EVALUATION AND VALIDATION OF PAVEMENT DISTRESS AND PERFORMANCE MODELS FOR A PAVEMENT MANAGEMENT SYSTEM USING AUTOMATED ASPHALT CONDITION DATA

by

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ABSTRACT

STEVEN LEE JAMES. Evaluation and validation of pavement distress and performance models for a Pavement Management System using automated asphalt condition data. (Under the direction of DR. DON CHEN)

Since 2011, the North Carolina Department of Transportation (NCDOT) has implemented an automated data collection process for their Pavement Management System (PMS). This study was conducted to update NCDOT's PMS with the availability of new automated network data from 2014. Distress indices were developed using NCDOT's Maximum Allowable Extent (MAE) method and a composite performance index was developed using the Analytic Hierarchy Process (AHP). To predict calculated distress and performance indices over time, non-linear sigmoidal models were developed. These models, developed exclusively with 2014 data were then visually compared to previously developed models. A visual comparison indicated that models developed in this study varied significantly compared to models developed using automated data from 2012 and 2013. Models developed in this study present better performance ratings in years 0 to 10 compared to previously developed models. From years 11 to 20, models developed in this research present higher deterioration rates compared to previous research. This indicates a more responsive PMS where timely maintenance strategies should be implemented to help eliminate excessive deterioration of roadways. For statistical conclusions, confidence intervals were developed for the b variable which controls the horizontal shift of a sigmoidal regression curve. Overall, most previously research b variables fell outside the upper bound of the interval. This statistically confirms the results of the visual comparison between models.

ACKNOWLEDGMENTS

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CHAPTER 1: INTRODUCTION

1.1 Background

Roadways are an essential component of a country's transportation network system. An efficient and effective roadway network provides economic and societal benefits such as agricultural and rural development; industry and trade; and access to education, health care, and recreation (Queiroz and Gautam 1995 and Young 2008). The World Bank's analysis on road infrastructure and economic development provides insight on how significant roads are to the success of a nation. This worldwide study consisted of a cross-section analysis of data from data 98 countries and a time-series analysis of US data since 1950. The conclusions of this research revealed a statistically significant relationship between economic development, in terms of per capita gross national product (GNP), and road infrastructure, in terms of per capita length of paved road (Queiroz and Gautam 1995).

The US road network, exceeding 8.65 million lane-miles, is the world's largest roadway network (Roadtraffic Technology 2014). To provide quality and an acceptable level of service to the public, State Highway Agencies within the US must maintain and continually improve a constantly expanding roadway system. The issue within the US is that the investment needed to fund surface transportation infrastructure is no longer meeting the needs of the system. With a limited budget and a constantly deteriorating roadway network, asset management plays a crucial role in the success of transportation agencies. Asset management, as described by Has et al (2001) is "a systematic process of maintaining, upgrading and operating physical assets cost-effectively."

A PMS is a transportation asset management tool used by SHAs to make appropriate decisions on how to optimally maintain its network of roadways and provide an adequate level of service to the public. According to the American Association of State Highway and Transportation Officials (AASHTO), a PMS, is "a set of tools or methods that assist decision-makers in finding optimum strategies for providing, evaluating, and maintaining pavements in a serviceable condition over a period of time." With the use of a PMS, transportation officials and engineers utilize a strategic planning tool that provides objective and data driven funding decisions that optimizes the total performance of the entire roadway network.

Currently, SHAs are shifting from a PMS that implements manually collected pavement condition data, which is collected by windshield evaluations, to a PMS that implements automated data, which is collected by vehicles equipped with high speed cameras and sensors. The NCDOT is one of many SHAs who are beginning to implement new technology into their PMS to increase the systems effectiveness. Since 2011, the NCDOT has begun collecting pavement distress data using a new automated approach. This method differs from the manual method and takes advantage of high-speed imaging, sensor technology, and image processing, all which is expected to increased data quantity, subjectivity, repeatability, and safety to roadway evaluators. Since implementing this new data collection method, a methodology for developing distress and performance models using automated data has been researched (Dye 2014). However, with the availability of data from 2014, NCDOT's PMS must be updated by comparing previously developed asphalt models to models developed exclusively with new data. These models will present different regression coefficients, which will in turn affect asset management analysis factors such as deterioration rates and trigger point values.

1.2 Research Need and Significance

There is a need to develop and validate asphalt pavement deterioration models based on 2014 automated data for the following reasons:

1) Accuracy and suitability of pavement deterioration models are crucial to the success of NCDOT's PMS and their application of maintenance and rehabilitation strategies. Initial automated models based on 2012 and 2013 data were developed in a previous study (Dye 2014). As with any new system, the first years of initiation are often a transition period. Since the development of the first automated models, the algorithm used to process raw data has changed. Because of the changes in data collection, there is a need to develop new distress and performance models that has the potential to present different deterioration rates.
2) Once new models are developed, an evaluation and validation process will occur to determine the models compatibility with previously developed manual and automated models. Since NCDOT's automated data collection method is relatively new and still in development, it is essential to compare the deterioration rates of each model to determine how effective this new data collection method is in terms of pavement performance.

This research has been conducted to address these needs and the following outcomes are expected: asphalt pavement overall performance and individual distress predictions, updated maintenance trigger points, and an overall evaluation on models developed during this transition from manual to automated data collection.

1.3 Research Objectives

The objectives of this research project are: (a) to develop new asphalt distress and performance models; (b) to calculate maintenance, rehabilitation, and reconstruction trigger points for asphalt distress types; and (c) to compare newly developed distress and performance models to models developed in previous research studies (Chen et al. 2013 and Dye 2014).

1.4 Report Organization

- An introduction to this research project, its significance and overall objectives are presented in Chapter 1.
- A literature review on pavement management systems and its various components is provided in Chapter 2.
- The framework and methodology used to develop distress and performance models and calculate trigger points is discussed in Chapter 3.
- Chapter 4 presents the results of this study.
- Chapter 5 presents the comparisons of the models developed in this study to models developed in previous research by Chen et al. (2013) and Dye (2014).
- Chapter 6 discusses the major findings, conclusion, and recommendations based on this research study.
- Appendices A through H present asphalt distress models consisting of alligator cracking, transverse cracking, longitudinal cracking, longitudinal lane joint cracking, raveling, non-wheel path patching, wheel path patching, and raveling, respectively. Appendix I includes all asphalt performance models.

1.5 Scope and Limitations

The limitation of this research study was that only one year (2014) of automated asphalt condition data was used. Since NCDOT's raw data processing algorithm changed in 2014, multiple years' worth of data could not be utilized since it varied. However, this issue signified the importance of comparing the differences between models developed in Dye's research in 2014 (which applied NCDOT's automated data collected in 2012 and 2013) and Chen's research in 2013 (which applied NCDOT's manual data). A methodology of developing distress and performance models and comparing the various phases of research was developed in this research. This allowed the researcher to visually interpret the differences between models developed with manual data, models developed using automated data from 2012 and 2013, and models developed using automated data from 2014.

CHAPTER 2: LITERATURE REVIEW

2.1 Pavement Management System Background

According to AASHTO (2001), the amount of money spent on roadways is much less than what is needed. The need for effectively managing available funds is crucial with more than half of all roads in the United States in fair, mediocre, or poor condition. Past research indicates that it costs a SHA less to maintain roadways at a reasonable level of serviceability when a PMS is effectively implemented in management decisions (Peterson, 1977).

As defined by the Organization of Economic and Cooperative Development (OECD), a PMS is "the process of coordinating and controlling a comprehensive set of activities in order to maintain pavements, so as to make the best possible use of resources available, i.e. maximize the benefit for society" (OECD 1987). The idea of pavement management can date back to the Roman Empire, who constructed and maintained a network of roads throughout Europe that remain in use more than 2,000 years later (Abrams 2013). Although the basic theory of a PMS can be traced back over 2,000 years to when roads were first built and maintained, the origination of an integrated and systematic approach to pavement management did not begin until the mid-1960's (Haas et al 2001). In 1980, the Arizona Department of Transportation (AZDOT) developed the first network-level PMS based on a linear optimization model to help minimize roadway maintenance costs. Pavement management has undergone significant advancements since Arizona's first network-level PMS. In 1991, the Intermodal Surface Transportation Efficiency Act (ISTEA) was passed with the help of the Federal Highway Administration (FHWA). This federal bill established pavement condition factors to be incorporated in a PMS while mandating that each state was to have an operational PMS for principal arterials in place by January 13, 1993. Today, all 50 states have some form of a PMS that incorporates pavement condition data and analysis tools, which are used primarily to address maintenance and rehabilitation needs of existing roadways (AASHTO 2001).

A PMS is generally applied and used in two levels-network level and project level (AASHTO 1990). The goal of a network level PMS is to optimize the use of funds statewide and identify the budget that will have the greatest benefit. At a project level, consideration is given to alternative design, construction, maintenance, and rehabilitation activities for specific projects. This is accomplished by comparing the benefit of design alternatives and identifying the alternative with the least total cost over the projected life of the project (Utah Department of Transportation 2013).

2.2 NCDOT Pavement Management

NCDOT's Pavement Management Unit (PMU), a sector of the Division of Transportation (DOT), is responsible for approximately 80,000 miles of roadways spanning across 100 counties in North Carolina (Hauser et al 2005). According to KPMG Peat Marwick LLP (1998), NCDOT's PMU primary functions and responsibilities are to: "Manage the current maintenance management system to guide funding allocation to various roadway maintenance activities; Coordinate allocation of roadway maintenance funds-primary, secondary, urban, and contract resurfacing-based on established criteria;Coordinate and perform roadway maintenance activities, such as pavement patching, resurfacing, snow and ice removal, drainage, shoulders and drop-off, and guard rails".

To assist the NCDOT PMU with the functions and responsibilities listed above, the state has implemented a PMS that has been collecting data on pavement condition since 1982 (Mastin 2011). Manual data was used in 2012 by researchers at UNC Charlotte to validate and update NCDOT pavement performance models, pavement distress models, decision trees, and weight factors. The result of this research was an updated PMS used by the NCDOT PMU to strategically determine when to conduct preventive maintenance, light rehabilitation, heavy rehabilitation, and reconstruction (Thompson 2012).

2.3 Manual Data Collection

Manual or "windshield" data collection has been the primary method for collecting roadway condition data for SHAs since the initiation of the PMS. For manual data collection, pavement raters analyze the condition of roadways through windshield surveys, which involve driving at slow speeds along roadways or the shoulders of roadways. Personnel involved in windshield data collection are responsible for recording various distress types that can be seen from their vehicle. Observed distress types are recorded based on a severity rating of none (N), light (L), moderate (M), and severe (S). Typically, pavement rating crews using the windshield method can cover a distance of 125-200 miles in one day depending on the weather, number of lanes, and the condition of the roadway (Hartgen 1983).

This survey method is considered outdated with respect to today's technology and has a multitude of issues such as subjectivity, repeatability, and safety (Mastin 2011; Ong et al. 2010). Accuracy and reliability of pavement performance data has an effect on an entire pavement management system. For manual data collection, quantitative conditions of roadway performance may vary from rater to rater causing variability in data used to determine an overall performance index of roadway sections. The overall result of inconsistent performance indices on a PMS is consequential decision making processes that "undermine the effectiveness of, and confidence in, the pavement management process" (Flintsch and McGhee 2009). In addition to data variability, manual methods of data collection are time consuming and pose a safety risk for vehicle operators and pavement raters.

2.4 Automated Data Collection

An automated pavement condition survey consists of data collected by vehicles outfitted with digital line-scan cameras and non-contact sensors. According to Timm and McQueen (2004), these digital line-scan cameras are capable of capturing pavement images that can exceed a resolution of 6,000 pixels per line. These vehicles travel at normal speeds while distress classification software analyzes data collected, making this method cost-effective, safe and efficient. Through research and the availability of new technology, many SHAs are transitioning from manual pavement condition surveys to automated pavement condition surveys. This transition has taken place in attempt to eliminate safety risks, efficiency issues, and objectiveness that are present with manual surveys.

With increased interest to transition from manual to automated data, a multitude of research has been conducted to compare the two data collection techniques. Timm and McQueen (2004) conducted a study of manual versus automated pavement for the Alabama Department of Transportation, Groeger et al. (2003) conducted a similar study for the Naval Pavement Center of Expertise, and Wang et al. (2003) conducted a network crack study using automated data for Arkansas. The results of these studies found that automated pavement condition data is an appreciated tool that will benefit SHAs with less subjective and more accurate data, the ability to survey an entire network in a time efficient manner, and a safer means of collecting data on high-speed interstates.

This relatively new technology does not come without issues, however, previous research has shown that automated surveys are a feasible and efficient method for collecting pavement data (Groeger et al., 2003). One issue with this method is that most pavement management systems have been developed for manual data, which differs significantly from automated data. There are a multitude of different distress types collected with the use of the automated survey method as compared to the manual method as shown in Figure 1 (Chen 2009). This issue makes the transition to a fully automated system difficult for SHAs who are hesitant to redesign their PMS to be fully compatible with the automated survey method.

	Asphalt and Composite Pavements (Flexible Pavements in the manual method)	Jointed Concrete Pavements (JCPs)	Continuously Reinforced Concrete Pavements (CRCs)
Manual Collection Method	Alligator Cracking, Transverse Cracking, Rutting, Raveling, Oxidation, Bleeding, Patching	Concrete Patching, Asphalt Patching, Longitudinal Cracking, Transverse Cracking, Corner Breaks, Spalling, Joint Seal Damage, Faulting	Concrete Patching, Asphalt Patching, Longitudinal Cracking, Transverse Cracking, Punch Outs, Narrow Cracking, Y-Cracking
Automated Collection Method	Transverse Cracking, Longitudinal Cracking (Non-Wheel Path), Longitudinal Lane Joint Cracking, Alligator Cracking, Patching, Delamination, Bleeding, Rutting, Raveling, Reflection Cracking of Transverse Joints, Reflection Cracking of Longitudinal Joints,	Corner Breaks, Joint Seal Condition (Transverse and Longitudinal), Joint Spalling (Longitudinal), Linear Cracking (Transverse and Longitudinal), Shattered Slabs, PCC Patching and Deterioration, Asphalt Patching	Transverse Cracking, Clustered Cracking, Punchouts and Spalled "Y" Cracking, PCC Patching and Deterioration, Longitudinal Cracking, Joint Spalling (Longitudinal), Longitudinal Joint Seal Condition

FIGURE 1: NCDOT's manual data collection vs. automated data collection (Chen 2009)

The NCDOT has collected automated pavement condition data since 2011 with the publication of the agency's "Digital Imagery Distress Evaluation Handbook". This handbook specified that beginning in the fall of 2011, "interstate and primary condition surveys will be conducted using high speed digital imagery and automated/semi-automated data processing" (NCDOT 2011). Since then, two contractors have been acquired by the state for data collection purposes.

One contractor is responsible for collecting automated pavement condition data with distance measuring, laser, and imaging equipment in compliance with the Digital Imagery Distress Evaluation Handbook. NCDOT's automated distress handbook specifies that data collectors must survey the rightmost travel lane with downward digital images covering a width of fourteen feet. To ensure quality data with identifiable distresses, pavement condition surveys are not conducted when weather conditions result in poor roadway visibility (NCDOT 2011).

A separate contractor is responsible for evaluating the automated data and must comply with section 1.3 General Distress Evaluation Rules of NCDOT's automated distress handbook. There are a multitude of rules that the data processor must comply with, however in terms of this research, it is important to reference rule seven of section 1.3 which states how distresses will be rated and quantified (NCDOT 2011). In addition to section 1.3, the following standards are also examples of standards the data collector must comply with (refer to "NCDOT Digital Imagery Distress Evaluation Handbook" for a complete list of standards and procedures):

- Automated data collection equipment shall conform to the latest version of ASTM Designation E1656/E1656M "Standard Guide for Classification of Automated Pavement Condition Survey Equipment".
- All inertial profilers shall be a Class 1 Inertial Profiler per ASTM E950.
- Data collection contractor will evaluate pavement surface distresses on 100% of the pavement sections (continuous) utilizing the downward and forward perspective images.

2.5 Pavement Distress Types

Raw pavement condition data, obtained by manual or automated surveys, is typically converted into a composite index to represent an overall condition of a roadway section, trigger specific treatments, and predict future conditions (McGovern et al. 2013). To develop a composite performance index that takes multiple roadway conditions into account, individual pavement distress data (i.e. transverse cracking, longitudinal cracking, alligator cracking, etc.) are first defined and collected by an agency. The following subsections describe the various distress types collected for NCDOT's asphalt roadways.

2.5.1 Alligator Cracking

Alligator cracking, as shown in Figure 2, typically occurs in the wheel path area of a roadway that is subjected to repetitive traffic loads. This distress type is often referred to as fatigue cracking and has a crack pattern that resembles scales on an alligator's back. A low severity alligator crack, as defined by the NCDOT is a single sealed or unsealed longitudinal crack in the wheel path or an area of interconnecting cracks $\frac{1}{8}$ inch or less in width. Moderate severity cracks are defined as an area of interconnecting cracks, typically $\frac{1}{4}$ inch in width that form an alligator pattern. High severity occurs in an area of moderately or severely spalled cracks that are typically $\frac{3}{8}$ inches in width (NCDOT 2011).

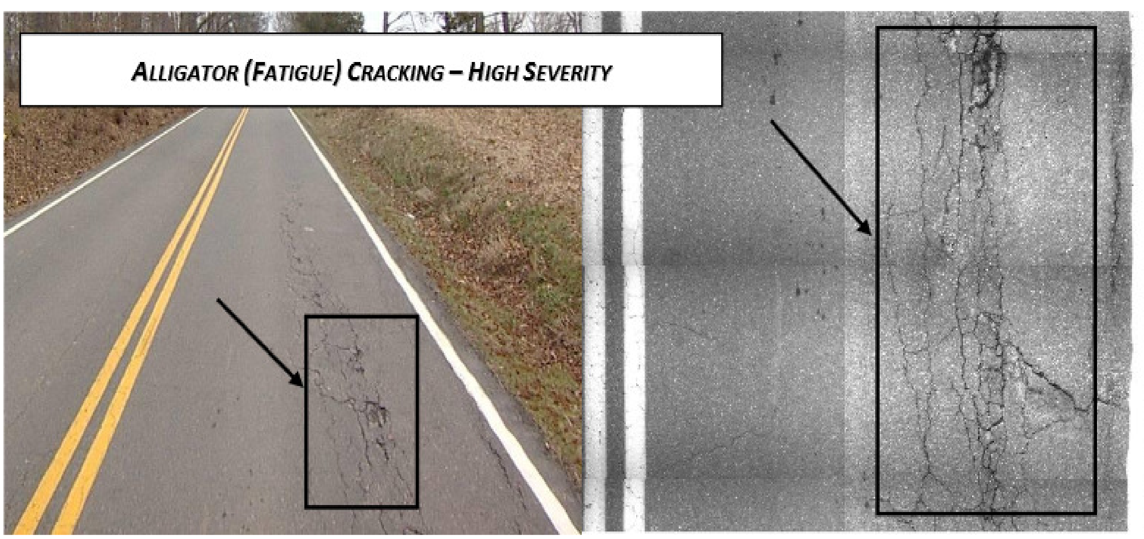

FIGURE 2: Alligator cracking (NCDOT, 2011)

2.5.2 Transverse Cracking

Transverse cracking, shown in Figure 3, is defined by the NCDOT as random cracks that run perpendicular to the pavement centerline. Transverse cracking that occurs over the joints over underlying jointed concrete pavement is referred to as reflective cracking. A low severity transverse crack is either 1) a sealed crack in good condition such that the cracks width cannot be determined or 2) a closed, unsealed crack less than $\frac{1}{4}$ inch in width. Moderate transverse cracking is classified as either 1) an open and unsealed crack between $\frac{1}{4}$ inch and $\frac{1}{2}$ inch in width or 2) any crack with adjacent transverse cracking within 5 to 10 feet. High severity cracking is defined as either 1) an open and unsealed crack greater than $\frac{1}{2}$ inch in width or 2) any crack with adjacent transverse cracking within 5 feet (NCDOT, 2011).

