be seen in Equation 2.

$$Y = b_0 + b_1 x \tag{2}$$

Where:

y = dependent variable

x = independent variable

b_0 and b_1 = coefficients

The polynomial model in another linear equation that can have a curved shape to model the data. This is due to the fact that polynomial regression creates a curvilinear relationship between the dependent and the independent variable, as seen in Equation 3 (Lewis et. all, 2013).

$$Y = b_0 + b_1 x + \ldots + b_n x^n \tag{3}$$

Where:

y = dependent variable

x = independent variable

b_0, b_1, b_n = coefficients

One of the non-linear functions that produces deterministic results is shown in Equation 4. The equation is known as a power curve. This has been proven to be useful in the field of pavement management (Lewis et. all, 2013).

$$Y = b_0 + b_1 x^{b_2} \tag{4}$$

Where:

y = dependent variable

x = independent variable

b_0, b_1, b_2 = coefficients

A graph with all three deterministic models overlaid can be seen in Figure 2. All three models were tested to visually compare the fit to the data between all three deterministic models in order to select the model that best fit the data. The NCDOT PMS currently uses distress and performance models developed using sigmoidal functions. Therefore, the sigmoidal model form was used to develop distress and performance models in this study.
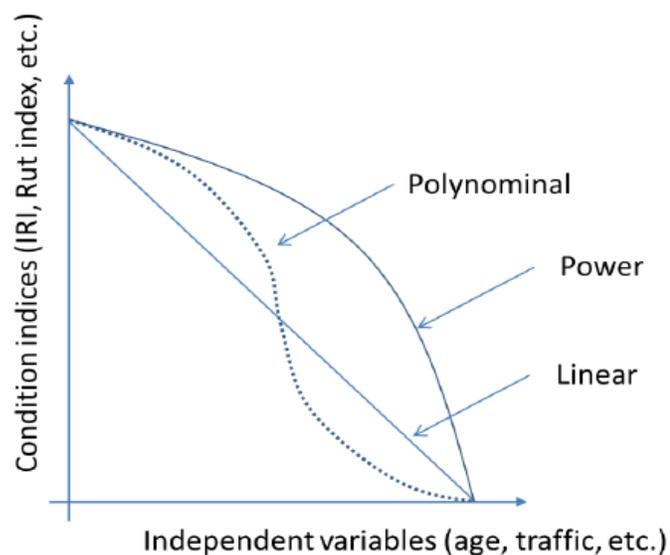
FIGURE 2: Regression analysis curves (Lewis et. all 2013)

The development of the performance models using the automated collected data was crucial step for the NCDOT engineers to be able to properly manage the roadway network. Understanding how the windshield and automated data collection methods worked was critical to understanding the differences and similarities between the two data collection methods. Many of the model development techniques using windshield data were applied to the development of the automated collected data performance indices and models.

CHAPTER 3: DEVELOPMENT OF DISTESS AND PERFORMANCE MODELS

This chapter is a summary of the methodologies used in the development of the distress and performance models. The development of the distress models are important because they are used to show the relationship between the distress index values and the pavement age (Chen, 2014). The performance models are used to predict future pavements conditions (Alkire, 2009). This chapter includes the work flow, programs, and processes that were used throughout the model development process.

3.1 Work Flow

This section is an introduction to the steps used to develop the distress and performance models. The development of the distress and performance models began upon receiving the raw automated data from the NCDOT.

- Step 1: Create a central database which combined the age, distress indices, and Annual Average Daily Traffic (AADT) files into one usable database, shown in Figure 3.

- Step 2: Create scatter plots to inspect for outliers and to remove any outliers using the percentile method, shown in Figure 4.

- Step 3: Develop linear regression methods to establish critical input initial estimates of the model variables that were used to develop sigmoidal models, as seen in Figure 5.

- Step 4: Use the initial input values from Step 3 as starter values for Table Curved 2D to develop the sigmoidal models, shown in Figure 6.

- Step 5: Evaluate the compatibility between the two data collection methods, seen in Figure 7.

- Step 6: Develop trigger points to be used to indicate maintenance action for a section of roadway, shown in Figure 8.

This completed the work flow for the development of the distress and performance models. There are more details about the steps discussed in the following sections.
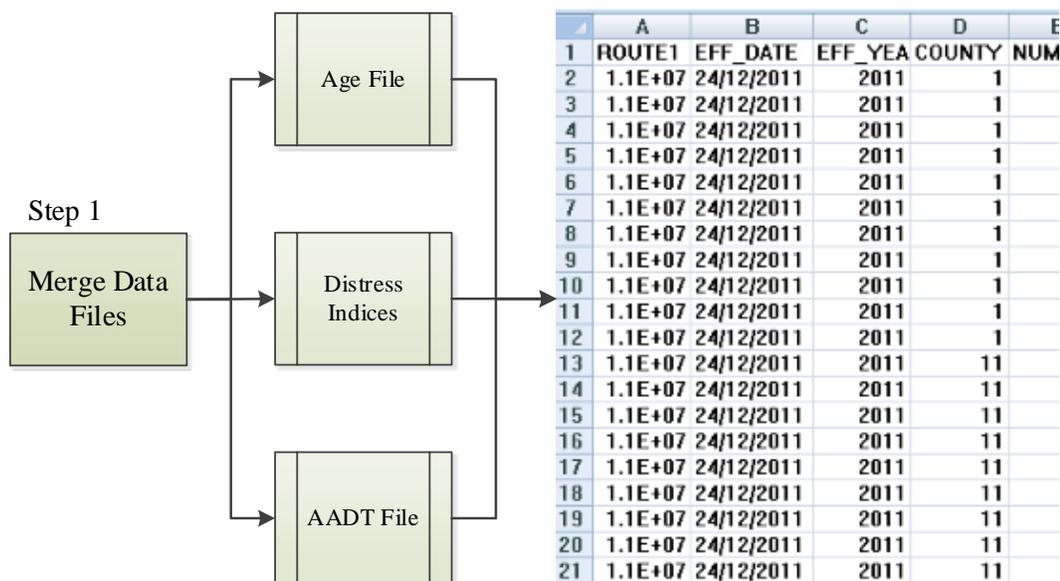
FIGURE 3: Work flow - data combination
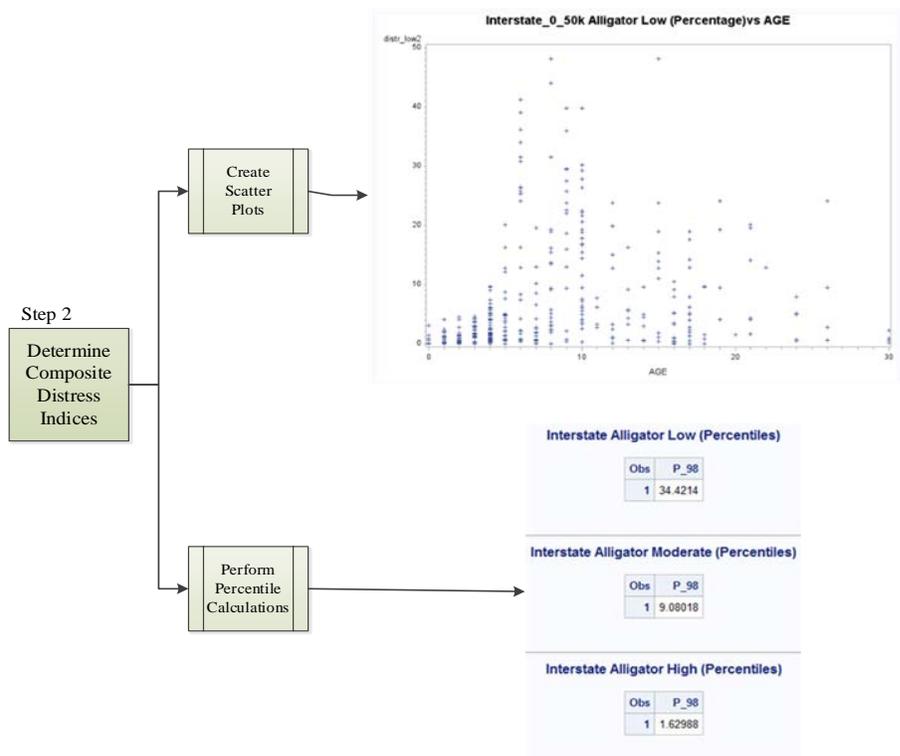
FIGURE 4: Work flow - developing indices
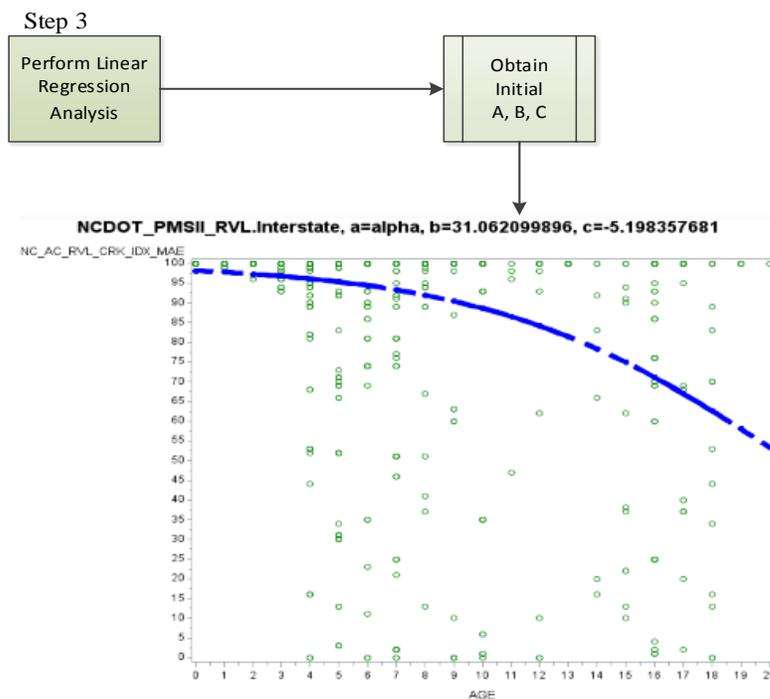
FIGURE 5: Work flow - developing performance

Step 4

Initial A/B/C → Import Data into TableCurve → Perform Non-Linear Regression Analysis → $y=\dfrac{a}{1+e^{\frac{x-b}{c}}}$

Import Data into TableCurve

Interstate
Rank 5 Eqn 8009 101(a)
r^2=1e-08 DF Adj r^2=0 FitStdErr=29.678054 Fstat=8.6200001e-06
a=20.481153
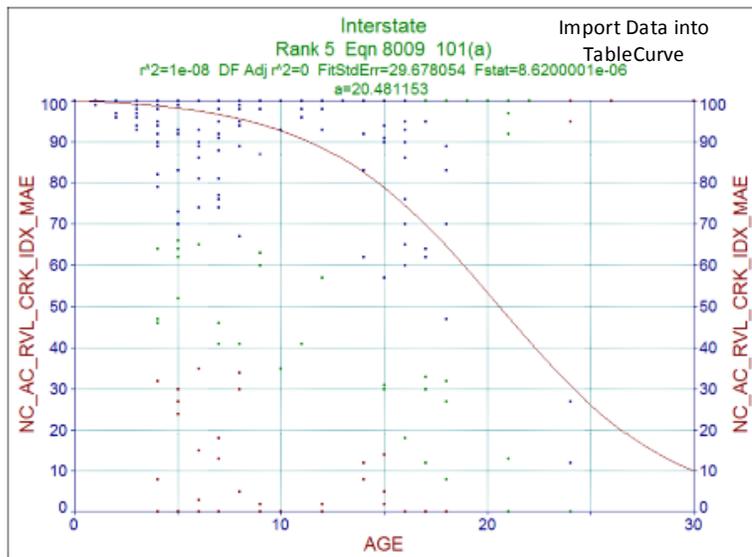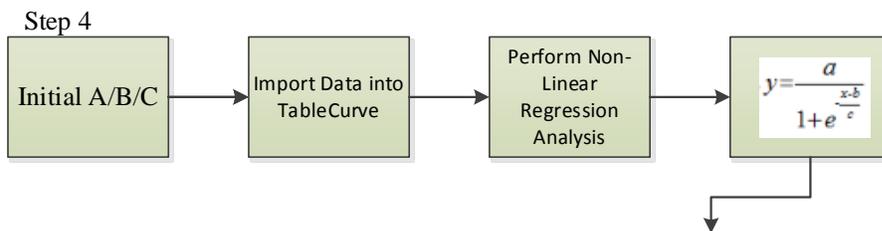
FIGURE 6: Work flow - creating performance curves

Step 5

Create Old/ New Graph Overlay → Visual Comparison →

US 5-15K
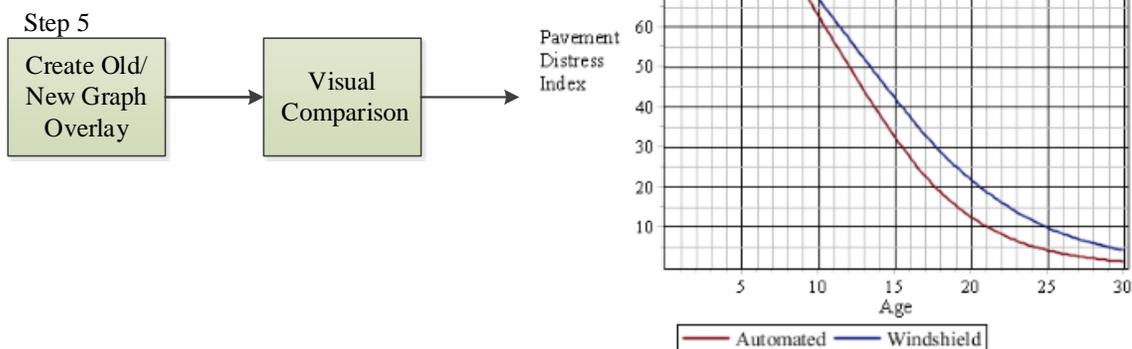
FIGURE 7: Work flow – compatibility test

Step 6
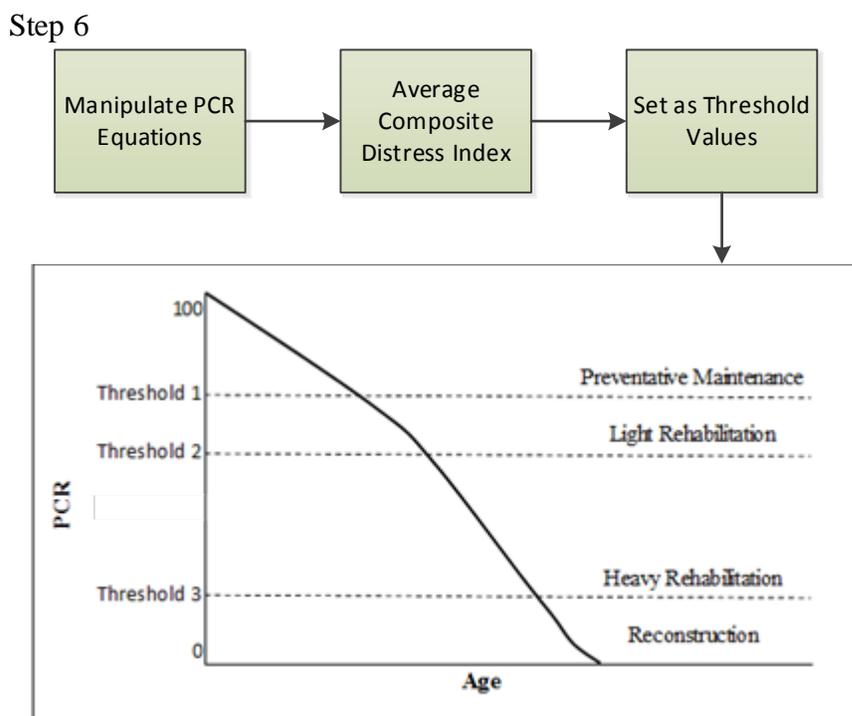
FIGURE 8: Work flow - trigger points

3.2 Programs Used for Model Development

The development of the distress and performance models from the automated data required the use of several software applications. Each software aided the researchers to combine multiple databases, batch process statistical analyses, create graphs, and compare model curves with greater reliability and consistency. The different software applications used in creating the distress and performance models are covered in the following sections.

3.2.1 Excel®

Microsoft Excel was selected because it allows the researcher to create and manipulate spreadsheets. Excel allows the user to input numerical values into columns and rows of the spreadsheet, and the Excel program allows the user to create calculations, graphs, and statistical analysis (Microsoft, 2014). Excel was used to format, tabulate, and

store the raw data. This spreadsheet was used as the base for other programs that will be used to develop the performance curves.

3.2.2 SAS ®

SAS is a linear and non-linear regression modeling software, and it was selected because it allows researchers, project managers, and application developers the ability to batch process many data entry and mathematical commands (SAS, 2014). Batch processing is the ability to run the same equation with different input values simultaneously. In this research, SAS was used to perform batch processing for each of the distresses for the different AADT families they represent, because the SAS software has the ability to use macros which saved time while repeating the same process for all the AADT families. It was also used to create the scatter plots, percentile data cleaning, and linear regression graphs for each roadway family.

3.2.3 TableCurve ®

TableCurve 2D is a data fitting software produced by Systat Software and it was selected because it allows engineers and researchers to efficiently develop different types of models that have one independent variable (Systat Software, 2014). In this study, TableCurve 2D was used to develop the final non-linear regression distress and performance curve models for each of the roadway families, because the software allowed users to define the model form.

3.2.4 Maple®

Maple (Version 17) was selected because it is a powerful mathematic equation solver for engineering, mathematics, and the sciences (Maplesoft, 2014). In this study, Maple was used to visually compare the difference between the automated performance

models against the windshield survey performance models. In addition, Maple was used to plot all the final distress and performance models.

3.3 Roadway Families

The NCDOT has four established classifications of roadways that make up the North Carolina roadway network. The roadway network contains Interstate, United States Highway (US), North Carolina Highway (NC), and Secondary Roads (SR). The roadways families are classified based on the Average Annual Daily Traffic (AADT) of the roadway. The roadways family that experiences the highest levels of AADT value is the Interstate system, and the AADT for the interstate system can range from 0 to more than 50,000 AADT. The US routes received the second highest traffic volume based on AADT levels which ranged from 0 to more than 15,000 AADT. The NC routes family are roadways that receive an AADT between 0 to more than 5,000 AADT.

Three of the four aforementioned classifications (Interstate, US, NC) had distress and performance models developed as a part of this study; however, the last classification (SR) did not have distress and performance models developed for it because no automated data were collected for SR roadways. However, the NCDOT has shown interest in developing the performance curves for the SR routes in a future study. The classifications for US and NC routes were further divided based on AADT to create models that better reflected patterns for those AADT levels. The US classification was split into three separate sections, the new AADT ranges for US classification were from 0 to 5,000, from 5,000 to 15,000, and to more than 15,000. These ranges for the classifications were selected based on recommendations by the NCDOT engineers. Similarly, the NC classification was split into three separate sections, the AADT ranges for NC classification were from 0 to 1,000,

from 1,000 to 5,000, and to more than 5,000. These ranges were also selected based on recommendations by the NCDOT engineers. The complete breakdown of all four classifications can be seen in Table 3.

TABLE 3: Roadway families

Classification	AADT
Interstate	All
US	0-5k
	5-15k
	more than 15k
NC	0-1k
	1-5k
	more than 5k
SR	All

3.4 Data Collection

The data for this project was collected using the automated data collection process. This was done throughout the 14 districts in North Carolina. The NCDOT contracted private vendors to collect the raw automated data. Once the data was collected, the NCDOT sent the 2012 and 2013 year survey data to the University of North Carolina at Civil Engineering Technology and Construction Management department. This data was delivered electronically in the form of Excel files. However, it is important to note that not all data from the 14 districts were available in the 2012 and 2013 survey years. Figure 9 shows the NCDOT's 14 districts, and Table 4 shows a list of all the districts where survey data were available.

FIGURE 9: North Carolina DOT 14 districts (NCDOT, 2014)

TABLE 4: List of data by division

Division	Asphalt Data		JCP Data	
	2012	2013	2012	2013
1		✓		✓
2	✓	✓		
3	✓	✓		
4	✓	✓	✓	✓
5	✓	✓	✓	✓
6	✓	✓		
7	✓	✓	✓	✓
8	✓	✓	✓	✓
9	✓	✓		✓
10	✓	✓		
11	✓	✓		✓
12	✓	✓		✓
13	✓	✓		✓
14	✓	✓		✓

The automated surveys collected a large amount of data entries. However, only selected data entries, known as key entries, were used in the development of the distress and performance models. The key entries that were used in this study are listed below.

- Route Number: identifies the roadway section

- County: identifies the roadway's county

- Distress Severity Levels: None (N)/Light (L)/ Moderate (M)/Severe (S)

- Offset Begin: beginning milepost of the roadway section surveyed

- Offset End: end of milepost of the roadway section surveyed

- AADT: annual average daily traffic

- Year of Rehabilitation: last time the roadway was rehabilitated

3.5 Model Form Selection

Selecting an appropriate distress and performance equation to model the data was essential to developing accurate final models. The selected model had to be compatible with the NCDOT's computer software package Agile-Assets. The software can accept seven model forms which are shown in Figure 10. The model selected was the sigmoidal equation. As described in the previous section, this model was selected because among the seven forms the sigmoidal curves fit the data best.

Exponential
Hyperbolic
Inverse Exponential
Linear
Piecewise Linear
Power
Sigmoidal

FIGURE 10: List of NCDOT approved performance index curves

There are five subcategories of sigmoidal equations. Carrillo and Gonzalez (2002) discussed all five variants of the sigmoidal models. These models are the Logistic, Gompretz, Richards, Weibull, and Morgan-Mercer-Flodin equations. In this study, after testing all these five model forms, the equation that best fit data was a variant of the logistic sigmoidal equation which can be seen in Equation 5. It is important to note that this

equation was manipulated to the form seen in Equation 6, because it was necessary to find initial values that would be used to better fit the sigmoidal model to the data. That process is discussed in the next section of this report.

In Equation 5, the "a" coefficient is the initial starting point for the distress and performance values, and it was determined that the "a" coefficient would go through (0,100) point. Thus making the "a" coefficient equal to 100 for the initial input. This was because it is assumed the pavement have a perfect distress rating right after a new construction or a maintenance action. The "b" coefficient denotes the horizontal shift in the curve, and movement in the curve. The "c" variable denotes the slope of the curve, which represents the deterioration rate of the pavement. Equation 6 allows for the initial estimates for the "b/c" coefficients to be determined. The reason only the initial "b/c" coefficients were to be determined was because the "a" coefficient was set to 100.

$$y = \frac{a}{1 + e^{-\frac{x-b}{c}}} \qquad (5)$$

From (5) the following was obtained:

Let

$$a = 100$$

$$\ln y = \ln 100 - \ln(1 + e^{-\frac{x-b}{c}})$$

Then,

$$\ln\left(1 + e^{-\frac{x-b}{c}}\right) = \ln 100 - \ln y$$

Then, the exponential was taken on both sides.

$$\left(1 + e^{-\frac{x-b}{c}}\right) = e^{\ln 100 - \ln y}$$

Then,

$$e^{-\frac{x-b}{c}} = e^{\ln 100 - \ln y} - 1$$

Then, the natural logarithm was taken on both sides of the equation.

$$-\frac{x-b}{c} = \ln\left(e^{\ln 100 - \ln y} - 1\right)$$

Let

$$Y = \ln\left(e^{\ln 100 - \ln y} - 1\right) \text{ , then}$$

$$Y = -\frac{1}{c}x + \frac{b}{c} \tag{6}$$

Where:

x = Age

a, b, c = Coefficients

y = Distress Index

Y = Performance Index

Divergence is the phenomenon that allow the output results to vary when entered into a non-linear equation. Sigmoidal curves experience this trait and this caused the coefficients to vary with each trail run. Therefore, to make the non-linear models to converge, the optimum initial a/b/c coefficients should be estimated and used in non-linear sigmoidal analyses. This reduced the amount of iterations required before convergence is achieved.

3.6 Development of Distress Indices and Models

The distress indices and distress models were developed to predict the deterioration for asphalt and Jointed Concrete Pavement (JCP) pavements based on a particular distress.

The process began by developing the distress indices, and those indices were used to develop the distress models.

3.6.1 Normalizing the Data

The distress and performance models were developed using normalized data. The data was normalized because the distresses were recorded in different units, as shown in Table 2. The resulting normalized data became unitless, and allowed for the distress models to be compared against one another. The data was normalized using the NCDOT High Speed Distress Manual (2011). The equations used to normalize each distress can be seen in Table 5 and Table 6.

The alligator distress data was normalized using the process in the following example. Since alligator cracking was recorded in square feet, the distress needed to be divided by length, the factor 7, and 5,280 to make the distress unitless. The length is the distance of the roadway section for which the distress was surveyed. The factor 7 represents the width of the wheel paths. The 5,280 is a conversion factor to covert the length from miles into feet. A similar process was used to normalize the remaining asphalt pavement distresses, and for all the JCP distresses.

TABLE 5: Asphalt pavement condition data normalization

Distress	Normalization Equation
Alligator Cracking	Alligator Cracking / (Length * 7 * 5280)
Patching Area - WP	Patching Area / (Length * 7 * 5280)
Maximum Average Rut Depth	100 - 100 (Maximum Average Rut Depth)^2
Transverse/Reflective Transverse Cracking	(Transverse Cracking + Reflection Transverse Cracking) / Length * 5280)
Patching Area - NWP	Patching Area / (Length * (Section Width / Number of Lanes) * 5280)
Longitudinal Cracking	Longitudinal Cracking / (Length * 5280)
Longitudinal Lane Joint Cracking	Longitudinal Lane Joint Cracking / (Length * 5280)
Raveling	Raveling / (Length * 5280 * Section Width /Number of Lanes)

TABLE 6: JCP pavement condition data normalization

Distress	Normalization Equation
Asphalt Patch	Asphalt Patch / Length
Corner Break	Corner Break / Length
Joint Fault	Joint Fault / Length
Longitudinal Cracking	Longitudinal Cracking / Length
Longitudinal Joint Spalled	Longitudinal Joint Spalled / Length
PCC Patch	PCC Patch / Length
Transverse Cracking	Transverse Cracking / Length
Transverse Joint Spalled	Transverse Joint Spalled / Length

3.6.2 Developing Maximized Allowable Extent (MAE) Values

The MAE values are weights that are built into the distress index calculator, and the MAE values are based on four levels of threshold values: N = None, L = Light, M =

Moderate, and S = Severe (N/L/M/S) (NCDOT PCSM, 2012). The MAE values are used

to rate the importance of the amount of N/L/M/S that occurs for a distress, and this is done

to make sure that distress severity levels are rated appropriately.

3.6.2.1 Existing Windshield MAE Process

The existing MAE threshold values worked well to determine the distress indices

for the windshield data, and it was determined that new MAE threshold values for the

automated collected data could be developed using the same process developed for the

windshield data. The windshield method was studied and the following example describes

how MAE values are used to calculate the existing distress indices, as shown in Figure 11.

The low_sev_in = 0, med_sev_in = 20, and high_sev_in = 40 in the orange box

represent the normalized amount of distress that is recorded for each severity. In this

example, it is demonstrating for this section of roadway that 0% low severity occurred,

20% moderate severity occurred, and 40% high severity occurred.

Figure 11 also shows the existing MAE amounts that were used for the alligator

cracking distress for the windshield data. They can be seen under the line labeled MAE

Amounts. These MAE values are used to weight the normalized distress in the orange box

to develop the overall distress index for the windshield alligator cracking. In this example,

low_sev_mae_in is 100, med_sev_ mae_in is 80, and high_sev_ mae_in is 50. This means

to up to 100% of the low severity, up to 80% of the moderate severity, and up to 50% of

the high severity of alligator cracking will be counted.

Figure 11 also shows the existing Threshold Amount. The Threshold value is the

lowest score possible when the severity occurs for a distress by itself (NCDOT PCSM

2012). For example, if only the low severity level occurred for alligator cracking and 100%

low severity was recorded, the alligator cracking index value is 75. Similarly, if only the moderate severity level occurred for alligator cracking and 80% moderate severity was recorded, the alligator cracking index value is 40, and if only the high severity level occurred for alligator cracking and 50% high severity was recorded, the alligator cracking index value is 0.

The final distress index value was calculated using the embedded equations built into d2c and d23 shown in Figure 11. The d2c calculation is the summation of the previous step and d3c is built on the results of d2c. The final distress index value for alligator cracking which was 100 minus d3c which resulted in a distress index value of 17, as shown in yellow in Figure 11.

f_mae(a.ALGTR_LOW_PCT,a.ALGTR_MDRT_PCT, a.ALGTR_HGH_PCT,null,100, 80, 50,75,40,0,0,0,0)

INPUTS		
OUTPUT		

Distress Values passed into the function. Distresses with less than three severities should pass null to low then med in that order. Function return MAE index with 100 as good 0 as bad

low_sev_in	0	
med_sev_in	20	*OK* - Sum distress total is 100 or less
high_sev_in	40	

The normalizing factor will normalize absolute distress amounts null indicates no normailzation required

normalizing_in	null

MAE Amounts (Low Med and High) are the Extent amounts that maximize deduction for that severity

low_sev_mae_in	100
med_sev_mae_in	80
high_sev_mae_in	50

Threshold Amounts are lowest possible score for that severity when it occurs alone

low_sev_threshold_in	75
med_sev_threshold_in	40
high_sev_threshold_in	0

Begin deduct scores are the extent value when point deductions begin for each severity level

low_sev_begin	0	distr_low	0
med_sev_begin	0	distr_med	20
high_sev_begin	0	distr_high	40

d1	0		
d2	15	d2c	15
d3	80	d3c	83

Alligator Cracking Index Value	17	

FIGURE 11: Existing distress index calculator using MAE

3.6.2.2 Automated MAE development

Once the process for calculating the distress index was understood the next step was to develop the MAE values for each distress using the automated data. This was done to replace the MAE values used by the windshield collected data. The process of developing MAE values for the automated collected data began by developing scatter plots in order to remove outliers. An example of the scatter plot for alligator cracking can be seen in Figure 12. It can be observed that the scatter plots revealed the existence of outliers.

To develop accurate distress models, it was important to identify and remove outliers from the data set.
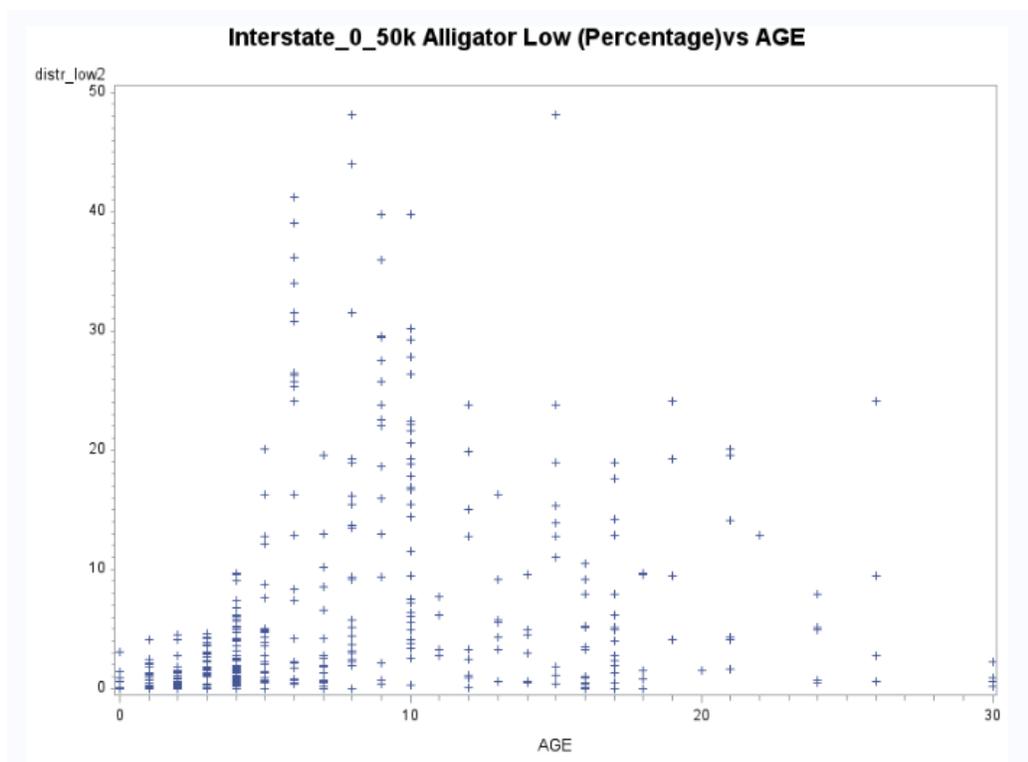

FIGURE 12: SAS ® generated scatter plots

Percentiles were used to remove the outliers from the data. Predetermined percentiles limits as cut off points for acceptable and unacceptable data were established using a three step process. The first step was to determine the level at which the percentile would be set. During the course of the research SAS was used to test several percentile levels. This was done to make a comparison between different percentile levels, for example, thresholds of 90th, 95th, 98th, and 99th percentiles were used to see which level removed only the extreme outliers. The threshold for every distress at low, moderate, and high severity was determined to the 98th percentile.