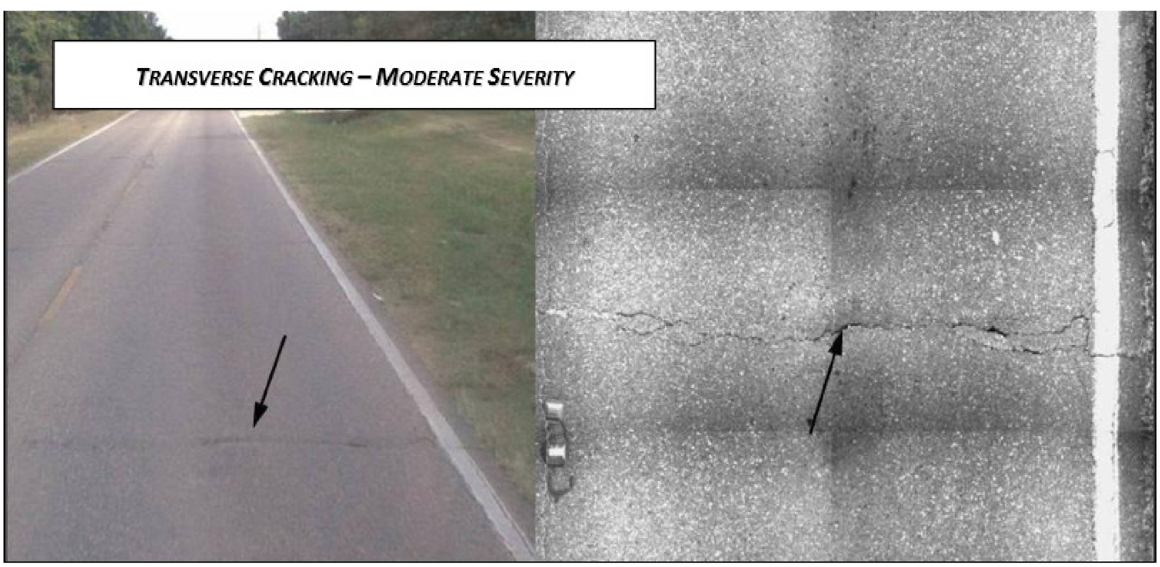

FIGURE 3: Transverse cracking (NCDOT, 2011)

2.5.3 Longitudinal Cracking

Longitudinal cracks run parallel to the centerline of a roadway as shown in Figure 4. The NCDOT only classifies longitudinal cracks outside the wheel paths. Cracks running parallel to the centerline of a roadway and occur inside the wheel paths are classified as low severity alligator cracking. A low severity longitudinal crack is defined as either 1) a crack with sealant in good condition such that the crack width cannot be determined or 2) a closed and unsealed crack less than $\frac{1}{4}$ inch in width. Moderate severity is not collected by the NCDOT, however, high severity is classified as either 1) an open and unsealed crack or 2) any sealed or unsealed crack with adjacent random cracking (NCDOT, 2011).

FIGURE 4: Longitudinal cracking (NCDOT, 2011)

2.5.4 Longitudinal Lane Joint Cracking

Longitudinal lane joint cracking, shown in Figure 5, is crack that runs parallel to the centerline of a roadway and occurs between two lanes where a fresh batch of hot-mix asphalt (HMA) has been laid adjacent to an existing lane. The NCDOT collects only low and high severity levels of this distress type. Low severity consists of either 1) a longitudinal paving joint with sealant in good condition such that the width cannot be determined or 2) an open and unsealed joint. High severity is defined as a longitudinal lane joint crack with severe spalling or adjacent random cracking (NCDOT, 2011).

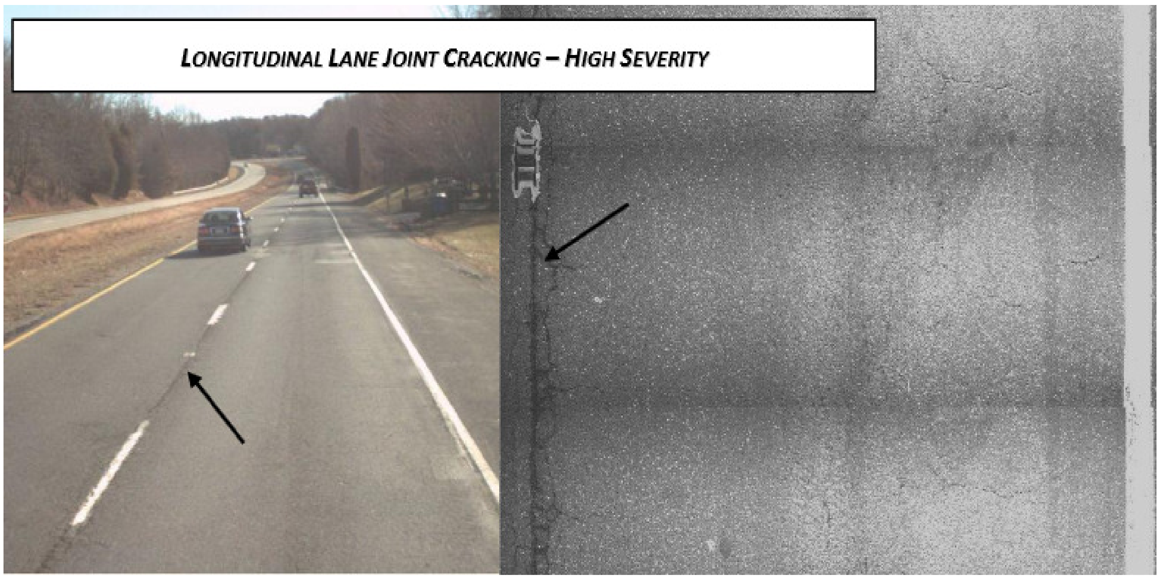

FIGURE 5: Longitudinal lane joint cracking (NCDOT, 2011)

2.5.5 Patching

Patching, as shown in Figure 6, is an area located inside or outside of a roadways wheel path where asphalt has been removed and replaced, or where additional material has been placed on the surface to cover cracking or other distresses. No severity level is specified for patching as only the amount, in square feet, is recorded (NCDOT, 2011).

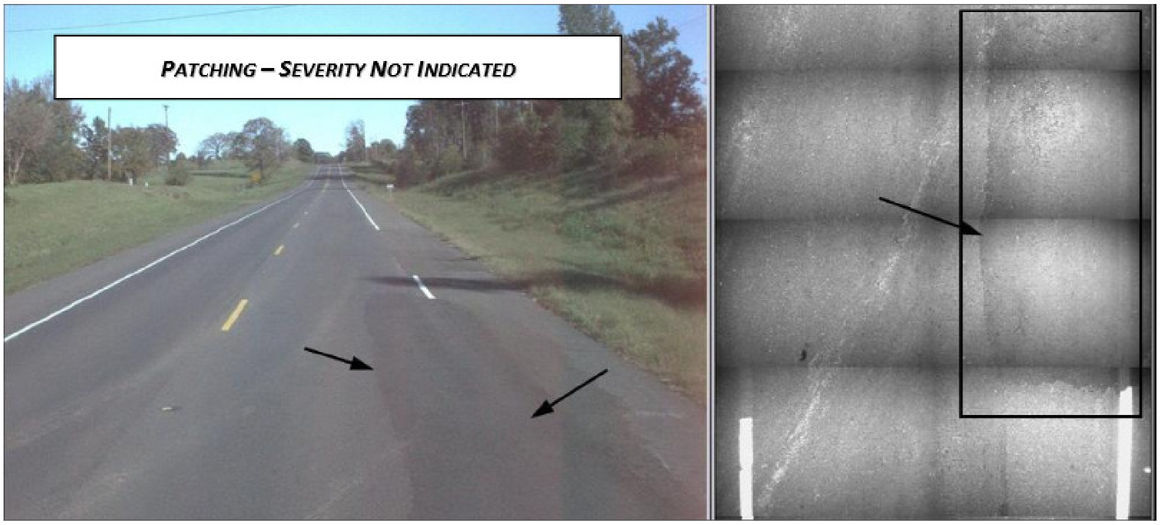

FIGURE 6: Patching (NCDOT, 2011)

2.5.6 Rutting

As shown in Figure 7, rutting is a longitudinal surface depression in the wheel path of a roadway. This distress type is collected using a laser sensor technology, which provides a profile of the pavement surface. The NCDOT calculates rut depths using an automated roadway profiler. Low severity is classified as a rut depth less than 0.25 inches; moderate severity consists of rut depths between 0.25 inches and 0.50 inches; and high severity consists of rut depths greater than 1.0 inches (NCDOT, 2011).

FIGURE 7: Rutting (NCDOT, 2011)

2.5.7 Raveling

Raveling, shown in Figure 8, is the wearing of an asphalt roadways surface and is caused by aggregate separation or loss of asphalt binder. Low severity is classified by the NCDOT as small amounts of aggregate loss and wear. Moderate severity consists of stripping areas less than one square foot and high severity consists of large areas, greater than one square foot (NCDOT, 2011).

FIGURE 8: Raveling (NCDOT, 2011)

2.6 Composite Pavement Performance Index

There are various methods SHAs use to combine individual pavement distress types into a single composite index that describes the total performance of a roadway. There is also no unanimous composite index scale that is used from state to state as some agencies calculate a present serviceability rating (PSR), present serviceability index (PSI), or pavement condition index (PCI) (Ganesan et al. 2006). The PSR, a rating of pavement performance based on ride quality, was developed in the 1960s at the AASHO Road Test (TRB 2007). After the AASHO Road Test, the U.S. Army Corps of Engineers (USACE) developed the PCI, a more objective and complex index valued from 0 to 100. The USACE's PCI was further standardized in ASTM D5340 and ASTM D6433. This method, or variations of this method, is used by many SHAs because various distresses and their severity result in deductions from the "perfect" condition, valued at 100. Timm and McQueen (2004) call this method the "deduct value approach" in which a composite index is deducted from a perfect score based on distress severity and an associated weight factor correlating to the type of distress and its effect on the overall performance. This method is used by ALDOT, which uses a composite pavement condition index called Pavement Condition Rating (PCR). In addition to ALDOT, NCDOT also uses PCR to rate pavement conditions. An adequate pavement condition rating for NCDOT's network is defined as a PCR index of 80 or greater (NCDOT 2010). If a roadway's PCR value is less than 80 it is selected as a candidate for maintenance, rehabilitation, or reconstruction and further analysis is conducted.

2.7 Analytic Hierarchy Process

The use of the Analytic Hierarchy Process (AHP) provides an effective approach to evaluate a situation or alternative in terms of multiple criteria. AHP is a multi-criteria decision-making approach introduced by Thomas L. Saaty in 1977. This methodology uses a hierarchical structure to break a problem down into major components such as objectives, criteria, sub criteria, and alternatives. Data pertaining to the overall objective is derived using a set of pairwise comparisons, which is used to determine the weights or importance of certain criteria (Triantaphyllou and Mann 1995). Sun and Gu (2011) have researched the advantages of using AHP and have developed a new methodology for pavement condition assessment and project prioritization using this process. Because it is difficult and subjective to directly assign weights to various performance indicators, Sun and Gu used AHP to determine weight factors for individual performance indicators such as roughness, deflection index, deterioration ratio, rut depth, and friction coefficient.

To determine weight factors for individual pavement distresses, Sun and Gu surveyed a group of 34 pavement engineers to develop a paired comparison matrix. The survey involved discussions, negotiations, and trade-offs between Sun, Gu, and pavement engineers to develop a single paired comparison matrix for asphalt and concrete pavements of the freeway in Jiangsu Province, China. With the use of algorithms, a weight vector is derived from a paired comparison matrix (Forman and Gass 2001; Sun and Grenberg 2006).

Weight factors for individual pavement indices can be developed using this method to eliminate subjectivity and provide a composite performance index that correlates closely to the actual performance of a roadway.

2.8 Pavement Performance Modeling

The ability to evaluate current pavement conditions and forecasted future pavement conditions is essential in supporting various pavement management decisions (i.e. preventive maintenance, light rehabilitation, heavy rehabilitation, and reconstruction). Pavement deterioration or pavement performance modeling is a key function of a PMS. Pavement deterioration results from many factors such as traffic, climate, materials, layer thickness, layer type, and construction methods (McGovern et al. 2013).

Based off pavement condition data, pavement performance models are developed to predict the behavior of pavements over time, which are used to determine appropriate activities that extend the serviceability of a roadway. Pavement performance models may be deterministic or probabilistic (Lytton 1987). The Transportation Research Board (TRB) states that "deterministic models use regression equations to describe the evolution of pavement condition over time, whereas probabilistic models use Markov chains for the same purpose". Deterministic models predict a single dependent value such as PCR or PSI from one or more independent variables such as age or traffic volume. In comparison to deterministic models, probabilistic models predict a probability distribution of PCR, PSI, etc. There are significant advantages and disadvantages associated with deterministic and probabilistic models. These advantages and disadvantages of probabilistic and deterministic modeling have been researched by many State's PMS to determine what method works for their specific system. In 2001, the Maryland State Highway Administration (MDSHA), along with Axiom Decision Systems (AXIOM), developed an asset management system to improve the state's pavement management services. Both deterministic and probabilistic models were compared in the process. It was determined that the probabilistic modeling approach offered a better modeling solution at the network level where “prediction of condition in the form of distributions is adequate” (Hedfi and Stephanos 2001). At the project level, where a specific prediction value is better suited, the probabilistic model does not provide a SHA the ability to determine specific predications of pavement performance. Because of the need for both network and project level funding allocation, it was concluded by MDSHA and AXIOM that both deterministic and probabilistic modeling approaches were necessary for its PMS.

In 2008 a case study, following the 7th International Conference on Managing Pavement Assets, was conducted for the Arizona Department of Transportation (ADOT). This case study compared the probabilistic and deterministic pavement management analysis. ADOT previously implemented a PMS that used the probabilistic Markov process and a linear programming model to sustain the state’s pavement network at specified levels with a long-term budget constraint. In 2001, ADOT contracted Stantec Consulting to develop and implement a new deterministic modeling approach to predict pavement performance and an associated marginal cost-effectiveness. This case study, comparing both modeling methods, concluded that both systems closely predicted pavement performance although the deterministic model resulted in slightly closer values to the actual measured conditions (Bekheet et al. 2008). In reviewing both ADOT’s and MDSHA’s comparison between probabilistic and deterministic pavement performance models, it is evident that both approaches will successfully predict pavement performance but the deterministic model methodology provides the distinct ability to address needs on both a project and network level. Along with ADOT, the Washington State Department of

Transportation (WSDOT) and Michigan Department of Transportation (MDOT) also have developed empirical-deterministic models to predict pavement performance over time.

2.8.1 Family Modeling Approach

Performance models can be applied to a group of similar pavements that are considered to perform similarly. This method is called "family modeling" for a group of similar pavements and "section modeling" for independent pavements. A "family" of pavements should be grouped so that they have the same surface type, functional classification (Interstate/U.S/state highway/local road), and traffic volume (Chen et al. 2013).

The family modeling method is used by many state DOTs. According to Applied Pavement Technology (2010) "approximately 84 percent of state agencies had developed performance models. 73 percent of them were created for pavement families, 10 percent for individual pavement sections, and 17 percent used a combination of family and section models". The U.S. Army Construction Engineering Research Laboratory (USACERL) (1990) has developed a technique for family modeling which consists of defining pavement families, filtering data, conducting data outlier analysis, developing family models, and predicting the pavement section condition.

Like many states, NCDOT uses deterministic models to estimate PCR and individual distress for roadway families. NCDOT groups pavements according to pavement type, functional classification, and traffic. Pavement performance models predict PCR and are used for Cost-Benefit-Analysis while the pavement distress models predict individual pavement distress and are used to trigger treatment selections (Chen et al. 2013).

2.9 Decision Trees

Decision trees are used to establish a criteria for when to perform various maintenance strategies such as minor maintenance and overlay. Each "branch" on a decision tree represents a condition such as pavement type, distress type and severity, traffic volume, and functional classification (Hicks et al. 2000). Once a composite performance index is established and analyzed it can trigger a particular treatment on a PMS decision tree based on its overall condition or specific distress. Hicks et al. (2000) identified that the issue with decision trees based on a composite performance index is the inability to appropriately address actual distress conditions such as cracking. Because of this, Hicks et al. (2000) developed decision trees using a range of trigger values that independently address pavement roughness, rutting, cracking, and raveling.

NCDOT uses decision trees in their PMS to determine when to conduct various maintenance activities. Similar to Hicks decision trees, NCDOT uses a range of trigger values that independently address pavement distress (alligator cracking, bleeding, transverse cracking, raveling, oxidation, rutting, etc.) and are based on pavement type (asphalt and JCP) and two highway functional classifications (interstate and non-interstate) (Chen et al. 2013).

2.10 Model Comparison Strategies

Pavement distress and performance models allow a PMS to quantitatively predict a roadways overall condition over time. If these prediction models are developed every time new data is available, a comparison can be used to differentiate between alternative models and uncover aspects of the PMS framework that require further elaboration or research (Schunn and Wallach, 2005). In order to determine a models effectiveness and applicability, each developed model must be evaluated to validate if there if is a difference in data quality and performance predictions over time. This is referred to as the goodness-of-fit (GOF) of a model and according to Schunn and Wallach, there are two different ways to evaluate this measure.

The first method uses graphical presentation methods, which allow for visual comparisons to be made. The second method uses numerical measures of GOF, which provide summary measures of the overall accuracy of models. There are numerous measures of GOF, which include the R^2 statistic and the standard error of regression. These measures indicate how well data fits a model and can be used to select a best-fit model. Although these measures provide an objective and quantitative means to analyze how well a model fits data, these methods are difficult to apply to this research due to the nature of the data. Since network level pavement data has many outliers and non-linear sigmoidal regression analysis is used, the R^2 and standard error do no provide an appropriate measure of how well these models fit the given data. Because of this issue, distress and performance models were compared by overlaying regression curves developed in this research and regression curves developed in previous research. This allowed for comparisons to be made in practical terms i.e. deterioration rates and their effect on maintenance activities.

To statistically determine if the difference in pavement performance predictions a 95% confidence interval was calculated for the optimum *b* variable of a model. This variable, which controls the horizontal shift of the prediction model was determined in the TableCurve 2D software. If the *b* variable of previous research fell outside the 95% confidence interval, the models were considered to be statistically different.

CHAPTER 3: RESEARCH METHODOLOGY

This chapter presents the methodology to update NCDOT's pavement management system. Past research has been conducted by Chen et al. (2013) and Dye (2014) that have established a methodology for developing distress and performance models, determining trigger points on decision trees. When new automated data is available to a PMS, it is important that the data be analyzed and compared to previously collected data to ensure data quality within the system. This study will be conducted to provide the NCDOT with distress and performance models based on data collected in 2014. Once these distress and performance models are developed a comparison between developed models will validate the effectiveness of data collected from 2014. The following sections within this chapter will present the computer software programs, work flow, data collection, and processes used to update NCDOT's PMS.

3.1 Computer Programs Utilized

To conduct this research a variety of software applications were used for data processing, statistical analysis, and model development. The following subsections will discuss the various software that was utilized and their overall function.

3.1.1 Microsoft Excel®

To develop a database for this research Microsoft Excel was selected as the main data storage software. All data received by the NCDOT was in the form of Microsoft Excel files. Data received for this project was be merged, processed, and exported in .xls format. Once the central database was developed and exported as Microsoft Excel files, they served as the main source of data for other programs selected for statistical analysis and model development.

3.1.2 SAS®

For data processing and statistical analysis purposes, SAS was selected for this research. This software package provides the ability to perform linear and non-linear regression analysis and analyze large amounts of data. Since this research deals with large amounts of data, SAS was be used to create scatter plots, remove outliers, and perform regression analysis for each of the various roadway families.

3.1.3 TableCurve 2D®

To develop the final non-linear sigmoidal regression models for each roadway family, TableCurve 2D was used. This software package, created by Systat Software Inc., automated the curve fitting process and statistically ranked a list of candidate regression equations.

3.1.4 Maple®

To plot all final distress and performance models and compare automated performance models against previous NCDOT performance models, Maple computer software was used. This software package will provided the ability to graphically visualize the distress and performance model results.

3.2 Work Processes

This section presents a summary of the steps used for this research project. The development of updated distress and performance models began upon receiving data from the NCDOT. Once all pertinent data was collected the following steps were carried out:

Step 1: Develop a central database by merging files containing automated distress data and pavement information.

Step 2: Determine distress indices by normalizing data, developing scatter plots and percentile limits, and determining maximized allowable extent (MAE) values.

Step 3: Develop distress models for each distress type.

Step 5: Determine a composite performance index using the AHP process to determine appropriate weights for each type of distress.

Step 6: Develop performance models for each roadway family.

Step 7: Calculate maintenance, rehabilitation, and reconstruction trigger points.

Step 8: Conduct a comparison between previously developed models and models developed in this study.

3.3 Data Collection

The NCDOT contracts automated data collectors and evaluators who collect and process automated pavement data in accordance to the NCDOT Digital Imagery Distress Evaluation Handbook discussed earlier in section 2.4 of the literature review. Data using this method is currently collected for Interstate, US, and NC roadways (SR not surveyed) in all fourteen divisions shown in Figure 9. For this research, no data was physically collected, therefor, specific testing protocols and procedures were not used. The various distress types and their recorded units that were used in this research are listed in Table 1.