The second step was to average the distress ratings at the 98th percentile. The average were taking for every family on the same distress level. The third step was to assign the averages as the new automated collected data MAE values. An example of the percentiles for alligator cracking at low, moderate, and high severity levels for the Interstate family can be seen in Figure 13.

Interstate Alligator Low (Percentiles)

Obs	P_98
1	34.4214

Interstate Alligator Moderate (Percentiles)

Obs	P_98
1	9.08018

Interstate Alligator High (Percentiles)

Obs	P_98
1	1.62988

FIGURE 13: SAS output of percentiles

Figure 14 shows the distress index calculation for alligator cracking for the Interstate family using the input values from Figure 13. The process that was used in the windshield method to calculate the distress index is the same method used to calculate the distress index for the automated method. An example using alligator cracking is shown in Figure 14. The low_sev_in = 10, med_sev_in = 5, and high_sev_in = 1 in the orange box represent the normalized amount of distress that is recorded for each severity. In this

example, for this section of roadway 10% low severity, 5% moderate severity, and 1% high severity of alligator cracking were observed.

The lines under MAE Amounts in Figure 14 show the new MAE amounts for the alligator cracking distress for the automated collected data. These are the new MAE values that were determined using the percentiles. They are low_sev_mae_in = 34.42, med_sev_mae_in = 9.08, and high_sev_ mae_in = 1.63. In this example 10% low severity (up to 34.42%) was observed, 5% moderate severity (up to 9.80%) was observed, and 1% severity (up to 1.63%) was observed. The corresponding alligator cracking index value is 24.

f_mae(a.ALGTR_LOW_PCT,a.ALGTR_MDRT_PCT, a.ALGTR_HGH_PCT,null,100, 80, 50,75,40,0,0,0,0)							
INPUTS							
OUTPUT							
Distress Values passed into the function. Distresses with less than three severities should pass null to low then med in that order. Function return MAE index with 100 as good 0 as bad							
low_sev_in	10						
med_sev_in	5	*OK* - Sum distress total is 100 or less					
high_sev_in	1						
The normalizing factor will normalize absolute distress amounts null indicates no normailzation requir							
normalizing_in	null						
MAE Amounts (Low Med and High) are the Extent amounts that maximize deduction for that severity							
low_sev_mae_in	34.42						
med_sev_mae_in	9.08						
high_sev_mae_in	1.63						
Threshold Amounts are lowest possible score for that severity when it occurs alone							
low_sev_threshold_in	75						
med_sev_threshold_in	40						
high_sev_threshold_in	0						
Begin deduct scores are the extent value when point deductions begin for each severity level							
low_sev_begin	0		distr_low	10			
med_sev_begin	0		distr_med	5			
high_sev_begin	0		distr_high	1			
d1	7.263219						
d2	33.03965		d2c	37.90312			
d3	61.34969		d3c	75.99937			
Alligator Cracking Index Value	24.00						

FIGURE 14: Distress index calculator using MAE

3.6.3 Developing Distress Models

The development of the distress models began after determining the MAE values so the composite indices could be calculated for the automated data. Those values they were entered into TabelCurve 2.0 to develop the distress models. The first prompt to begin TableCurve was to define the X (age) axis and Y (distress) axis, and an example of this prompt can be seen in Figure 15. Once the axis was defined, the next step was to define the User Define Function (UDF), as shown in Figure 16.
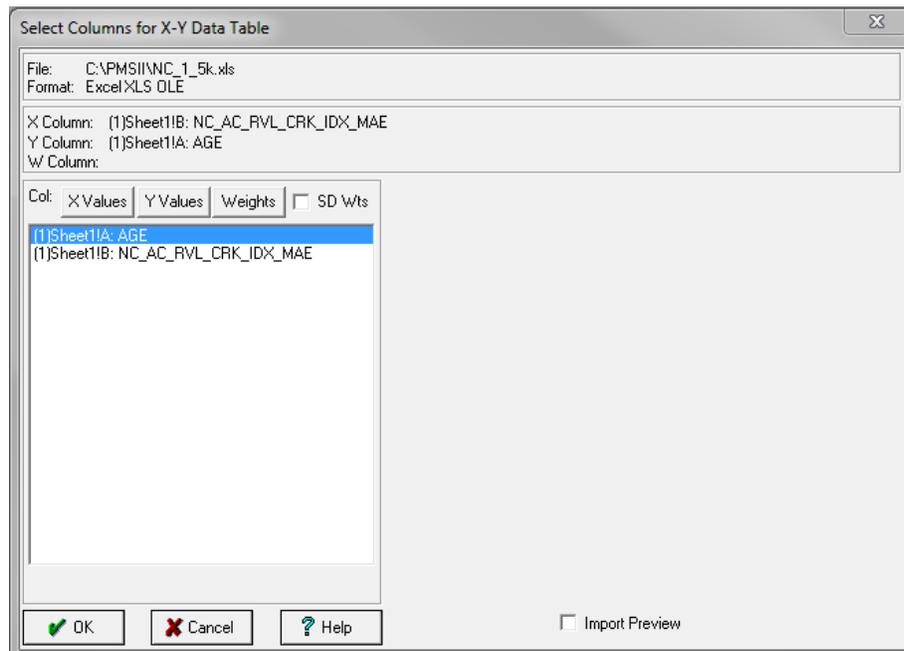
FIGURE 15: TableCurve x axis and y axis prompt
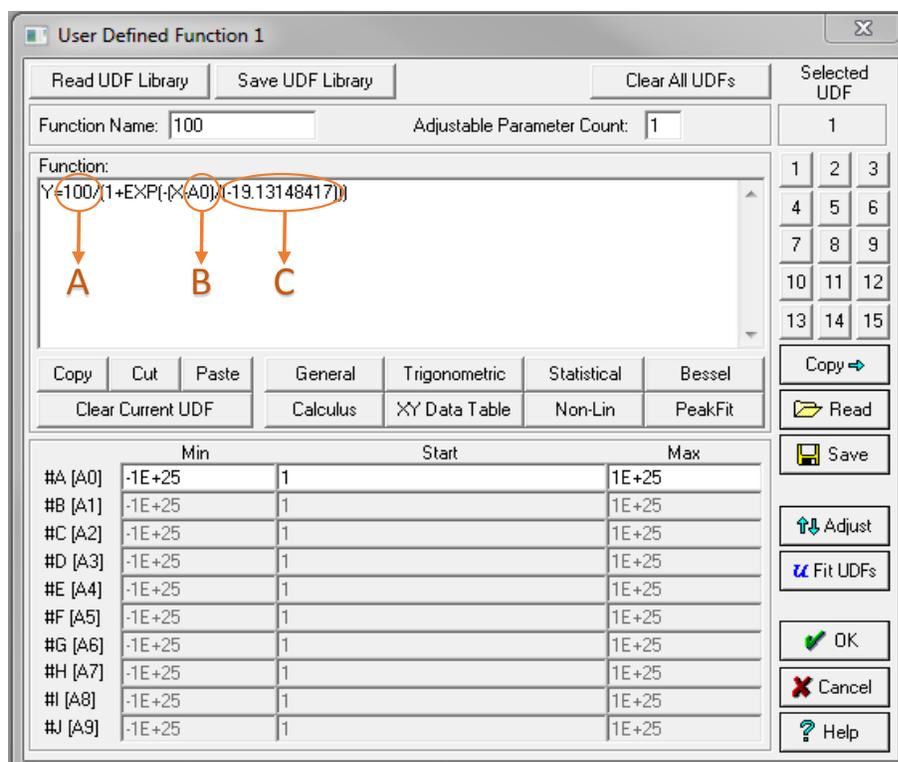
FIGURE 16: TableCurve UDF interface

In order to use the UDF function, one dependent variable and one or more independent variables had to be assigned to the equation. The same sigmoidal equation from Equation 5 was used for the UDF. The pavement age was the independent variable and distress indices were the dependent variable. To best optimize the performance curves the a/c coefficients were locked, forcing the values constant. The b variable was allowed to change. The a coefficient was fixed in this equation and was set to the value that allowed the distress curve cross at (0, 100). The c variable was fixed based on the results of the initial a/b/c coefficients. Therefore, the b coefficient was the one unlocked. The reason the b coefficient was allowed to change was to optimize the horizontal shift of the curve, therefore, allowing the curve to better reflect the data. The final equations and graphs

produced can be seen in the results section of this report. An example of a TableCurve graph can be seen in Figure 17.
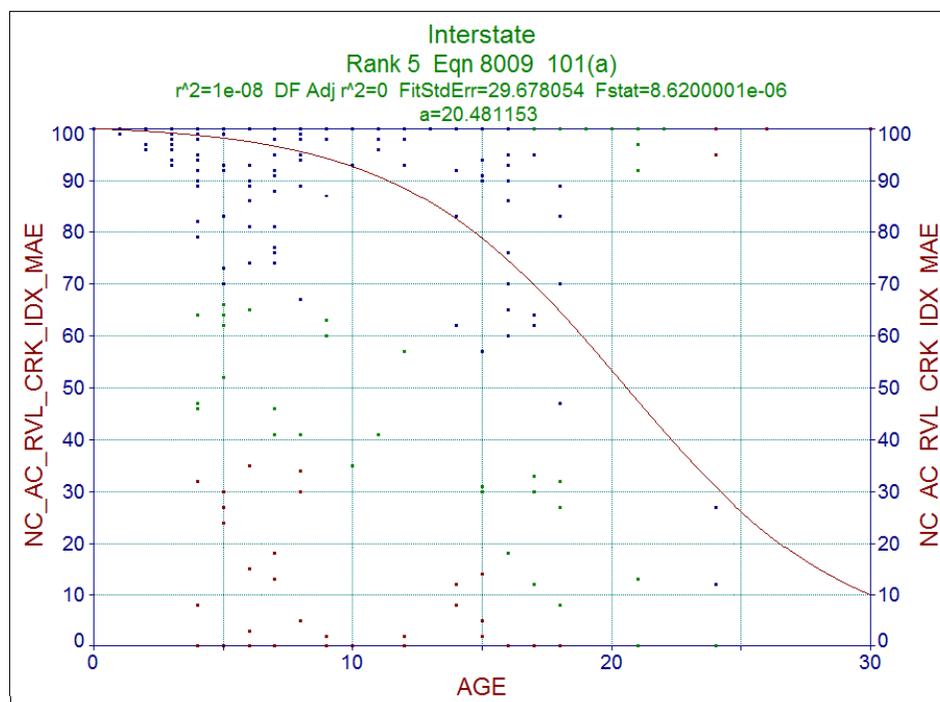
FIGURE 17: Performance curve from TableCurve 2D

The graphs produced in TableCurve are color coded. The different colors on the graph represent the standard error in the deviation of the data points. The blue represents the data points that are within one standard errors of the fitted curve, green represents the data points that are within two standard errors of the fitted curve, and red represents the data points that are within three standard errors of the fitted curve. The curve is influenced by all data points, the standard errors were determined after the curve was developed.

3.7 Development of Performance Indices and Models

The development of the performance models was a multi-step process that resulted in models that could be used by the NCDOT personnel to predict the behavior of the

pavement, as well as, determine the appropriate maintenance action of the roadway. The dependent variable used for developing the performance curve was PCR. The process used to develop the performance models is described in the following sections of this chapter.

3.7.1 Development of Performance Indices

As discussed in section 2.3, a PCR rating system is a point based deduction matrix that removes points depending on the amount of distresses on the roadway. PCR starts from a value of 100 for a perfect roadway without any distress, and deduction values are assigned based on the severity levels and the frequency of the distresses (Reza et. all, 2005). In the past, the PCR values were developed for the NCDOT windshield survey data. However, the method for collecting and analyzing the automated data is different in that the windshield data is categorical, while the automated data is numerical. Therefore, a new set of composite indices needed to be developed so that proper weights for each of the distresses could be assigned. This would ensure the new PCR models would properly fit the automated data.

The composite index was developed using a Multiple-Criteria Decision Making (MCDM) method developed by Thomas Saaty (2008), known as the Analytical Hierarchy Process (AHP). The AHP method was chosen because it is a powerful tool that can solve complex problems, such as determining weight factors, and it removes user subjectivity from the selection process (Triantaphyllou, 1995). The AHP process described by Thomas Saaty can be seen below in Table 7 (Saaty, 2008).

The first step was to calculate the weights for the automated data, and the new composite index was developed using the existing NCDOT windshield deduction algorithm for the PCR calculations. An example of the existing deduction algorithm can

be seen in Table 8, using the alligator cracking distress. The next step was to average results from the low, moderate, and severe calculations, as shown in Table 8. The same process was used for the remaining distresses, and the results are in Table 9. Once the averages were calculated, they were used to create the matrix shown in Table 10. The values from Table 10 were inserted in an AHP calculator in order to determine the eigenvectors, which can be seen in Table 11. The eigenvectors were weight of different distresses and used to develop the PCR values, which can be seen in Equation 7.

TABLE 7: AHP process

Step	Action
1	Define the problem
2	Structure hierarchy
3	Construct pairwise comparison matrices
4	Weight each element and add the weighed values to obtain its overall priority (eigenvectors)

TABLE 8: Example of PCR calculation for asphalt pavements

Distress	Severity Level	Deduction	Average
Alligator Cracking	L- Light	3.3 points - 10% to 90%: 1 point >90% (3.3*9+1*0.1=29.8 points)	42 = average of L/M/S
	M - Moderate	7.5 points - 10% t0 40%: 2 points >40% (7.5*4+2*6=42 points)	
	S - Severe	15 points - 10% to 20%: 3 points >20% (15*2+3*8=54 points)	

TABLE 9: The average PCR values for asphalt pavement

Distress	Average
Alligator Cracking	42
Transverse/Reflective Transverse Cracking	17
Longitudinal Cracking	9
Longitudinal Lane Joint	7*
Raveling	7
Patching Area - WP	12
Patching Area - NWP	7*
Rutting - Max Avg. Depth	18
* Use the smallest value because its non-load related	

TABLE 10: Pairwise matrix for asphalt PCR calculation

Distress	ALGTR	TRA	LNG	LNG JNT	RVL	WP	NWP	RUT
Alligator Cracking (ALGTR)	**42/42 = 1.00**	42/17 = 2.47	42/9 = 4.67	42/7 = 6.00	42/7 = 6.00	42/12 = 3.50	42/7 = 6.00	42/18 = 2.33
Transverse/Reflective Transverse Cracking (TRA)	17/42 = 0.40	**17/17 = 1.00**	17/9 = 1.89	17/7 = 2.43	17/7 = 2.43	17/12 = 1.42	17/7 = 2.43	17/18 = 0.94
Longitudinal Cracking (LNG)	9/42 = 0.40	9/17 = 0.53	**9/9 = 1.00**	9/7 = 1.29	9/7 = 1.29	9/12 = 0.75	9/7 = 1.29	9/18 = 0.50
Longitudinal Lane Joint (LNG JNT)	7/42 = 0.17	7/17 = 0.41	7/9 = 0.78	**7/7 = 1.00**	7/7 = 1.00	7/12 = 0.58	7/7 = 1.00	7/18 = 0.39
Raveling (RVL)	7/42 = 0.17	7/17 = 0.41	7/9 = 0.78	7/7 = 1.00	**7/7 = 1.00**	7/12 = 0.58	7/7 = 1.00	7/18 = 0.39
Patching Area - WP (WP)	12/42 = 0.29	12/17 = 0.71	12/9 = 1.33	12/7 = 1.71	12/7 = 1.71	**12/12 = 1.00**	12/7 = 1.71	12/18 = 0.67
Patching Area - NWP (NWP)	7/42 = 0.17	7/17 = 0.41	7/9 = 0.78	7/7 = 1.00	7/7 = 1.00	7/12 = 0.58	**7/7 = 1.00**	7/18 = 0.39
Rutting - Max Avg. Depth (RUT)	18/42 = 0.43	18/17 = 1.06	18/9 = 2.00	18/7 = 2.57	18/7 = 2.57	18/12 = 1.50	18/7 = 2.57	**18/18 = 1.00**

TABLE 11: AHP eigenvector for asphalt pavement

Distress	Eigenvectors
Alligator Cracking	0.354
Transverse/Reflective Transverse Cracking	0.141
Longitudinal Cracking	0.077
Longitudinal Lane Joint	0.059
Raveling	0.059
Patching Area - WP	0.1
Patching Area - NWP	0.059
Rutting - Max Avg. Depth	0.015

$$PCR = 0.354*ALGTR + 0.141*TRA + 0.077*LNG + 0.059*LNG\ JNT$$

$$+ 0.059*RVL + 0.10*WP + 0.059*NWP + 0.015*RUT \tag{7}$$

Where:

PCR = Pavement Condition Rating

ALGTR = Alligator Cracking Index

TRA= Transverse Cracking Index

LNG= Longitudinal Index

LNG JNT = Longitudinal Lane Joint Index

RVL = Raveling Index

WP = Wheel Path Patching

NWP = Non Wheel Path Patching

RUT = Rutting Index

The JCP composite indices were developed in the same manner as the asphalt composite index. The main difference, however, was with the NCDOT's previous

pavement deduction values. An example of the existing windshield JCP deduction value can be seen in Table 12. The summary of the new deduction values for JCP automated data can be seen in Table 13. The JCP AHP matrix, Table 14, was used to calculate the eigenvectors, which are summarized in Table 15. The final JCP PCR equation can be seen in Equation 8.

TABLE 12: Example of deduction values for PCR calculation for JCP pavements

Distress	Severity Level	Deduction	Average
Corner Breaks	L- Light	0.1 points / 1% (0.1*10 = 1.0)	5.7
	M - Moderate	0.15 points / 1% (0.15*10 = 1.5)	
	S - Severe	0.375 points / 1% to 80%: 0.1 points / 1% >80% (0.375*8+0.1*2=3.2)	

TABLE 13: Average deduction PCR values for JCP pavement

Distress	Average
PCC Patch	18
Transverse Cracking	9.6
Longitudinal Cracking	9.6
Asphalt Patch	18
Transvers Joint Spalled	8.5
Longitudinal Joint Spalled	8.5
Corner Break	5.7
Joint Fault	8.5

TABLE 14: AHP matrix for JCP pavement

Distress	TRNSVRS CRK	LNGTDNL CRK	CON PATCH	ASPHLT PATCH	TRNSVRS SPLL	LNGTDNL JNT SPLL	CRNR	FAULT
Transverse Cracking (TRNSVRS CRK)	**9.6/9.6 = 1.0**	9.6/9.6 = 1.0	9.6/18 = 0.53	9.6/18 = 0.53	9.6/8.5 = 1.13	9.6/8.5 = 1.13	9.6/5.7 = 1.68	9.6/8.5 = 1.13
Longitudinal Cracking (LNGTDNL CRK)	9.6/9.6 = 1.0	**9.6/9.6 = 1.0**	9.6/18 = 0.53	9.6/18 = 0.53	9.6/8.5 = 1.13	9.6/8.5 = 1.13	9.6/5.7 = 1.68	9.6/8.5 = 1.13
PCC Patch (CON PATCH)	18/9.6 = 1.88	18/9.6 = 1.88	**18/18 = 1.0**	18/18 = 1.0	18/8.5 = 2.12	18/8.5 = 2.12	18/5.7 = 3.16	18/8.5 = 2.12
Asphalt Patch (ASPHLT PTCH)	18/9.6 = 1.88	18/9.6 = 1.88	18/18 = 1.0	**18/18 = 1.0**	18/8.5 = 2.12	18/8.5 = 2.12	18/5.7 = 3.16	18/8.5 = 2.12
Transvers Joint Spalled (TRNSVRS SPLL)	8.5/9.6 = 0.89	8.5/9.6 = 0.89	8.5/18 = 0.47	8.5/18 = 0.47	**8.5/8.5 = 1.0**	8.5/8.5 = 1.0	8.5/5.7 = 1.49	8.5/8.5 = 1.0
Longitudinal Joint Spalled (LNGTDNL JNT SPLL)	8.5/9.6 = 0.89	8.5/9.6 = 0.89	8.5/18 = 0.47	8.5/18 = 0.47	8.5/8.5 = 1.0	**8.5/8.5 = 1.0**	8.5/5.7 = 1.49	8.5/8.5 = 1.0
Corner Break (CRNR)	5.7/9.6 = 0.59	5.7/9.6 = 0.59	5.7/18 = 0.32	5.7/18 = 0.32	5.7/8.5 = 0.67	5.7/8.5 = 0.67	**5.7/5.7 = 1.0**	5.7/8.5 = 0.67
Joint Fault (FALUT)	8.5/9.6 = 0.89	8.5/9.6 = 0.89	8.5/18 = 0.47	8.5/18 = 0.47	8.5/8.5 = 1.0	8.5/8.5 = 1.0	8.5/5.7 = 1.49	**8.5/8.5 = 1.0**

TABLE 15: Final eigenvector weights for JCP PCR calculation

Distress	Eigenvectors
Transverse Cracking	0.111
Longitudinal Cracking	0.111
PCC Patch	0.208
Asphalt Patch	0.208
Transverse Joint Spalled	0.098
Longitudinal Join Spalled	0.098
Corner Break	0.066
Joint Fault	0.098

PCR = 0.111* TRNSVRS CRK + 0.111* LNGTDNL CRK + 0.208* CON PATCH +

0.208* ASPHLT PTCH + 0.098* TRNSVRS SPLL + 0.098* LNGTDNL JNT SPLL +

0.066* CRNR + 0.098* FALUT   (8)

Where:

PCR = Pavement Condition Rating

TRNSVRS CRK = Transverse Cracking

LNGTDNL CRK = Longitudinal Cracking

CON PATCH = PCC Patch

ASPHLT PTCH = Asphalt Patch

TRNSVRS SPLL = Transvers Joint Spalled

LNGTDNL JNT SPLL = Longitudinal Joint Spalled

CRNR = Corner Break

FALUT = Joint Fault

3.7.2 Development of Performance Models

The development of the asphalt and JCP pavements performance curves followed a similar process as the distress curves. Similarly, the UDF function required the input of one dependent variable and one or more independent variables. Using the same sigmoidal equation from Equation 5, the age input was the independent variable and the PCR was the dependent variables. The sigmoidal equation was entered into the UDF interface using the initial a/b/c coefficients for each roadway family. Once the equations were loaded into the UDF interface, TableCurve allowed the variables to be locked or unlocked. To best optimize the performance curves, the a/c coefficients were lock, forcing the values constant, and the b coefficient was allowed to fluctuate. The final a/b/c coefficients and a sample graph can be seen in Section 4.2 of this report, while a complete list of all the performance curves can be seen in Appendix B - K.

3.8 Model Validation

3.8.1 Verifying Performance Curve Fit

Verifying the model fits to the data is as important as developing the models itself, and the goodness of fit (GoF) was used to verify how well the model fit. GoF indicators are usually used to explain how well a developed model fits a data set, and represent the discrepancy between the observed values and the expected vales under a statistical model (Maydeu-Olivares and Garcia-Forero, 2010). There are two common methods that can be used to test the goodness of fit (GoF) for a non-linear regression models. The first is to use the R^2 statistic, and the second is to use the standard error of the regression.

R^2 is commonly used GoF indicator. Often times it is used to prove the fit quality of a linear regression curve. It has been proven that by adding predictors to a model it will always increase the R^2; therefore, by adding more terms it will appear that the new model is a better fit (Frost 2014). Venugopalan and Shamasundaran (2003) strongly suggest the use of residuals analysis to overcome that problem. However, one major limitation is that the R^2 statistic is not compatible with non-linear regressions models, and that is why the R^2 statistic was not used.

The more appropriate statistic to choose is the standard error of the regression (S). The S statistic is the average distance that the observed values fall from the regression line, this can be seen in Figure 19 (Frost 2014). The S value indicates how accurate the model is based on the average units of the response variable. The lower the S value the better the model fits the data.
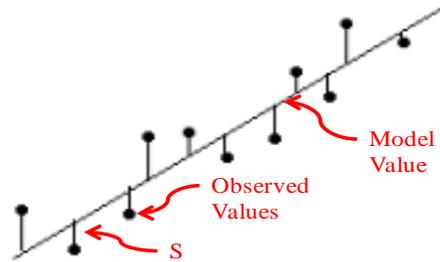
FIGURE 18: S observation residual plot (Frost 2014)

However, it was decided that a visual comparison would provide a better validation than the Standard Error of the Regression because for each roadway family there was only one mode. Since there was only one model per family the comparison for the Standard Error of the Regression cannot be performed. Therefore, the distress and performance automated data models were plot against their equivalent families from the windshield data to investigate if there were similarities between the models. The graph overlays should be similar because the data they represent should be the same except for the data collection method. The visual inspection indicated that the models are robust because the overall trends in the windshield and automated models are similar, as described in the next section.

3.8.2 Windshield Data Models vs Automated Data Models

Once the performances models were created, Maple software was then used to compare the automated data models to windshield models by overlaying the two types of models. Comparing the models can show the compatibility between the windshield performance curves and the automated performance curves (Sivaneswaran et. al, 2004). Comparing the curves will also reveal if the decision trees used by the windshield surveys will be compatible with the automated surveys or if new decision trees will need to be developed. As an example, a representative graph overlay of an alligator automated performance curve and an alligator windshield data performance curve can be seen below

for Interstate, US, and NC routes in Figures 18, 19, and 20 respectively. It can be concluded that automated models are compatible to the windshield models.

In these figures, the red line represents the windshield data curve and the blue line represents the automated data curve. It is visually noticeable that windshield and automated data curves are similar. Therefore, the existing decisions trees used by the NCDOT are still compatible. However, new trigger points need to be developed for the automated data which is discussed in the following section.

There are two windshield data models for the interstate family, as seen in Figure 19. However, for the automated data model there was only one model for the interstate family, because the two interstate families from the windshield data were combined into one family for the automated data model. This was done because of the amount automated collected data available.
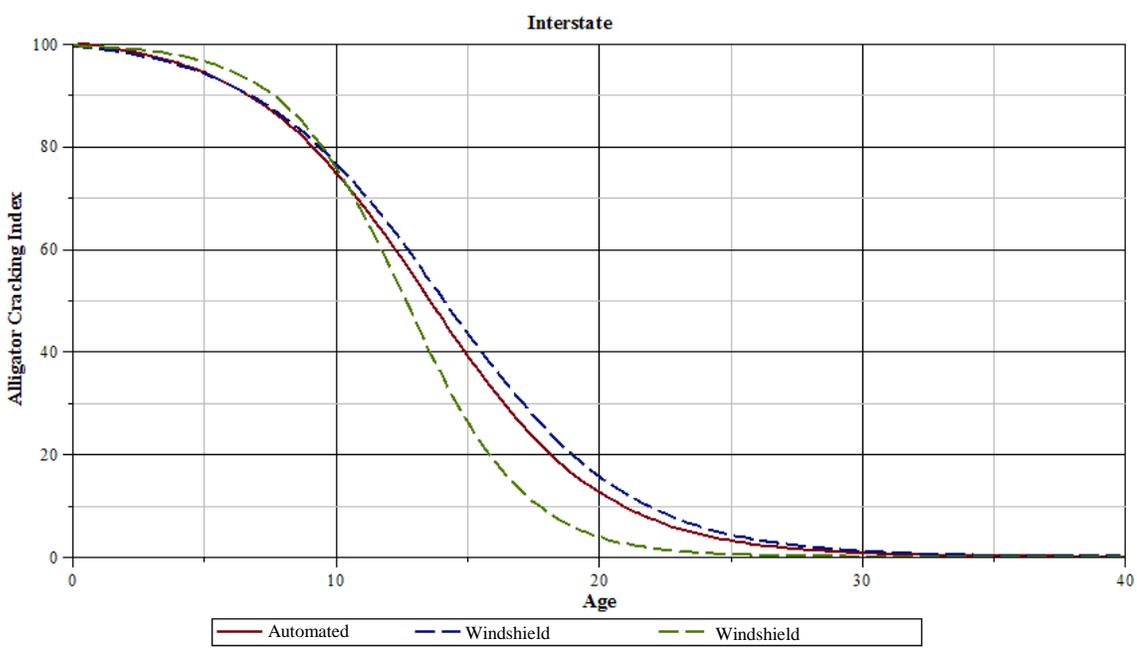

FIGURE 19: Interstate route - windshield vs automated curve
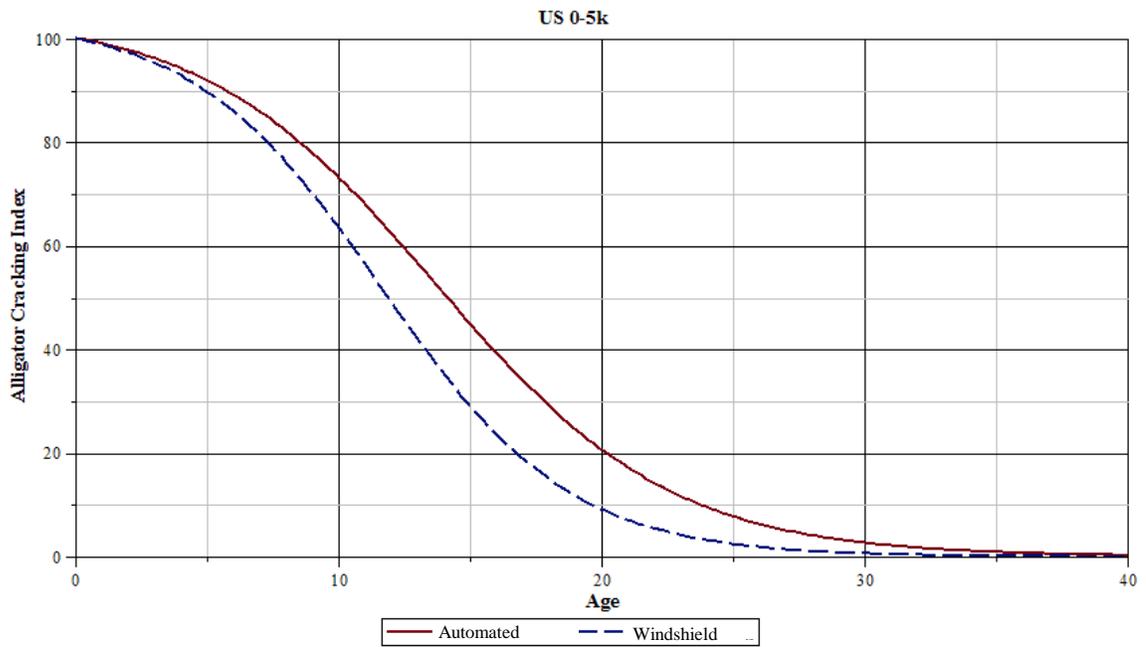
FIGURE 20: US route - windshield vs automated curve
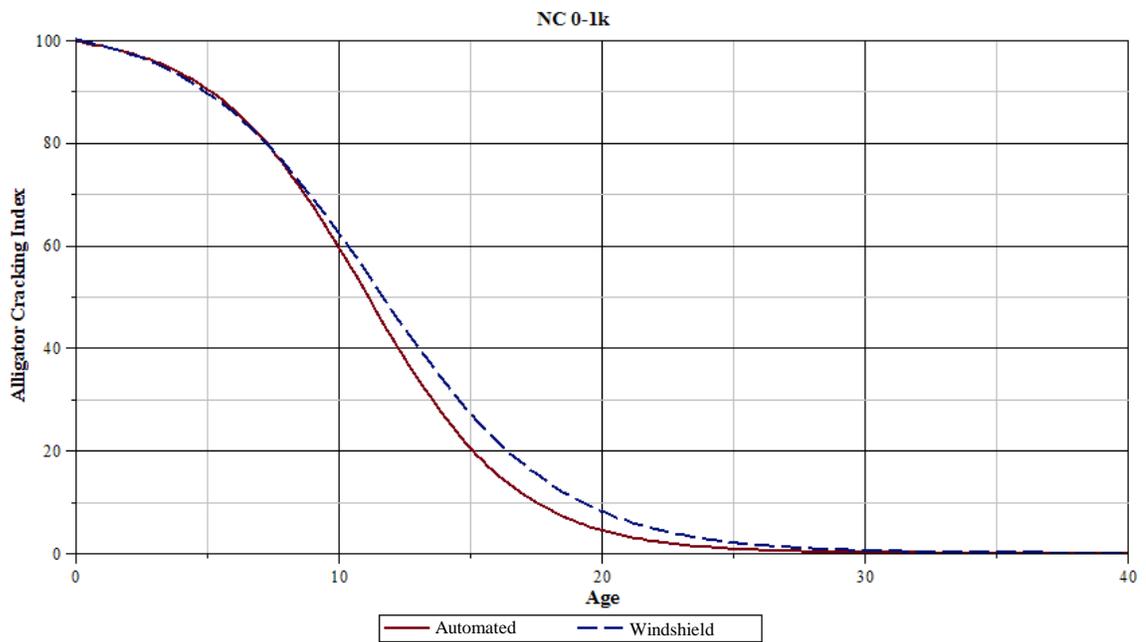
FIGURE 21: NC route - windshield vs automated curve

CHAPTER 4: DEVELOPMENT OF TRIGGER POINTS FOR AUTOMATED DATA

According to Merriam-Webster Dictionary (2014), a trigger point is a condition or state that causes an event to take place. The NCDOT has been using trigger points to initiate a maintenance plan based on pavement performance, which is evaluated based on four treatment zones: preventative maintenance, light rehabilitation, heavy rehabilitation, and complete reconstruction. As shown in Figure 22, the Y axis is the PCR value of the pavement, and the X axis is the AGE of the pavement. The dashed lines represent the boundaries of the treatment zone, which are where the trigger points occur.