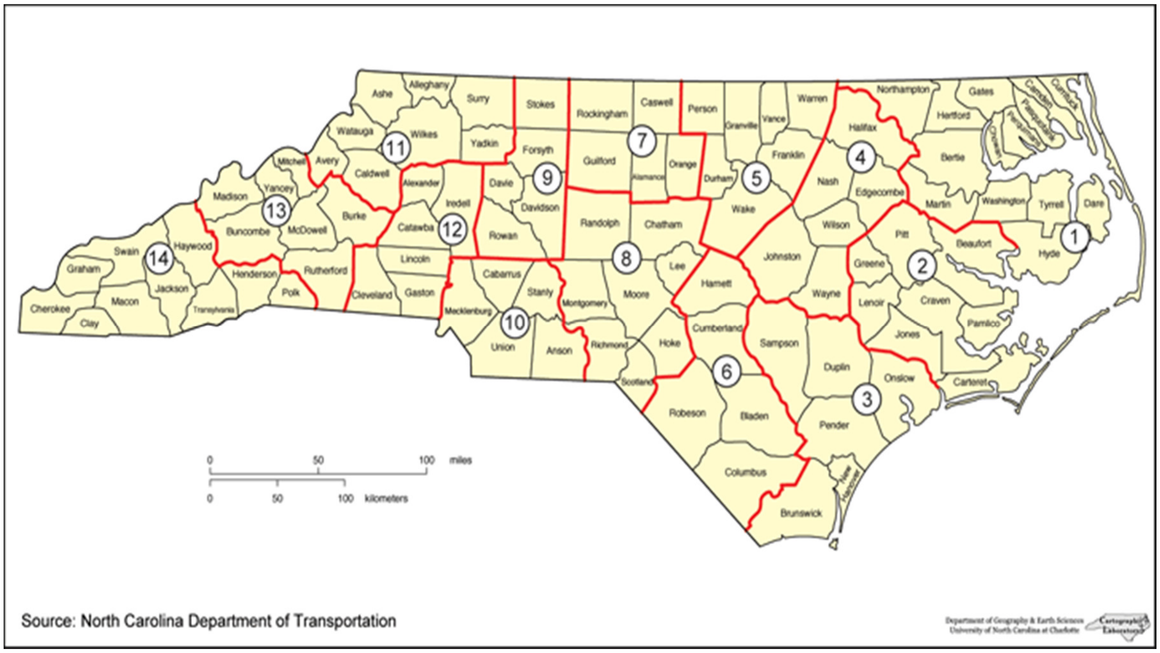

FIGURE 9: NCDOT divisions

TABLE 1: NCDOT recorded pavement distresses

Distress	**Units**
Alligator Cracking	Square feet
Patching	Square feet
Delamination	Square feet
Rutting	Average depth in inches
Bleeding	Square feet
Transverse Cracking	Linear feet
Non-Wheel Path Longitudinal Cracking	Linear feet
Longitudinal Lane Joint Cracking	Linear feet
Raveling	Square feet

3.3.1 Data Sources

Three data sources, *Automated_ASP*, *AGE,* an *AADT*, were obtained from the NCDOT for this research. These three databases include all the raw data that were used to develop asphalt distress indices and model their regression overtime. As shown in Figure 10, the *Automated_ASP* database included the following information:

- ROUTE1 – eight-digit code that describes:
  - Route type (1=Interstate, 2=US, 3=NC)
  - Route code (1=alternative, 2=bypass, etc.)
  - Direction (0=interstate, 4=southbound, etc.)
  - Additional five digit identification code
- EFF_YEAR – year of pavement condition survey
- COUNTY – county identification number
- OFFSET_FROM – milepost (MP) to the nearest 0.001 mile that identifies the beginning point of the roadway section being surveyed.
- OFFSET_TO – MP to the nearest 0.001 mile that identifies the ending point of the roadway section being surveyed.
- LENGTH – length of roadway section surveyed (miles)
- Pavement Distress Data:
  - Distress Severity Levels – Low (L), Moderate (M), High (H)
  - Extent of distress – depending on the distress type (alligator cracking, transverse cracking, etc.) the extent of each distress severity is quantified in terms of linear feet, square feet or other units as applicable (NCDOT 2011).

ROUTE1	EFF_YEAR	COUNTY	OFFSET_FROM	OFFSET_TO	LENGTH	ALGTR_LOW_SF	ALGTR_MDRT_SF	ALGTR_HGH_SF
10000095	2014	66	0	1.81	1.81	1742	0	0
10000095	2014	66	1.81	3.11	1.3	87	0	0
10000095	2014	66	3.11	4.58	1.47	168	0	0
10000095	2014	66	4.58	6.58	1.995	95	0	0
10000095	2014	66	6.58	7.501	0.908	0	0	0
10400095	2014	66	0	1.495	1.495	379	0	0
10400095	2014	66	1.495	2.905	1.41	1113	0	0
10400095	2014	66	2.905	4.375	1.47	1433	0	0
10400095	2014	66	4.375	6.375	1.993	403	0	0
10400095	2014	66	6.375	7.49	1.096	5587	0	0
20000013	2014	8	0	2	1.997	2847	0	0
20000013	2014	8	2	3.98	1.983	1858	0	0
20000013	2014	8	3.98	6.35	2.37	1498	0	0
20000013	2014	8	6.35	8.35	1.997	2539	0	0
20000013	2014	8	8.35	9.556	1.193	9680	0	0
20000013	2014	8	13.066	13.812	0.755	1490	15	0
20000013	2014	8	14.086	16.049	1.963	9942	554	67
20000013	2014	8	16.049	18.136	2.091	9899	406	50
20000013	2014	8	18.136	20.225	2.089	12279	341	18

FIGURE 10: Automated_ASP database *note: only alligator cracking is listed; other distress information is provided but not shown in this figure*

The database *Age*, as shown in Figure 11, included the following information:

- ROUTE – eight digit route number
- COUNTY – county identification number
- OFFSET_FROM – begin MP of the roadway section that has received maintenance
- OFFSET_TO – end MP of the roadway section that has received maintenance
- LENGTH – length of roadway section surveyed (miles)
- EFF_Year – year of roadway condition survey
- YEAR_LAST_REHAB – year roadway section received rehab (PCR and Distress Indices are reset to 100)
- YEAR_CONSTR – year roadway section was built

ROUTE	COUNTY	OFFSET_FROM	OFFSET_TO	LENGTH	EFF_YEAR	YEAR_LAST_REHAB	YEAR_CONSTR
10000095	64	3.002	10.306	7.304	2012	1977	1977
10000095	64	10.306	14.626	4.32	2012	1978	1978
10000095	64	14.626	18.313	3.687	2012	1978	1978
10000095	64	18.313	18.333	0.02	2012	1978	1978
10000095	64	18.333	19.408	1.075	2012	2004	1978
10000095	64	19.408	26.224	6.816	2012	2004	1968
10000095	66	0	0.94	0.94	2012	1999	1963
10000095	66	0.94	0.99	0.05	2012	1963	1963
10000095	66	0.99	1.12	0.13	2012	2007	1963
10000095	66	1.12	7.49	6.37	2012	2007	1963
10000095	78	11.47	12.147	0.677	2012	1997	1972
10000095	78	13.137	13.511	0.374	2012	1997	1972
10000095	78	13.511	13.904	0.393	2012	1997	1956
10000095	78	13.904	14.046	0.142	2012	1997	1956
10000095	78	16.588	20.247	3.659	2012	2004	1956
10000095	78	20.247	21.528	1.281	2012	2004	1956
10000095	78	21.528	21.917	0.389	2012	2004	1962
10000095	78	21.917	21.927	0.01	2012	2004	1962
10000095	78	21.927	22.133	0.206	2012	1995	1962

FIGURE 11: Age database

The database *AADT*, as shown in Figure 12, includes the following information:

- COUNTY – county identification number
- ROUTE1 – eight digit route number
- OFFSET_FROM – begin MP of the roadway section with AADT information
- OFFSET_TO – end MP of the roadway section with AADT information
- AADT – Annual Average Daily Traffic

COUNTY	ROUTE1	OFFSET_FROM	OFFSET_TO	AADT
66	10000095	0	2	20500
66	10000095	2	4	19000
66	10000095	4	4.85	19000
66	10000095	4.85	6.85	20000
66	10000095	6.85	8.688	21000
66	10000095	8.688	10.688	21000
66	10000095	10.688	12.688	19000
66	10000095	12.688	13.592	18000
66	10000095	13.592	15.592	18000
66	10000095	15.592	16.915	18000
66	10000095	16.915	18.915	24000
66	10000095	18.915	20.894	23500
66	10000095	20.894	22.894	23500
66	10000095	22.894	24.099	23500
66	10000095	24.099	26.099	23500
66	10000095	26.099	28.099	23000
66	10000095	28.099	30.342	23000
66	10400095	0	2	23000
66	10400095	2	3.97	23000

FIGURE 12: AADT database

3.3.2 Data Merging

To determine distress indices and evaluate a roadway's performance over time, each of the three databases were merged together using a SAS code. The central database developed in SAS was exported as an .xls file that contained all information needed to determine distress indices and model network level roadway conditions over time. It is important to note that for each of the three databases, OFFSET_FROM and OFFSET_TO points for each roadway were different, as shown in Figure 13.

Automated_ASP Database

ROUTE1	EFF_YEAR	COUNTY	OFFSET_FROM	OFFSET_TO	LENGTH	ALGTR_LOW_SF	ALGTR_MDRT_SF	ALGTR_HGH_SF
10000095	2014	66	0	1.81	1.81	1742	0	0
10000095	2014	66	1.81	3.11	1.3	87	0	0
10000095	2014	66	3.11	4.58	1.47	168	0	0
10000095	2014	66	4.58	6.58	1.995	95	0	0
10000095	2014	66	6.58	7.501	0.908	0	0	0
10400095	2014	66	0	1.495	1.495	379	0	0
10400095	2014	66	1.495	2.905	1.41	1113	0	0
10400095	2014	66	2.905	4.375	1.47	1433	0	0

vs.

Age Database

ROUTE	COUNTY	OFFSET_FROM	OFFSET_TO	LENGTH	EFF_YEAR	YEAR_LAST_REHAB	YEAR_CONSTR
10000095	64	3.002	10.306	7.304	2012	1977	1977
10000095	64	10.306	14.626	4.32	2012	1978	1978
10000095	64	14.626	18.313	3.687	2012	1978	1978
10000095	64	18.313	18.333	0.02	2012	1978	1978
10000095	64	18.333	19.408	1.075	2012	2004	1978
10000095	64	19.408	26.224	6.816	2012	2004	1968
10000095	66	0	0.94	0.94	2012	1999	1963
10000095	66	0.94	0.99	0.05	2012	1963	1963
10000095	66	0.99	1.12	0.13	2012	2007	1963
10000095	66	1.12	7.49	6.37	2012	2007	1963
10000095	78	11.47	12.147	0.677	2012	1997	1972
10000095	78	13.137	13.511	0.374	2012	1997	1972

vs.

AADT Database

COUNTY	ROUTE1	OFFSET_FROM	OFFSET_TO	AADT
66	10000095	0	2	20500
66	10000095	2	4	19000
66	10000095	4	4.85	19000
66	10000095	4.85	6.85	20000
66	10000095	6.85	8.688	21000
66	10000095	8.688	10.688	21000
66	10000095	10.688	12.688	19000
66	10000095	12.688	13.592	18000
66	10000095	13.592	15.592	18000

FIGURE 13: Differences between databases

This situation occurs because the beginning and ending points of maintenance and traffic data differ from the beginning and ending points of pavement condition data. This problem, illustrated in Figure 14, had to be addressed to combine pavement condition, age and AADT data.

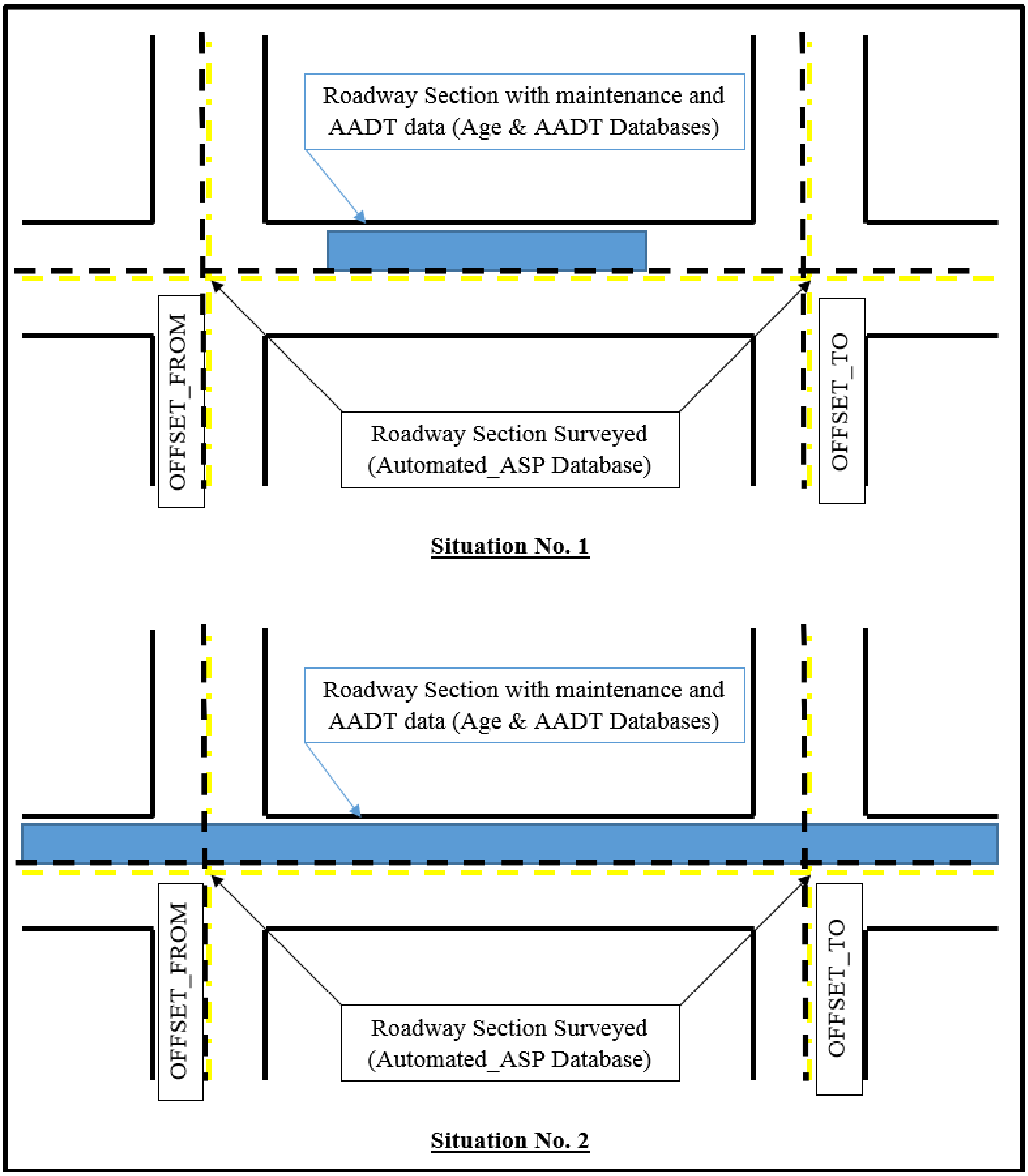

FIGURE 14: Spatial differences in data

To merge data, related fields within each of the three databases were extracted and placed in the central database. This was a two-step process consisting of:

1) Merging Automated_ASP and AADT databases using matching fields (county number, route number, OFFSET_FROM, and OFFSET_TO) to create a temporary database.

2) Merging the temporary database containing pavement condition and AADT data with the Age database using matching fields (county number, route number, OFFSET_FROM, and OFFSET_TO).

For step one, a SAS code was written to compare the *Automated_ASP* and *AADT* databases in terms of OFFSET_FROM and OFFSET_TO values. To do this, two tables were developed as shown in Figure 15.

Table A				**Table B**		
Automated_ASP Database				**AADT Database**		
ROUTE	OFFSET_FROM	OFFSET_TO		ROUTE	OFFSET_FROM_B	OFFSET_TO_B
10000095	0	1.81		10000095	0	2
10000095	1.81	3.11		10000095	2	4
10000095	3.11	4.58		10000095	4	4.85
10000095	4.58	6.58		10000095	4.85	6.85
10000095	6.58	7.501		10000095	6.85	8.688
…..	…..	…..		…..	…..	…..

FIGURE 15: Data merging comparison example

To extract data with similar spatial references, a set of merging rules were written is SAS. For the AADT database, the OFFSET_FROM and OFFSET_TO variables were renamed to OFFSET_FROM_B and OFFSET_TO_B. This was done to compare the

Automated_ASP database's OFFSET_FROM and OFFSET_TO values to the *AADT* database. A data entry was either deleted or merged depending on the following rules:

a. **if** $\mathrm{OFFSET\_FROM} >= \mathrm{OFFSET\_TO\_B}$ $then\ delete$

b. **if** $\mathrm{OFFSET\_TO} <= \mathrm{OFFSET\_FROM\_B}$ $then\ delete$

c. **if** $\mathrm{OFFSET\_FROM} >= \mathrm{OFFSET\_FROM\_B}$ **and** $\mathrm{OFFSET\_TO} <= \mathrm{OFFSET\_TO\_B}$ $then\ merge$

d. **if** $\mathrm{OFFSET\_FROM\_B} \leq \mathrm{OFFSET\_FROM} \leq \mathrm{OFFSET\_TO\_B}$ **and** $\mathrm{OFFSET\_TO} \geq \mathrm{OFFSET\_TO\_B}$ *then apply the following:*

   a. **if** $(\mathrm{OFFSET\_TO\_B} - \mathrm{OFFSET\_FROM}) >= (\mathrm{OFFSET\_FROM} - \mathrm{OFFSET\_FROM\_B})$ *then merge*

For step two, a separate SAS code was written to compare the *Age* database to the merged *Automated_ASP* and *AADT* database. Similar to step one, two tables were created and compared to either merge or delete data entries. For the *Age* database the OFFSET_FROM and OFFSET_TO variables were renamed to Begin_MP and End_MP. Once the variables were renamed, each table was compared and data was either merged into the final database or deleted using the following merging rules:

a. **if** $\mathrm{End\_MP} <= \mathrm{OFFSET\_FROM}$ **or** $\mathrm{Begin\_MP} >= \mathrm{OFFSET\_TO}$ $then\ delete$

b. **if** $\mathrm{Begin\_MP} < \mathrm{OFFSET\_FROM}$ **and** $\mathrm{End\_MP} < \mathrm{OFFSET\_TO}$ **and** $\mathrm{End\_MP} - \mathrm{OFFSET\_FROM} > \mathrm{OFFSET\_FROM} - \mathrm{Begin\_MP}$ *then merge*

   a. **or** $\mathrm{Begin\_MP} < \mathrm{OFFSET\_FROM}$ **and** $\mathrm{End\_MP} >= \mathrm{OFFSET\_TO}$ *then merge*

   b. **or** $\mathrm{Begin\_MP} >= \mathrm{OFFSET\_FROM}$ **and** $\mathrm{End\_MP} < \mathrm{OFFSET\_TO}$ *then merge*

c. **or** $\text{Begin\_MP} = \text{OFFSET\_FROM}$ **and** $\text{End\_MP} >= \text{OFFSET\_TO}$ *then merge*

d. **or** $\text{Begin\_MP} > \text{OFFSET\_FROM}$ **and** $\text{End\_MP} = \text{OFFSET\_TO}$ *then merge*

e. **or** $\text{Begin\_MP} > \text{OFFSET\_FROM}$ **and** $\text{End\_MP} > \text{OFFSET\_TO}$ **and** $\text{OFFSET\_TO} - \text{Begin\_MP} > \text{End\_MP} - \text{OFFSET\_TO}$ *then merge*

Once databases were merged, the data was then subdivided into families for data analysis. The data was sorted and divided according to roadway classification (Interstate, U.S., and N.C.) and AADT levels. A total of seven asphalt roadway families, shown in Table 2, were defined based on roadway classification and their AADT values.

TABLE 2: Asphalt roadway families

Roadway Classification	**AADT**	**Family**
Interstate	All	Interstate
US Routes	0-5K	US 0-5K
	5-15K	US 5-15K
	15K-plus	US 15K-plus
NC Routes	0-1K	NC 0-1K
	1-5K	NC 1-5K
	5K-plus	NC 5K-plus

3.4 Data Analysis

The following sections describe how data was analyzed to calculate asphalt pavement distress indices, develop a composite performance index, and model performance over time.

3.4.1 Distress Data Normalization

Since asphalt distress types are recorded in differing units of measurement, a data normalization process was used to develop distress indices. To develop indices that are unit-less and describe the overall frequency and severity of individual distresses, raw data was normalized using the data normalization equations shown in Table 3 (Dye, 2014). For example, the alligator distress type is recorded in square feet. To obtain a value that was unit-less and could be used in the distress index calculation process, the initial raw data was divided by length and the factors of 7 and 5,280. The length is the distance (in miles) of the roadway section where the distress was surveyed. The conversion factors 7 and 5,280 represent the width of the wheel path and the conversion of length from feet to miles, respectively. The same process was used to normalize the remaining asphalt distress types based on the normalization equations shown in Table 3 (Dye, 2014).