4.1 Threshold Values

The PCR value between 100 and Threshold 1 will fall into the preventative maintenance zone, the PCR value between Threshold 1 and Threshold 2 will fall into the light rehabilitation zone, the PCR value between Threshold 2 and Threshold 3 will fall into the heavy rehabilitation zone, and the PCR value between Threshold 3 and 0 will fall into the reconstruction zone of the roadway. The PCR threshold values of 80, 60, and 30 were used in this research. The curve in Figure 22 show the location of the threshold values and the treatment zones.
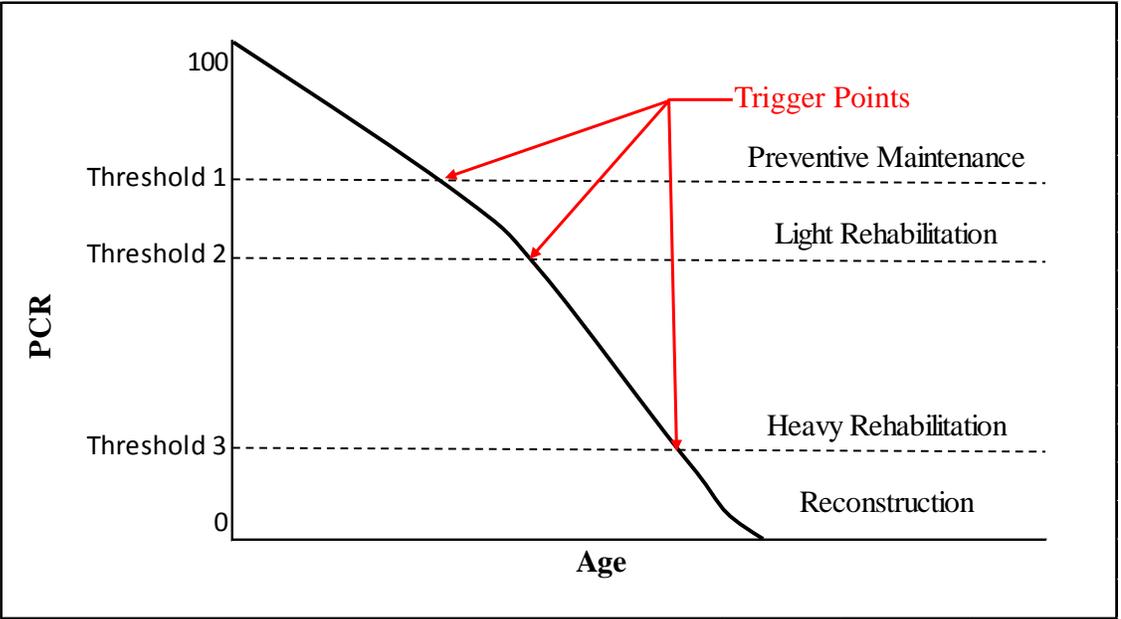
FIGURE 22: Generic PCR trigger point graph

4.2 Developing Trigger Points

The asphalt and JCP trigger points were determined using Equation 7 and Equation 8. The equations were set equal to the 80/60/30 threshold levels. Then the equations were manipulated until the individual distress trigger values for Threshold 1, Threshold 2, and Threshold 3 could be determined.

4.2.1 Trigger Points for Asphalt Pavements

To determine trigger points for asphalt pavements, the first step was to take Equation 7 and solve for a single distress. For this example alligator cracking was used. The relative importance for alligator cracking (Table 16) were entered into equation 7. Then the trigger point equation for alligator cracking can be written as shown in Equation 9.

The next step was to set Equation 9 equal to the 80/60/30 threshold values, and then the trigger values for alligator cracking were solved. The resulting trigger values for asphalt are shown in Table 18.

PCR = 0.354*ALGTR + 0.141*(.4* ALGTR) + 0.077*(.21* ALGTR) + 0.059*(.17* ALGTR) + 0.059*(.17* ALGTR) + 0.10*(.29* ALGTR) + 0.059*(.17* ALGTR) + 0.150*(.43* ALGTR)   (9)

Where:

PCR = Pavement Condition Rating

ALGTR = Normalized Alligator Cracking Index

TABLE 16: Eigenvectors used to develop asphalt trigger points

Distress	ALGTR	TRA	LNG	LNG JNT	RVL	WP	NWP	RUT
Alligator Cracking (ALGTR)	42/42 = 1.00	42/17 = 2.47	42/9 = 4.67	42/7 = 6.00	42/7 = 6.00	42/12 = 3.50	42/7 = 6.00	42/18 = 2.33
Transverse/Reflective Transverse Cracking (TRA)	17/42 = 0.40	17/17 = 1.00	17/9 = 1.89	17/7 = 2.43	17/7 = 2.43	17/12 = 1.42	17/7 = 2.43	17/18 = 0.94
Longitudinal Cracking (LNG)	9/42 = 0.40	9/17 = 0.53	9/9 = 1.00	9/7 = 1.29	9/7 = 1.29	9/12 = 0.75	9/7 = 1.29	9/18 = 0.50
Longitudinal Lane Joint (LNG JNT)	7/42 = 0.17	7/17 = 0.41	7/9 = 0.78	7/7 = 1.00	7/7 = 1.00	7/12 = 0.58	7/7 = 1.00	7/18 = 0.39
Raveling (RVL)	7/42 = 0.17	7/17 = 0.41	7/9 = 0.78	7/7 = 1.00	7/7 = 1.00	7/12 = 0.58	7/7 = 1.00	7/18 = 0.39
Patching Area - WP (WP)	12/42 = 0.29	12/17 = 0.71	12/9 = 1.33	12/7 = 1.71	12/7 = 1.71	12/12 = 1.00	12/7 = 1.71	12/18 = 0.67
Patching Area - NWP (NWP)	7/42 = 0.17	7/17 = 0.41	7/9 = 0.78	7/7 = 1.00	7/7 = 1.00	7/12 = 0.58	7/7 = 1.00	7/18 = 0.39
Rutting - Max Avg. Depth (RUT)	18/42 = 0.43	18/17 = 1.06	18/9 = 2.00	18/7 = 2.57	18/7 = 2.57	18/12 = 1.50	18/7 = 2.57	18/18 = 1.00

4.2.2 Trigger Points for JCP Pavements

To determine trigger points for JCP pavements, the first step was to take Equation 8 and solve for a single distress, for this example transverse cracking was used. The relative

importance for transverse cracking (Table 17) were entered into Equation 8. Then the trigger point equation for transverse cracking can be written as shown in Equation 10.

The next step was to set Equation 10 equal to 80/60/30 threshold values, and then the trigger values for the transverse cracking were solved. The resulting trigger values for JCP are shown in Table 19.

PCR = 0.111* TRNSVRS CRK + 0.111* (1.0* TRNSVRS CRK) + 0.208* (1.88*

TRNSVRS CRK) + 0.208* (1.88* TRNSVRS CRK) + 0.098* (.89* TRNSVRS CRK) +

0.098* (.89* TRNSVRS CRK) + 0.066* (.59* TRNSVRS CRK) + 0.098* (.89*

TRNSVRS CRK)   (10)

Where:

PCR = Pavement Condition Rating

TRNSVRS CRK = Normalized Transverse Cracking

TABLE 17: Eigenvectors used to develop JCP trigger points

Distress	TRNSVRS CRK	LNGTDNL CRK	CON PATCH	ASPHLT PTCH	TRNSVRS SPLL	LNGTDNL JNT SPLL	CRNR	FAULT
Transverse Cracking (TRNSVRS CRK)	**9.6/9.6 = 1.0**	9.6/9.6 = 1.0	9.6/18 = 0.53	9.6/18 = 0.53	9.6/8.5 = 1.13	9.6/8.5 = 1.13	9.6/5.7 = 1.68	9.6/8.5 = 1.13
Longitudinal Cracking (LNGTDNL CRK)	9.6/9.6 = 1.0	**9.6/9.6 = 1.0**	9.6/18 = 0.53	9.6/18 = 0.53	9.6/8.5 = 1.13	9.6/8.5 = 1.13	9.6/5.7 = 1.68	9.6/8.5 = 1.13
PCC Patch (CON PATCH)	18/9.6 = 1.88	18/9.6 = 1.88	**18/18 = 1.0**	18/18 = 1.0	18/8.5 = 2.12	18/8.5 = 2.12	18/5.7 = 3.16	18/8.5 = 2.12
Asphalt Patch (ASPHLT PTCH)	18/9.6 = 1.88	18/9.6 = 1.88	18/18 = 1.0	**18/18 = 1.0**	18/8.5 = 2.12	18/8.5 = 2.12	18/5.7 = 3.16	18/8.5 = 2.12
Transvers Joint Spalled (TRNSVRS SPLL)	8.5/9.6 = 0.89	8.5/9.6 = 0.89	8.5/18 = 0.47	8.5/18 = 0.47	**8.5/8.5 = 1.0**	8.5/8.5 = 1.0	8.5/5.7 = 1.49	8.5/8.5 = 1.0
Longitudinal Joint Spalled (LNGTDNL JNT SPLL)	8.5/9.6 = 0.89	8.5/9.6 = 0.89	8.5/18 = 0.47	8.5/18 = 0.47	8.5/8.5 = 1.0	**8.5/8.5 = 1.0**	8.5/5.7 = 1.49	8.5/8.5 = 1.0
Corner Break (CRNR)	5.7/9.6 = 0.59	5.7/9.6 = 0.59	5.7/18 = 0.32	5.7/18 = 0.32	5.7/8.5 = 0.67	5.7/8.5 = 0.67	**5.7/5.7 = 1.0**	5.7/8.5 = 0.67
Joint Fault (FALUT)	8.5/9.6 = 0.89	8.5/9.6 = 0.89	8.5/18 = 0.47	8.5/18 = 0.47	8.5/8.5 = 1.0	8.5/8.5 = 1.0	8.5/5.7 = 1.49	**8.5/8.5 = 1.0**

4.2.3 Final Threshold and Composite Index Values

The composite index was the last step in developing the trigger points for the automated collected data. This was performed by taking an average of all the individual distress index calculated in sections 4.2.1 and 4.2.2. The averages were taken because some of the asphalt and JCP individual distress indices had a value greater than 100 which is not reasonable. This is possibly because some relative importance values used by the NCDOT are too high.

The averages for asphalt pavements can be seen in Table 18. The composite distress trigger values with a threshold level at 80 was calculated to be 52. This means when each distress index reaches 52 its PCR value will reach 80, and a maintenance action will be triggered.

TABLE 18: Asphalt trigger point values

PCR Threshold	ALGTR	TRA	LNG	LNG JNT	RVL	WP	NWP	RUT	Average Composite Distress Index
80	145.4	58.9	32.7	24.2	24.2	41.6	24.2	62.4	**52**
60	109.1	44.2	24.5	18.2	18.2	31.2	18.2	46.8	**39**
30	54.5	22.1	12.3	9.1	9.1	15.6	9.1	23.4	**19**

The averages for JCP can be seen in Table 19. The composite distress trigger value with a threshold level at 80 was calculated to be 70. This means when each distress index value reaches 70, its PCR value will reach 80, and a maintenance action will be triggered.

TABLE 19: JCP trigger point values

PCR Threshold	TRNSVRS CRK	LNGTDNL CRK	CON PATCH	ASPHLT PATCH	TRNSVRS SPLL	LNGTDNL JNT SPLL	CRNR	FAULT	Average Composite Distress Index
80	61.32	61.32	115.45	115.45	54.38	54.38	36.50	54.38	**70**
60	45.99	45.99	86.59	86.59	40.79	40.79	27.38	40.79	**52**
30	22.99	22.99	43.29	43.29	20.39	20.39	13.69	20.39	**26**

CHAPTER 5: RESULTS

5.1 Distress Models

All distress models consist of the dependent variable which is the distress index for each of the respective distresses and the independent variable which is the age of the pavement.

It is also important to note that the "a" coefficient may not always be 100 for all distress models. This is because after determining the optimized b and c coefficients the starting point on the graph was not always at (0,100). In order to correct this issue, the "a" coefficient was adjusted until all distress models curves started at (0,100).

It is important to note that the MAE values were developed based on the L/M/S severity levels; however, not every distress model contains low, moderate, or severe data. This is because not all distresses are recorded in low, moderate, and severe severities. For example, longitudinal lane joint cracking was only recorded when the distress was severe. That is why in Table 21 only the MAE severe value is available.

5.1.1 Alligator Cracking

The complete set of distress curves for alligator cracking can be seen in Appendix B. The a/b/c coefficients used to create the sigmoidal distress curves for alligator cracking are included in Table 20. An example of the alligator cracking distress curve can be seen in Figure 23.

TABLE 20: Sigmoidal distress models parameters for alligator cracking

| Distress	Family	a	b	c	Low Severity MAE In	Med Severity MAE In	High Severity MAE In
Alligator Cracking	Interstate	101.8	13.44	-3.35	41.68	7.29	3.35
	US 0-5k	104.5	13.72	-4.46			
	US 5-15k	109.5	11.35	-4.79			
	US 15k+	111.3	8.59	-3.90			
	NC 0-1k	102.0	11.00	-2.91			
	NC 1-5k	107.0	12.13	-4.63			
	NC 5k+	108.0	11.48	-4.54			
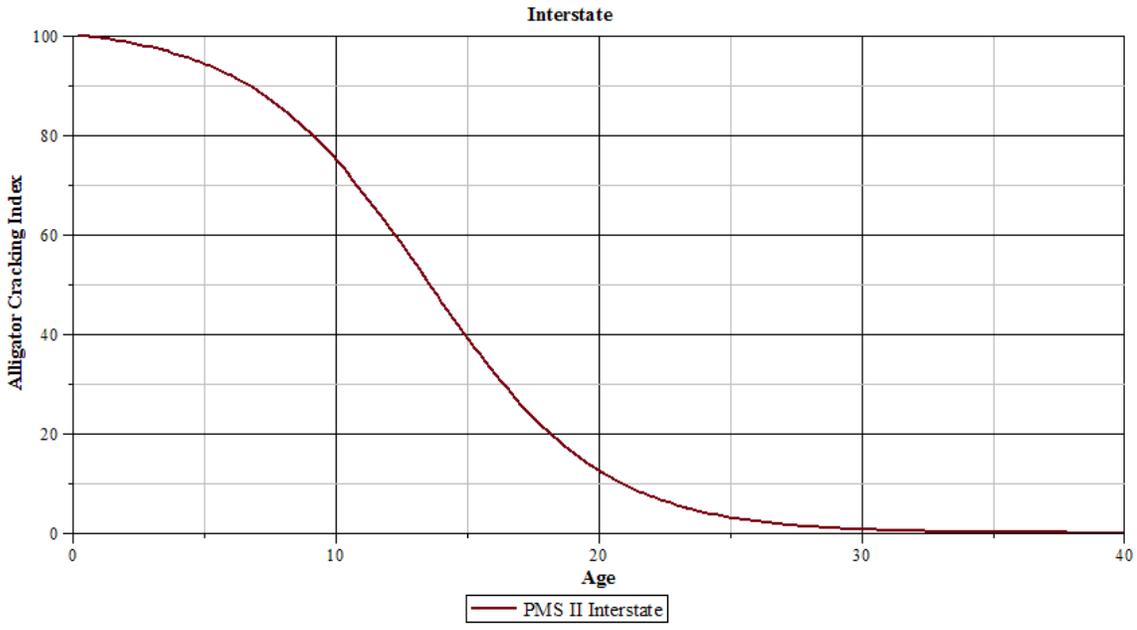
FIGURE 23: Alligator cracking distress model

5.1.2 Transverse Cracking

The complete set of distress curves for transverse cracking can be seen in Appendix

C. The a/b/c coefficients used to create the sigmoidal distress curves for transverse cracking

are included in Table 21. An example of the transverse cracking distress curve can be seen in Figure 24.

TABLE 21: Sigmoidal distress models parameters for transverse cracking

| Distress	Family	a	b	c	Low Severity MAE In	Med Severity MAE In	High Severity MAE In
Transverse Cracking	Interstate	103.0	16.39	-4.82	5.96	3.62	1.36
	US 0-5k	101.1	10.91	-2.48			
	US 5-15k	101.5	12.58	-3.04			
	US 15k+	102.1	11.33	-3.01			
	NC 0-1k	101.0	9.54	-2.13			
	NC 1-5k	101.0	11.13	-2.54			
	NC 5k+	101.8	10.75	-2.67			
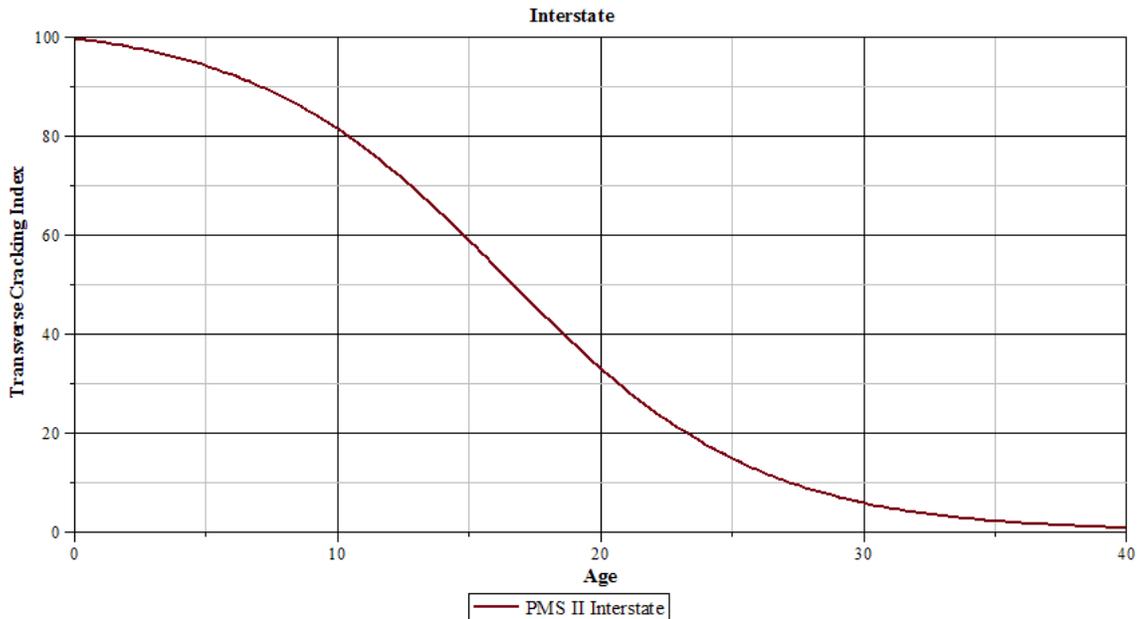
FIGURE 24: Transverse cracking distress model

5.1.3 Longitudinal Models

The complete set of distress curves for longitudinal cracking can be seen in Appendix D. The a/b/c coefficients used to create the sigmoidal distress curves for longitudinal cracking are included in Table 22. An example of the longitudinal cracking distress curve can be seen in Figure 25.

TABLE 22: Sigmoidal distress models parameters for longitudinal cracking

| Distress	Family	a	b	c	Low Severity MAE In	Med Severity MAE In	High Severity MAE In
Longitudinal Cracking	Interstate	100.0	16.57	-2.28	4.58	0	7.04
	US 0-5k	100.0	14.47	-1.91			
	US 5-15k	100.0	15.32	-2.09			
	US 15k+	100.0	12.18	-1.34			
	NC 0-1k	100.0	12.36	-1.28			
	NC 1-5k	100.0	13.76	-1.65			
	NC 5k+	100.0	13.97	-1.59			
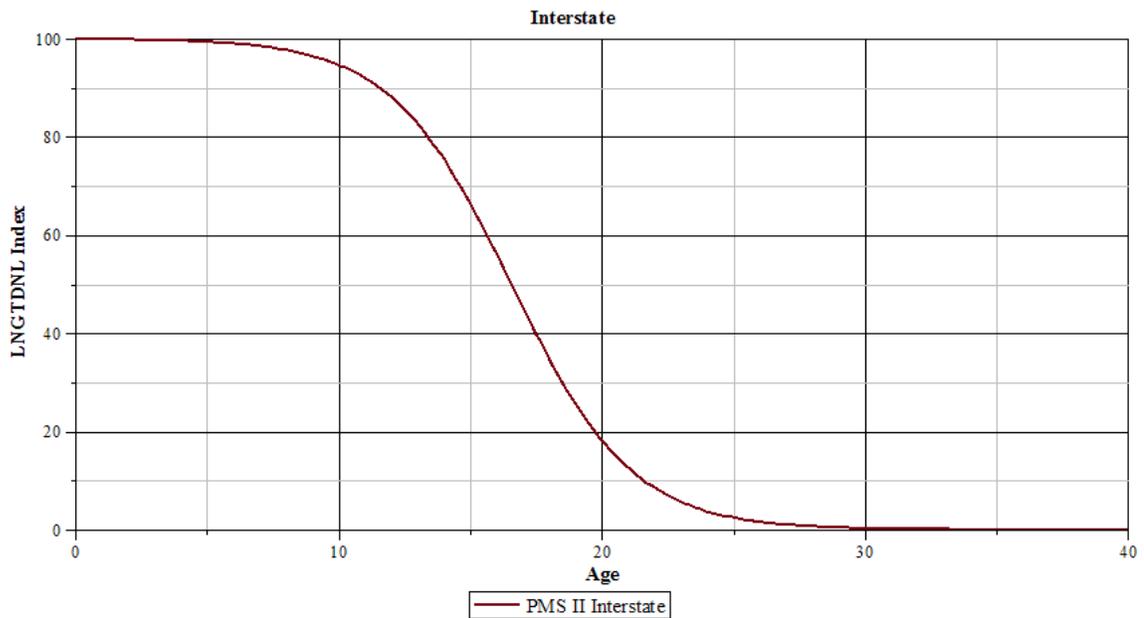
FIGURE 25: Longitudinal cracking distress model

5.1.4 Longitudinal Lane Joint Models

The complete set of distress curves for longitudinal lane joint cracking can be seen in Appendix E. The a/b/c coefficients used to create the sigmoidal distress curves for longitudinal lane joint cracking are included in Table 23. An example of this distress curve can be seen in Figure 26.

TABLE 23: Sigmoidal distress models parameters for longitudinal lane joint cracking

| Distress	Family	a	b	c	Low Severity MAE In	Med Severity MAE In	High Severity MAE In
Longitudinal Lane Joint Cracking	Interstate	100.0	18.76	-2.62	1.57	0	0
	US 0-5k	100.0	13.50	-1.80			
	US 5-15k	100.0	15.93	-2.24			
	US 15k+	100.0	21.51	-3.06			
	NC 0-1k	100.0	16.71	-2.29			
	NC 1-5k	100.0	17.46	-2.39			
	NC 5k+	100.0	13.87	-1.86			
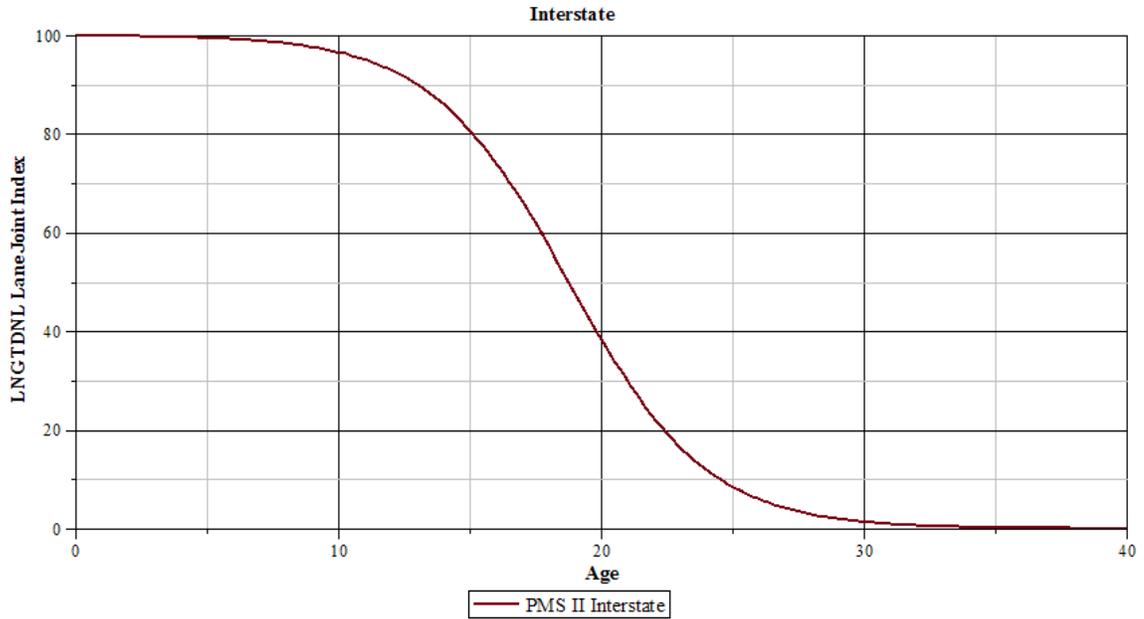
FIGURE 26: Longitudinal lane joint cracking distress model

5.1.5 Raveling

The complete set of distress curves for raveling can be seen in Appendix F. The a/b/c coefficients used to create the sigmoidal distress curves for raveling are included in Table 24. An example of the raveling distress curve can be seen in Figure 27.

TABLE 24: Sigmoidal distress models parameters for raveling

| Distress	Family	a	b	c	Low Severity MAE In	Med Severity MAE In	High Severity MAE In
Raveling	Interstate	100.0	17.10	-2.78	34.92	34.54	31.35
	US 0-5k	100.3	30.41	-5.26			
	US 5-15k	101.8	22.59	-5.66			
	US 15k+	105.0	20.95	-6.99			
	NC 0-1k	100.8	16.45	-3.48			
	NC 1-5k	100.5	22.64	-4.35			
	NC 5k+	100.5	21.18	-4.07			

Interstate
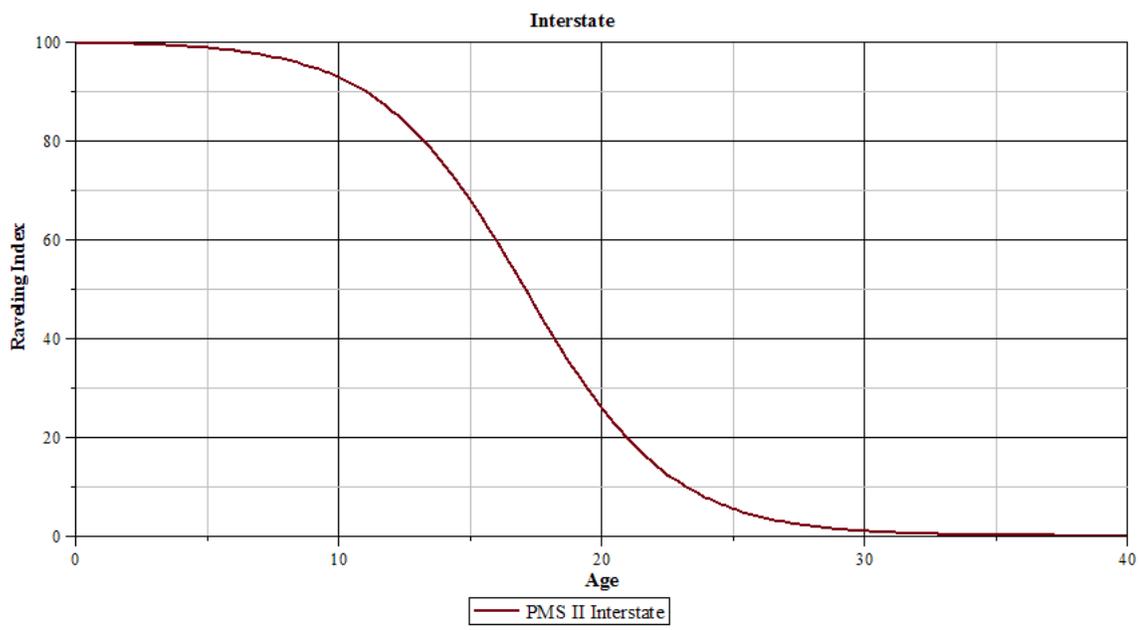

FIGURE 27: Raveling distress model

5.1.6 Wheel Path Patching Models

The complete set of distress curves for wheel path patching can be seen in Appendix

G. The a/b/c values used to create the sigmoidal distress curves for wheel path patching are

included in Table 25. An example of the wheel path patching distress curve can be seen in

Figure 28.