TABLE 3: Asphalt raw data normalization equations

Distress	Normalization Equation
Alligator Cracking	$\frac{Alligator\ Cracking}{(Length * 7 * 5280)}$
Patching Area-Wheel Path	$\frac{Patching\ Area}{(Length * 7 * 5280)}$
Maximum Average Rut Depth	$100 - 100\ (Maximum\ Average\ Rut\ Depth)^2$
Transverse/Reflective Cracking	$\frac{Trans\ Crck + Reflective\ Trans\ Crck}{(Length * 5280)}$
Patching Area-Non Wheel Path	$\frac{Patching\ Area}{(Length * \left(\frac{Section\ Width}{Number\ of\ Lanes}\right) * 5280}$
Longitudinal Cracking	$\frac{Longitudinal\ Cracking}{(Length * 5280)}$
Longitudinal Lane Joint Cracking	$\frac{Longitudinal\ Lane\ Cracking}{(Length * 5280)}$
Raveling	$\frac{Raveling}{(Length * \left(\frac{Section\ Width}{Number\ of\ Lanes}\right) * 5280}$

3.4.2 Distress Index Calculation

A distress rating, according to the NCDOT Pavement Condition Survey Manual (2011), is a composite score for a roadway section combining each of the three distress severity levels: Low (L), Moderate (M), and High (H). To calculate the distress index for each distress type, the Maximized Allowable Extent (MAE) method used in previous NCDOT manual data research was used (Chen, 2013). To calculate distress indices, the NCDOT MAE spreadsheet shown in Figure 16 was used.

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	**2.604**					
med_sev_in	**0**	*OK* - Sum distress total is 100 or less				
high_sev_in	**0**					
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	32.496					
med_sev_mae_in	2.65					
high_sev_mae_in	0.399					
Threshold Amounts are lowest possible score for that severity when it occurs alone						
low_sev_threshold_in	60					
med_sev_threshold_in	30					
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	2.604		
med_sev_begin	0		distr_med	0		
high_sev_begin	0		distr_high	0		
d1	3.20532					
d2	0		d2c	3.20532		
d3	0		d3c	3.20532		
Alligator Cracking Index Value	**96.7947**					

FIGURE 16: Distress index calculation

As shown in Figure 16, this method consisted of defining both MAE amounts (low_sev_mae_in, med_sev_mae_in, high_sev_mae_in) and threshold values (low_sev_threshold_in, med_sev_threshold_in, high_sev_threshold_in). The MAE amounts represent the maximum percentage of light, moderate, and high severities that will be rated for each distress type and the MAE threshold values represent the lowest possible index rating when a distress severity occurs by itself. For example, in Figure 16, alligator cracking MAE amounts were determined to be 32.496, 2.650, and 0.399 for low severity, moderate severity, and high severity respectively. The MAE threshold values in this example were 60, 30, and 0 for low severity, moderate severity, and high severity respectively. If a roadway section was to only contain 32.496 percent low severity alligator cracking, the distress index would be 60. Similarly, if a roadway section was to only have 2.650 percent moderate severity alligator cracking, the distress index would be 30. If only 0.399 percent of high severity was recorded, the distress index would be 0.

For the particular example shown in Figure 16, 2.604 percent of low severity alligator cracking was observed on a section of asphalt pavement and no moderate or high severity was present. The normalized data was entered into the orange input cells and the resulting alligator cracking index was calculated in the yellow output cell as 96.795, indicating this section of roadway had minimal alligator cracking. This process was utilized in SAS to analyze the large quantity of data provided by the NCDOT.

To determine MAE amounts for the distress index calculator, normalized distress data was used and scatterplots were developed for low, moderate, and high severities. Figure 17 displays a scatterplot developed for low severity alligator cracking. Scatterplots were developed for each roadway family and each distress severity.

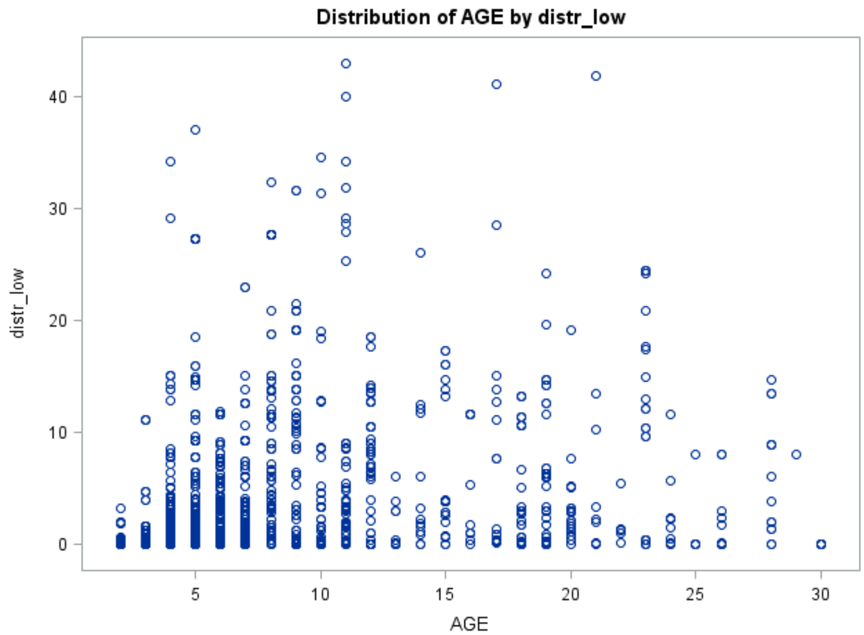

FIGURE 17: Scatterplot developed for MAE amounts

Once scatterplots for each distress severity were developed, the 98th percentile limits were calculated. The 98th percentile represents the percentage of distress that is present on a roadway section. Figure 17 displays the scatterplot of low severity alligator cracking for the interstate family. Figure 18 displays the calculated alligator cracking percentiles for low, moderate, and high severities for the interstate family. These percentile values were calculated for each roadway family (Interstate, US, NC) and were then averaged for each severity level (low, moderate, high). Once the average percentiles were determined, these values were entered into the MAE spreadsheet as the MAE amounts to calculate distress indices.

Interstate Alligator Low (Percentiles)

P_98
27.2495

Interstate Alligator Moderate (Percentiles)

P_98
3.21391

Interstate Alligator High (Percentiles)

P_98
0.66598

FIGURE 18: 98th percentile of interstate alligator cracking

As shown in Figure 18, the low severity percentile was calculated to be 27.25%. This means that 98% of interstate roadway sections exhibited 27.25% or less of low severity alligator cracking. Similarly, 98% of interstate roadway sections exhibited 3.21% or less of moderate severity alligator cracking and 0.67% or less of high severity alligator cracking.

3.4.3 Data Cleaning Process

Once distress indices were calculated using the MAE process, scatterplots were developed to compare distress index to age. The scatterplot shown in Figure 19 provides an example of this process.

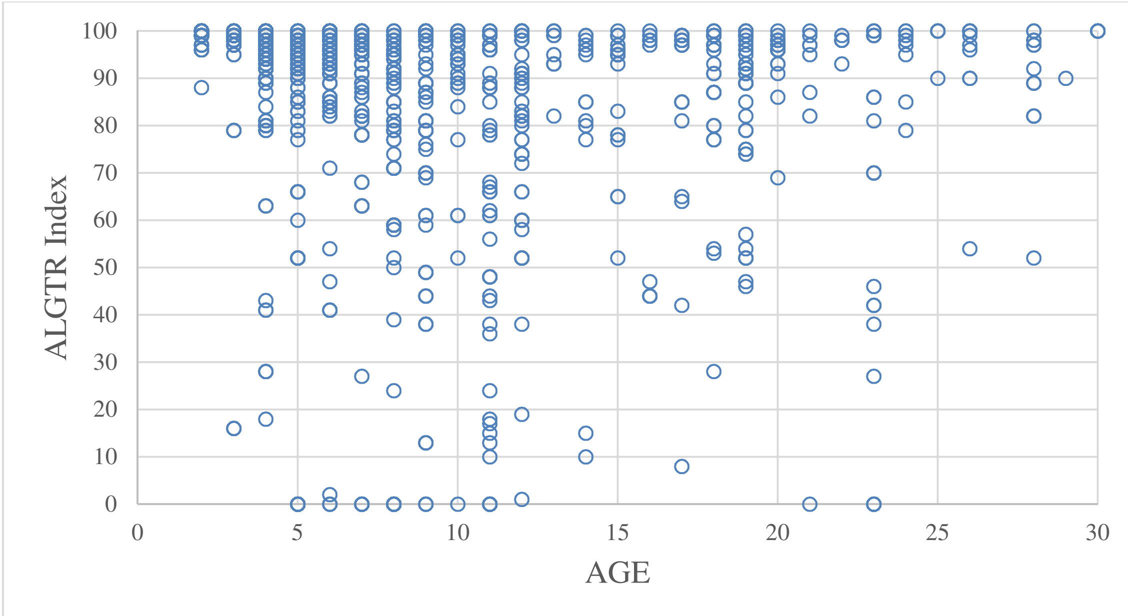

FIGURE 19: Initial scatterplot of Interstate alligator cracking vs. age

As shown in Figure 19, there were no obvious trends found from these distress versus age scatterplots. This was also an issue with the PCR versus age scatterplots as well. The reason for this issue is due to the existence of large amounts of outliers. To address this issue an outlier removal process was carried out. Outliers were removed based on the principle that a roadways condition deteriorates over time. During this process each scatterplot was analyzed to remove outliers from the data set. Data points were removed in the lower left and upper right bounds of the scatterplots. Once outliers were removed, scatterplots were redeveloped as shown in Figure 20. It is important to note that original data points were preserved as much as possible during this data cleaning process to eliminate user subjectivity while developing models.

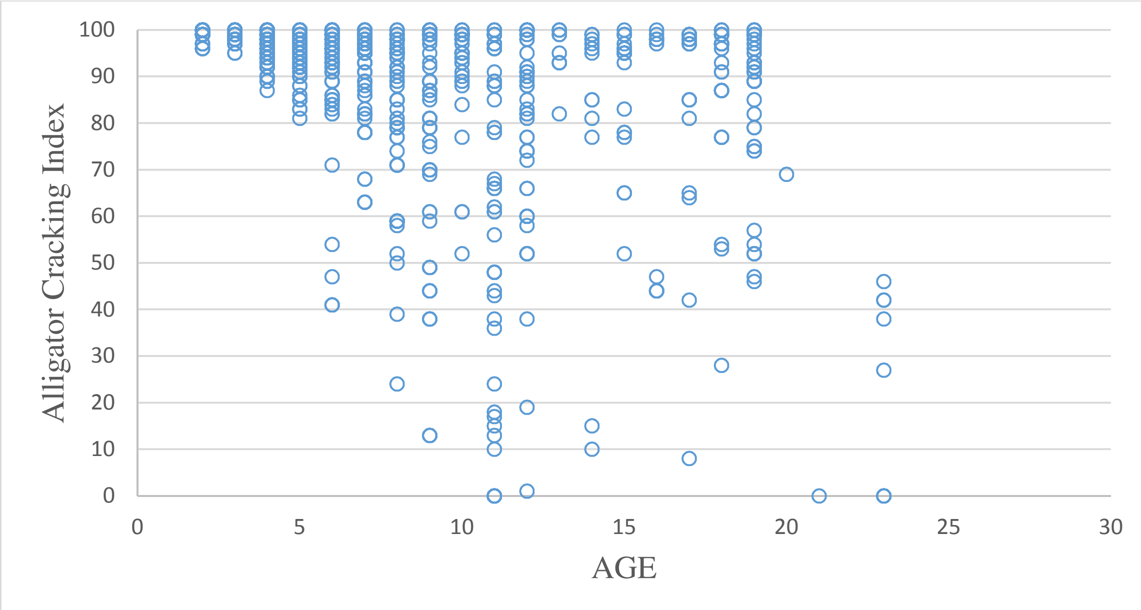

FIGURE 20: Cleaned scatterplot of Interstate alligator cracking vs. age

3.4.4 Model Selection

The NCDOT PMS accepts the seven types of distress and performance model types shown in Table 4.

TABLE 4: NCDOT approved model types

Model Type
Exponential
Hyperbolic
Inverse Exponential
Linear
Piecewise Linear
Power
Sigmoidal

Based on research conducted by Chen et al (2013), the sigmoidal form best fits pavement performance over time due to its "S-shaped" regression curve. There are five variations to the sigmoidal regression, which include the Logistic, Gompretz, Richards, Weibull, and Morgan-Mercer-Flodin. It was determined in a study conducted in 2002 by Carrillo and Gonzalez, that a variation of the logistic sigmoidal equation, shown in Equation 1, best fits pavement deterioration predictions over time.

$$y = \frac{a}{1+e^{\frac{x-b}{c}}} \qquad \text{Equation 1}$$

Where:

$x =$ age

$a, b, c =$ Model Coefficients

$y =$ Distress or Performance Index

The model coefficient a represents the initial value for the distress and performance curves. The coefficient b controls the curve's horizontal shift along the x-axis and c controls the slope. Both b and c represent a pavements deterioration rate over time.

3.4.5 Initial Coefficient Estimate

Since this data has many outliers and there are no obvious trends, nonlinear regression will always result in a different set of optimal a, b, and c variables. Because of this discrepancy in regression analysis, it is an essential step in the model development to initially estimate *a, b*, and *c* variables.

Since pavements are assumed to have a perfect initial rating after construction or maintenance, the initial value used for coefficient a was estimated to be 100. Using Equation 1, defined in section 3.4.4, and the estimated a coefficient of 100, Equation 2 was derived, allowing for the initial estimate of b and c coefficients. This equation was derived using the following steps:

Let,

$$a = 100$$

Then,

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

Taking the natural logarithm yields,

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

Then,

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

The exponential was taken,

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

Then,

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

The natural logarithm was taken,

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

Let,

$$Y = \ln(e^{\ln(100) - \ln(y)} - 1)$$

Then,

$$Y = -\frac{1}{c}x + \frac{b}{c} \qquad \text{Equation 2}$$

Once outliers were removed, a regression analysis was performed in SAS using Equation 2. This provided the initial estimates of *b* and *c* variables. Figure 21 is a SAS output that displays the initial estimates of variables *a, b,* and *c* for alligator cracking models. It should be noted, that this figure only displays the SAS output for alligator cracking, however, this process was repeated for each distress type as well as PCR models.

Gplot: ALGTR.Interstate, a=100, b=21.971101372, c=-4.107431649
Gplot: ALGTR.US_0_5k, a=100, b=18.322650727, c=-4.163286626
Gplot: ALGTR.US_5_15k, a=100, b=17.596581524, c=-3.975835234
Gplot: ALGTR.US_15kplus, a=100, b=17.873747606, c= -4.09794067
Gplot: ALGTR.NC_0_1k, a=100, b= 24.45264101, c=-5.274459417
Gplot: ALGTR.NC_1_5k, a=100, b=21.014975456, c=-4.439177078
Gplot: ALGTR.NC_5kplus, a=100, b=20.468876435, c=-4.877300863

FIGURE 21: Initial estimate of sigmoidal equation variables

3.4.6 Final Distress Model Development

Once initial variable estimates were determined, calculated distress indices determined using the MAE spreadsheet were imported into TableCurve 2D to develop the most optimum sigmoidal distress models. This process consisted of first importing the calculated distress values and the corresponding pavement age. The initial TableCurve 2D interface, shown in Figure 22, displays how the data was imported into this software. The x-axis was defined with the age variable and the y-axis was defined as the distress index.

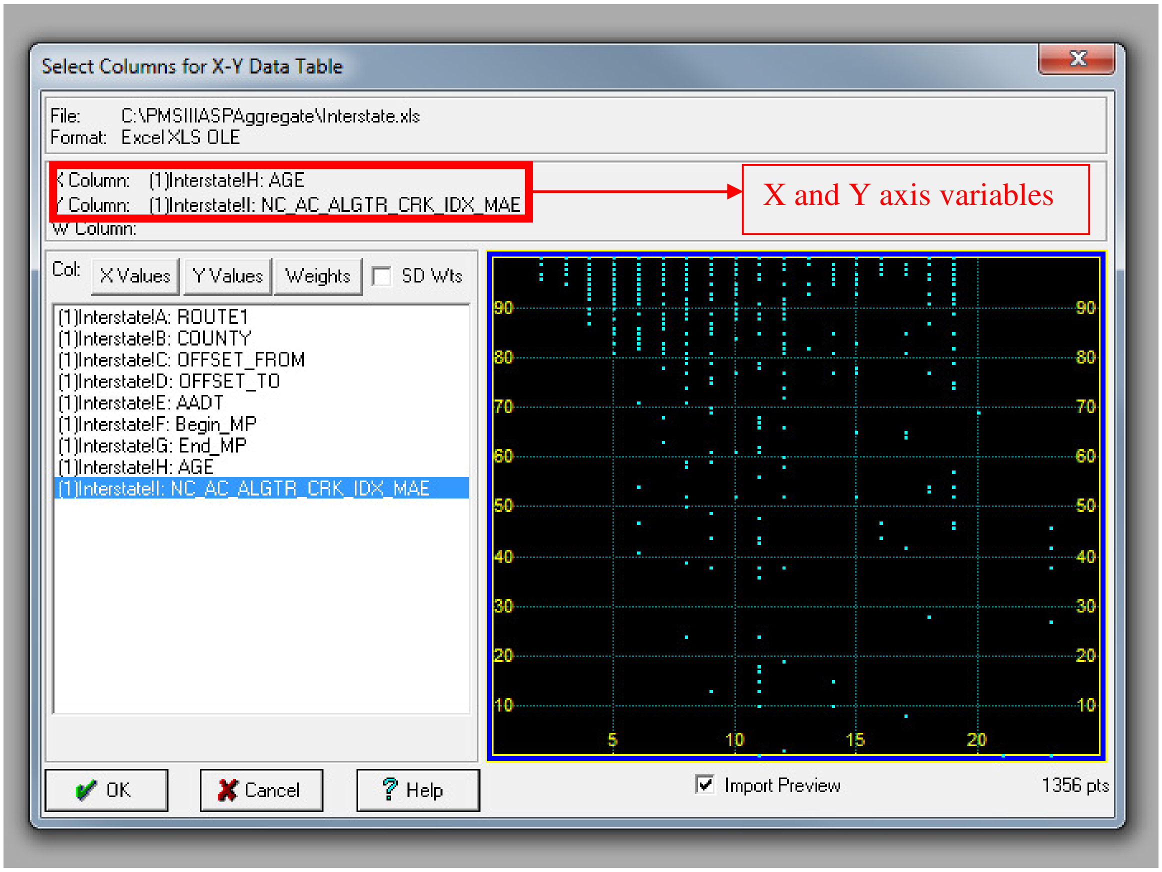

FIGURE 22: TableCurve 2D x-axis and y-axis interface

Once data was imported into TableCurve 2D and the x-axis and y-axis were defined, the next step was to import the User Defined Function (UDF). The user defined function imported into TableCurve 2D was the sigmoidal regression equation, as defined in Equation 1. Once the UDF was imported, *a*, *b*, and *c* variables of the sigmoidal equation had to be defined. The initial *c* variable estimate, calculated in SAS was used in this step, as shown in Figure 23. The *a* and *b* coefficients were then estimated in TableCurve 2D to develop the final model. There were fifteen different model selections that were generated by TableCurve 2D once variables were defined. These fifteen model selections presented differing *a* and *b* coefficient estimations. The curve that had a y-intercept of 100 and fit the data best, as shown in Figure 24, was selected as the best-fit-model and results were confirmed with engineers at the NCDOT.