TABLE 25: Sigmoidal distress models parameters for WP patching

Distress	Family	a	b	c	Low Severity MAE In	Med Severity MAE In	High Severity MAE In
Patching Area WP	Interstate	100.0	14.67	-1.96	13.11	0	0
	US 0-5k	100.0	18.14	-2.76			
	US 5-15k	100.0	18.81	-2.92			
	US 15k+	100.0	20.50	-3.38			
	NC 0-1k	100.0	20.07	-3.11			
	NC 1-5k	100.0	18.00	-2.68			
	NC 5k+	100.0	18.39	-3.01			
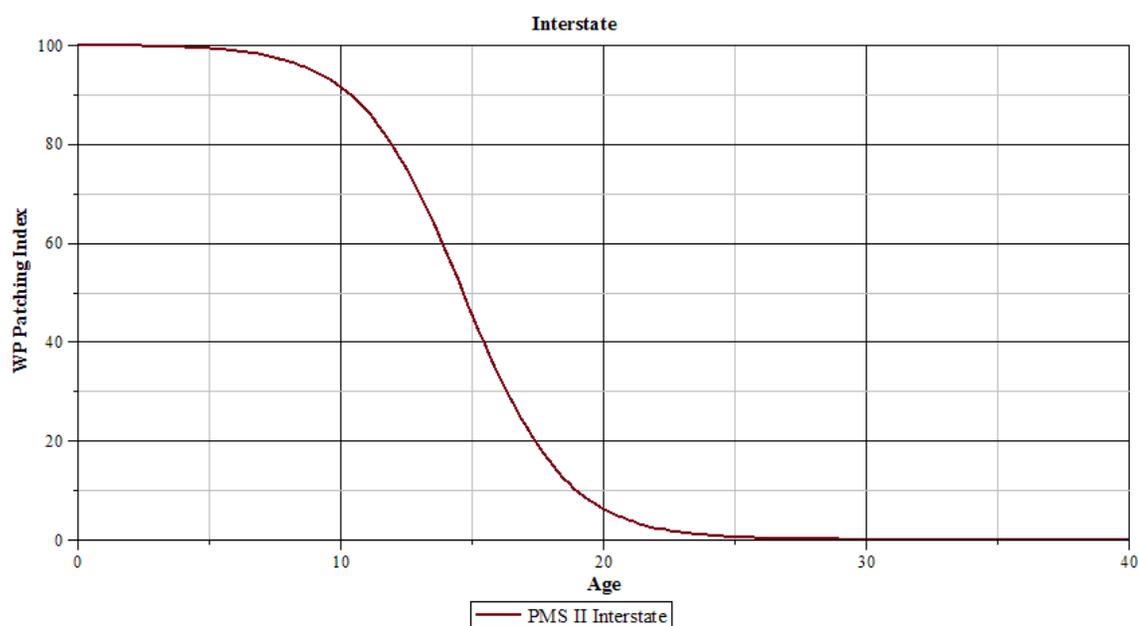
FIGURE 28: WP patching distress model

5.1.7 Non-Wheel Path Patching Models

The complete set of distress curves for non-wheel path patching can be seen in Appendix H. The a/b/c values coefficients to create the sigmoidal distress curves for non-wheel path patching are included in Table 26. An example of the non-wheel path patching distress curve can be seen in Figure 29.

TABLE 26: Sigmoidal distress models parameters for NWP patching

Distress	Family	a	b	c	Low Severity MAE In	Med Severity MAE In	High Severity MAE In
Patching Area NWP	Interstate	100.0	18.77	-2.59			
	US 0-5k	100.0	21.86	-3.26			
	US 5-15k	100.0	24.41	-3.70			
	US 15k+	100.0	22.45	-3.63	17.72	0	0
	NC 0-1k	100.0	24.24	-3.73			
	NC 1-5k	100.0	21.04	-3.10			
	NC 5k+	100.0	21.31	-3.39			
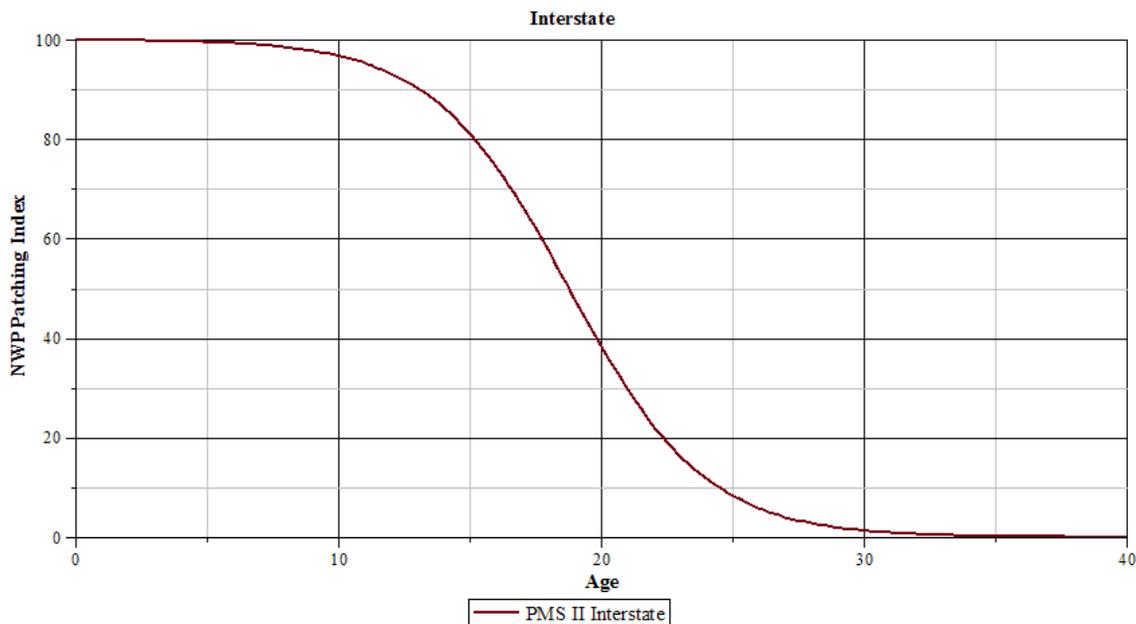
FIGURE 29: NWP patching distress model

5.1.8 Rutting

Rutting was a unique distress because its depth is collected whereas area or length is collected for other types of distresses. Tests showed that a power function fits the rutting data better than the sigmoidal equation. The power function used is as follows: Rutting Index $= 100 - a*Age^{1.5}$. The rutting distress models using the power curve function can be

seen in Appendix I. The coefficient used to create the power distress curves for rutting is

included in Table 27. An example of the rutting distress model can be seen in Figure 30.

TABLE 27: Distress models parameters for rutting

Distress	Family	a	Low Severity MAE In	Med Severity MAE In	High Severity MAE In
Rutting	Interstate	0.99			
	US 0-5k	0.94			
	US 5-15k	1.02	Rutting Index = 100 - a*Age^1.5		
	US 15k+	0.95			
	NC 0-1k	1.00			
	NC 1-5k	0.94			
	NC 5k+	0.94			
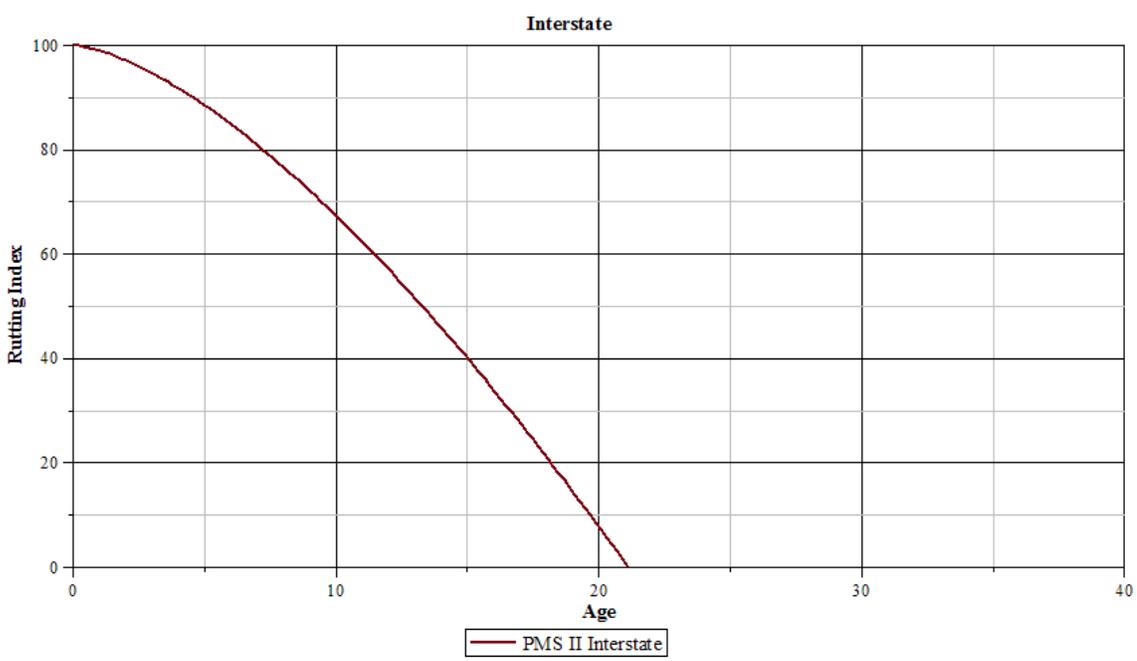
FIGURE 30: Rutting distress curve

5.1.9 JCP

The complete set of distress curves for JCP pavements can be seen in Appendix F.

The a/b/c coefficients used to create the sigmoidal distress curves for JCP are included in

Table 28. An example of the JCP distress curve can be seen in Figure 31.

TABLE 28: Sigmoidal distress models parameters for JCP

| Pavement	Distress	a	b	c	Low Severity MAE In	Med Severity MAE In	High Severity MAE In
JCP	Asphalt Patch	100.0	15.05	-2.20	20.24	0.00	0.00
	Corner Break	100.2	17.55	-2.95	6.01	0.00	0.00
	Joint Fault	100.3	25.70	-4.49	60.21	10.03	1.40
	Longitudinal Cracking	102.5	14.36	-3.87	43.28	0.00	26.60
	Longitudinal Joint Spalled	100.0	17.82	-5.31	86.09	0.00	0.00
	PCC Patch	100.0	19.97	-3.20	15.76	0.00	0.00
	Transverse Cracking	102.0	19.42	-5.11	37.81	0.00	27.61
	Transverse Joint Spalled	100.0	14.94	-3.39	91.27	28.66	22.92
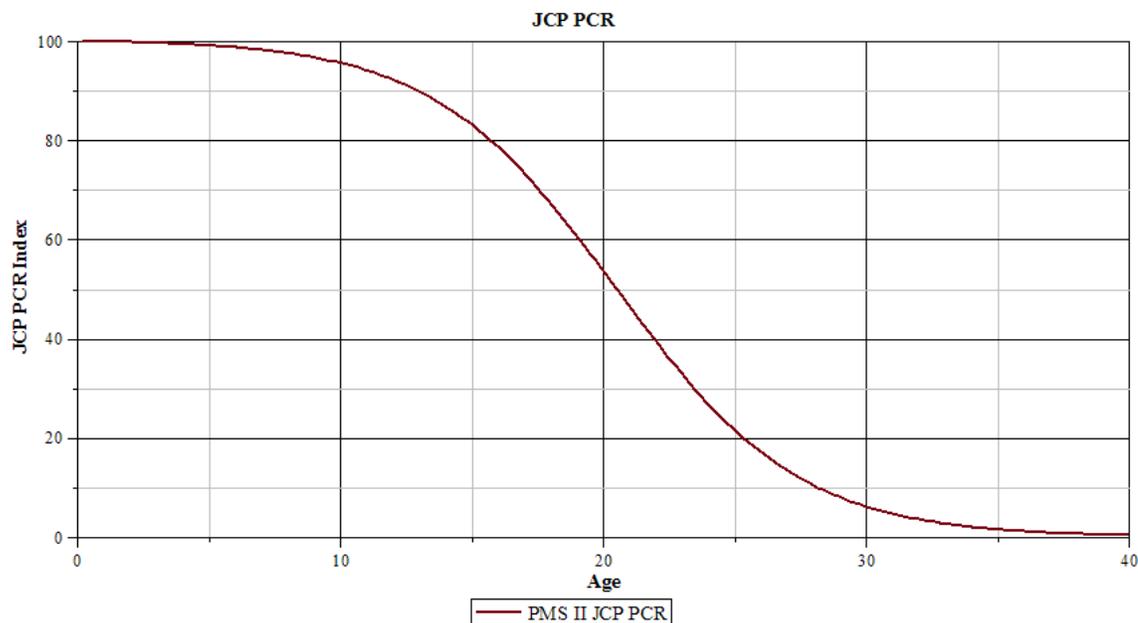
FIGURE 31: JCP performance curve

5.2 Performance Models

5.2.1 Asphalt Models

The complete performance curves for asphalt pavements can be seen in Appendix J. The complete set of a/b/c coefficients for asphalt pavements used with the sigmoidal equation are included in Table 29. An example of the asphalt performance curve can be seen in Figure 32.

TABLES 29: Sigmoidal distress models parameters for ASP

Pavement	Distress	a	b	c
ASP	Interstate	103.4	12.68	-3.83
	US 0-5k	110.0	14.57	-6.29
	US 5-15k	112.0	14.23	-6.73
	US 15k+	112.0	14.23	-6.73
	NC 0-1k	110.0	12.30	-5.33
	NC 1-5k	112.0	13.58	-6.52
	NC 5k+	112.0	13.51	-6.39
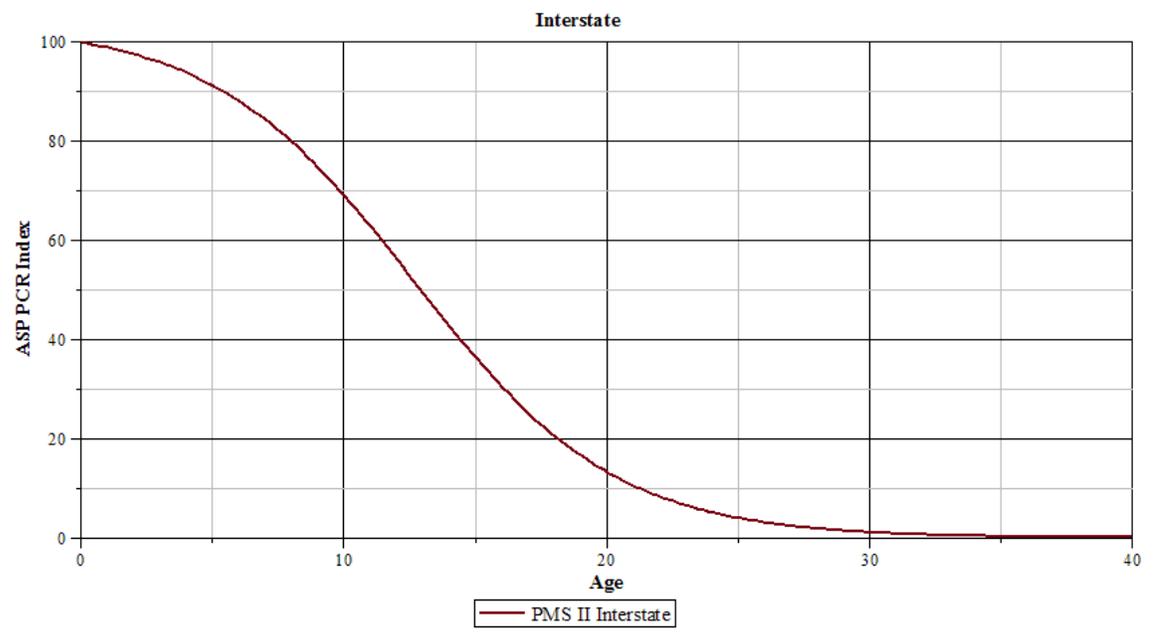
FIGURE 32: ASP performance model

5.2.2 Joint Concrete Pavement

The performance curve for joint concrete pavements (JCP) can be seen in Appendix

K. The a/b/c coefficients for JCP used with the sigmoidal equation are included in Table

30. An example of the JCP performance curve can be seen in Figure 33.

TABLE 30: Sigmoidal distress models parameters for JCP

Pavement	Distress	a	b	c
JCP	Interstate	100.3	20.49	-3.48
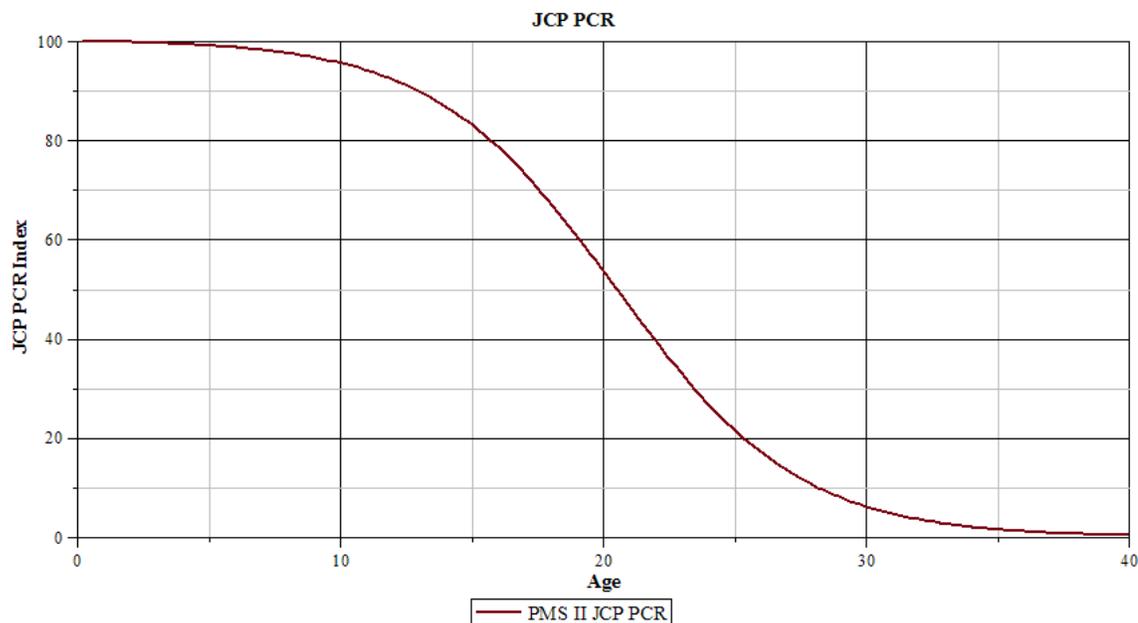
FIGURE 33: JCP performance model

5.3 Trigger Points

The triggers points on the decision trees can be used by the NCDOT for selecting appropriate maintenance action for a pavement based on the thresholds set for each distress. The threshold levels where set at 80, 60, and 30, which are corresponding to the preventive maintenance, light rehabilitation, heavy rehabilitation, and reconstruction treatment zones. The following sections show the final trigger points for asphalt and JCP pavements.

5.3.1 Asphalt Models

The trigger points for asphalt pavements can be seen in Table 31. As an example, the composite distress value with a threshold level at 80 was calculated to be 52. This means when each distress has a value equal to 52 the PCR value of 80 will be reached, and this will trigger a maintenance action. For example, if each individual distress index is 53,

preventative maintenance will be triggered; and if each individual distress index is 51, light rehabilitation maintenance will be triggered.

TABLE 31: Trigger points for asphalt pavements

Asphalt Trigger Points		
Threshold	Rating	Maintenance
80	52	100-80: Preventative Maintenance
60	39	80-60: Light Rehabilitation
30	19	60-30: Heavy Rehabilitation
0	0	30-0: Reconstruction

5.3.2 JCP

The trigger points for JCP pavements can be seen in Table 32. As an example, the composite distress value with a threshold level at 80 was calculated to be 70. This means when each distress has a value equal to 70 the PCR value of 80 will be reached, and this will trigger a maintenance action. For example if each individual distress index is 71, preventative maintenance will be triggered; and if each individual distress index is 69, light rehabilitation maintenance will be triggered.

TABLE 32: Trigger points for JCP pavements

JCP Trigger Points		
Threshold	Rating	Maintenance
80	70	100-80: Preventative Maintenance
60	52	80-60: Light Rehabilitation
30	26	60-30: Heavy Rehabilitation
0	0	30-0: Reconstruction

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

In this research, a systematic way to develop distress and performance models and determine trigger points on decision trees for a PMS was proposed and verified. Composite indices were developed using the MAE function and AHP process. The distress and performance models were developed using sigmoidal equations. The resulting models were used to determine the trigger point values so threshold levels could be used to initiate a maintenance action.

6.1 Conclusion

6.1.1 Developing Composite Indices

A systematic method of determine composite indices has been developed in this study. The distress and performance composite indices needed to be developed because the automated data consisted up to four severity levels for each distress. The severity levels are none (N), low (L), moderate (M), and severe (S). In order to predict pavement distresses, all of the severity levels needed to be combined into one index for the purpose of having one dependent variable that could be used to build the distress models.

The first step was to determine the MAE values that can be used to calculate the composite index. The automated data MAE values were determined by finding the appropriate percentiles of the raw data for each of the distresses. Once the appropriate percentile was determined, the corresponding distress values were averaged and entered into the MAE function. This allowed for the composite distress indices for asphalt and JCP

pavements to be calculated. The results were used to successfully develop the distress models.

The second step was to develop the composite performance index, PCR. This involved the use of the AHP to determine a weight factor for each type of the distresses. Then PCR values were used to develop the asphalt and JCP performance models.

6.1.2 Developing Distress and Performance Models

A comprehensive method of developing distress and performance models was proposed in this study. The non-linear sigmoidal model form was chosen to develop these models. The initial estimates of model parameters were obtained using regression analysis. The final estimates of model parameters were determined using TableCurve. The distress and performance automated models were then plot against their equivalent family curves developed from the windshield data to investigate if there were similarities between the models. A visual comparison was decided to be an appropriate inspection method for this study. Based on the results of the asphalt pavements, and as discussed in section 3.8, the windshield and the automated performance curves are comparable. However, it is important to note that the JCP pavements did not share these similarities. This is probably due to the small sample sizes of the automated data for JCP pavements.

The graphs for asphalt and JCP reveal one more trend. The automated data distress models show strong decreasing trends in the graphs between the 10th and 13th year of the pavement life cycle. This was to be expected when referenced with the NCDOT's "Proposed Life Cycle Cost Analysis Procedure Summary" (2013) document. Therefore, it is concluded that the performance models are robust.

6.1.3 Trigger Points

The trigger points were developed as a way to quantify the thresholds for each distress that can trigger a maintenance action. The trigger values provide NCDOT engineers with the ability to select the appropriate action for each of the distress ratings, and remove user subjectivity when selecting the maintenance action whether it be preventative maintenance, light rehabilitation, heavy rehabilitation, or complete reconstruction. The trigger points were developed using the manipulation of the asphalt and JCP PCR equations. This was done by taking the PCR equation and replacing the substituted distress with the relative importance from the substituting distress. The threshold values of different types of distress were then averaged and used as trigger point values.

6.2 Recommendations

There are a total of four recommendations based on the results of this study. It is recommended that an update of all of the newly developed models is needed when at least three years' worth of data is available. The distress and performance curves developed in this study were developed using only 2012 and 2013 automated data. Models developed using more data can better predict pavement performance and assist PMS engineers to make more appropriate maintenance decisions.

It is recommended to further divide the 18 roadway families into sub groups based on regions. The state of North Carolina has three main regions which are Mountains, Piedmont, and Coastal. Since it is intuitive, for example, that the Interstate roadways in the Mountain region would not be expected to perform the same as the ones in the Piedmont and the Coastal regions. Therefore, it is advised that separate families be developed to account for these geographically different regions.

It is recommended to develop distress and performance models for composite pavements. During the course of this study, the composite pavements were treated as a part of the asphalt pavements; however, composite pavements tend to deteriorate differently than asphalt pavements. Therefore, composite pavement models would help NCDOT engineers to better manage composite pavements.

It is recommended to develop the distress and performance models for the SR routes. These models were not developed during this study because currently the SR routes were not surveyed using the automated data collection system. This was due to the high cost of data collection. This is a recommended future update when the NCDOT has the ability to collect SR route distress data using the automated method.

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APPENDIX A: SAMPLE WINDSHIELD SURVEY FORM

Asphalt Concrete Pavement Deliverable Table (1/2)

Description	Field Name	Pavement Type	Units	Format	Field Type	Field Width	Dec.
Pavement Management System Location ID	PMS_LOC_IDENT	ALL		*	N	*	0
Eight Digit Route Number	ROUTE1	ALL		xxxxxxxx	C	8	0
Date Tested	EFF_DATE	ALL		DDMMYYYY	D	8	
Year	EFF_YEAR	ALL	Year	9999	N	4	0
County	COUNTY	ALL		999	N	3	0
Number of Lanes	NUMBER_OF_LANES	ALL		9	N	1	0
Cardinal Direction	NC_DRCTN_CD	ALL	N,S,E,W,I,O,B	x	C	1	0
PMS Direction	DRCTN_CLCTD_CD	ALL	I, D	x	C	1	0
Begin Milepost	OFFSET_FROM	ALL	Mile	999.999	N	7	3
End Milepost	OFFSET_TO	ALL	Mile	999.999	N	7	3
Length	LENGTH	ALL	Mile	999.999	N	7	3
Testing Speed	SPEED	ALL	MPH	99	N	2	0
IRI Left Wheelpath	LEFT_IRI	ALL	Inches/Mile	999	N	3	0
IRI Right Wheelpath	RIGHT_IRI	ALL	Inches/Mile	999	N	3	0
IRI Average	NC_IRI_L_R_AVG	ALL	Inches/Mile	999	N	3	0
Section Width	SEC_WIDTH	ALL	Feet	99	N	2	0
Transverse Cracking Low Severity	TRNSVRS_LOW_LF	AC/COMPOSITE	Linear Feet	99999	N	5	0
Transverse Cracking Moderate Severity	TRNSVRS_MDRT_LF	AC/COMPOSITE	Linear Feet	99999	N	5	0
Transverse Cracking High Severity	TRNSVRS_HGH_LF	AC/COMPOSITE	Linear Feet	99999	N	5	0
Longitudinal Cracking Low Severity	LNGTDNL_LOW_LF	AC/COMPOSITE	Linear Feet	99999	N	5	0
Longitudinal Cracking High Severity	LNGTDNL_HGH_LF	AC/COMPOSITE	Linear Feet	99999	N	5	0
Longitudinal Lane Joint Low Severity	LNGTDNL_LANE_JNT_LOW_LF	AC/COMPOSITE	Linear Feet	99999	N	5	0
Longitudinal Lane Joint High Severity	LNGTDNL_LANE_JNT_HGH_LF	AC/COMPOSITE	Linear Feet	99999	N	5	0
Reflective Transverse Cracking Low Severity	RFLCT_TRNSVRS_LOW_LF	AC/COMPOSITE	Linear Feet	9999	N	4	0
Reflective Transverse Cracking Moderate Severity	REFLCT_TRNSVRS_MDRT_LF	AC/COMPOSITE	Linear Feet	9999	N	4	0
Reflective Transverse Cracking High Severity	REFLCT_TRNSVRS_HGH_LF	AC/COMPOSITE	Linear Feet	9999	N	4	0
Reflective Longitudinal Cracking Low Severity	REFLCT_LNGTDNL_LOW_LF	AC/COMPOSITE	Linear Feet	99999	N	5	0
Reflective Longitudinal Cracking Moderate Severity	REFLCT_LNGTDNL_MDRT_LF	AC/COMPOSITE	Linear Feet	99999	N	5	0
Reflective Longitudinal Cracking High Severity	REFLCT_LNGTDNL_HGH_LF	AC/COMPOSITE	Linear Feet	99999	N	5	0
Alligator Cracking Low Severity	ALGTR_LOW_SF	AC/COMPOSITE	Square Feet	99999	N	5	0
Alligator Cracking Moderate Severity	ALGTR_MDRT_SF	AC/COMPOSITE	Square Feet	99999	N	5	0
Alligator Cracking High Severity	ALGTR_HGH_SF	AC/COMPOSITE	Square Feet	99999	N	5	0
Ravelling Low Severity	RVL_LOW_SF	AC/COMPOSITE	Square Feet	99999	N	5	0
Ravelling Moderate Severity	RVL_MDRT_SF	AC/COMPOSITE	Square Feet	99999	N	5	0
Ravelling High Severity	RVL_HGH_SF	AC/COMPOSITE	Square Feet	99999	N	5	0

Asphalt Concrete Pavement Deliverable Table (2/2)

Description	Field Name	Pavement Type	Units	Format	Field Type	Field Width	Dec.
Patching Area - wheel path	WP_PTCH_SF	AC/COMPOSITE	Square Feet	999999	N	6	0
Patching Area - Non wheel path	NWP_PTCH_SF	AC/COMPOSITE	Square Feet	999999	N	6	0
Delaminations Area	DLMN_SF	AC/COMPOSITE	Square Feet	9999	N	5	0
Bleeding Low Severity	BLD_LOW_SF	AC/COMPOSITE	Square Feet	9999	N	5	0
Bleeding High Severity	BLD_HGH_SF	AC/COMPOSITE	Square Feet	9999	N	5	0
Maximum Average Rut Depth	MAX_RUT_AVG	AC/COMPOSITE	Inch	9.99	N	5	2
Pavement Type	NC_PVMT_CD_ID	AC/COMPOSITE		xxx	C	3	
Filename	FILENAME	ALL		xxxxxxxx	C	8	
Start GPS Latitude	LAT_FROM	ALL		100	N	15	10
Start GPS Longitude	LONG_FROM	ALL		1000	N	15	10
End GPS Latitude	LAT_TO	ALL		100	N	15	10
End GPS Longitude	LONG_TO	ALL		1000	N	15	10