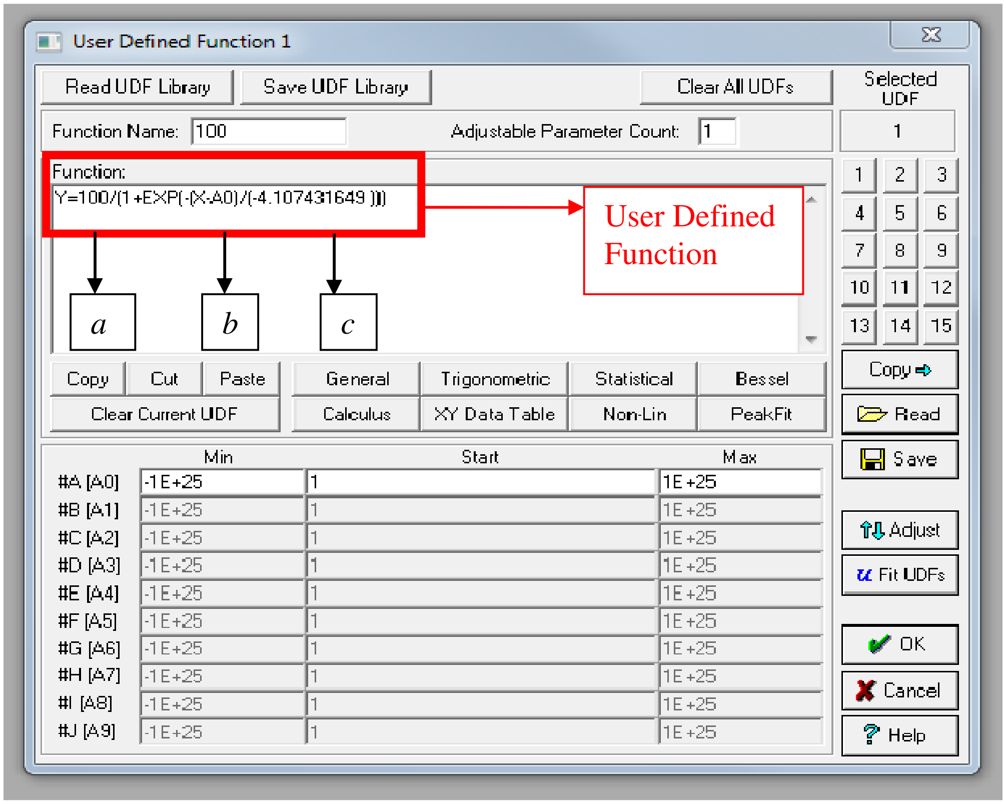

FIGURE 23: a, b, c variable optimization

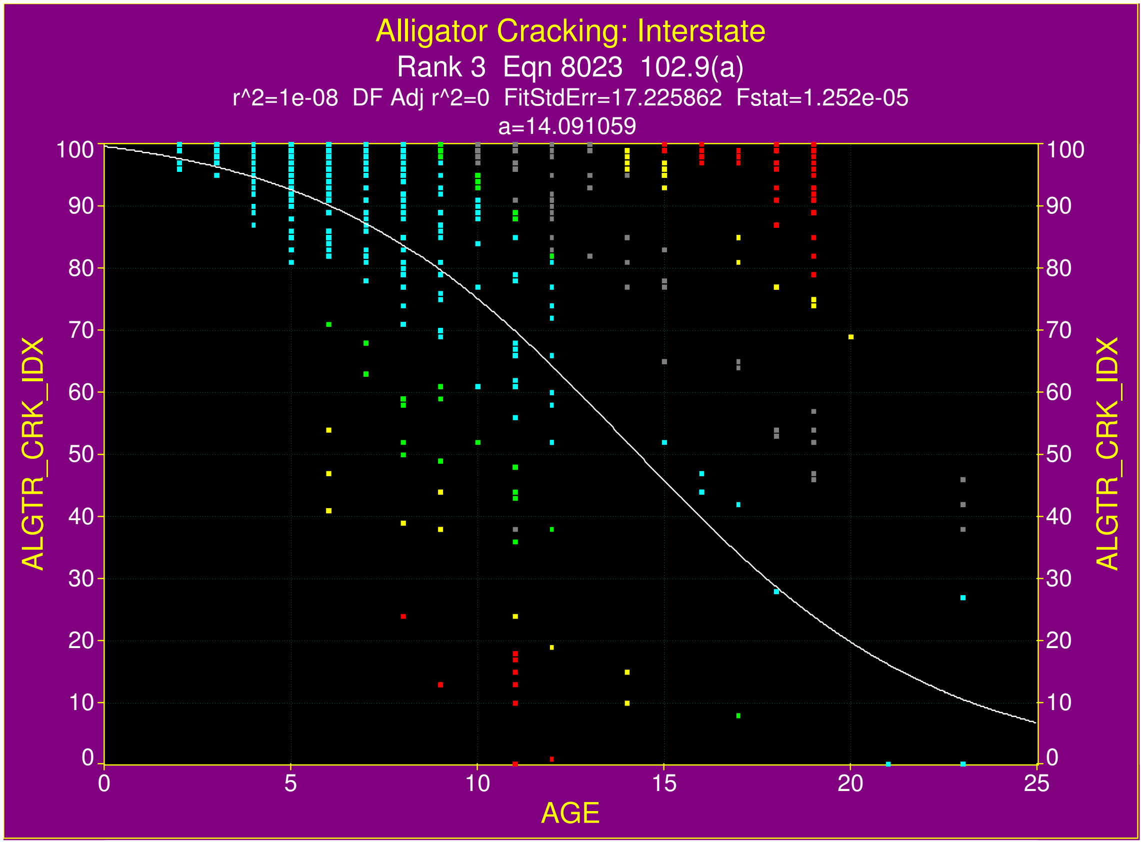

FIGURE 24: Best-fit model

3.4.7 Composite Performance Index

The NCDOT uses PCR, a composite performance index, to quantify the overall condition of roadways. PCR is calculated using Equation 3.

$$PCR = \sum_{i}^{n}(W.F._{i} \times \ Distress\ Index_{i}) \qquad \text{Equation 3}$$

Where:

$W.F._{i}$ = Weight Factor for distress type i

$Distress\ Index_{i} = 0 - 100$ index describing a distress's severity and extent

To develop a composite performance index that takes into account multiple criteria, the AHP method was used. The AHP method was chosen because it is an effective method for calculating weight factors and it eliminates user subjectivity when determining a variables importance.

To calculate the weight factors for each distress type the following steps were performed:

Step 1: Distress deductions points were calculated using existing NCDOT manual data algorithms shown in Table 5.

Step 2: Table 6 was developed by averaging the L/M/H deduction points for each distress type. This average value was considered the overall importance of a specific distress type. Table 7 provides an example of how the average deduction was obtained for alligator cracking.

TABLE 5: Asphalt distress deduction point system

Distress	Severity Level	Deduction
Alligator Cracking	(L)ight (M)oderate (H)igh	3.3 points – 10% to 90% ; 1 point > 90% 7.5 points – 10% to 40% ; 2 points > 40% 15 points – 10% to 20% ; 3 points > 20%
Transverse Cracking	(L)ight (M)oderate (H)igh	5 points 15 points 30 points
Rutting	(L)ight (M)oderate (H)igh	5 points 20 points 30 points
Raveling	(L)ight (M)oderate (H)igh	2 points 5 points 15 points
Patching	(L)ight (M)oderate (H)igh	5 points 10 points 20 points

TABLE 6: Asphalt distress relative importance table

Distress	Average L/M/S Deduction
Alligator Cracking	A=42
Transverse Cracking	B=17
Longitudinal Cracking	C=9
Longitudinal Lane Joint Cracking	D=7*
Raveling	E=7
Patching Area – WP	F=12
Patching Area – NWP	G=7*
Rutting – Max Avg. Depth	H=18
* non-load related: use the smallest deduction value	

TABLE 7: Alligator cracking average deduction calculation

Distress Type	Severity Level	Deduction	Average
Alligator Cracking	(L)ight	$(3.3 \times 9) + (1 \times 1) = 30.7$	42
	(M)oderate	$(7.5 \times 4) + (2 \times 6) = 42$	
	(H)igh	$(15 \times 2) + (3 \times 8) = 54$	

Step 3: Average L/M/H deduction values for each asphalt distress type was then entered into a pairwise comparison matrix and an AHP calculator in order to determine the matrix's eigenvalues. The resulting eigenvalues for each distress type represented the weight factors for the PCR index equation. Figure 25 displays the pairwise comparison matrix that was used for the AHP calculator.

Asphalt Distress Type	ALGTR	TRNSVRS	LNGTDNL	LNGTDNL_JNT	RVL	WP	NWP	RUT
Alligator Cracking (ALGTR)	=42/42	=42/17	=42/9	=42/7	=42/7	=42/12	=42/7	=42/18
Transverse Cracking (TRNSVRS)	=17/42	=17/17	=17/9	=17/7	=17/7	=17/12	=17/7	=17/18
Longitudinal Cracking (LNGTDNL)	=9/42	=9/17	=9/9	=9/7	=9/7	=9/12	=9/7	=9/18
Longitudinal Lane Joint Cracking (LNGTDNL_JNT)	=7/42	=7/17	=7/9	=7/7	=7/7	=7/12	=7/7	=7/18
Raveling (RVL)	=7/42	=7/17	=7/9	=7/7	=7/7	=7/12	=7/7	=7/18
Patching Area-Wheel Path (WP)	=12/42	=12/17	=12/9	=12/7	=12/7	=12/12	=12/7	=12/18
Patching Area-Non Wheel Path (NWP)	=7/42	=7/17	=7/9	=7/7	=7/7	=7/12	=7/7	=7/18
Rutting (RUT)	=18/42	=18/17	=18/9	=18/7	=18/7	=18/12	=18/7	=18/18

FIGURE 25: Pairwise comparison matrix

Step 4: To validate the results of the AHP method, a Consistency Index (CI) was calculated using Equation 4. If the CI value equals 0, there is no logical inconsistency among the pairwise comparison judgments and the judgment is considered 100 percent consistent (Shinohara and Osawa, 2007).

$$CI = \frac{(\lambda_{max} - n)}{(n-1)} \qquad \text{Equation 4}$$

Where;

CI = Consistency Index

λ_{max} = maximum eigenvalue

n = number of criteria

Step 5**:** The Consistency Ratio was then calculated using Equation 5.

$$CR = \frac{CI}{RI} \times 100 \qquad \text{Equation 5}$$

Where;

RI = Random matrix consistency index; RI = 1.41 for n = 8 (Kardi Teknomo 2015)

If the CR is less than or equal to 10 percent, the inconsistency is acceptable. If the CR is greater than 10 percent, comparisons must be re-examined and the process repeated (Kardi Teknomo 2015). Once the eigenvalues for each distress type were calculated using the AHP process, the PCR equation was developed. Equation 6 shows the equation that will be developed with the determination of each distresses weight factor.

$$\mathrm{PCR} = (\mathrm{W.F.}_i)(\mathrm{ALGTR\ CRCK}) + (\mathrm{W.F.}_i)(\mathrm{TRANS\ CRCK}) + (\mathrm{W.F.}_i)(\mathrm{LONG\ CRCK}) + (\mathrm{W.F.}_i)(\mathrm{LONG\ JNT\ CRCK}) + (\mathrm{W.F.}_i)(\mathrm{RAV}) + (\mathrm{W.F.}_i)(\mathrm{WP\ PATCH}) + (\mathrm{W.F.}_i)(\mathrm{NWP\ PATCH}) + (\mathrm{W.F.}_i)(\mathrm{RUT}) \qquad \text{Equation 6}$$

Where:

PCR = Pavement Condition Rating

$\mathrm{W.F.}_i$ = Distress Weight Factor

ALGTR CRCK = Alligator Cracking Index

TRANS CRCK = Transverse Cracking Index

LONG CRCK = Longitudinal Cracking Index

LONG JNT CRCK = Longitudinal Lane Joint Index

RAV = Raveling Index

WP PATCH = Wheel Path Patching

NWP PATCH = Non − Wheel Path Patching Index

RUT = Rutting Index

3.4.8 Composite Performance Models

Pavement performance models were developed using the same methodology used to model pavement distress. The sigmoidal regression equation given in Equation 1, was used to model composite condition indices in a PCR versus age performance model as shown in Figure 26. The initial a coefficient, representing the PCR index at year 0, was fixed at 100 to solve for initial b and c coefficients. TableCurve 2D was then used to enter the sigmoidal regression equation into the UDF interface using initially estimated model coefficients for each roadway family. Similar to developing the distress curves, the c variable was held constant while allowing the a and b variable to change. TableCurve 2D was then used to determine the final a, b, c coefficients that best fit the data and final performance models were graphed using the Maple Software.

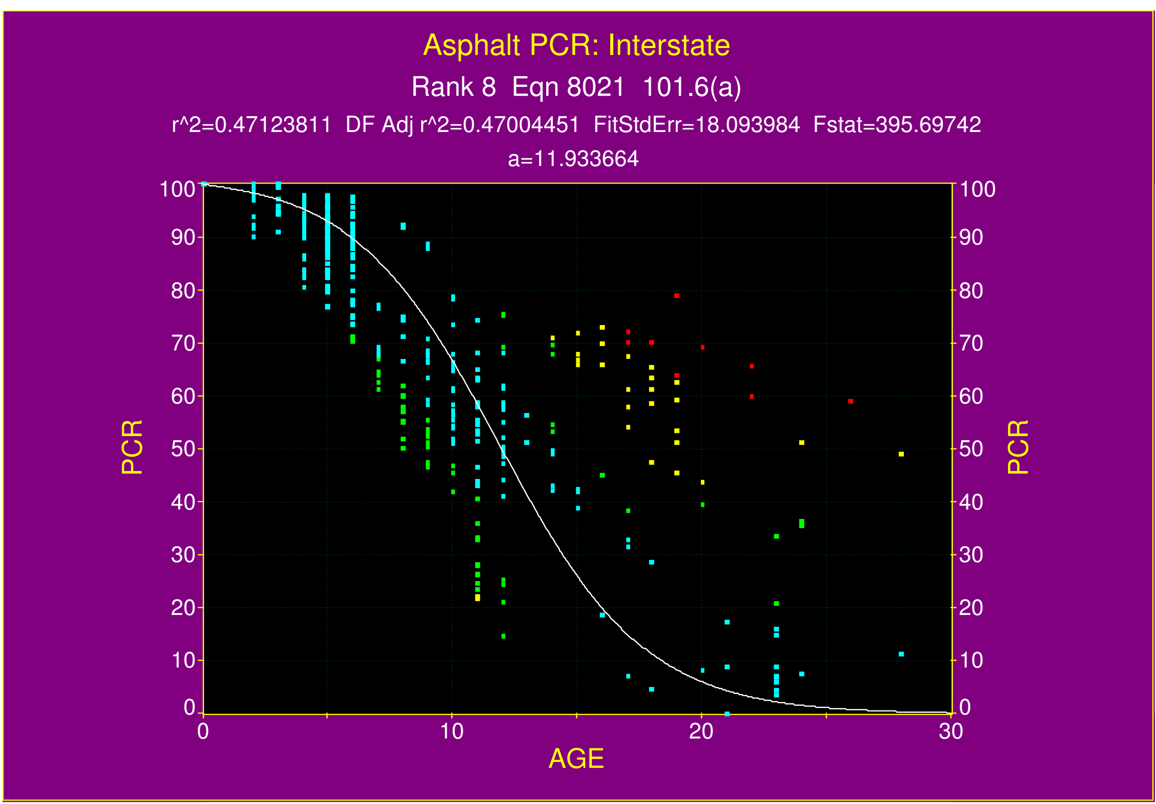

FIGURE 26: Composite performance model

3.4.9 Trigger Point Value Calculation

With the determination of a composite index and the development of pavement performance models, trigger points for decision trees were calculated using algebraic manipulation of the PCR equation. As shown in Figure 27, the NCDOT uses trigger points based on a roadway's PCR rating to determine an appropriate maintenance activity such as: preventative maintenance, light rehabilitation, heavy rehabilitation, and complete reconstruction. For this research the predefined PCR threshold values of 80, 60, and 30 were used for maintenance, rehabilitation, and reconstruction trigger points.

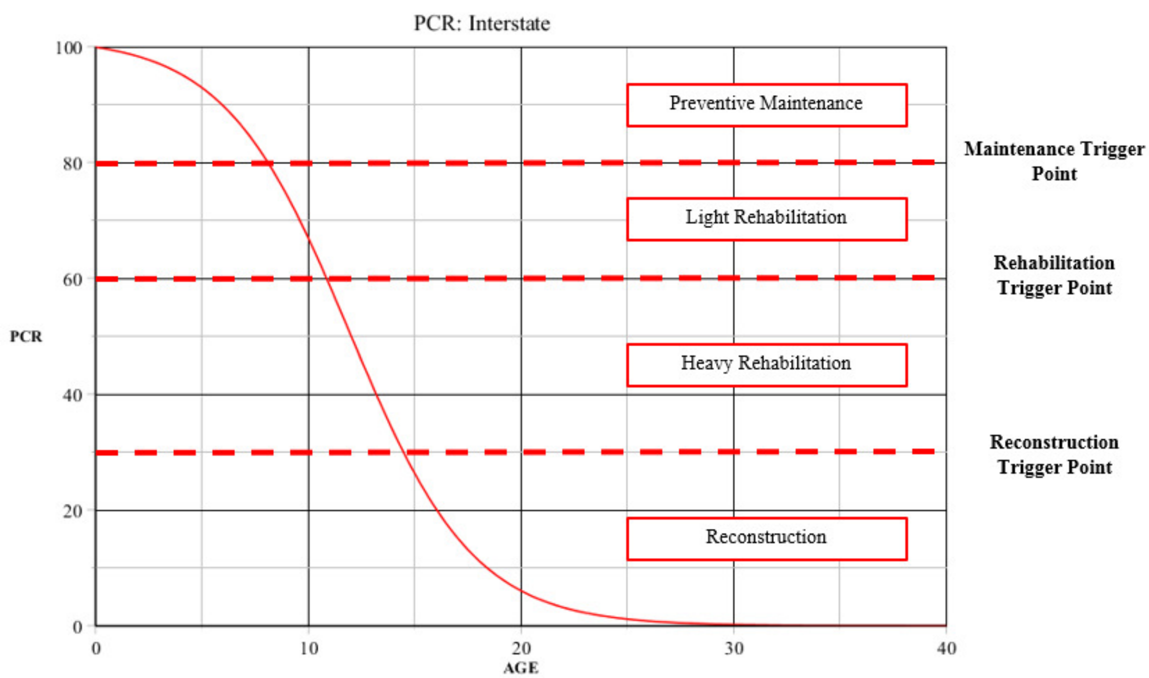

FIGURE 27: NCDOT PCR threshold values

The three PCR threshold values of 80/60/30 were used to determine the individual distress indices that will trigger a maintenance, rehabilitation, or reconstruction activity. To determine these values, the PCR equation and relative importance of each distress index was algebraically manipulated to determine each distress types trigger point. The first step was to take the PCR equation and solve for a single distress using the relative importance determined in the AHP process. An example of a trigger point equation for alligator cracking is shown in Equation 7.

$$\text{PCR} = (\text{W. F.}_{ALGTR})(\text{ALGTR CRCK}) + (\text{W. F.}_{TRNSVRS})(\text{Relative Weight}_{\text{B/A}}) + (\text{W. F.}_{LNGTDNL})(\text{Relative Weight}_{\text{C/A}}) + (\text{W. F.}_{LNGTDNL\ JNT})(\text{Relative Weight}_{\text{D/A}}) + (\text{W. F.}_{RVL})(\text{Relative Weight}_{\text{E/A}}) + (\text{W. F.}_{WP})(\text{Relative Weight}_{\text{F/A}}) + (\text{W. F.}_{NWP})(\text{Relative Weight}_{\text{G/A}}) + (\text{W. F.}_{RUT})(\text{Relative Weight}_{\text{H/A}}) \qquad \text{Equation 6}$$

Once the PCR equation was manipulated to solve for a single distress index, the PCR threshold values of 80/60/30 were set equal to the trigger point equation. An example of this calculation is provided in Equation 8.

$$80/60/30 = (\text{W. F.}_{ALGTR})(\text{ALGTR CRCK}) + (\text{W. F.}_{TRNSVRS})(\text{Relative Weight}_{\text{B/A}}) + (\text{W. F.}_{LNGTDNL})(\text{Relative Weight}_{\text{C/A}}) + (\text{W. F.}_{LNGTDNL\ JNT})(\text{Relative Weight}_{\text{D/A}}) + (\text{W. F.}_{RVL})(\text{Relative Weight}_{\text{E/A}}) + (\text{W. F.}_{WP})(\text{Relative Weight}_{\text{F/A}}) + (\text{W. F.}_{NWP})(\text{Relative Weight}_{\text{G/A}}) + (\text{W. F.}_{RUT})(\text{Relative Weight}_{\text{H/A}}) \qquad \text{Equation 7}$$

Using the PCR equation and the relative importance values, individual trigger points for each distress type were determined for each maintenance threshold. These trigger points can be used by the NCDOT to trigger various maintenance activities on a decision tree.

CHAPTER 4: RESULTS

4.1 Distress Models

4.1.1 Alligator Cracking

Alligator cracking distress models were developed for each asphalt roadway family. Figure 28 displays the alligator cracking model developed for the Interstate family and the complete set of models are provided in Appendix A. Table 8 displays the MAE values used to calculate the alligator cracking index and the coefficients that generated the best-fit distress model. The MAE_IN values were developed for light, moderate, and high severities of alligator cracking.