APPENDIX B: ALLIGATOR CRACKING

US 5-15k

US 15k plus

NC 0-1k

NC 1-5k

NC 5k plus

Alligator Cracking Index vs. Age

Legend: PMS II NC 5k plus — PMS I NC 5-15k — PMS I NC 15k plus
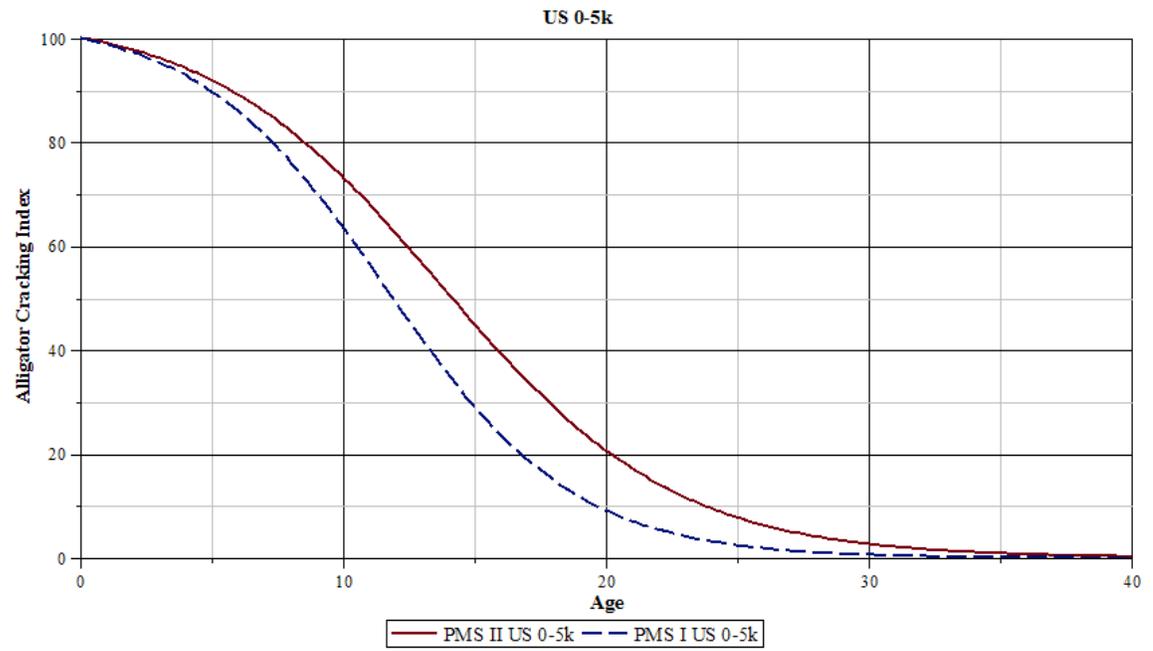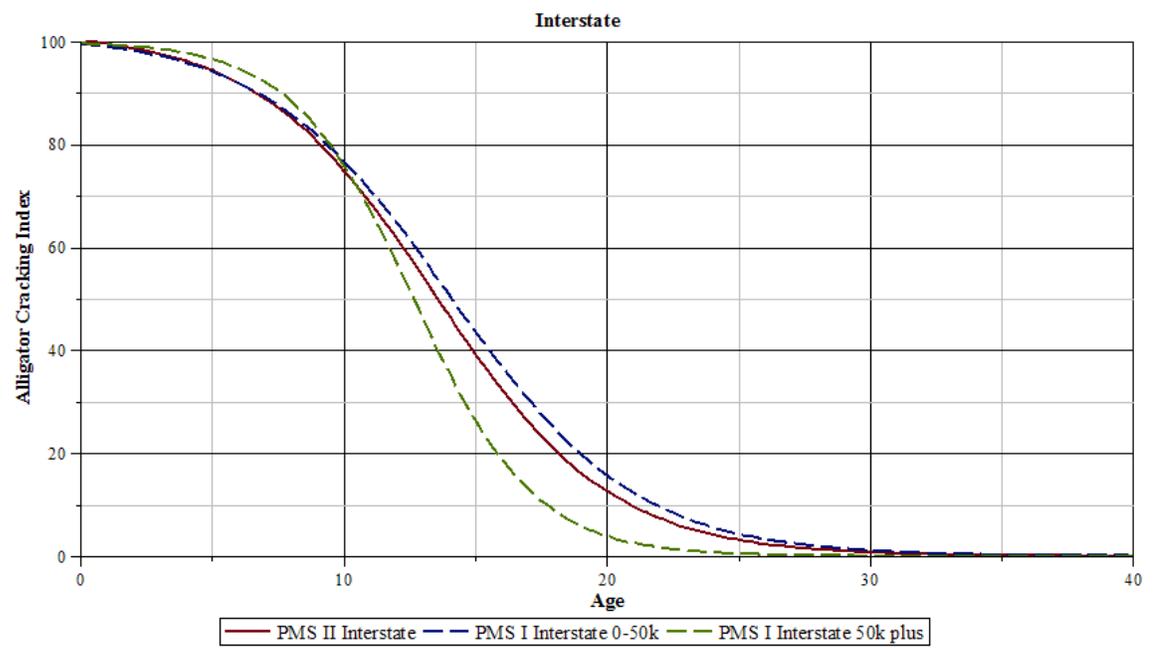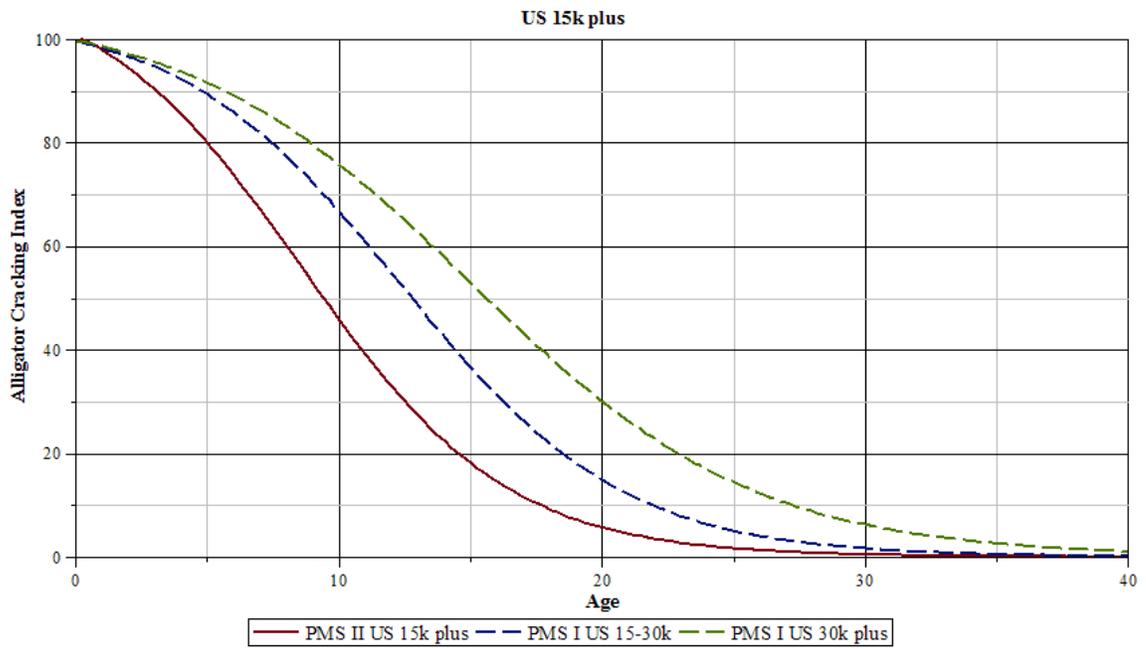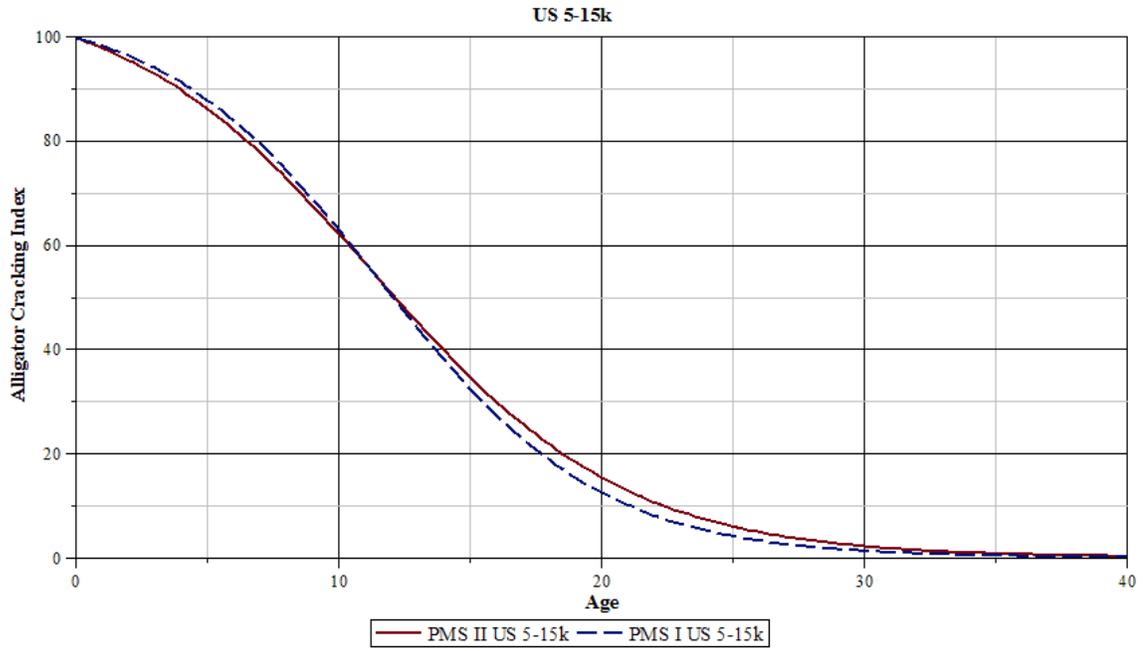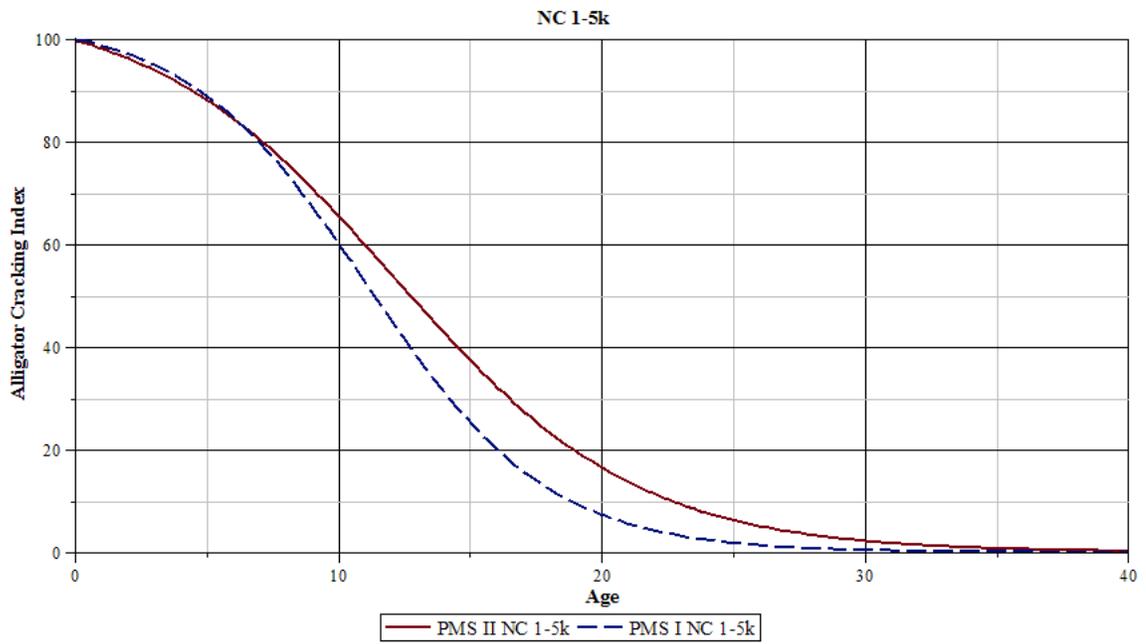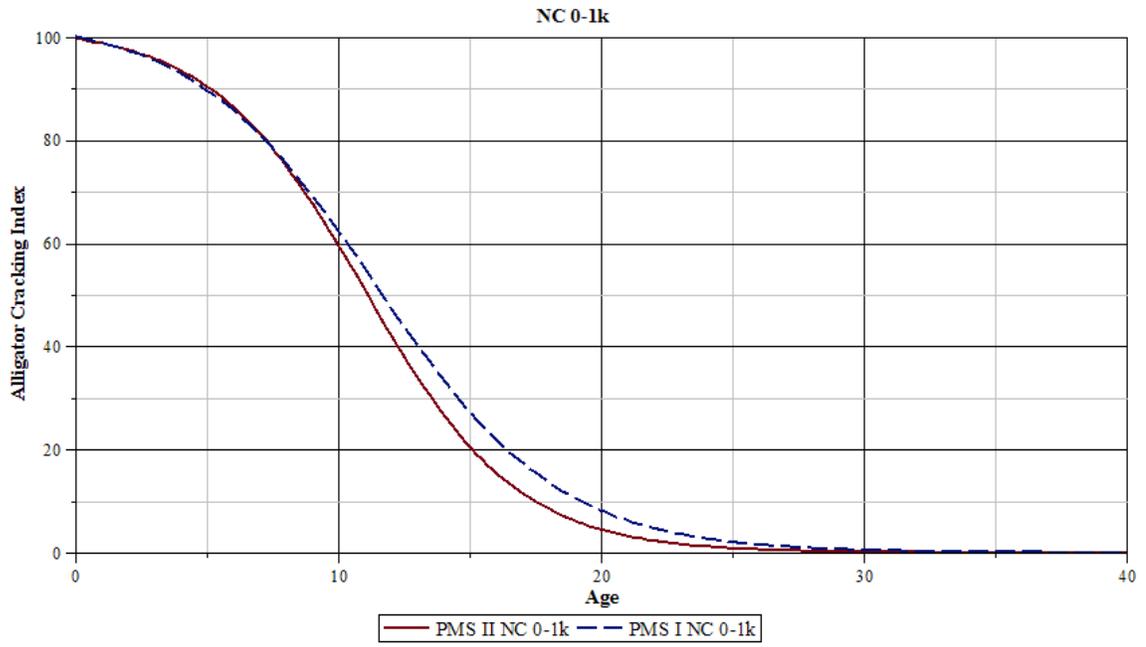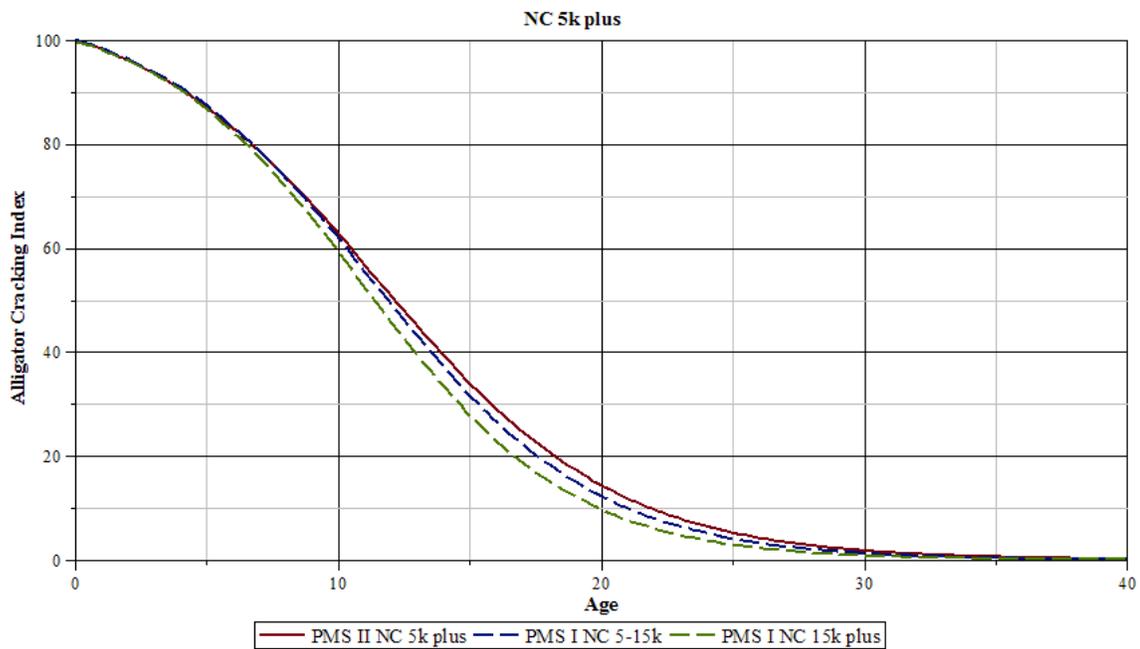
APPENDIX C: TRANSVERSE/REFLECTIVE TRANSVERSE CRACKING

NC 5k plus
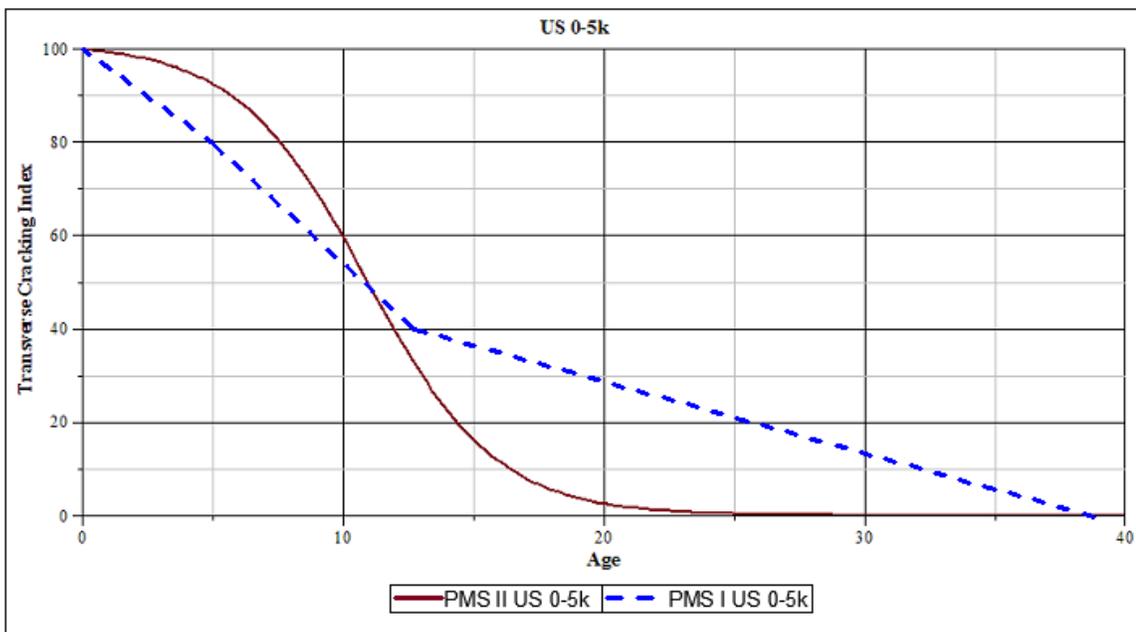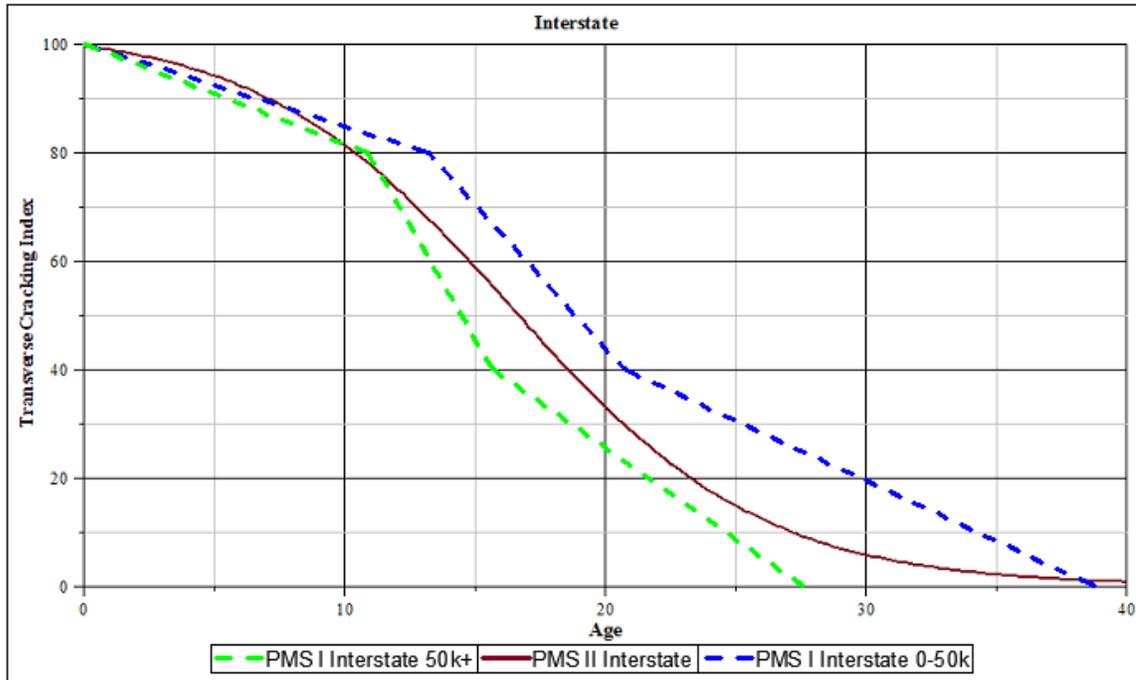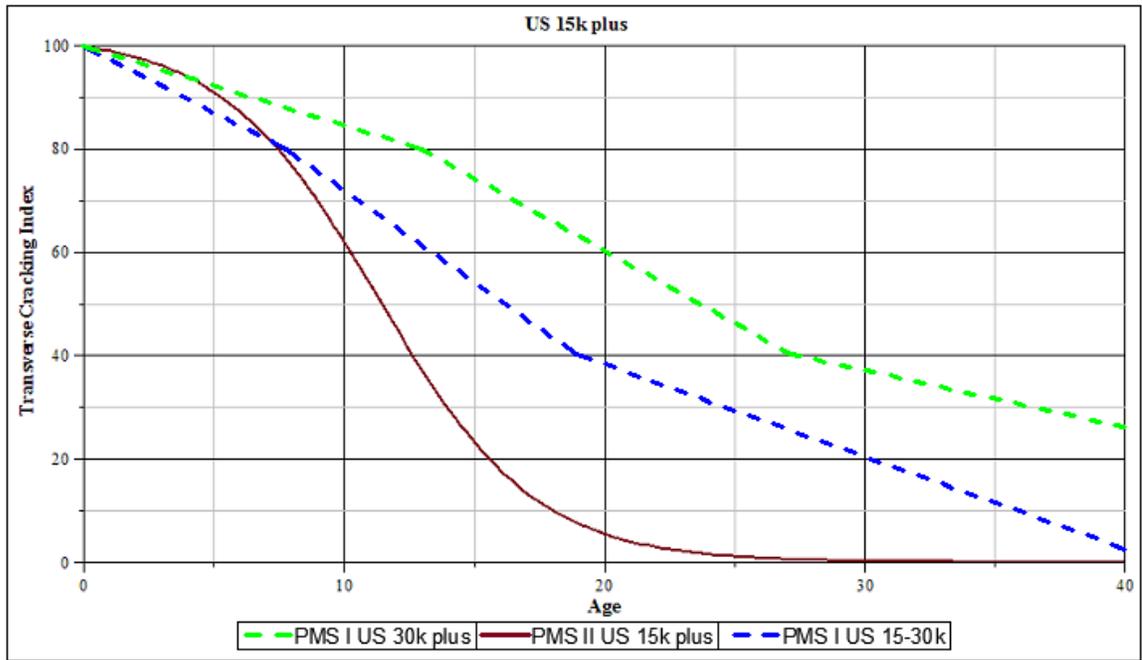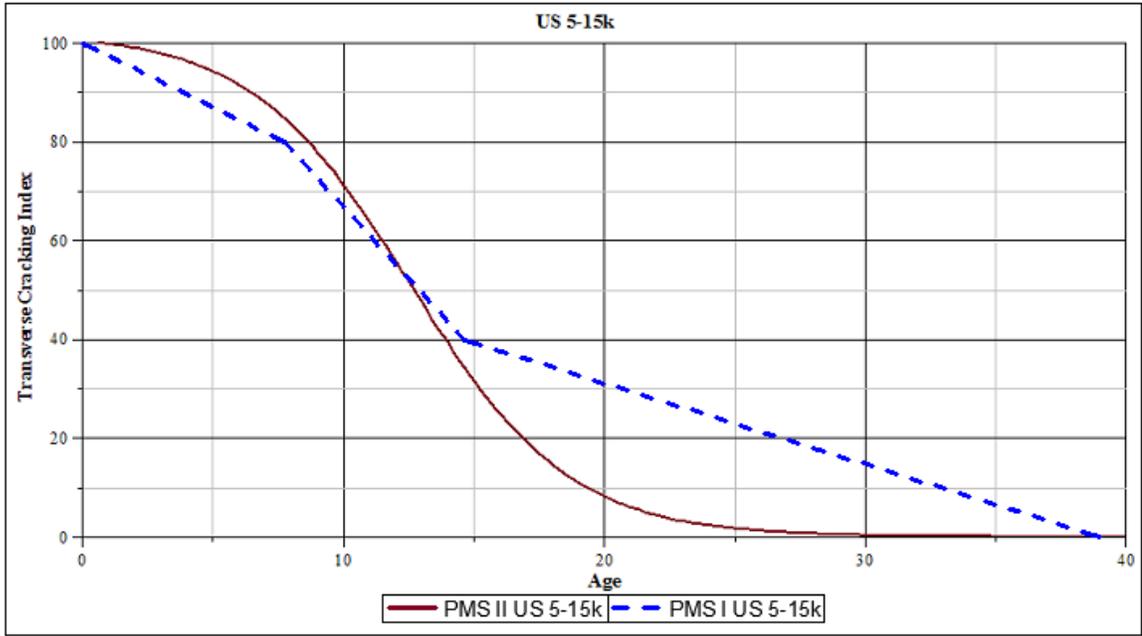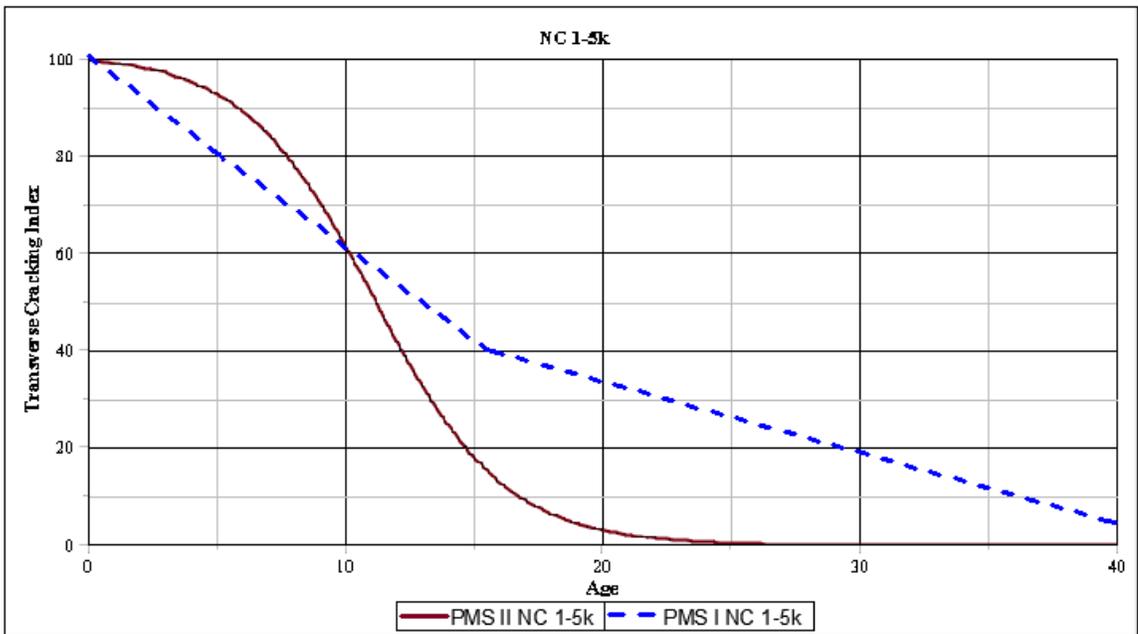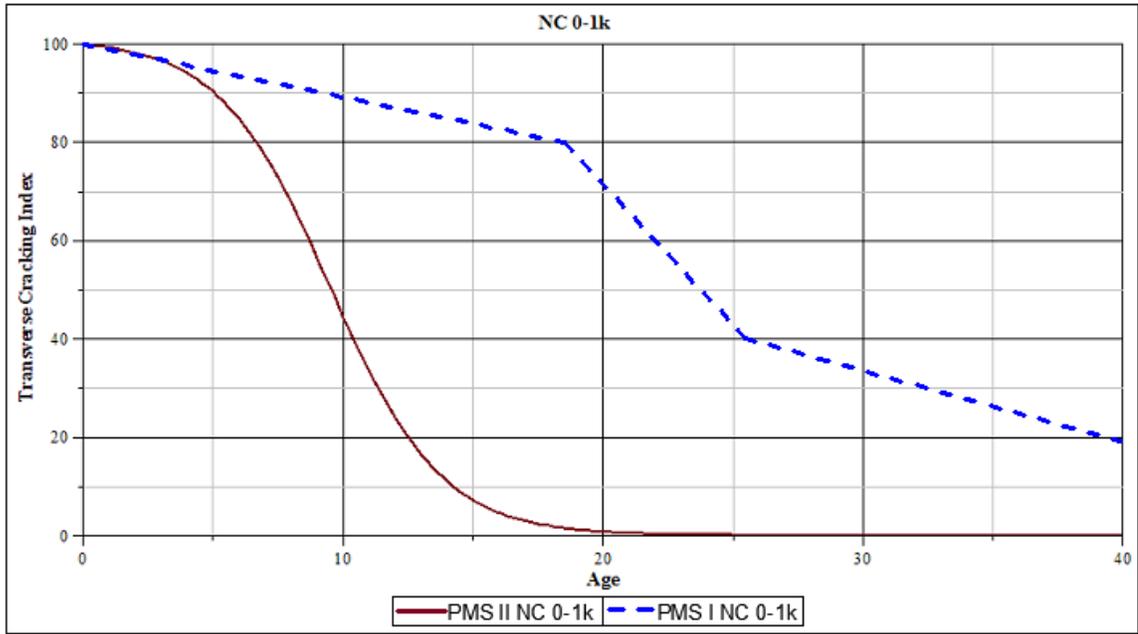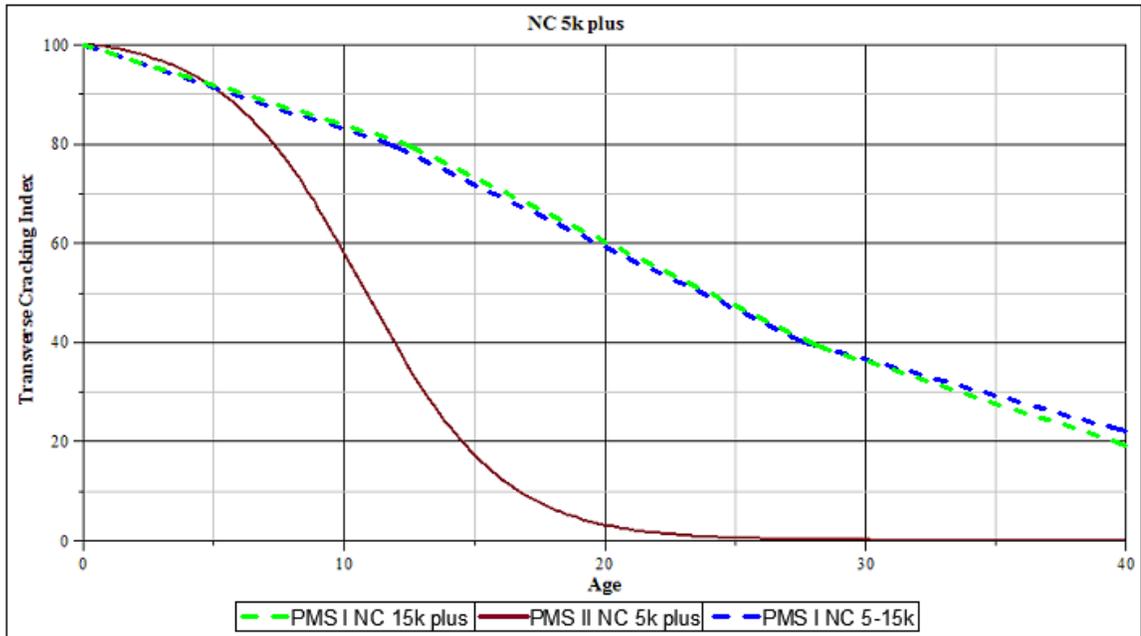
APPENDIX D: LONGITUDINAL CRACKING