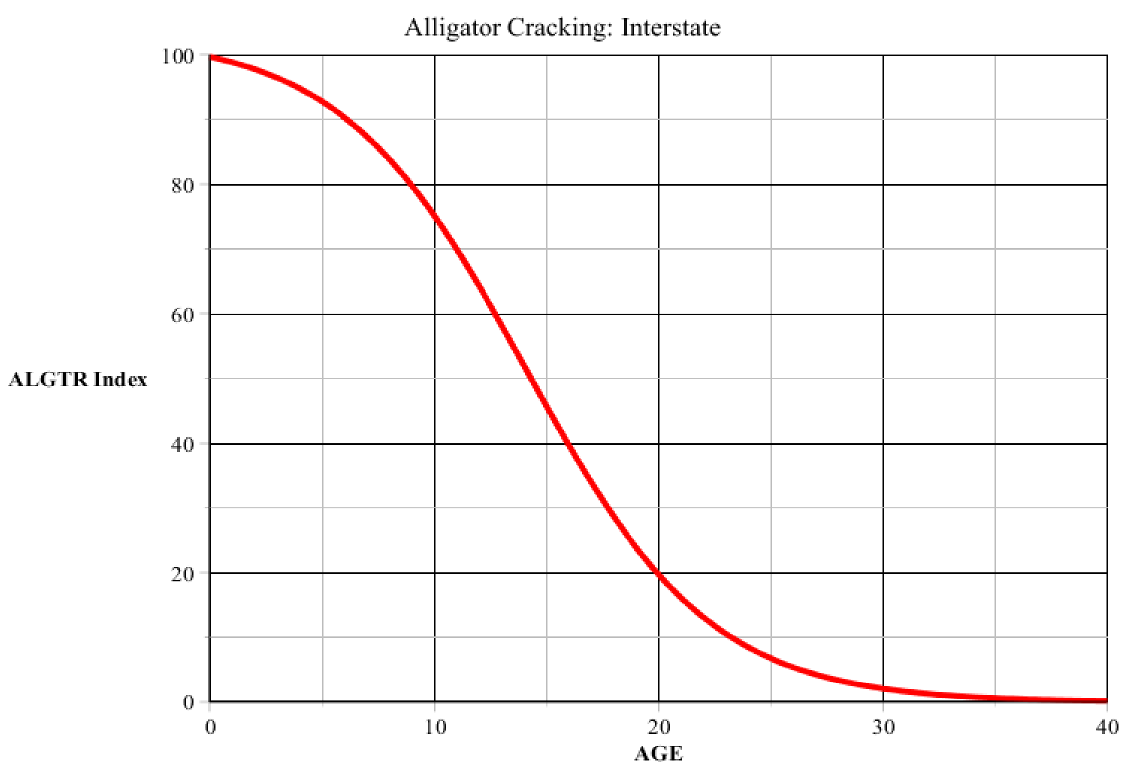

FIGURE 28: Interstate alligator cracking model

TABLE 8: Alligator cracking distress model parameters

Distress Type	Family	Model Coefficients a	b	c	Low Severity MAE Value	Med Severity MAE Value	High Severity MAE Value
Alligator Cracking (ALGTR)	Interstate	102.9	14.091	-4.107	32.496	2.65	0.399
	US 0-5K	104	13.268	-4.163			
	US 5-15K	105.5	11.486	-3.976			
	US 15K+	103.2	14.111	-4.098			
	NC 0-1K	103	18.495	-5.274			
	NC 1-5K	101	20.031	-4.439			
	NC 5K+	104	15.598	-4.877			

4.1.2 Transverse Cracking

Transverse cracking distress models were developed for each asphalt roadway family. Figure 29 displays the transverse cracking model developed for the Interstate family and the complete set of models are provided in Appendix B. Table 9 displays the MAE values used to calculate the transverse cracking index and the coefficients that generated the best-fit distress model. The MAE_IN values were developed for light, moderate, and high severities of alligator cracking.

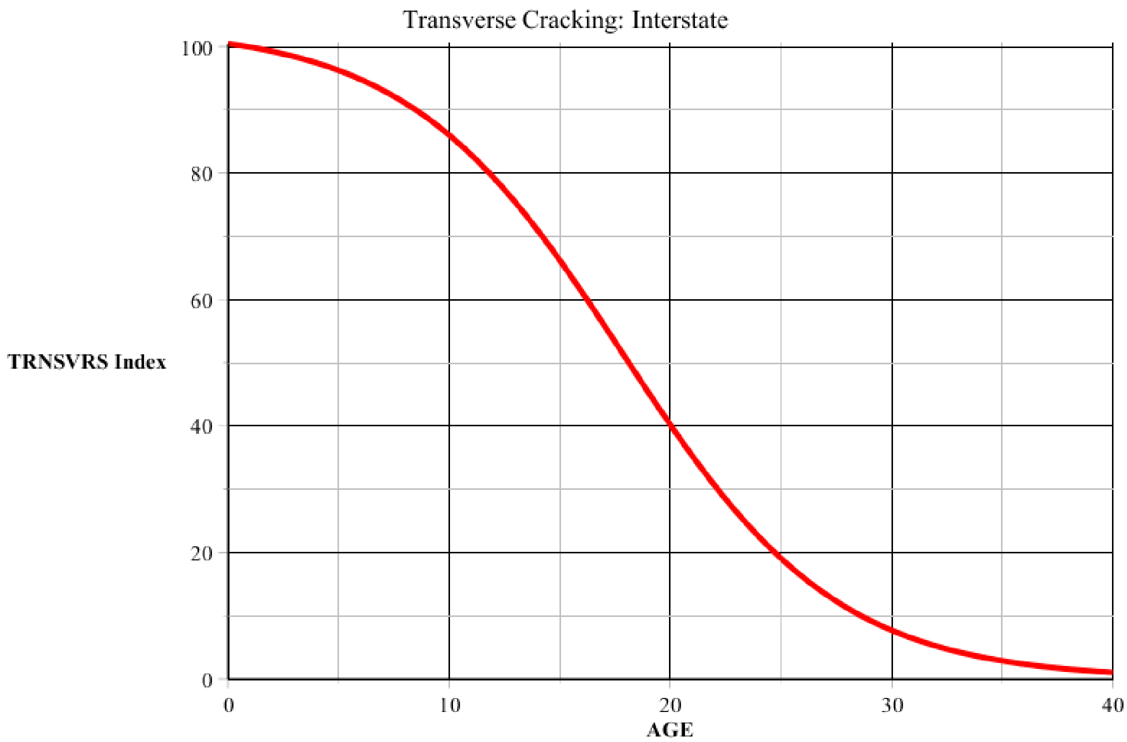

FIGURE 29: Interstate transverse cracking model

TABLE 9: Transverse cracking distress model parameters

Distress Type	Family	Model Coefficients			Low Severity MAE Value	Med Severity MAE Value	High Severity MAE Value
		a	b	c			
Transverse Cracking (TRNSVRS)	Interstate	103	17.847	-4.833	4.319	4.193	1.933
	US 0-5K	100.2	11.796	-1.973			
	US 5-15K	100.4	12.481	-2.269			
	US 15K+	101.6	11.946	-2.926			
	NC 0-1K	101	12.889	-2.999			
	NC 1-5K	100.3	11.175	-2.067			
	NC 5K+	100.4	13.054	-2.405			

4.1.3 Longitudinal Cracking

Longitudinal cracking distress models were developed for each asphalt roadway family. Figure 30 displays the longitudinal cracking model developed for the Interstate family and the complete set of models are provided in Appendix C. Table 10 displays the MAE values used to calculate the longitudinal cracking index and the coefficients that generated the best-fit distress model. The MAE_IN values were developed for light and high severities of longitudinal cracking as moderate severity is not collected for this distress type.

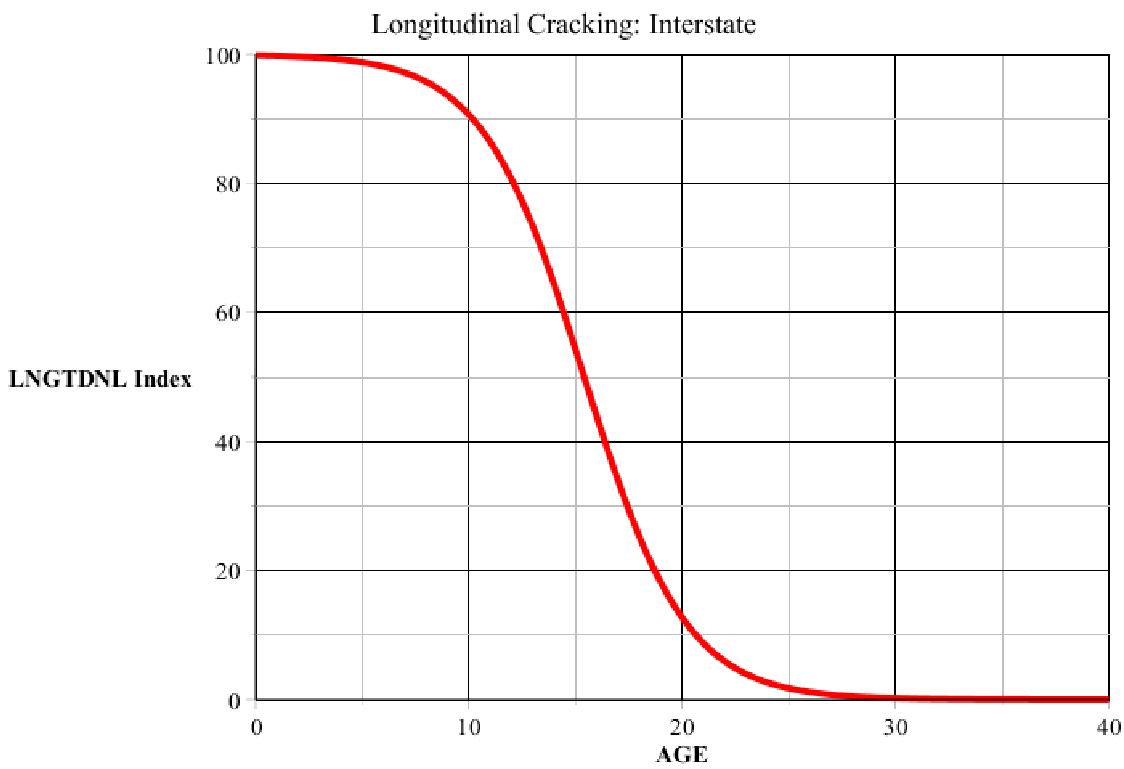

FIGURE 30: Interstate longitudinal cracking model

TABLE 10: Longitudinal cracking distress model parameters

Distress Type	Family	Model Coefficients a	b	c	Low Severity MAE Value	Med Severity MAE Value	High Severity MAE Value
Longitudinal Cracking (LNGTDNL)	Interstate	100	15.405	-2.385	4.681	0	1.996
	US 0-5K	100.2	13.903	-2.274			
	US 5-15K	100.2	13.622	-2.259			
	US 15K+	100.2	12.719	-2.145			
	NC 0-1K	100.3	14.050	-2.356			
	NC 1-5K	100.8	13.429	-2.531			
	NC 5K+	100.4	13.952	-2.562			

4.1.4 Longitudinal Lane Joint Cracking

Longitudinal lane joint cracking distress models were developed for each asphalt roadway family. Figure 31 displays the longitudinal lane joint cracking model developed for the Interstate family and the complete set of models are provided in Appendix D. Table 11 displays the MAE values used to calculate the longitudinal lane joint cracking index and the coefficients that generated the best-fit distress model. The MAE_IN value was developed solely for light severity of longitudinal lane joint cracking as moderate and high severities are not collected for this distress type.

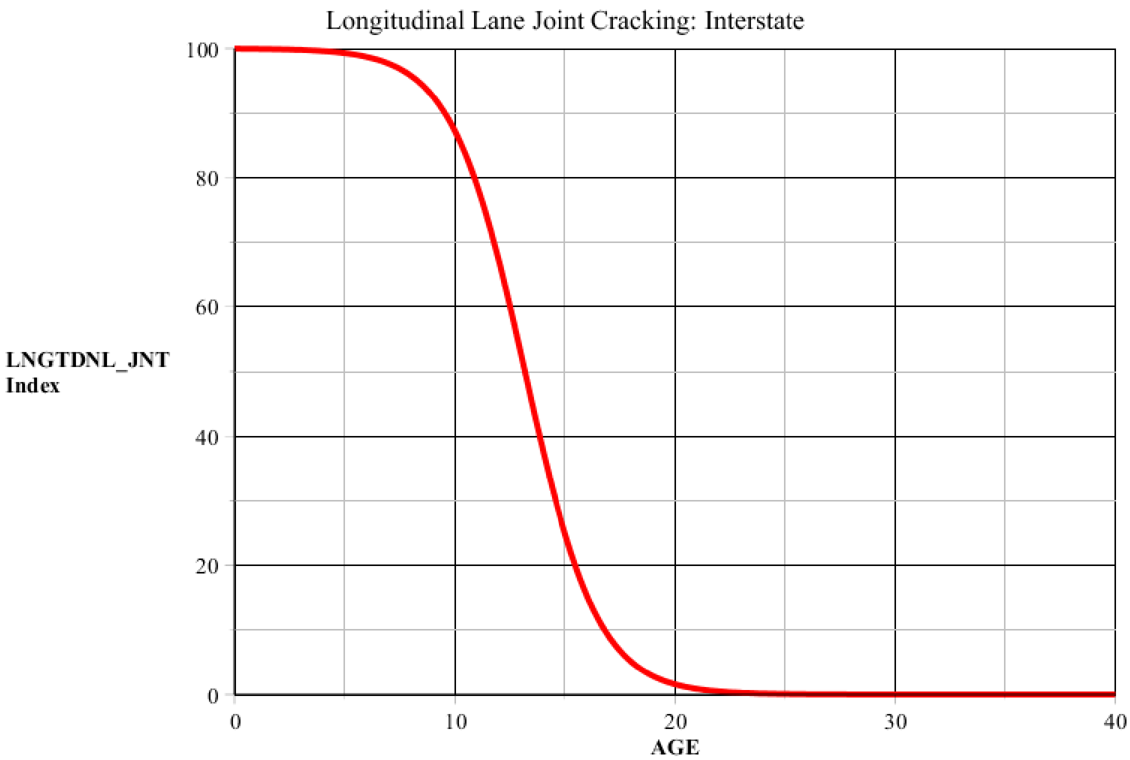

FIGURE 31: Interstate longitudinal lane joint cracking model

TABLE 11: Longitudinal lane joint cracking distress model parameters

Distress Type	Family	Model Coefficients			Low Severity MAE Value	Med Severity MAE Value	High Severity MAE Value
		a	b	c			
Longitudinal Lane Joint Cracking (LNGTDNL_JNT)	Interstate	100	13.184	-1.654	0.414	0	0
	US 0-5K	100.9	13.240	-2.063			
	US 5-15K	100.6	12.485	-1.752			
	US 15K+	101	13.225	-2.106			
	NC 0-1K	100	18.845	-2.348			
	NC 1-5K	100.3	15.977	-2.163			
	NC 5K+	100.3	14.816	-1.931			

4.1.5 Raveling

Raveling distress models were developed for each asphalt roadway family. Figure 32 displays the raveling model developed for the Interstate family and the complete set of models are provided in Appendix E. Table 12 displays the MAE values used to calculate the raveling index and the coefficients that generated the best-fit distress model. The MAE_IN values were developed for light, moderate, and high severities of raveling.

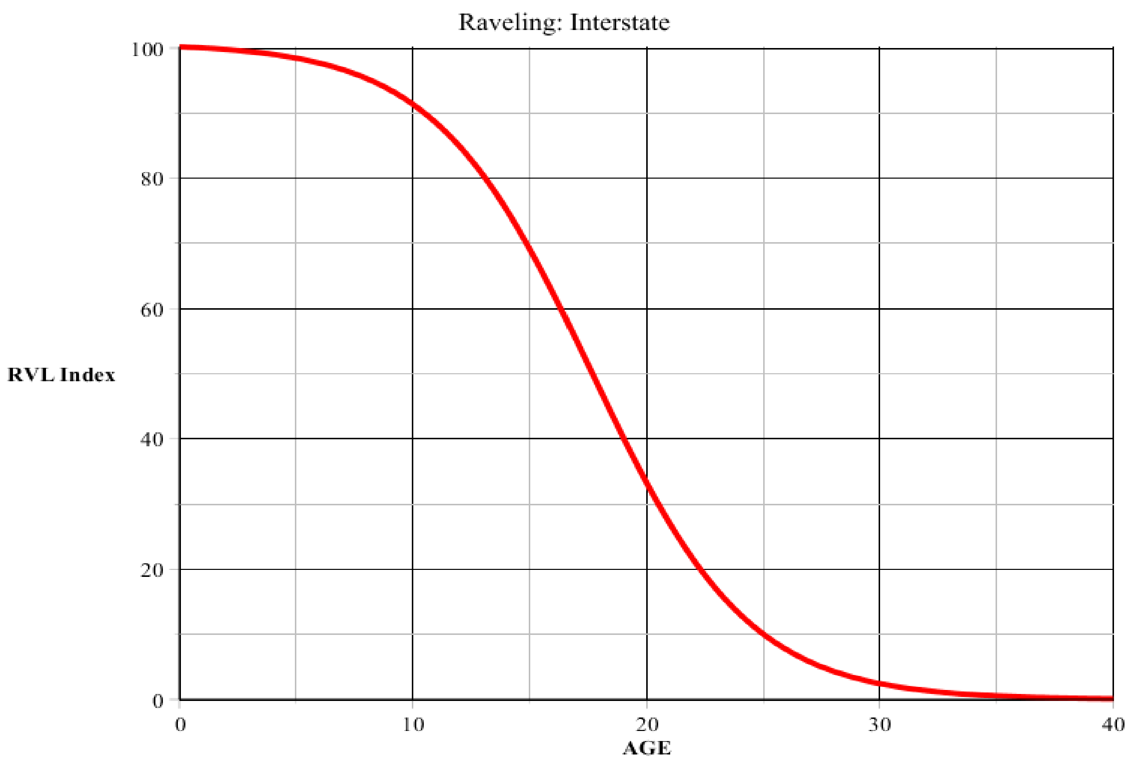

FIGURE 32: Interstate raveling model

TABLE 12: Raveling distress model parameters

Distress Type	Family	Model Coefficients			Low Severity MAE Value	Med Severity MAE Value	High Severity MAE Value
		a	b	c			
Raveling (RVL)	Interstate	100.7	17.635	-3.347	42.865	9.154	4.314
	US 0-5K	100.2	15.513	-2.686			
	US 5-15K	100.6	14.904	-2.926			
	US 15K+	101	13.698	-2.969			
	NC 0-1K	101.7	15.410	-3.757			
	NC 1-5K	101	14.271	-3.119			
	NC 5K+	102.2	12.419	-3.253			

4.1.6 Patching (Non-Wheel Path)

Non-wheel path patching distress models were developed for each asphalt roadway family. Figure 33 displays the non-wheel path patching model developed for the Interstate family and the complete set of models are provided in Appendix F. Table 13 displays the MAE values used to calculate the non-wheel path patching index and the coefficients that generated the best-fit distress model. The MAE_IN value was developed solely for light severity non-wheel path patching as moderate and high severities are not collected for this distress type.

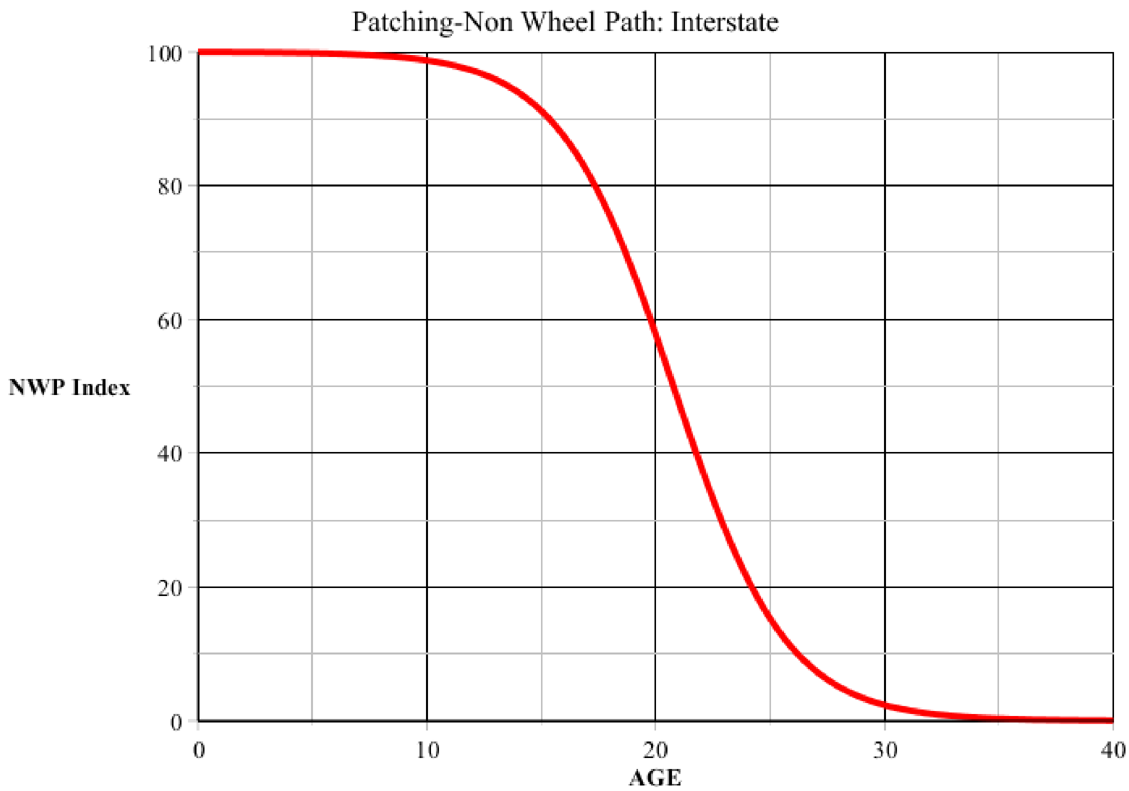

FIGURE 33: Interstate patching (non-wheel path) model

TABLE 13: Patching (non-wheel path) distress model parameters

Distress Type	Family	Model Coefficients			Low Severity MAE Value	Med Severity MAE Value	High Severity MAE Value
		a	b	c			
Patching (Non-Wheel Path) (NWP)	Interstate	100	20.777	-2.469	3.967	0	0
	US 0-5K	100	19.720	-3.069			
	US 5-15K	100.3	20.436	-3.759			
	US 15K+	100	17.789	-2.807			
	NC 0-1K	100.6	19.639	-3.259			
	NC 1-5K	100.6	18.452	-2.996			
	NC 5K+	101	18.671	-3.599			

4.1.7 Patching (Wheel-Path)

Wheel path patching distress models were developed for each asphalt roadway family. Figure 34 displays the wheel path patching model developed for the Interstate family and the complete set of models are provided in Appendix G. Table 14 displays the MAE values used to calculate the wheel path patching index and the coefficients that generated the best-fit distress model. The MAE_IN value was developed solely for light severity wheel path patching as moderate and high severities are not collected for this distress type.