US 5-15k

PMS II US 5-15k

US 15k plus

PMS II US 15 k plus

NC 0-1k

PMS II NC 0-1k

NC 1-5k

PMS II NC 1-5k

NC 5k plus
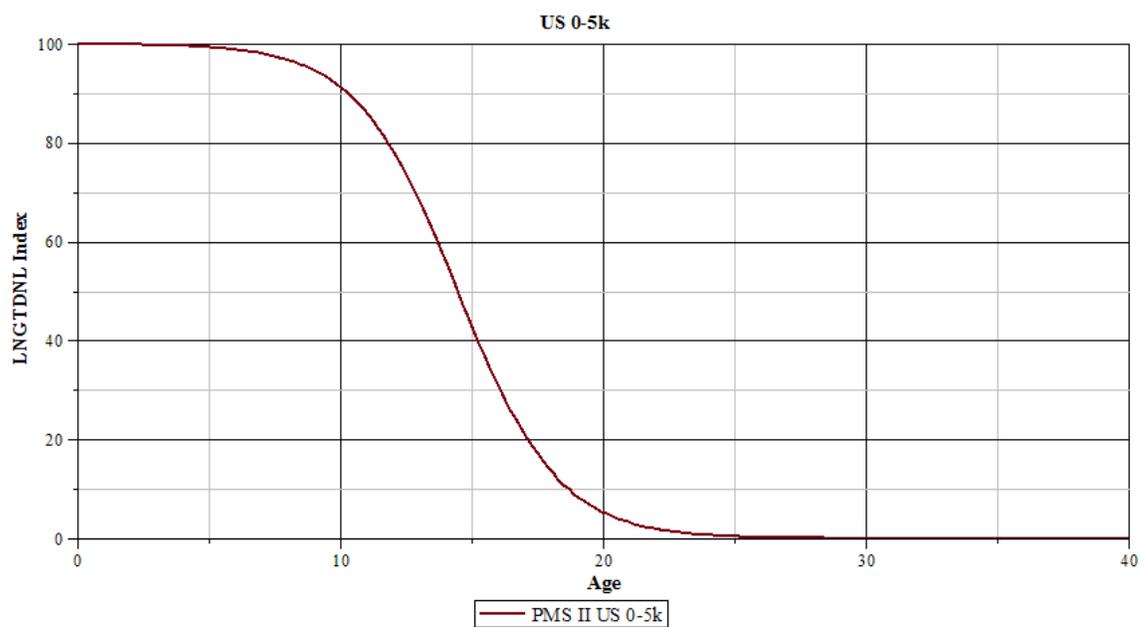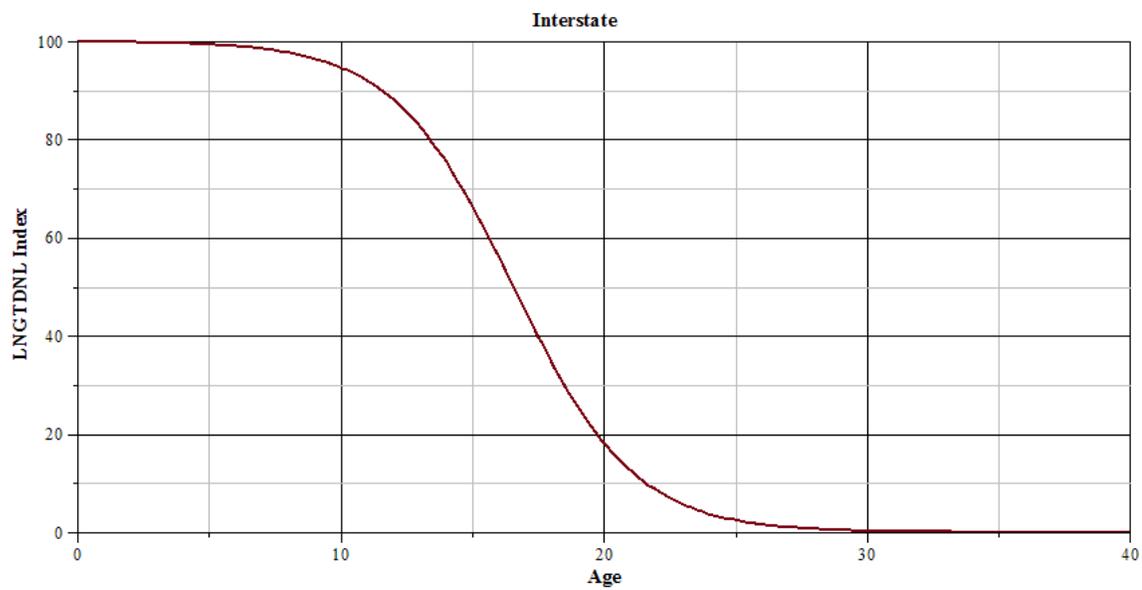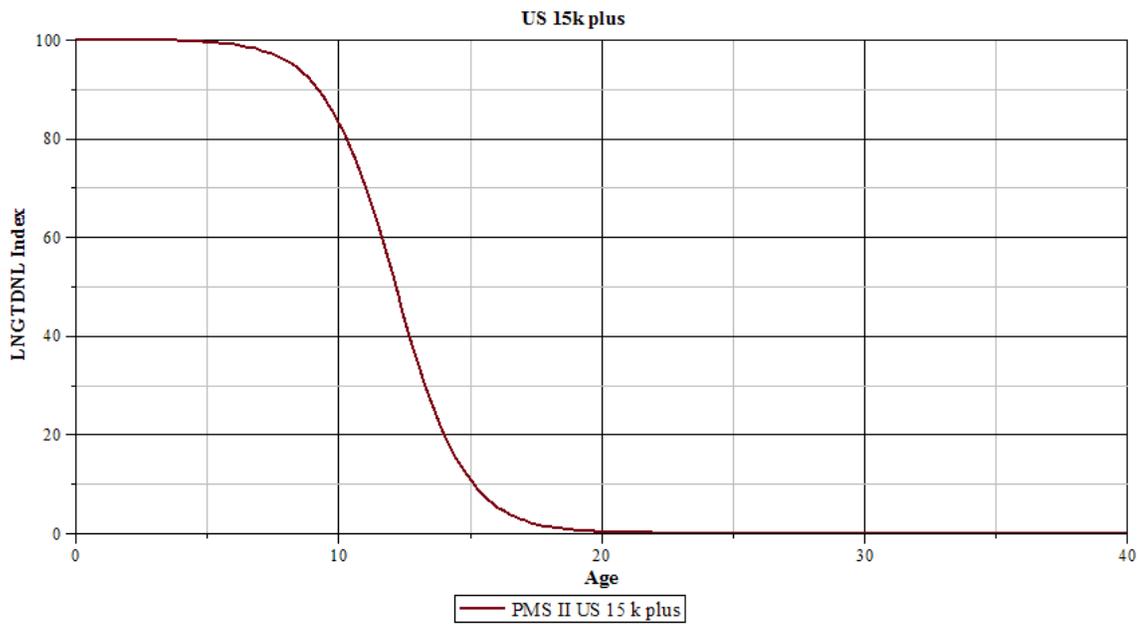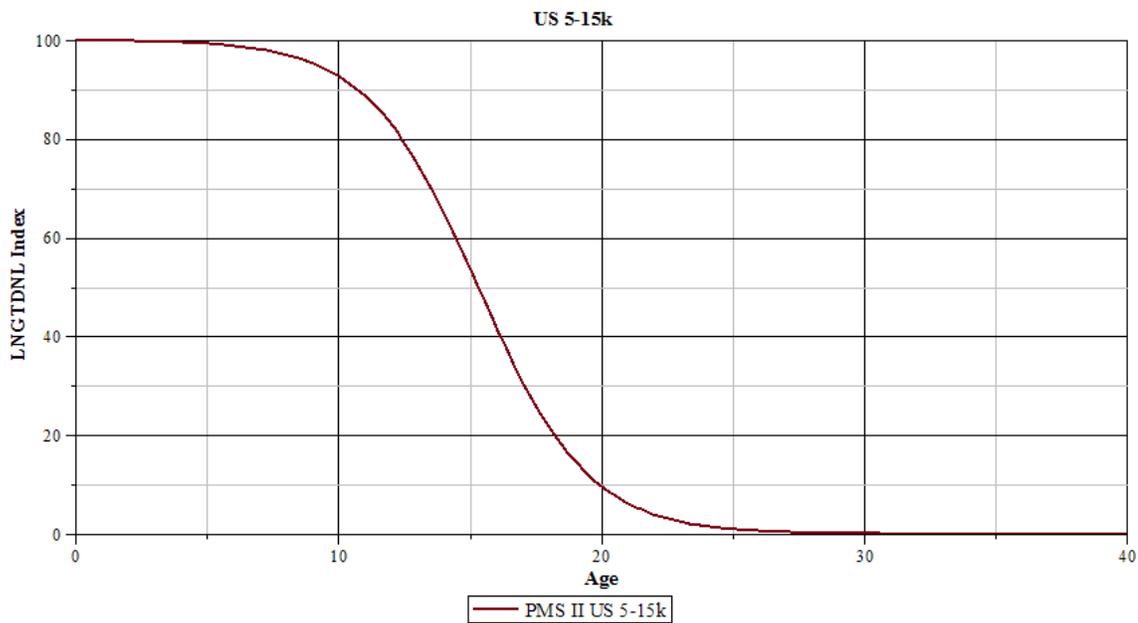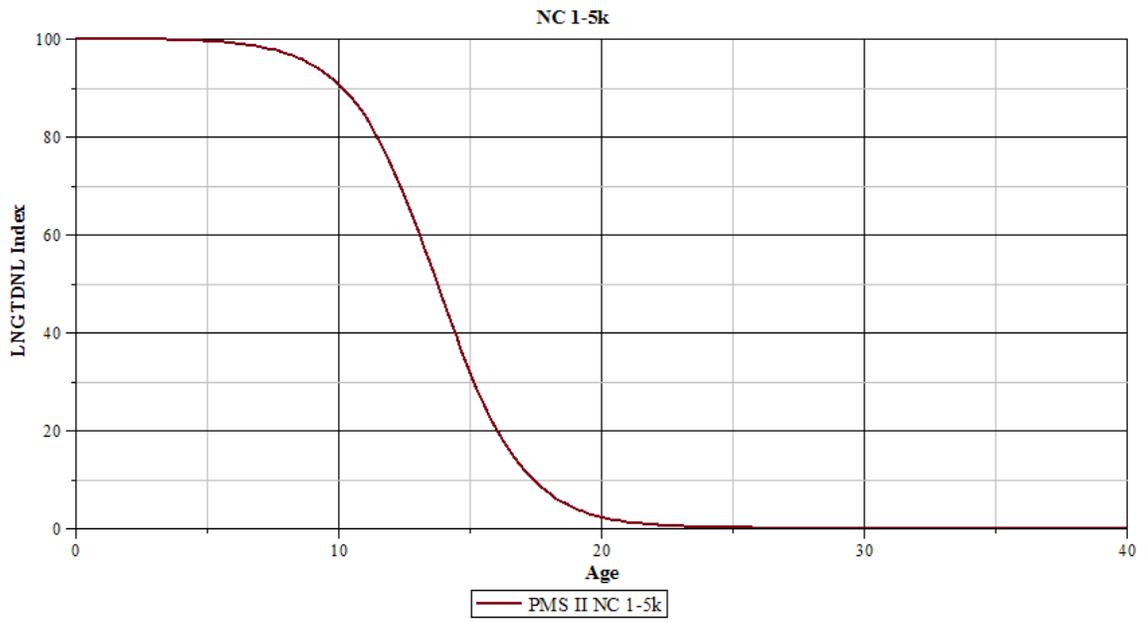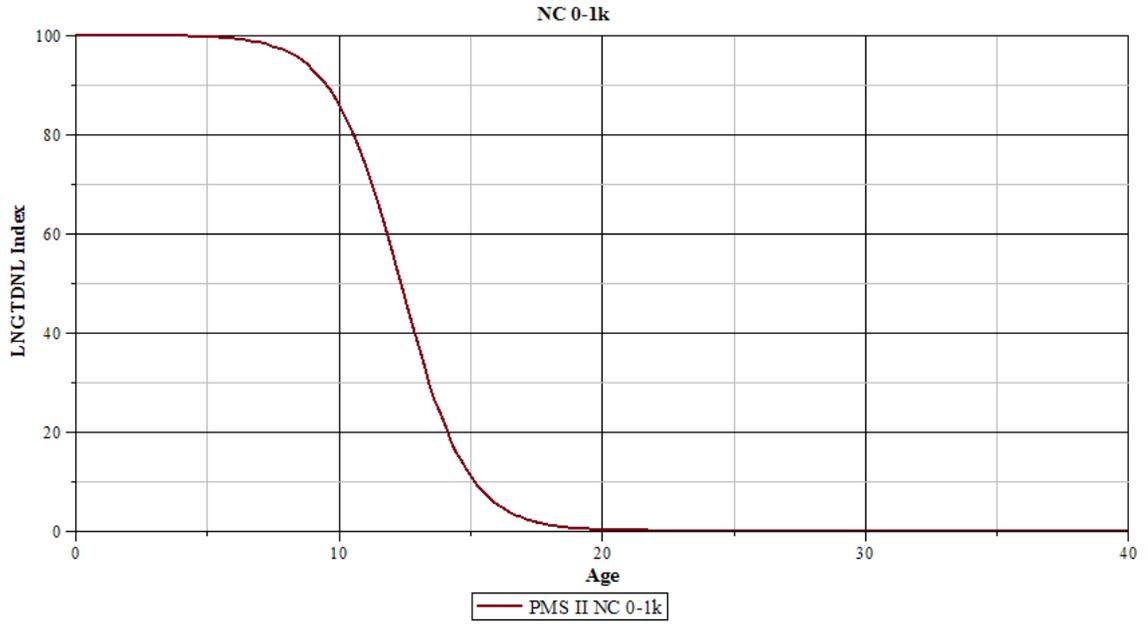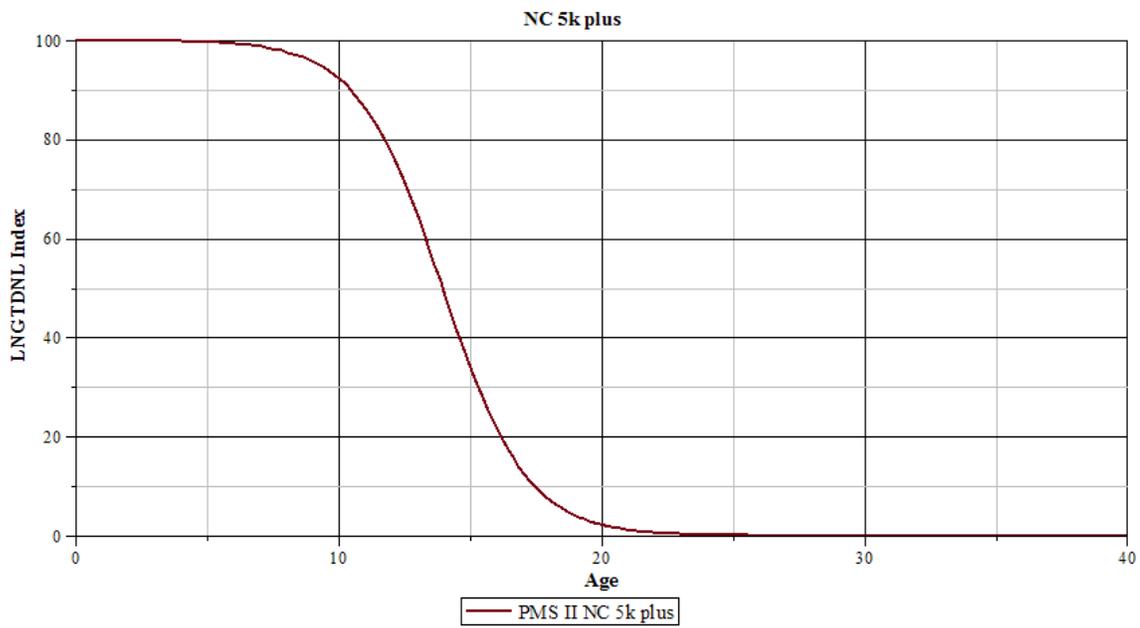
APPENDIX E: LONGITUDINAL LANE JOINT CRACKING

US 5-15k

US 15k plus

NC 0-1k

NC 1-5k

NC 5k plus

PMS II NC 5k plus

APPENDIX F: RAVELING

US 5-15k

US 15k plus

NC 0-1k

PMS II NC 0-1k

NC 1-5k

PMS II NC 1-5k

NC 5k plus

PMS II NC 5k plus
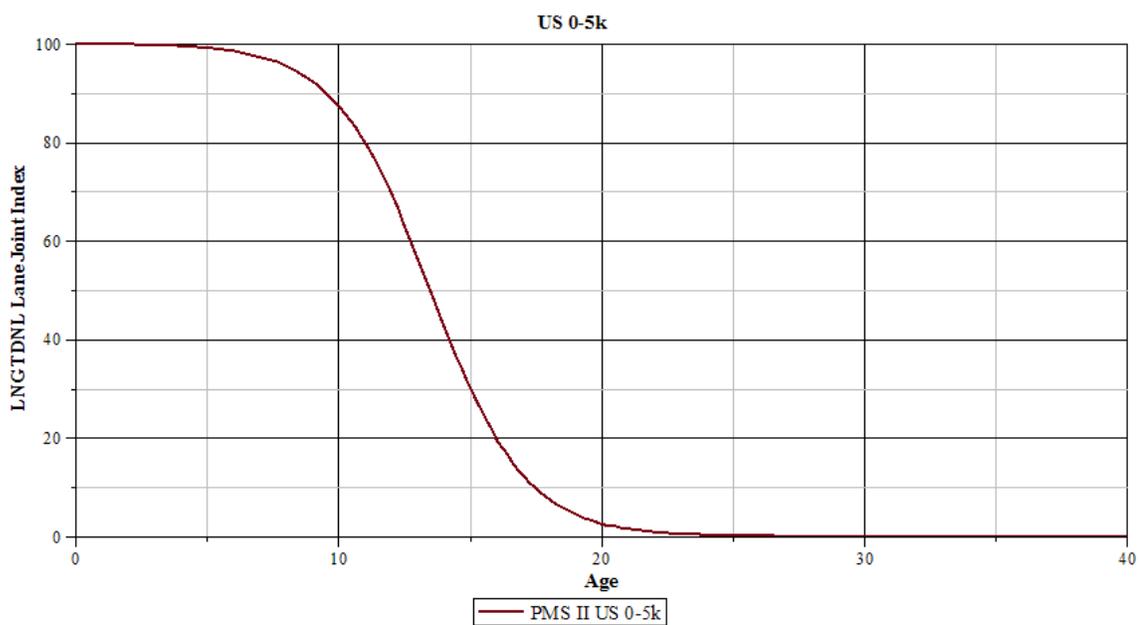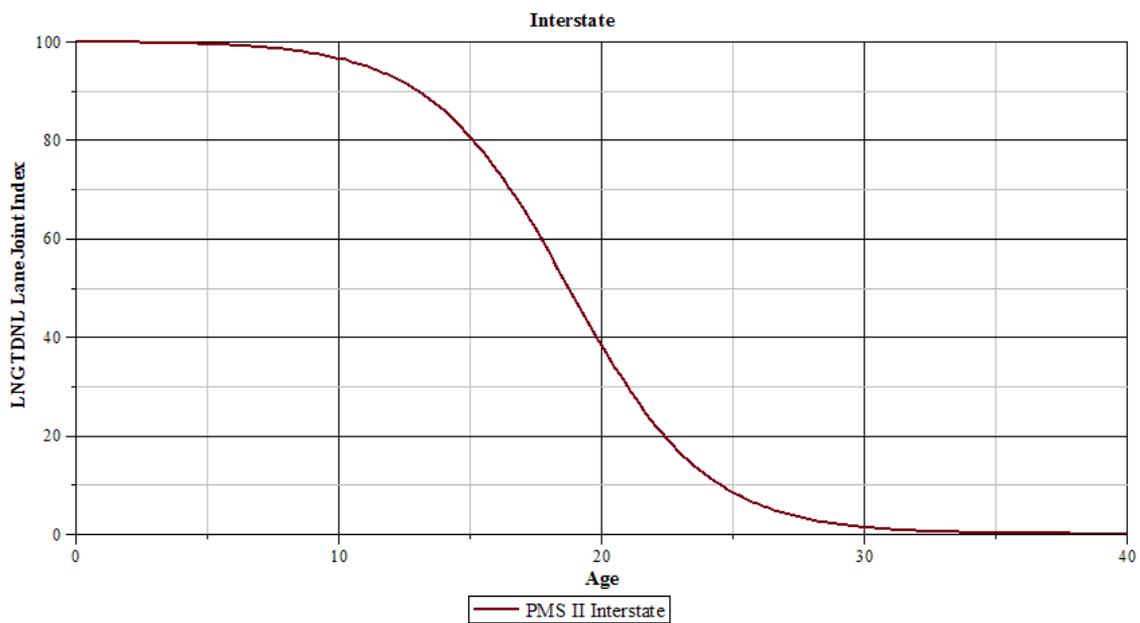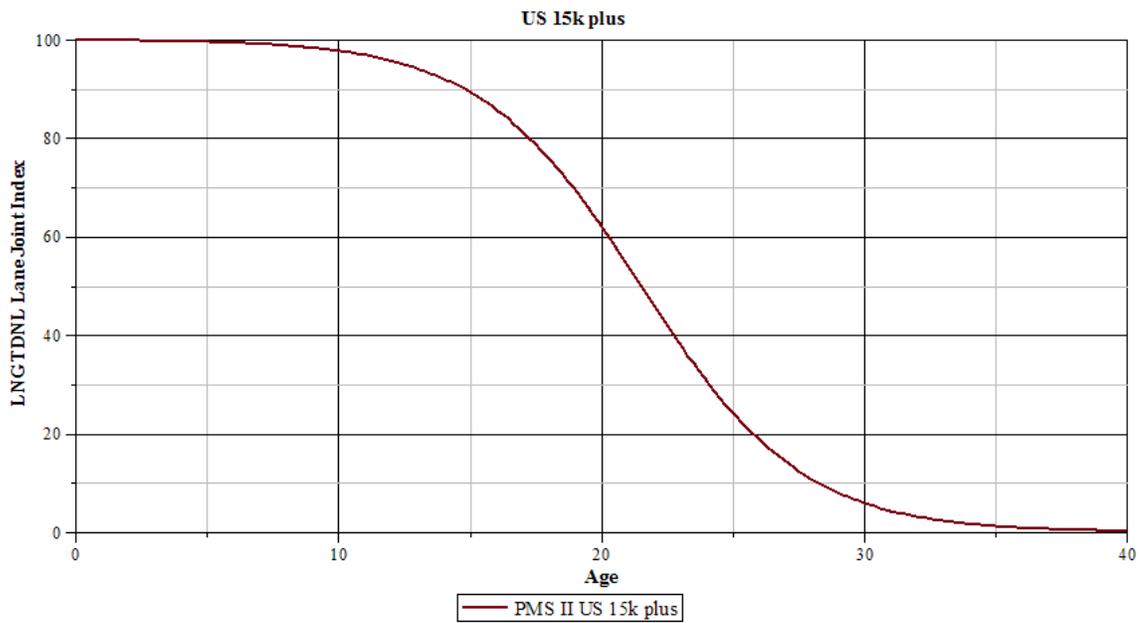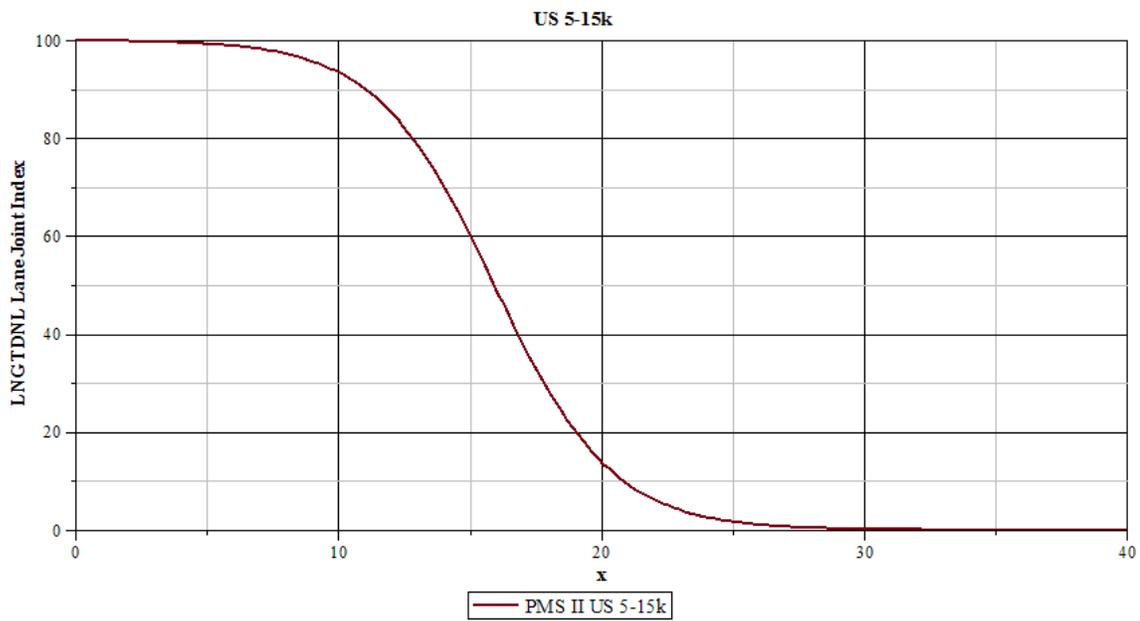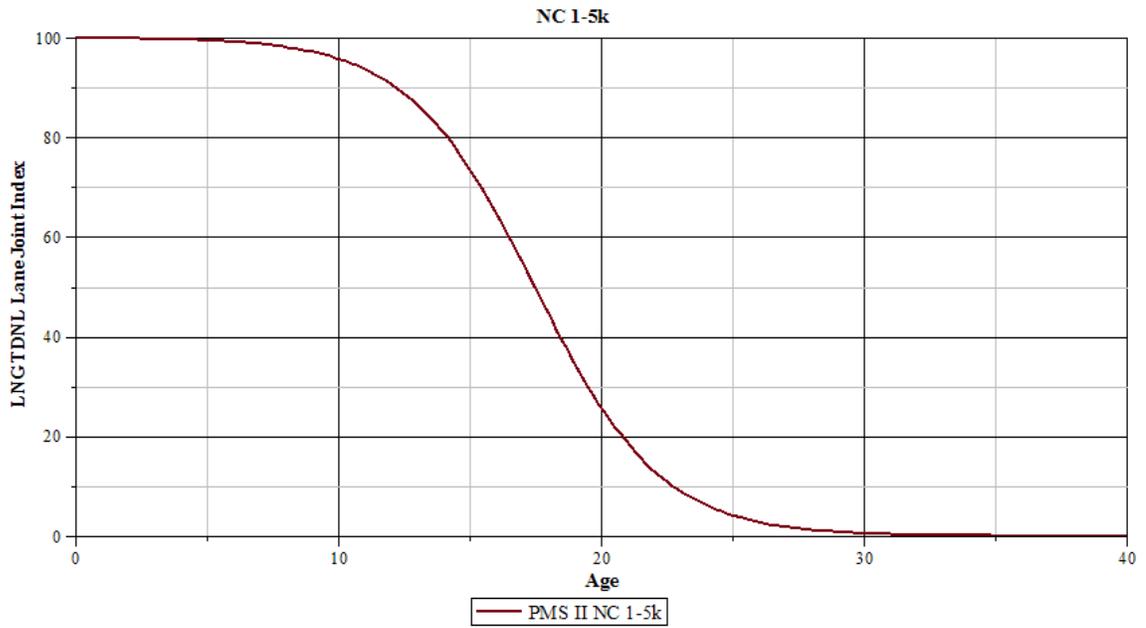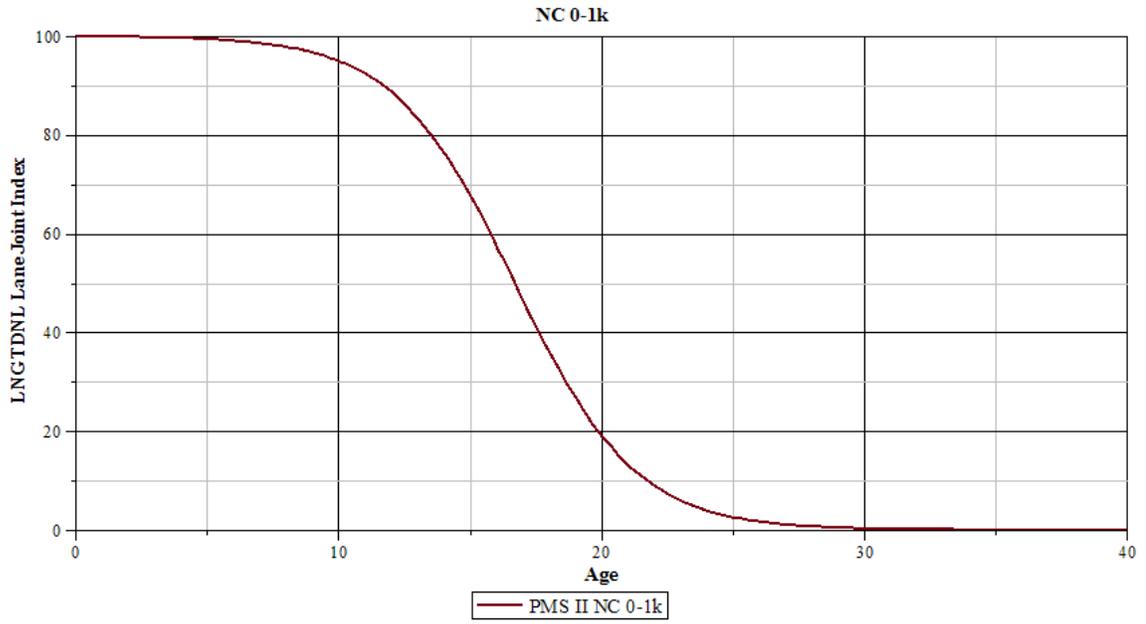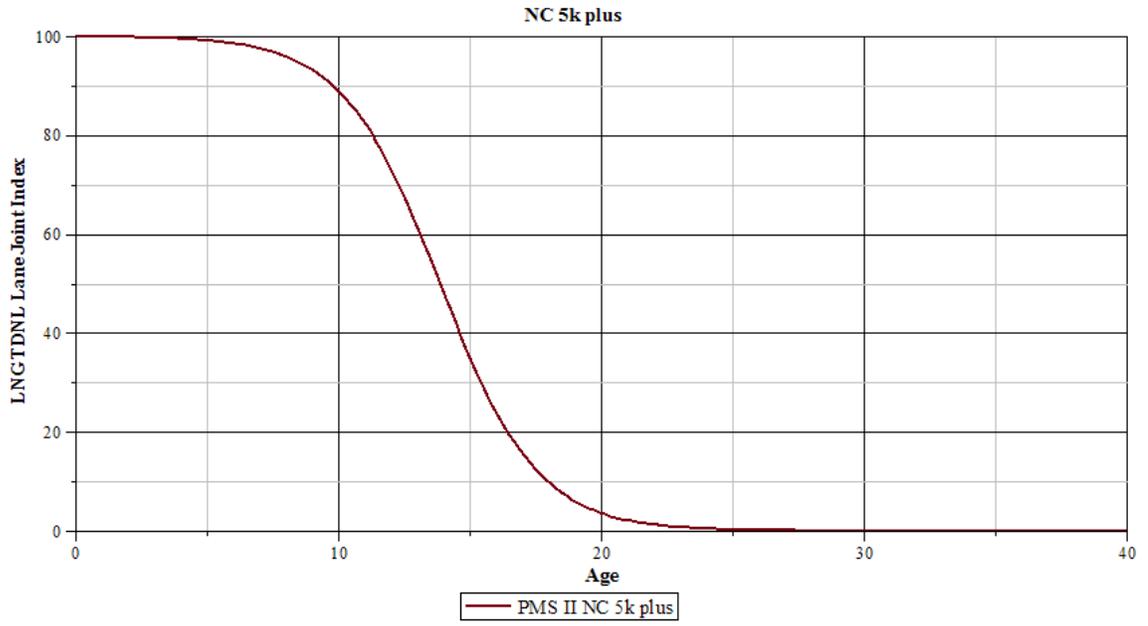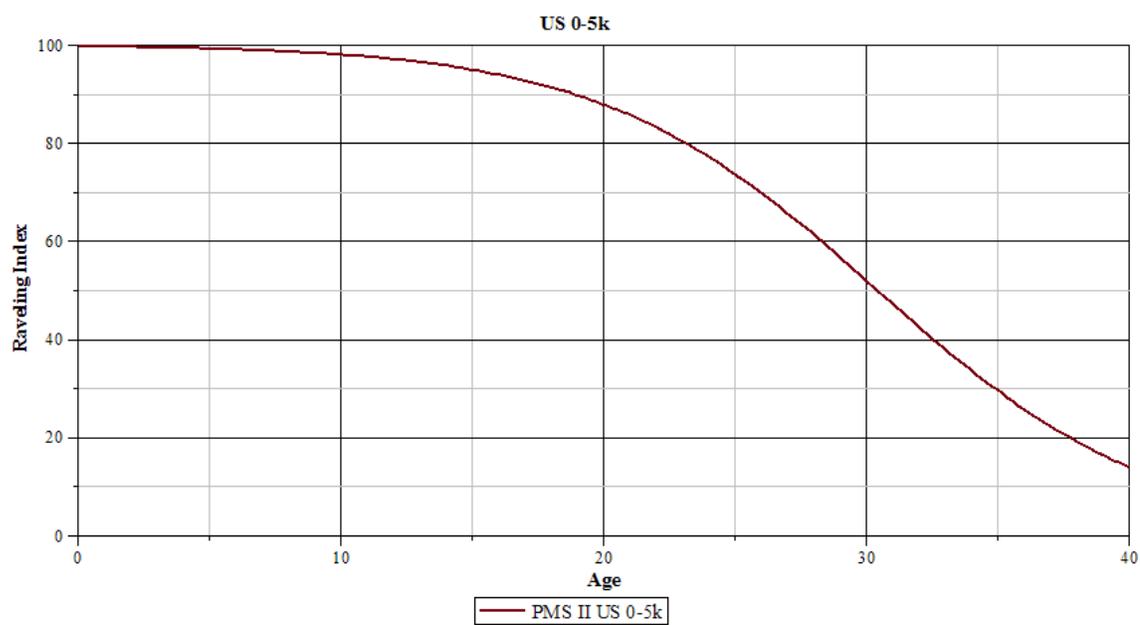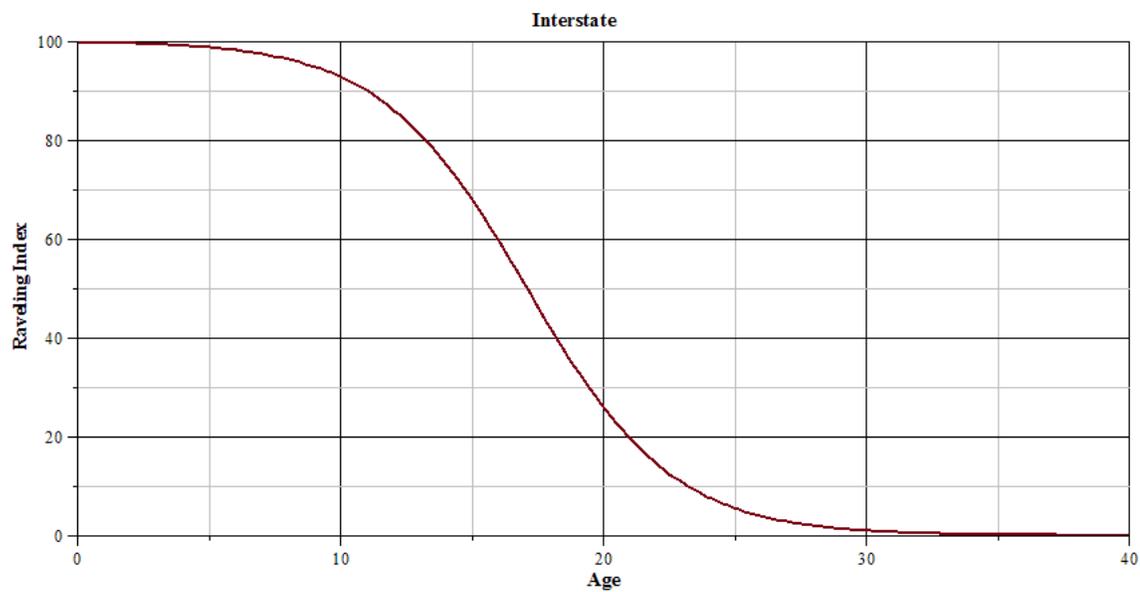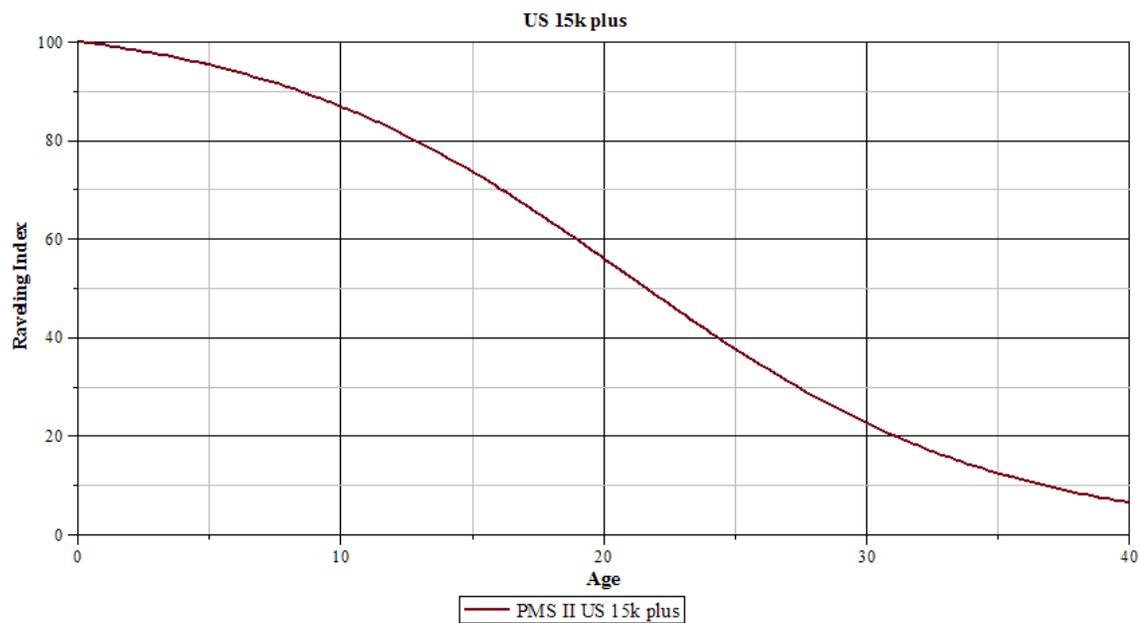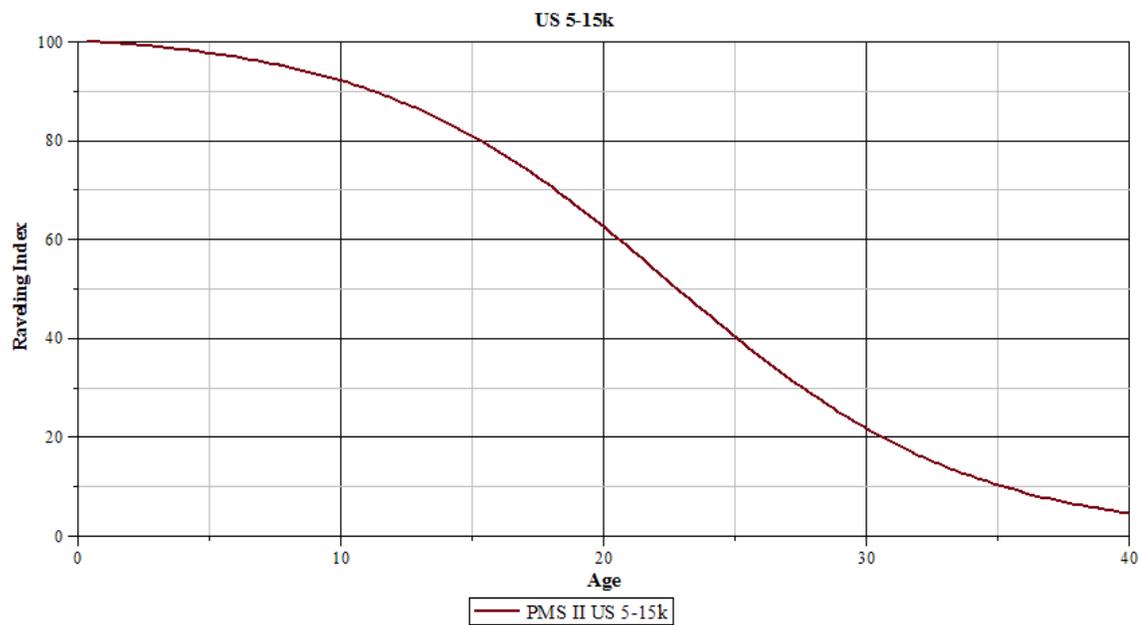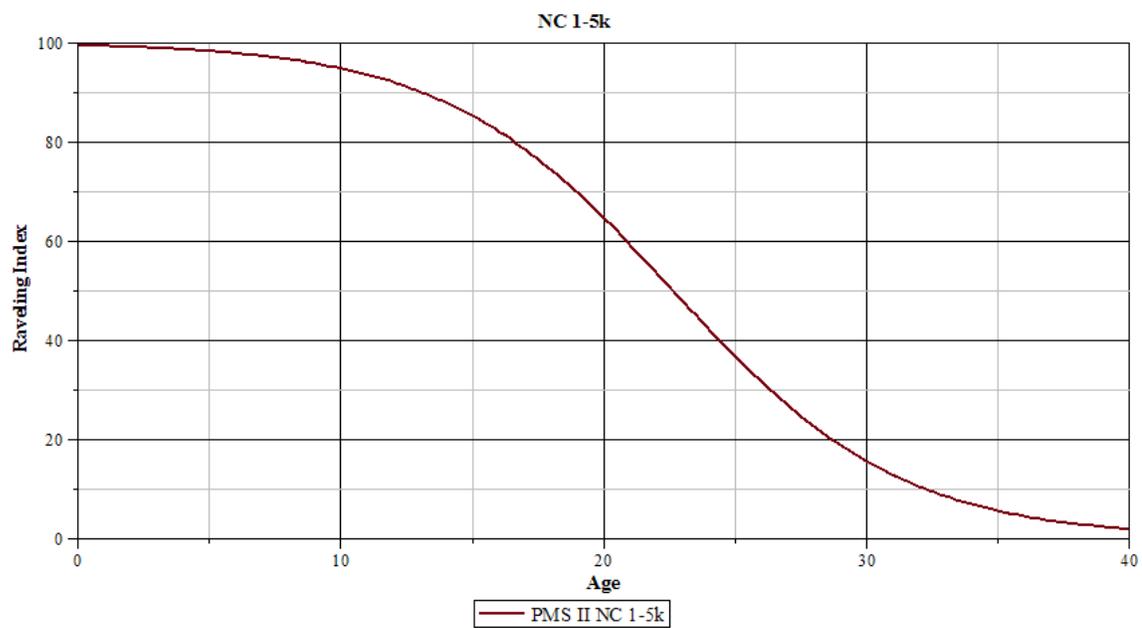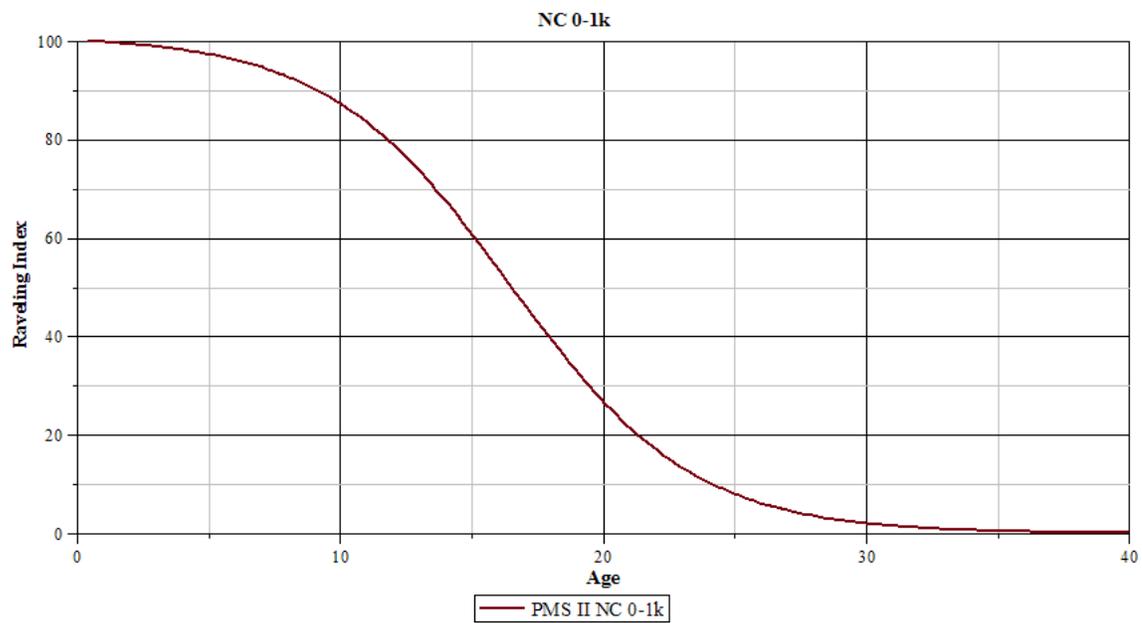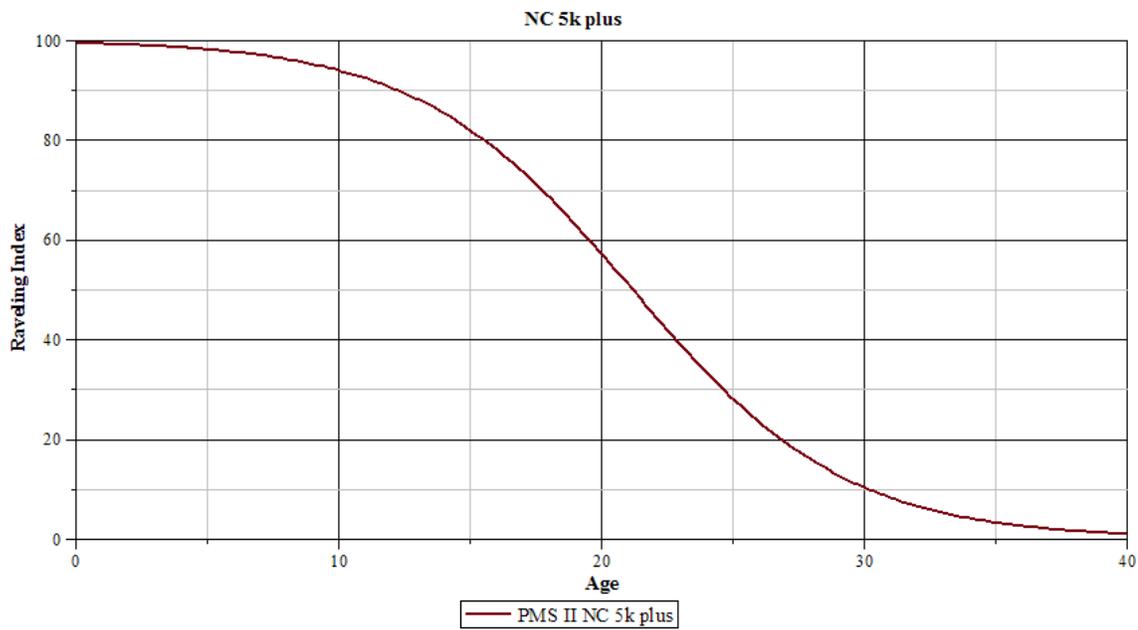
APPENDIX G: PATCHING AREA - WP