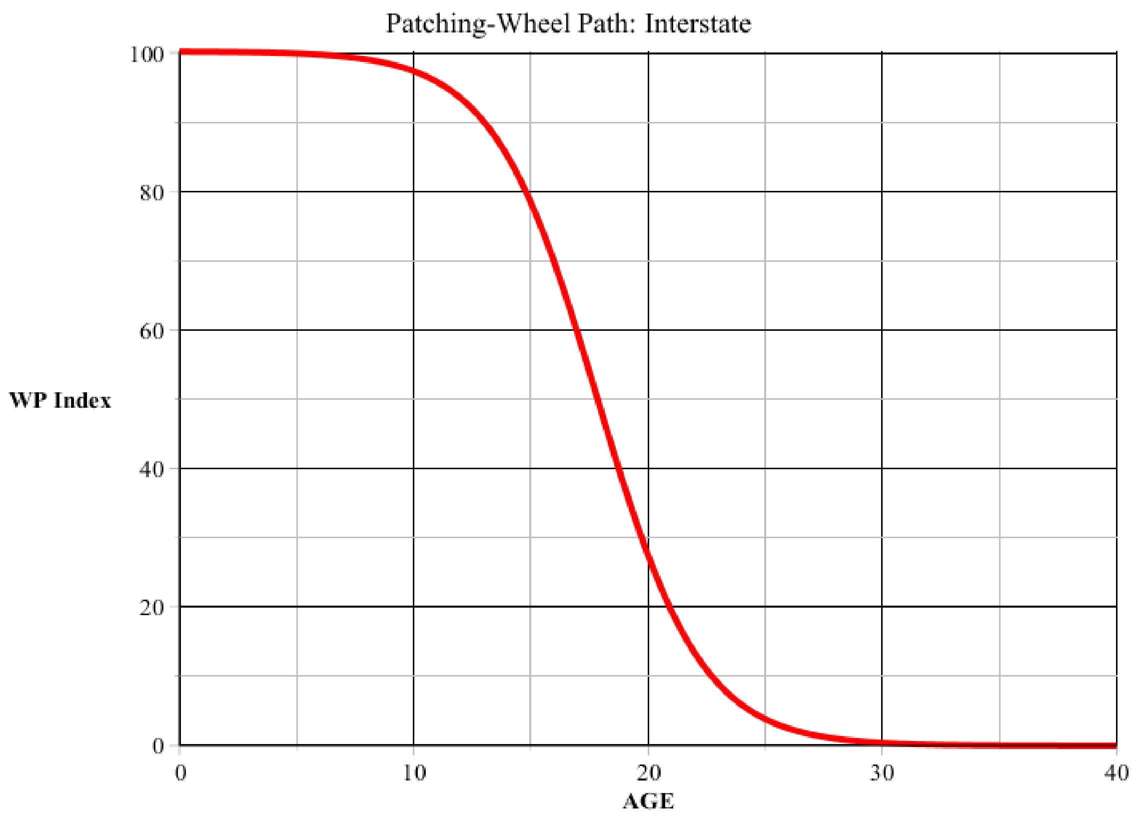

FIGURE 34: Interstate patching (wheel path) model

TABLE 14: Patching (wheel path) distress model parameters

Distress Type	Family	Model Coefficients			Low Severity MAE Value	Med Severity MAE Value	High Severity MAE Value
		a	b	c			
Patching (Wheel Path) (WP)	Interstate	100.2	17.837	-2.222	12.887	0	0
	US 0-5K	100.4	21.822	-3.938			
	US 5-15K	101	19.322	-4.238			
	US 15K+	100.3	18.401	-3.290			
	NC 0-1K	101	17.749	-3.002			
	NC 1-5K	100.8	18.259	-3.495			
	NC 5K+	101.9	16.452	-4.011			

4.1.8 Rutting

Sigmoidal regression analysis of this distress type was found not to fit the data appropriately since this distress is measured in depth rather than area or length. Analysis showed that the power function fit the rutting data better than the sigmoidal equation. The power function used to model this distress type is as follows:

$Rutting\ Index = 100 - a \times (Age)^{1.5}$.

Figure 35 displays the rutting model developed for the Interstate family and the complete set of models are provided in Appendix H. Table 15 displays the power function used to calculate the rutting index and the coefficients that generated the best-fit distress model.

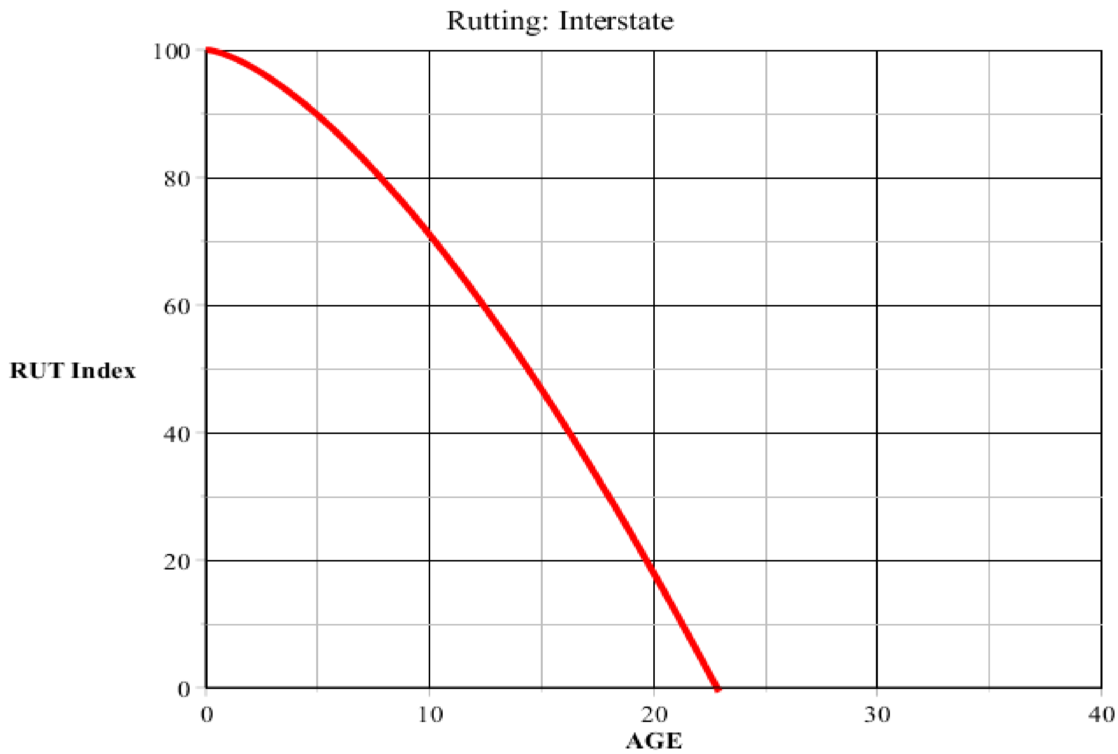

FIGURE 35: Interstate rutting model

TABLE 15: Rutting distress model parameters

Distress Type	Family	Model Coefficients a	Low Severity MAE Value	Med Severity MAE Value	High Severity MAE Value
Rutting (RUT)	Interstate	0.917	$\text{Rutting Index} = 100 - (a \times AGE)^{1.5}$		
	US 0-5K	0.995			
	US 5-15K	1.021			
	US 15K+	0.984			
	NC 0-1K	1.002			
	NC 1-5K	1.023			
	NC 5K+	1.014			

4.2 Composite Performance Index

As discussed previously in section 3.4.7, a composite performance index was developed using the AHP method. Distress deduction points, shown in Table 5 of section 3.4.7 were calculated for each distress type and averaged to determine distress importance. Table 6, shown in section 3.4.7 displays the average deduction points calculated for each distress.

The average deduction points calculated using NCDOT's deduction point system were then transferred into a pairwise comparison matrix as shown in Figure 31 located in section 3.4.7. The pairwise comparison matrix was then imported into an AHP calculator to determine each distress's weight factor. Table 17 displays the weight factors calculated using the AHP method. The consistency index was determined to be 0 using equation 4 presented in section 3.4.7. Using equation 5, also presented in section 3.4.7, the consistency ratio was determined to be 0. This indicated that the comparisons between each asphalt distress are adequate and no re-evaluation needed to occur.

TABLE 16: Weight factors for asphalt distresses

<table>
<tr><th>Asphalt Distress Type</th><th>Weight Factor</th><td rowspan="9">Max Eigen Value = 8
C.I. = 0 C.R. = 0</td></tr>
<tr><td>Alligator Cracking
(ALGTR)</td><td>0.353</td></tr>
<tr><td>Transverse Cracking (TRNSVR)</td><td>0.143</td></tr>
<tr><td>Longitudinal Cracking
(LNGTDNL)</td><td>0.076</td></tr>
<tr><td>Longitudinal Lane Joint Cracking
(LNGTDNL_JNT)</td><td>0.059</td></tr>
<tr><td>Raveling
(RVL)</td><td>0.059</td></tr>
<tr><td>Patching Area-Wheel Path (WP)</td><td>0.100</td></tr>
<tr><td>Patching Area-Non Wheel Path
(NWP)</td><td>0.059</td></tr>
<tr><td>Rutting
(RUT)</td><td>0.151</td></tr>
</table>

With the computation of weight factors for each distress type, the PCR formula was developed to be as follows:

$$PCR = 0.353(ALGTR) + 0.143(TRNSVRS) + 0.076(LNGTDNL) \\ + 0.059(LNGTDNL\ JNT) + 0.059(RVL) + 0.1(WP) + 0.059(NWP) \\ + 0.151(RUT)$$

Where:

PCR = Pavement Condition Rating

ALGTR = Alligator Cracking Index

TRNSVRS = Transverse Cracking Index

LNGTDNL = Longitudinal Cracking Index

LNGTDNL_JNT = Longitudinal Lane Joint Cracking Index

RVL = Raveling Index

WP = Patching (Wheel Path) Index

NWP = Patching (Non-Wheel Path) Index

RUT = Rutting Index

4.3 PCR Models

PCR models were developed using the calculated distress indices and the PCR equation defined in section 4.2. Figure 36 displays the PCR model developed for the Interstate family and the complete set of PCR models can be found in Appendix I. Table 18 includes the complete set of best-fit model parameters for each asphalt roadway family.

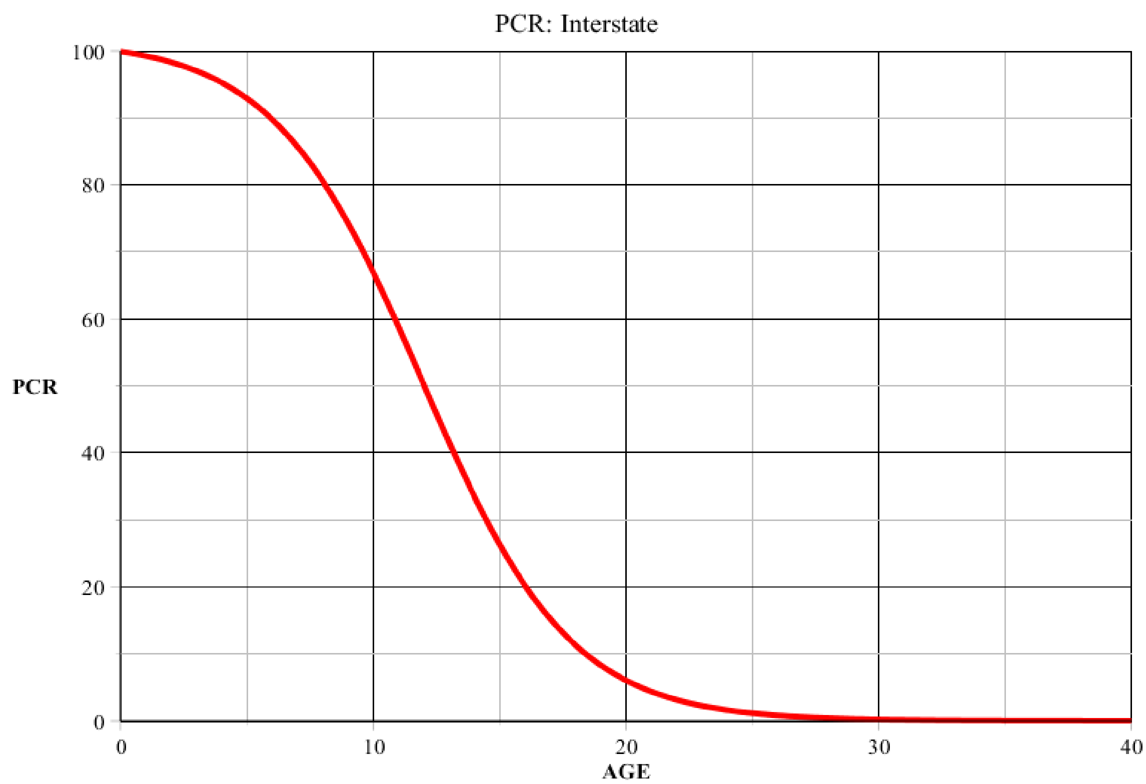

FIGURE 36: Interstate PCR model

TABLE 17: PCR model parameters

Family	Model Parameters		
	a	b	c
Interstate	101.6	11.934	-2.924
US 0-5K	104.7	10.842	-3.552
US 5-15K	102.9	12.157	-3.456
US 15K +	103.1	11.096	-3.216
NC 0-1K	104.4	11.884	-3.807
NC 1-5K	103.7	11.915	-3.616
NC 5K +	106.1	12.198	-4.368

4.4 Maintenance Trigger Points

As discussed in section 3.4.9, trigger points were calculated using the PCR equation and the NCDOT maintenance thresholds. Trigger points help aid the NCDOT in selecting appropriate maintenance actions when the overall pavement condition reaches a certain threshold. The PCR threshold levels the NCDOT uses are set at 80, 60 and 30, which correlate to preventative maintenance (100-80), light rehabilitation (80-60), heavy rehabilitation (60-30), and reconstruction (30-0). To calculate a specific distress trigger point, equation 8 presented in section 3.4.9 was used. This allowed for a distress index that triggers a maintenance activity to be solved for. Once distress indices were solved for, the average was taken for each PCR threshold. Table 19 presents the results of this process.

TABLE 18: Trigger point results

Asphalt Pavement Trigger Point Values									
PCR Threshold	ALGTR	TRNSVRS	LNGTDNL	LNGTDNL_JNT	RVL	WP	NWP	RUT	Average Composite Distress Index
80	121.1	49.0	26.0	20.2	20.2	34.6	20.2	51.9	42.9
60	90.8	36.8	19.5	15.1	15.1	26.0	15.1	38.9	32.2
30	45.4	18.4	9.7	7.6	7.6	13.0	7.6	19.5	16.1

CHAPTER 5: DISTRESS AND PERFORMANCE MODEL EVALUATION

The foundation of this research was to develop new distress and performance models using updated automated asphalt pavement condition data. This data, provided by the NCDOT was considered to be more suitable than previous automated data collected in 2012 and 2013 because of the change in their raw data processing algorithm.

Whenever new data is available, distress and performance models should be updated and compared to previously developed models to ensure that collected data is of quality and the overall PMS is effective. As indicated in section 2.10, the best method of comparing multiple models is the visual method. This method was implemented to compare newly developed distress and performance models (PMS III) to models that were developed using NCDOT's windshield data (PMS I) and also models that were developed using automated data from 2012 and 2013 (PMS II). The following sections within this chapter present the model comparisons between each phase of NCDOT's PMS.

5.1 Distress Model Comparisons

Distress models were compared between phase two and phase three of NCDOT's PMS. Phase two (PMS II) implemented automated data from 2012 and 2013 and phase three (PMS III) implemented automated data from 2014.

5.1.1 Alligator Cracking Comparison

Alligator cracking comparison models are shown in Figures 37 – 43. In practical terms, a majority of alligator cracking models developed in PMS II were consistent with the models developed in this research. The largest discrepancy between alligator cracking models occurred in the US roadway family with average annual daily traffic (AADT) exceeding 15,000 vehicles per day and the NC roadway family with an AADT of 0 – 1,000 vehicles per day as shown in Figures 40 and 41. In these two roadway families, PMS II models presented higher deterioration rates than PMS III models. To determine if there was a statistical difference between models, the *b* variable which controls the horizontal shift of the model was analyzed. If the *b* variable of PMS II models fell within the confidence interval of the models developed in this study there was no statistical difference in models. As shown in Table 19, there was a statistical difference at 95% confidence in 6 out of 7 models (85.7%).

TABLE 19: Alligator cracking confidence intervals

Model Family	**95% C.I. for b variable**	**PMS II b variable**
ALGTR Interstate	(13.79,14.39)	13.44
ALGTR US 0-5K	(13.07,13.47)	13.72
ALGTR US 5-15K	(11.34,11.64)	11.35*
ALGTR US 15K +	(13.84,14.39)	8.59
ALGTR NC 0-1K	(18.05,18.94)	11.00
ALGTR NC 1-5K	(19.78,20.28)	12.13
ALGTR NC 5K +	(15.41,15.78)	11.48
* denotes no statistical difference between models		