US 5-15k

WP Patching Index vs Age

— PMS II US 5-15k   – – PMS I US

US 15k plus

WP Patching Index vs Age

— PMS II NC 15k plus   – – PMS I US

NC 0-1k

WP Patching Index vs Age

Legend: PMS II NC 0-1k, PMS I NC

NC 1-5k

WP Patching Index vs Age

Legend: PMS II NC 1-5k, PMS I NC
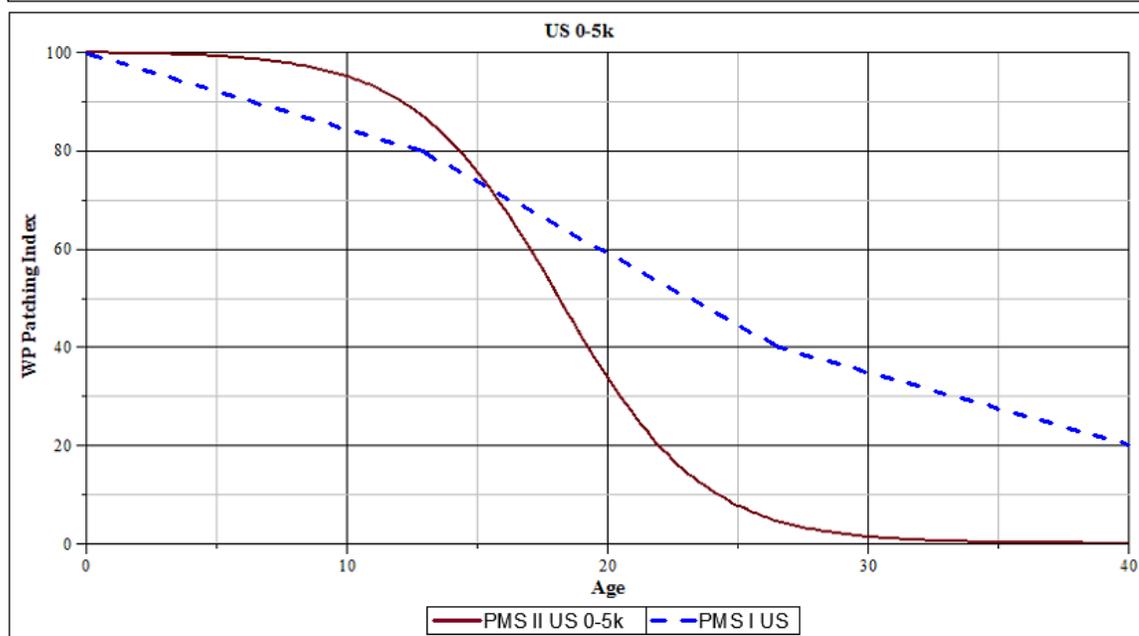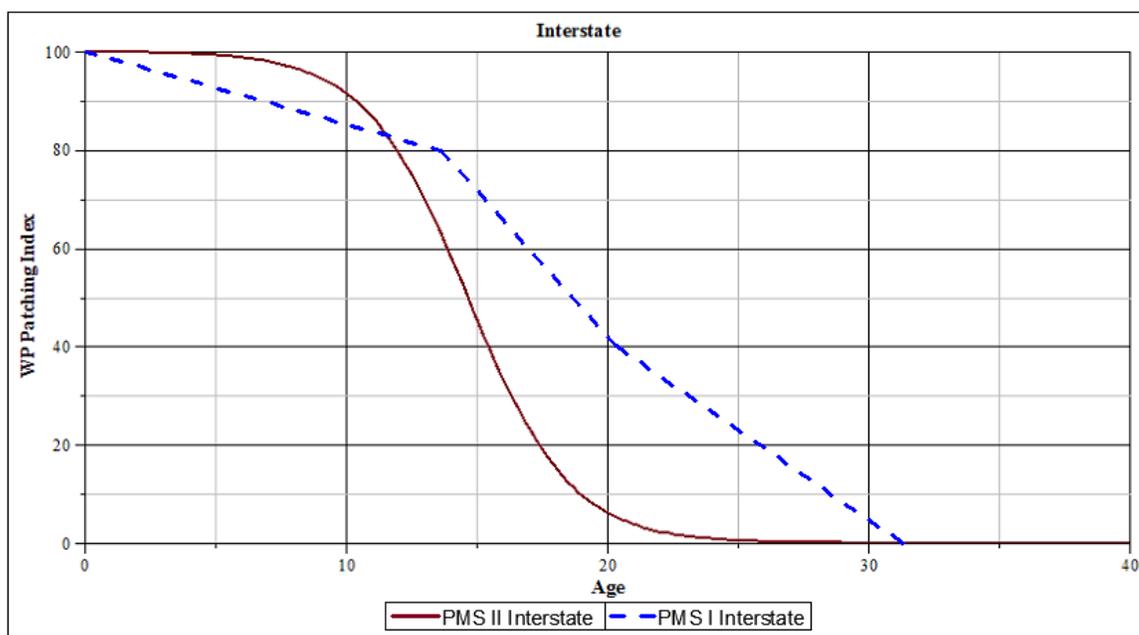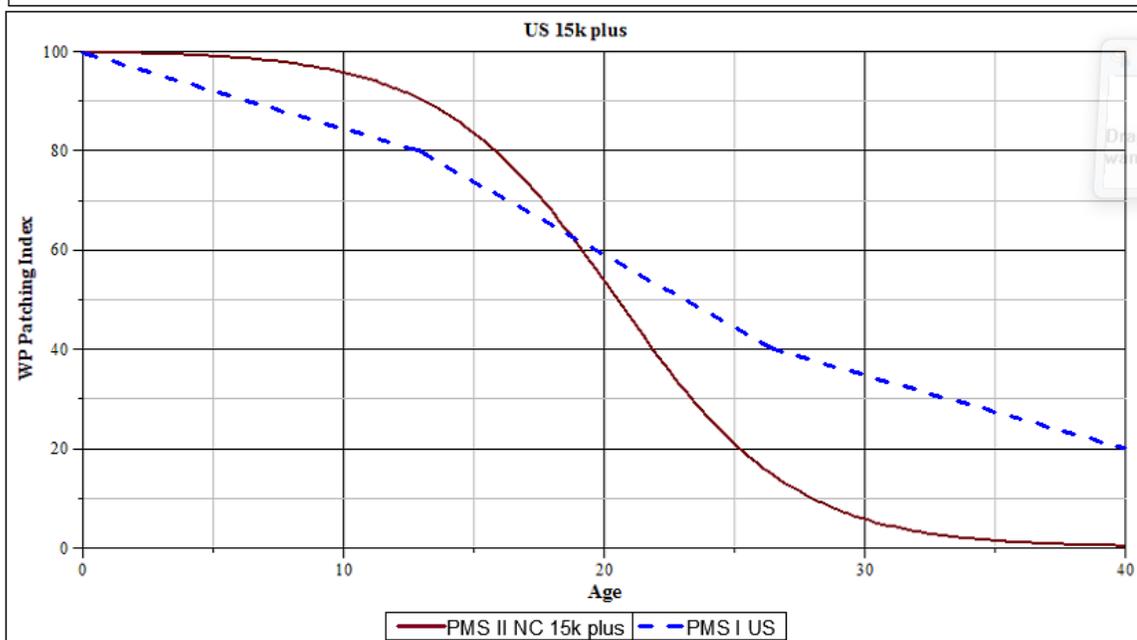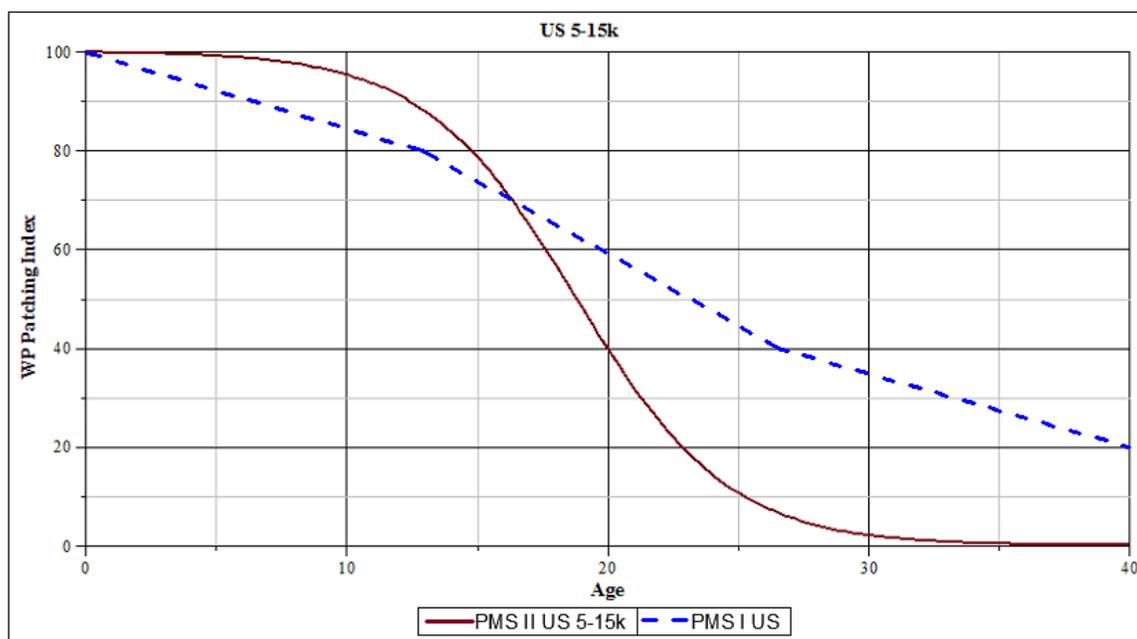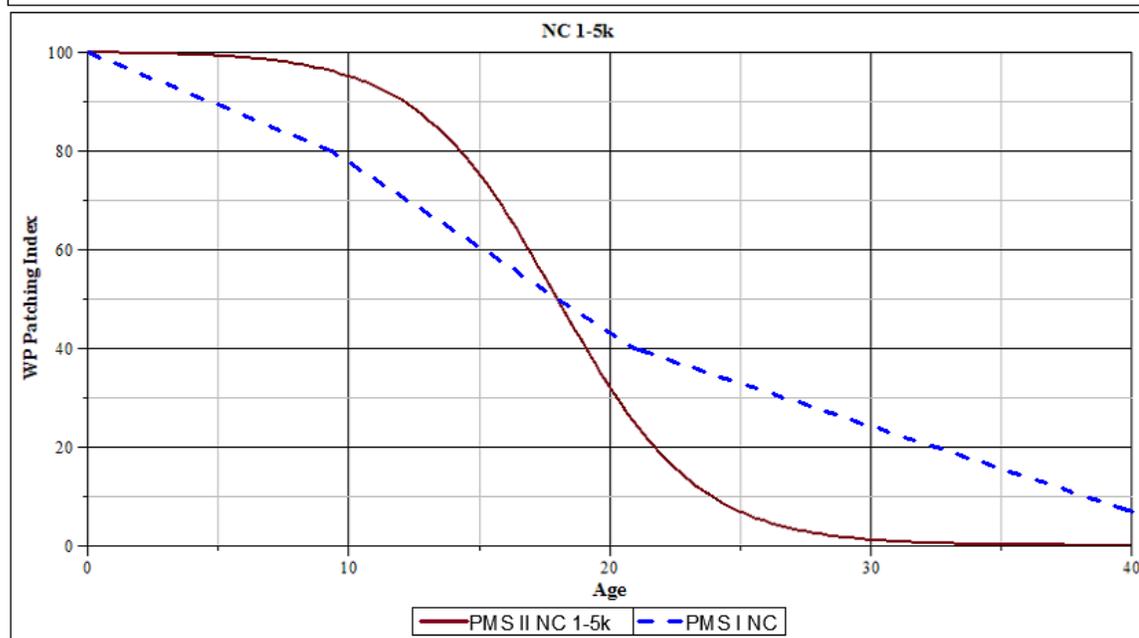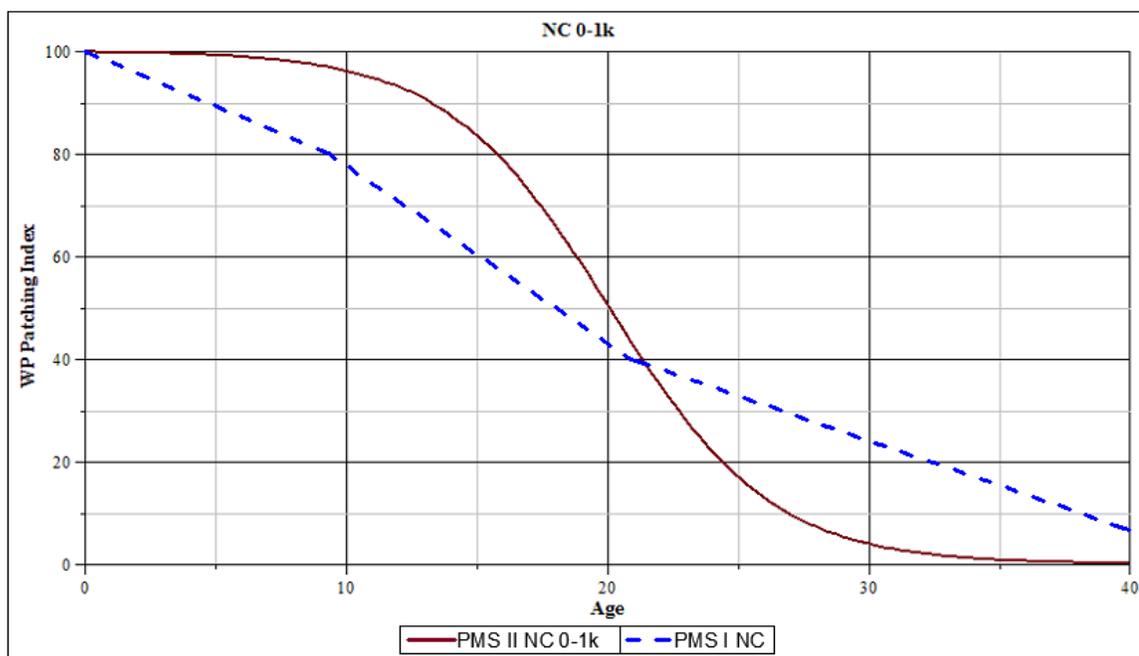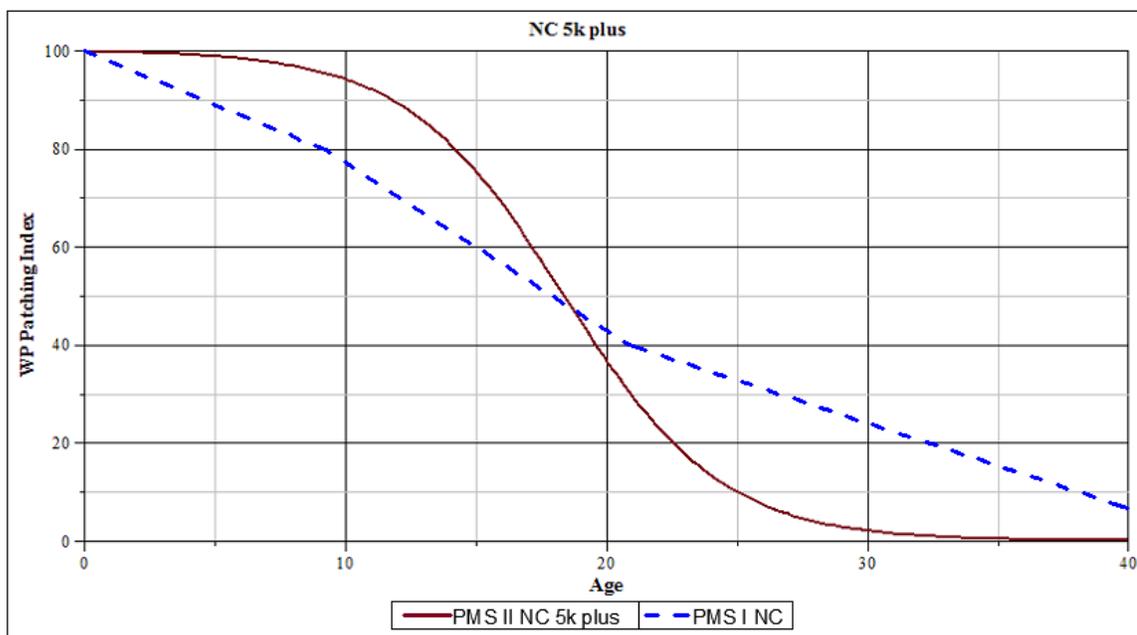
APPENDIX H: PATCHING AREA - NWP

NC 0-1k

NC 1-5k

NC 5k plus

PMS II NC 5k plus — PMS I NC

APPENDIX I: RUTTING

US 0-5k

US 5-15k

US 15k plus

NC 0-1k

NC 1-5k

NC 5k plus
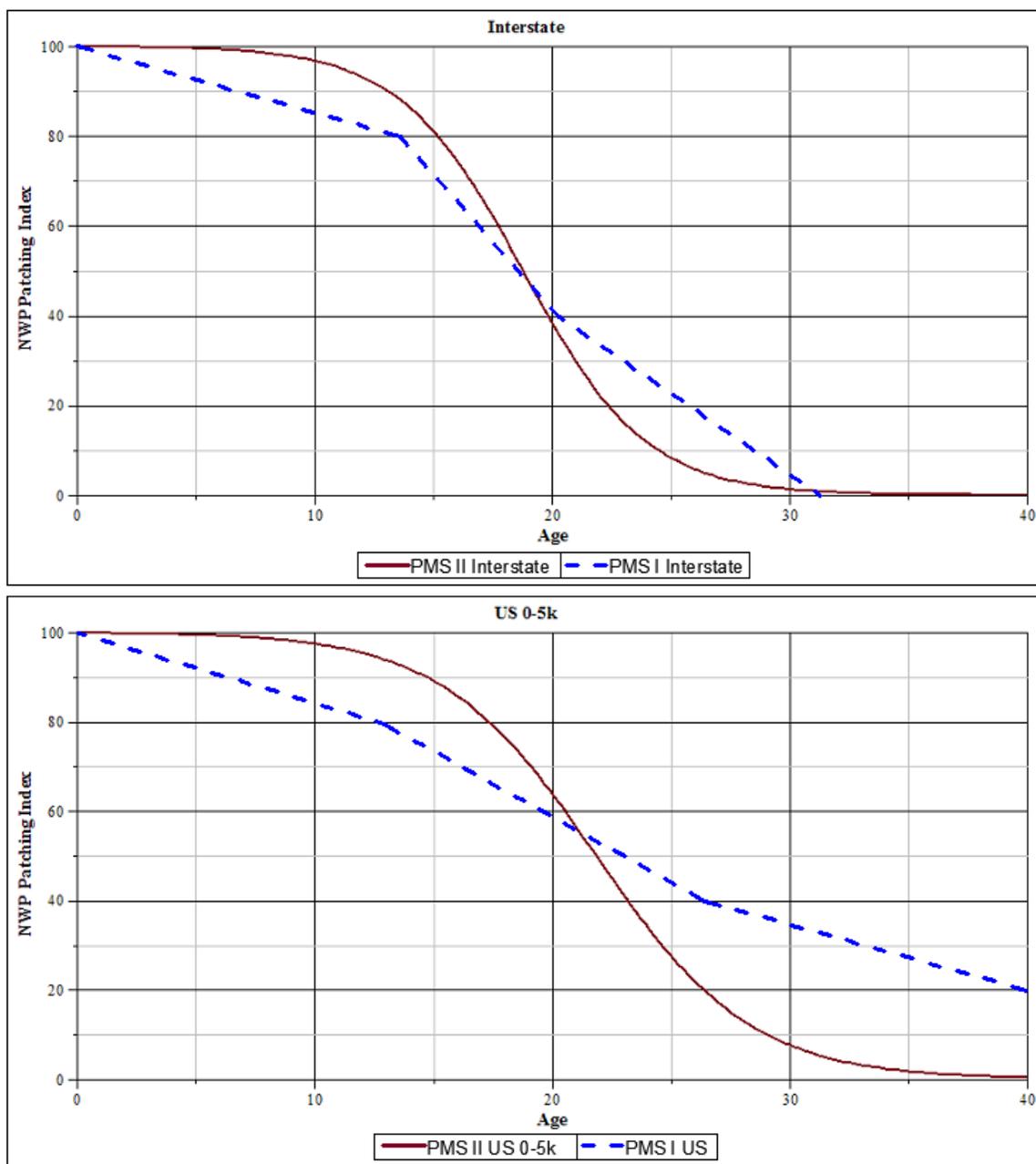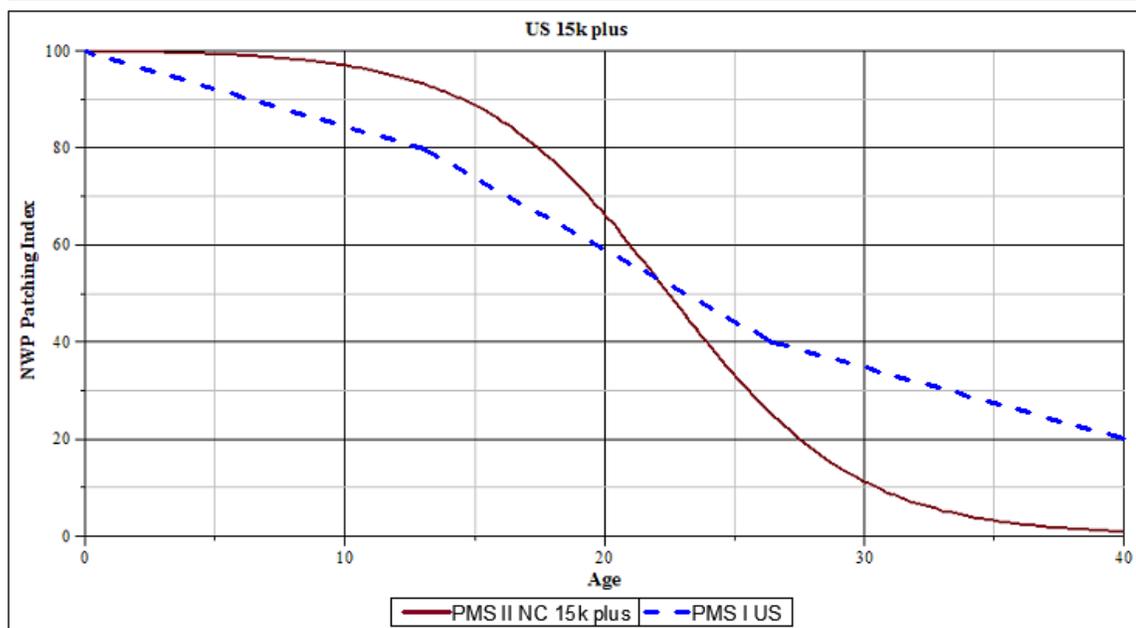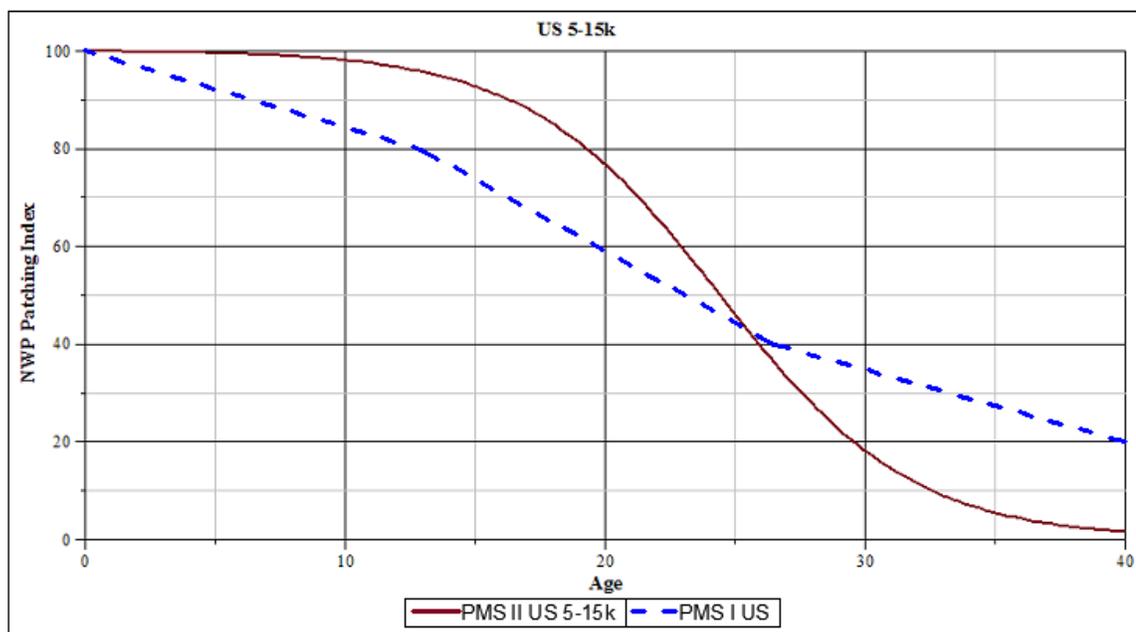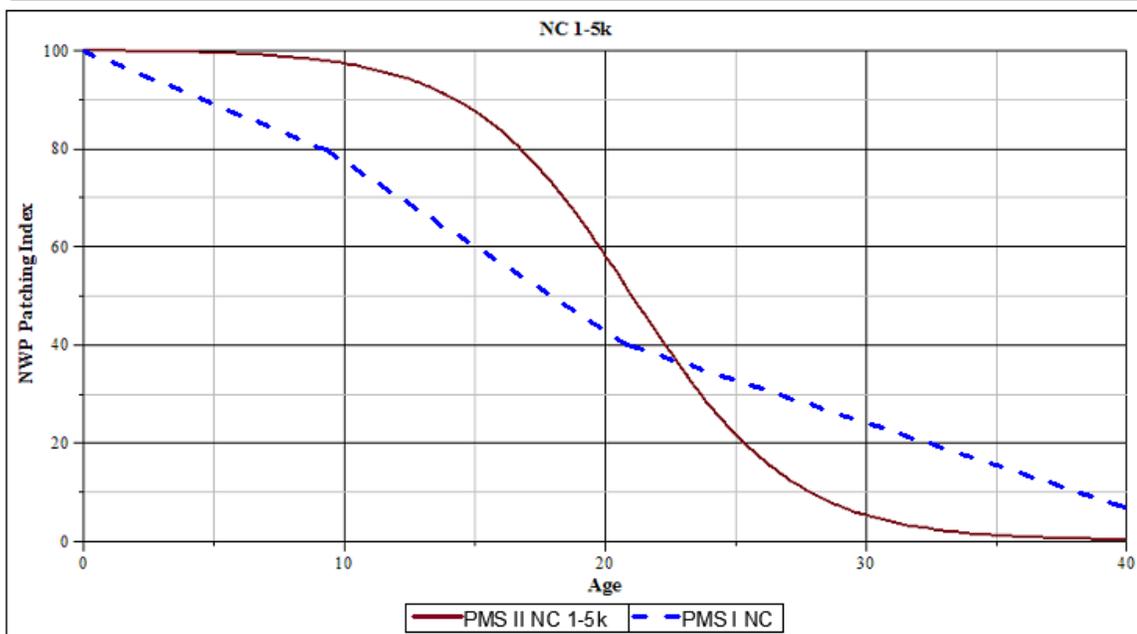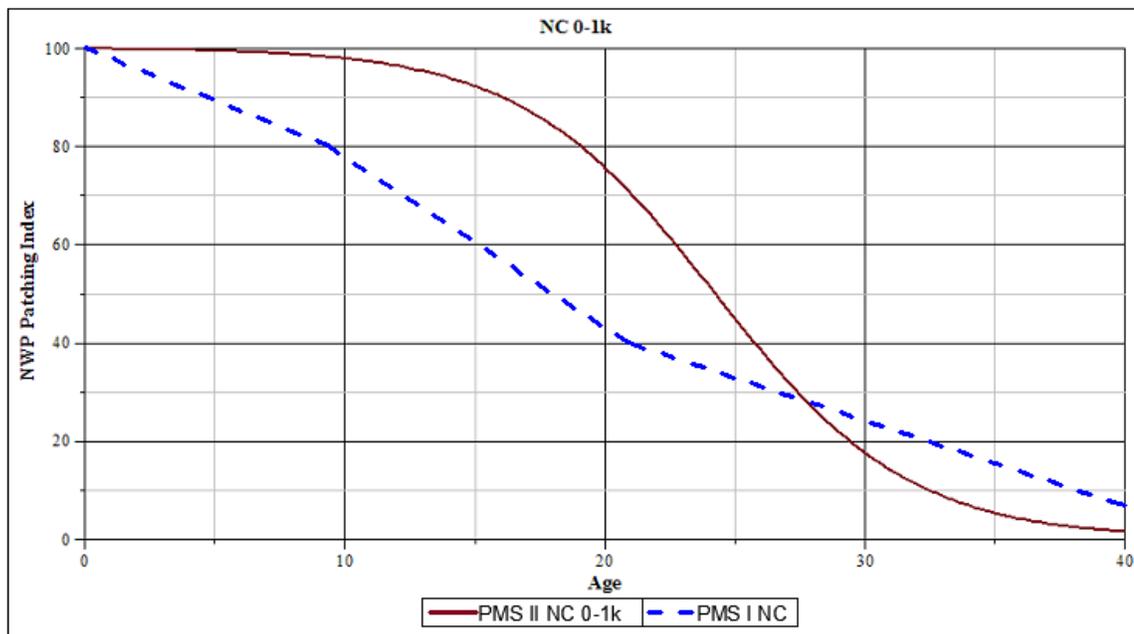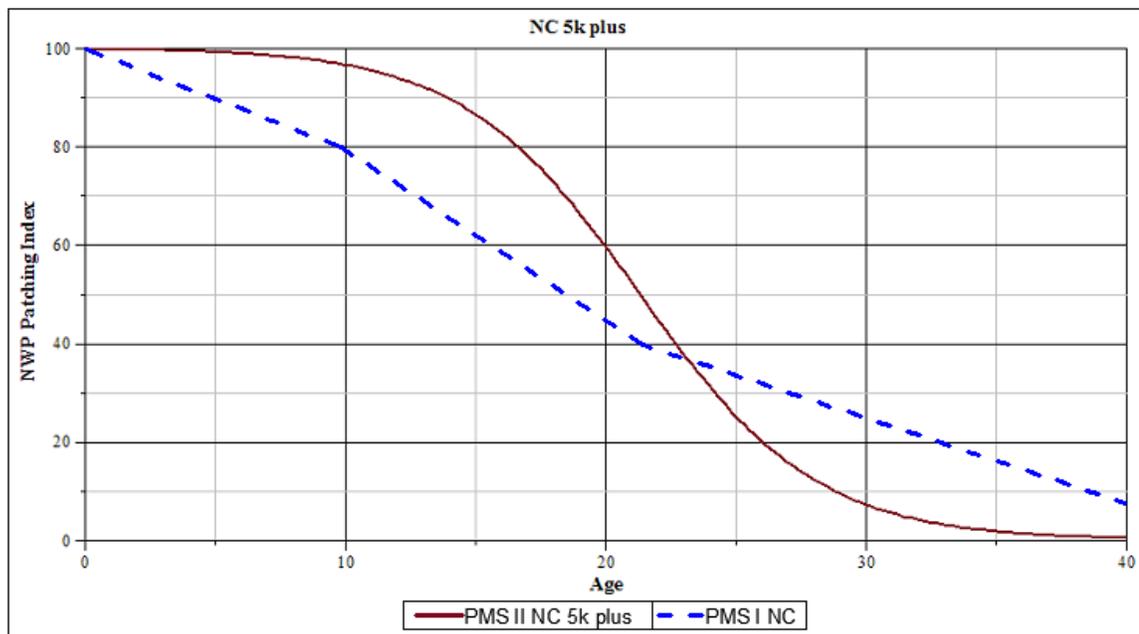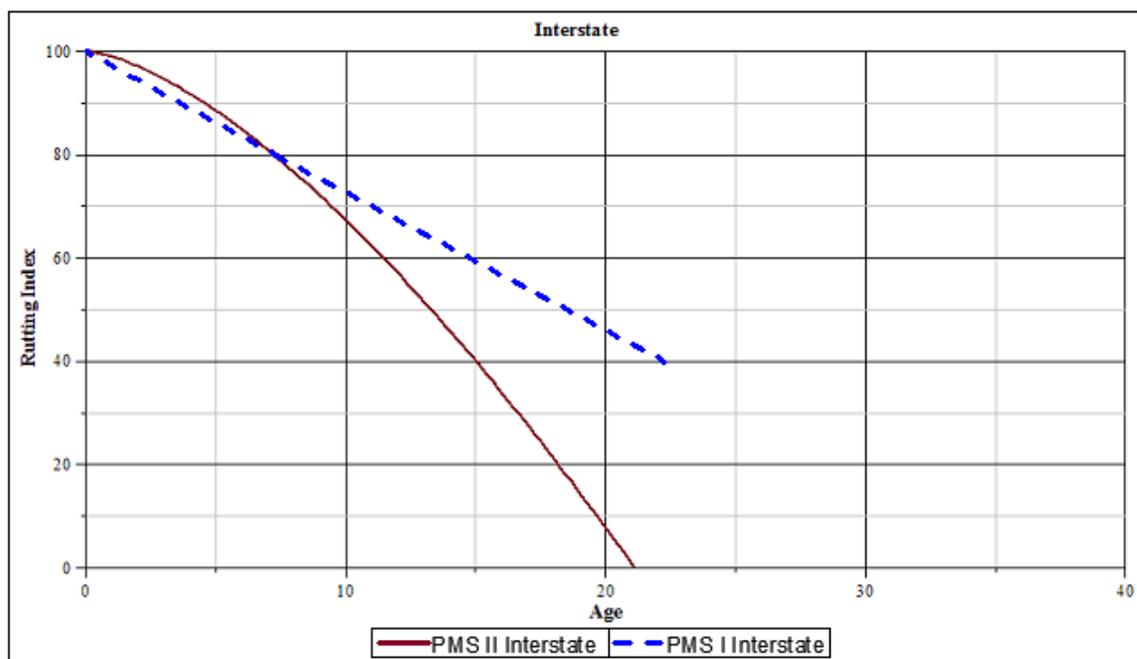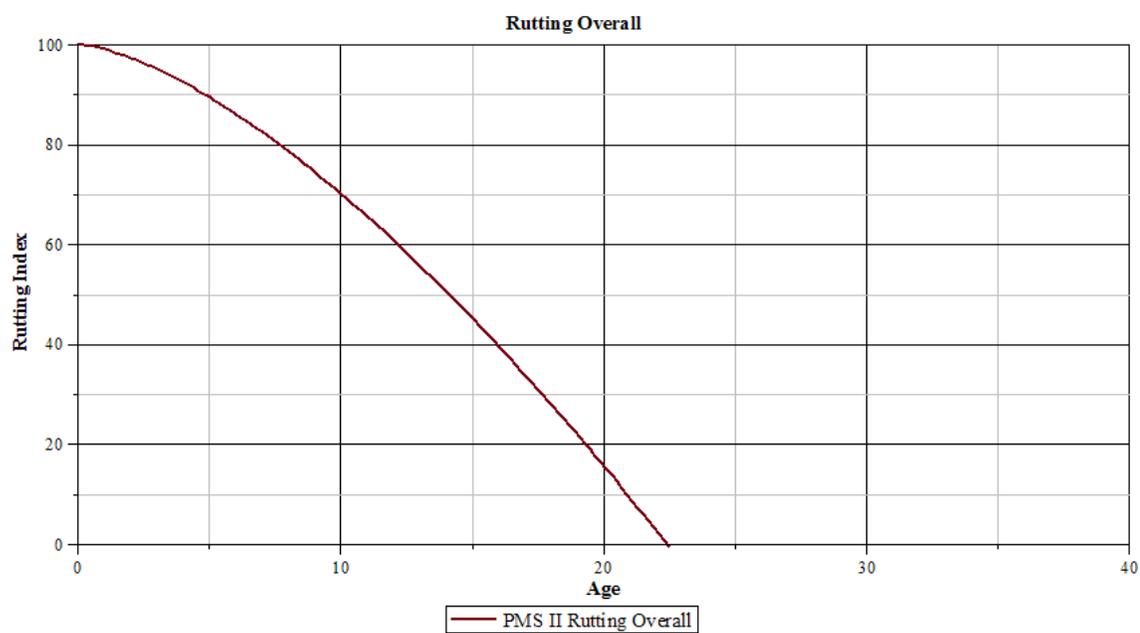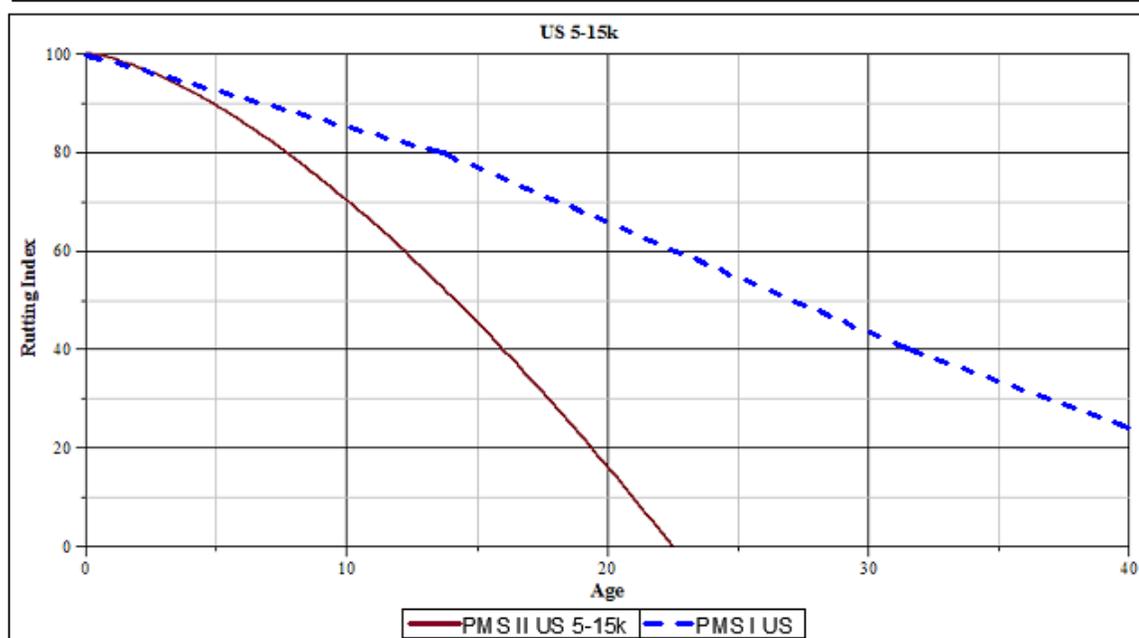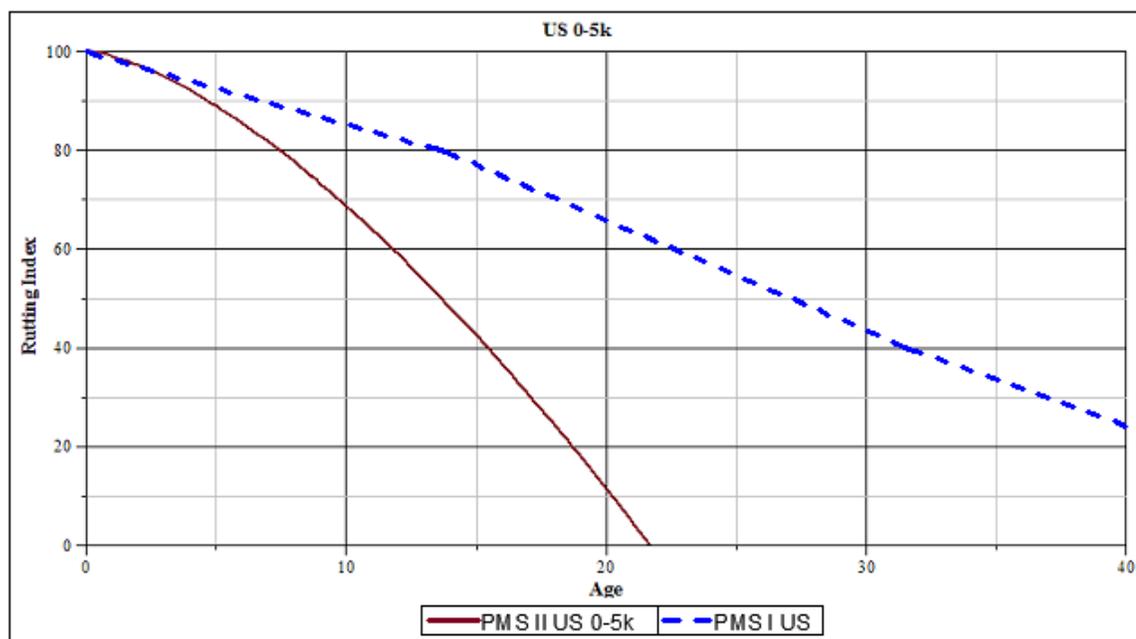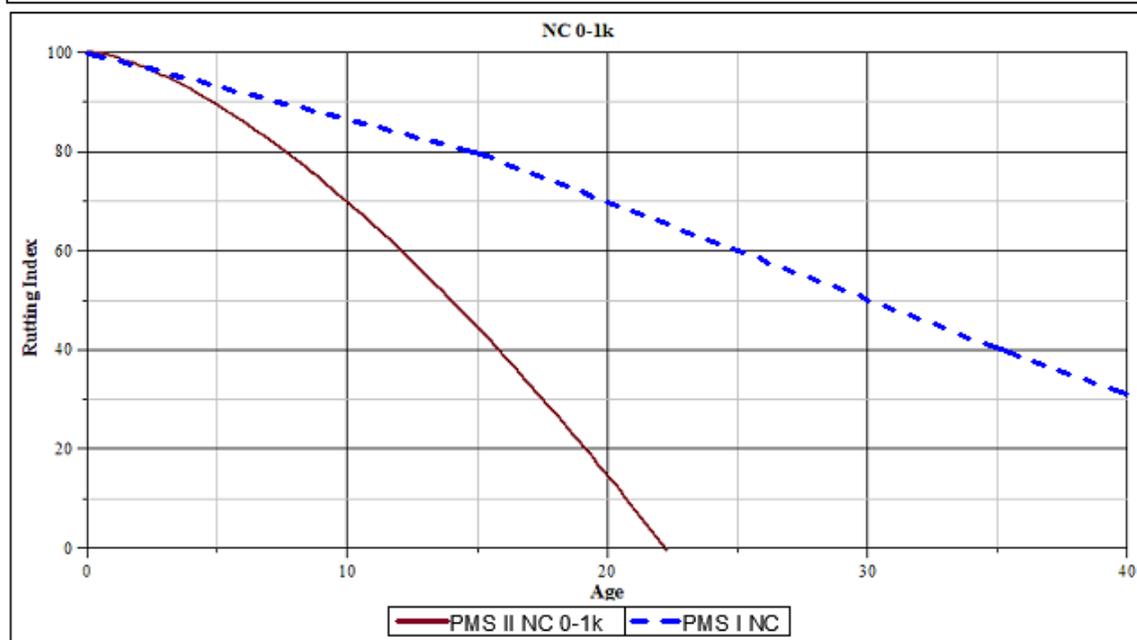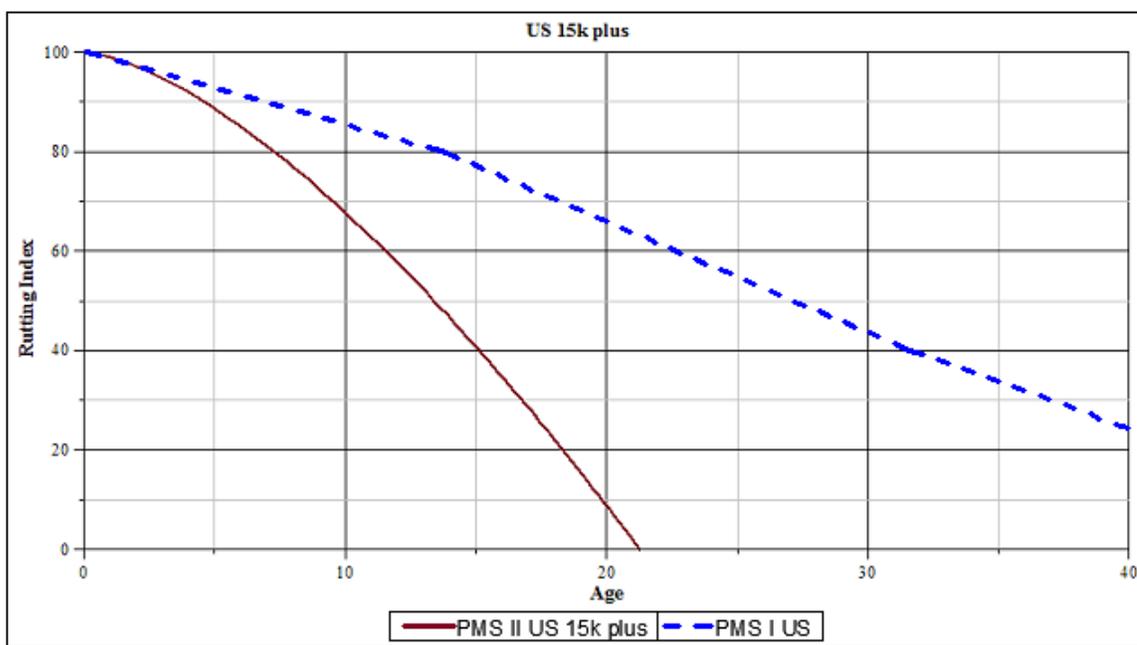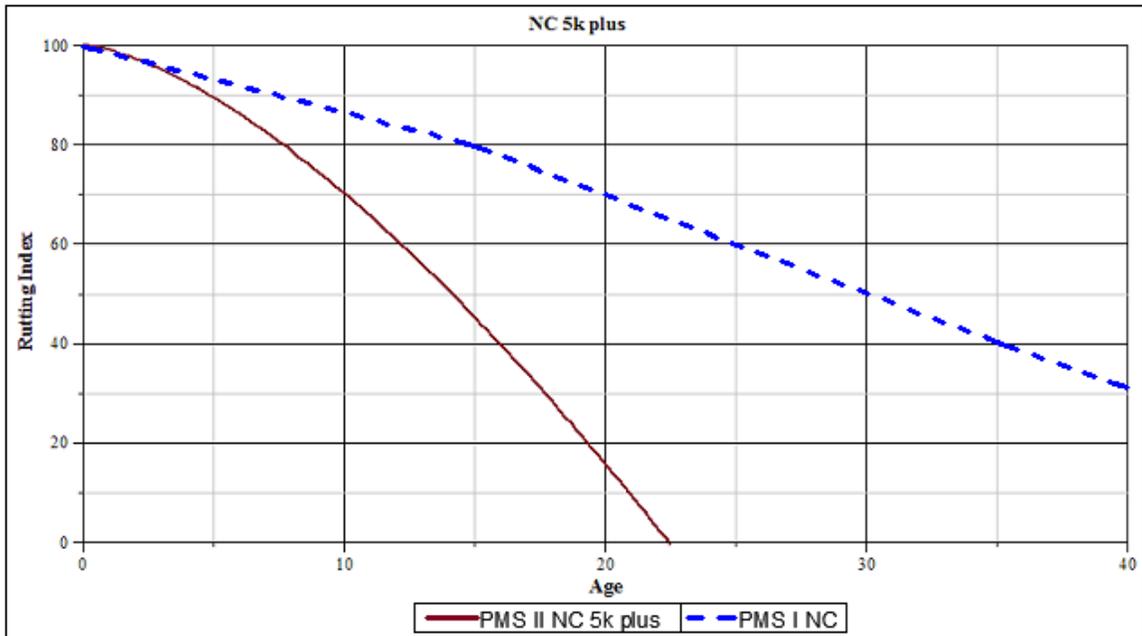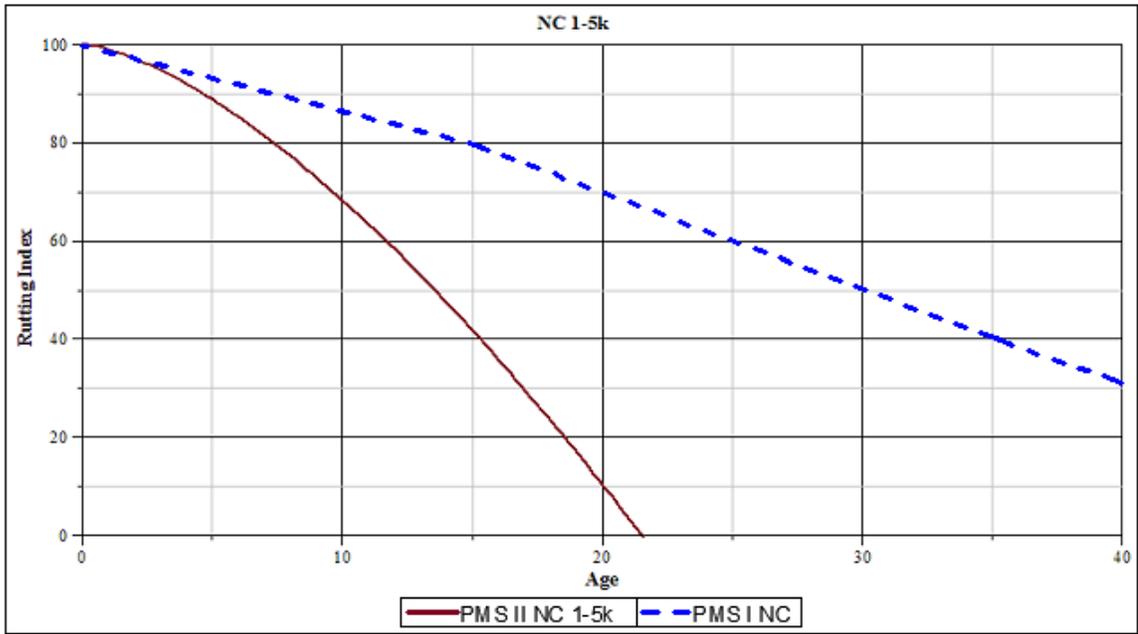
APPENDIX J: ASPHALT MODELS

ASP PCR Interstate

US 0-5k

US 5-15k

US 15k plus

NC 0-1k

PMS I NC 0-1k · PMS II NC 0-1k

NC 1-5k

PMS I NC 0-5k · PMS II NC 0-5k

NC 5k plus

APPENDIX K: JCP MODELS