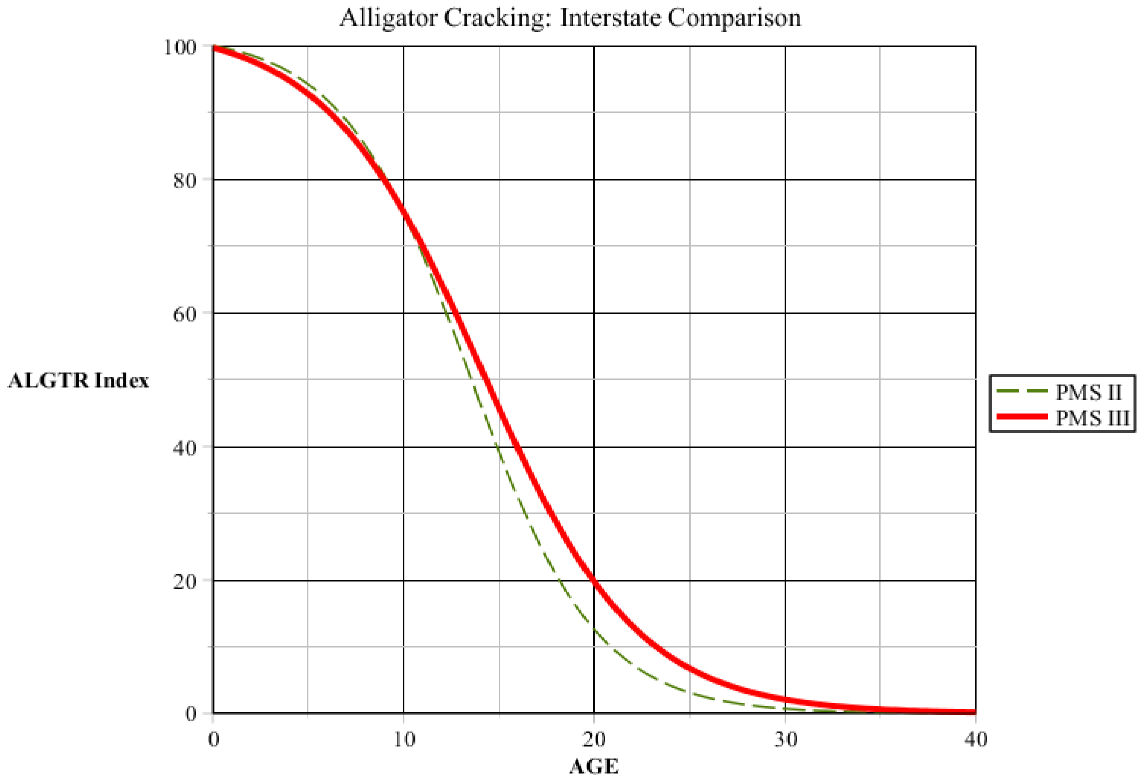

FIGURE 37: Alligator cracking – Interstate comparison

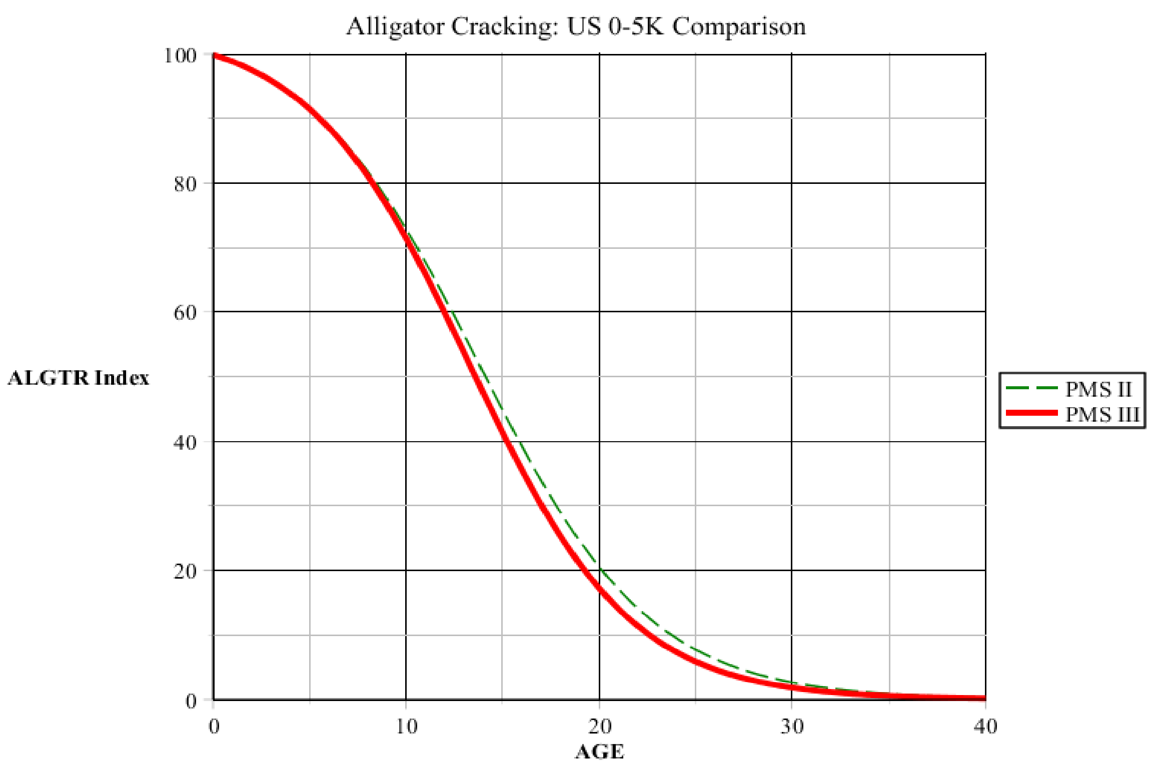

FIGURE 38: Alligator cracking – US 0-5K comparison

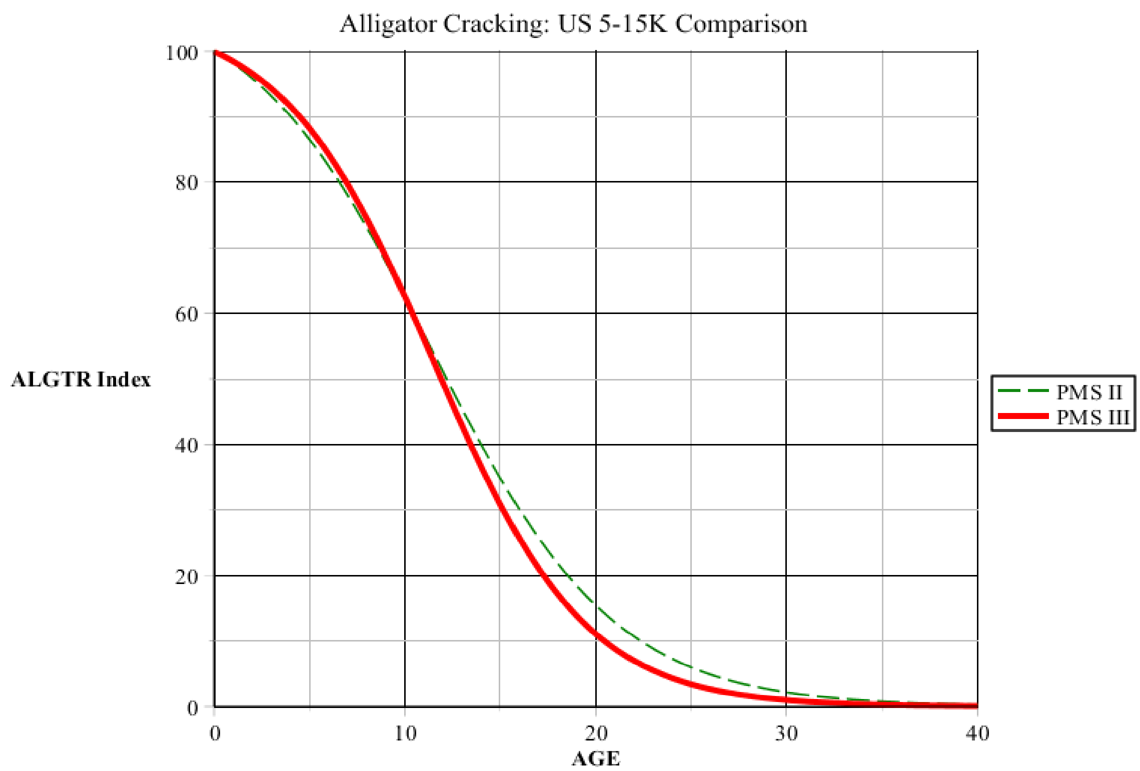

FIGURE 39: Alligator cracking – US 5-15K comparison

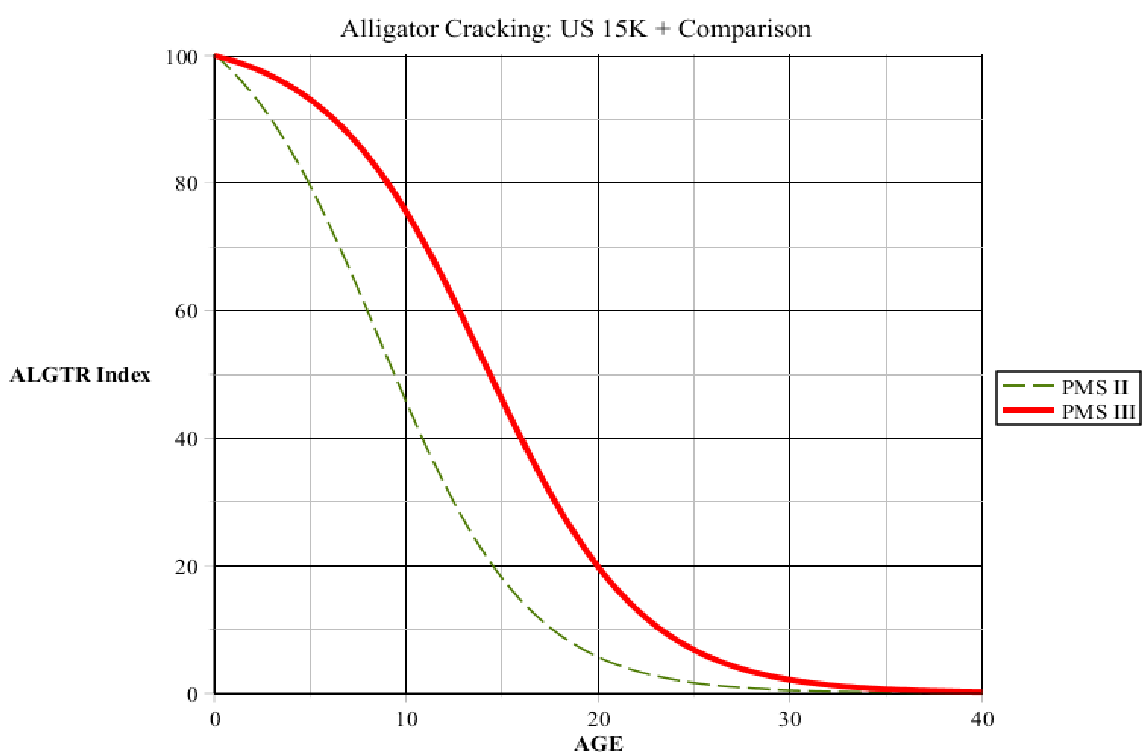

FIGURE 40: Alligator cracking – US 15K + comparison

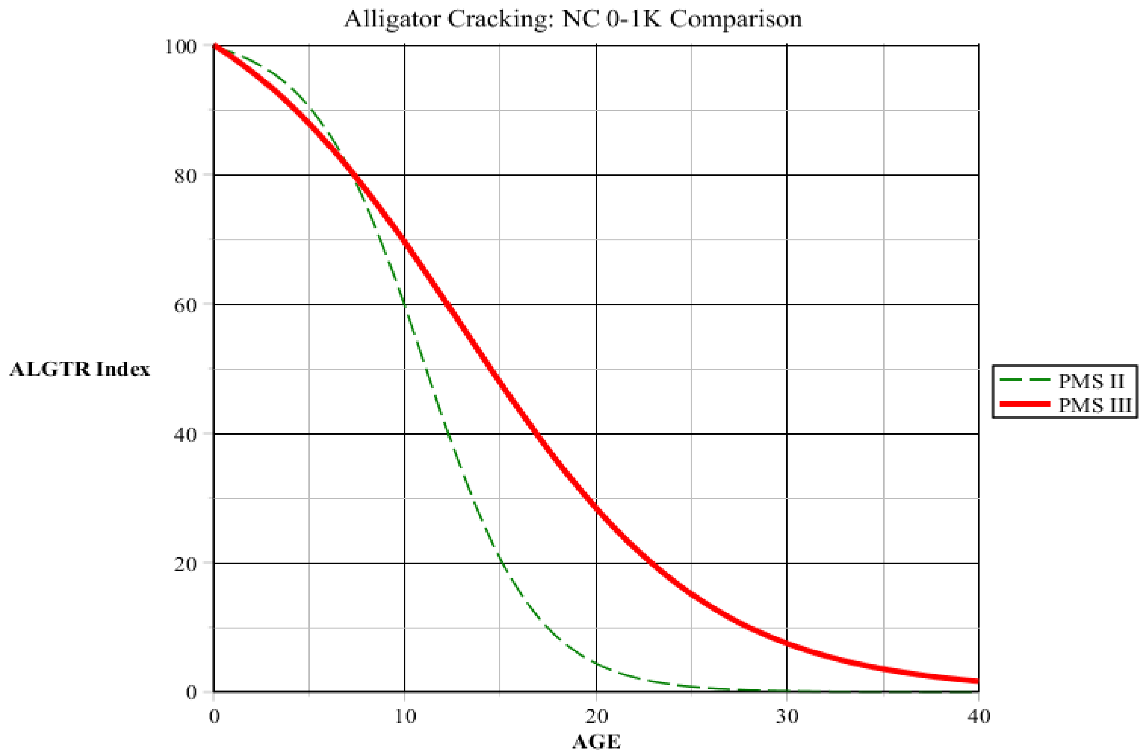

FIGURE 41: Alligator cracking – NC 0-1K comparison

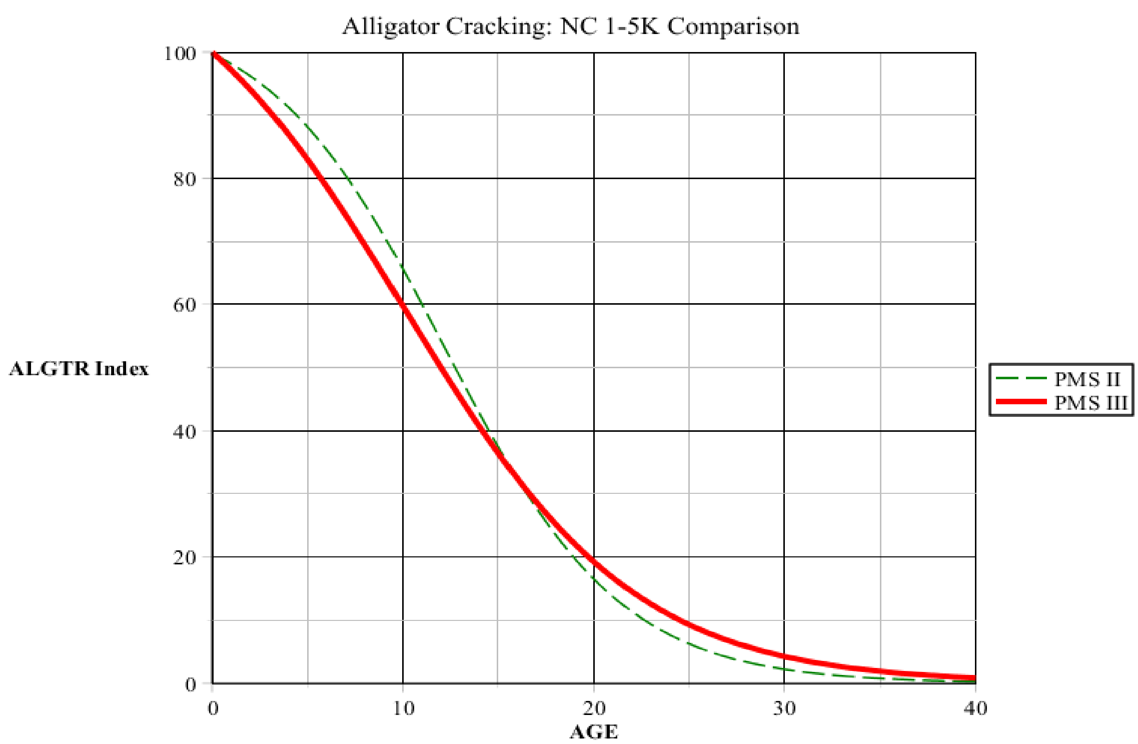

FIGURE 42: Alligator cracking – NC 1-5K comparison

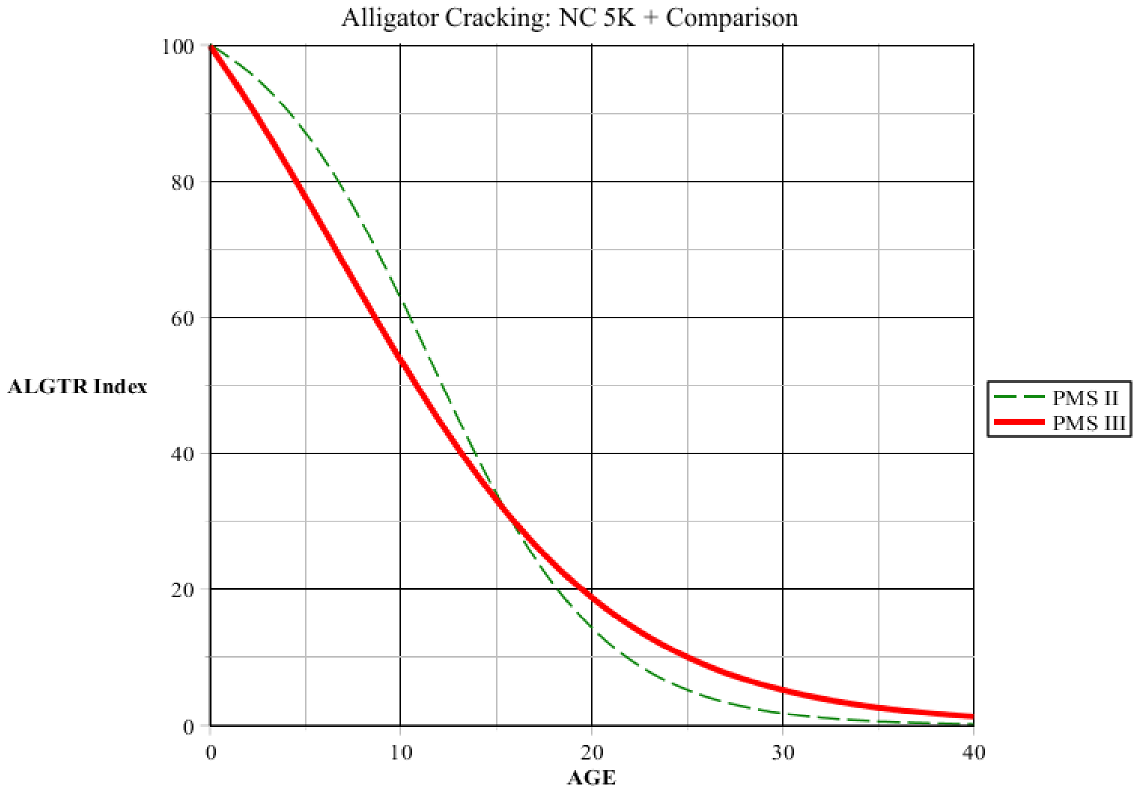

FIGURE 43: Alligator cracking – NC 5K + comparison

5.1.2 Transverse Cracking Comparison

Transverse cracking comparison models are shown in Figures 44 – 50. In practical terms, transverse cracking models developed in PMS II were fairly consistent with the models developed in this research. The largest discrepancy between these models occurred in the NC roadway family with an AADT of 0 – 1,000 vehicles per day and the NC roadway family with an AADT exceeding 5,000 vehicles per day, as shown in Figure 48 and 50 respectively. In these two roadway families, PMS II models presented higher transverse cracking deterioration rates than PMS III models. As shown in Table 20, at 95% confidence there was a statistical difference in 5 out of 7 (71.4%) models.

TABLE 20: Transverse cracking confidence intervals

Model Family	95% C.I. for b variable	PMS II b variable
TRNSVRS Interstate	(17.47,18.23)	16.39
TRNSVRS US 0-5K	(11.36,11.78)	10.91
TRNSVRS US 5-15K	(12.34,12.62)	12.58*
TRNSVRS 15K +	(11.70,12.19)	11.33
TRNSVRS NC 0-1K	(12.42,13.36)	9.54
TRNSVRS NC 1-5K	(11.02,11.33)	11.13*
TRNSVRS NC 5K +	(12.80,13.30)	10.75
* denotes no statistical difference between models		

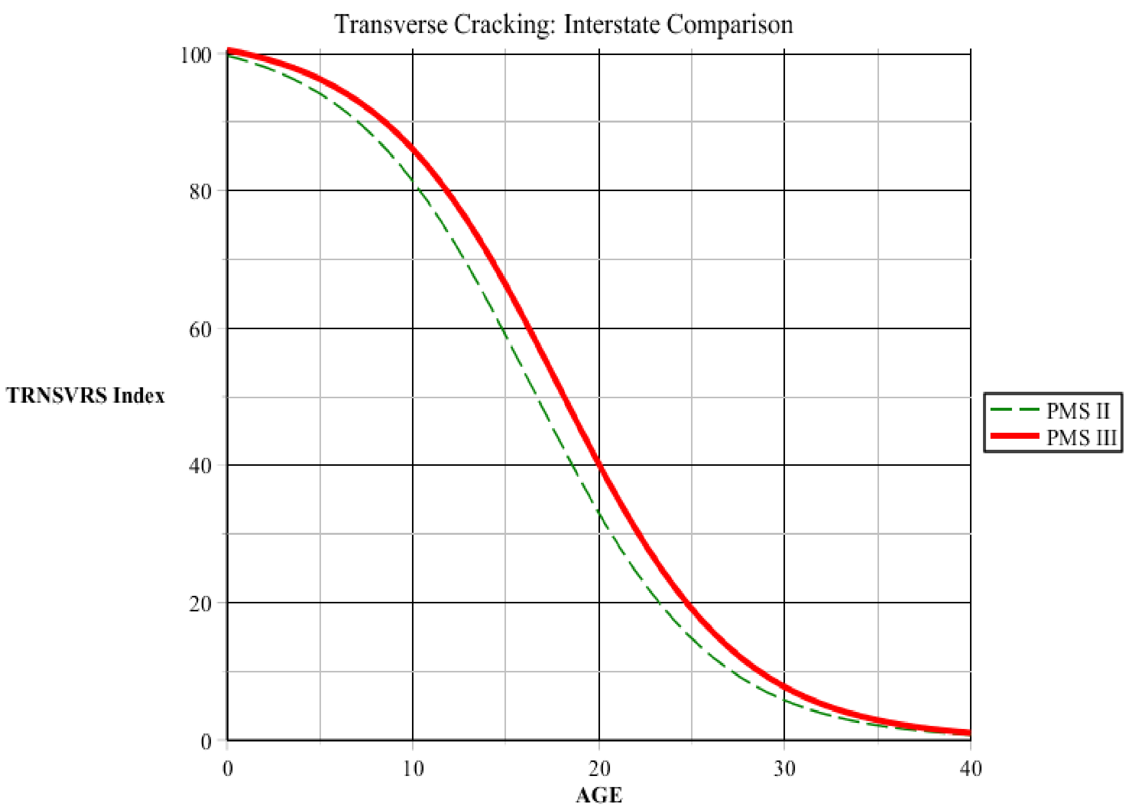

FIGURE 44: Transverse cracking – Interstate comparison

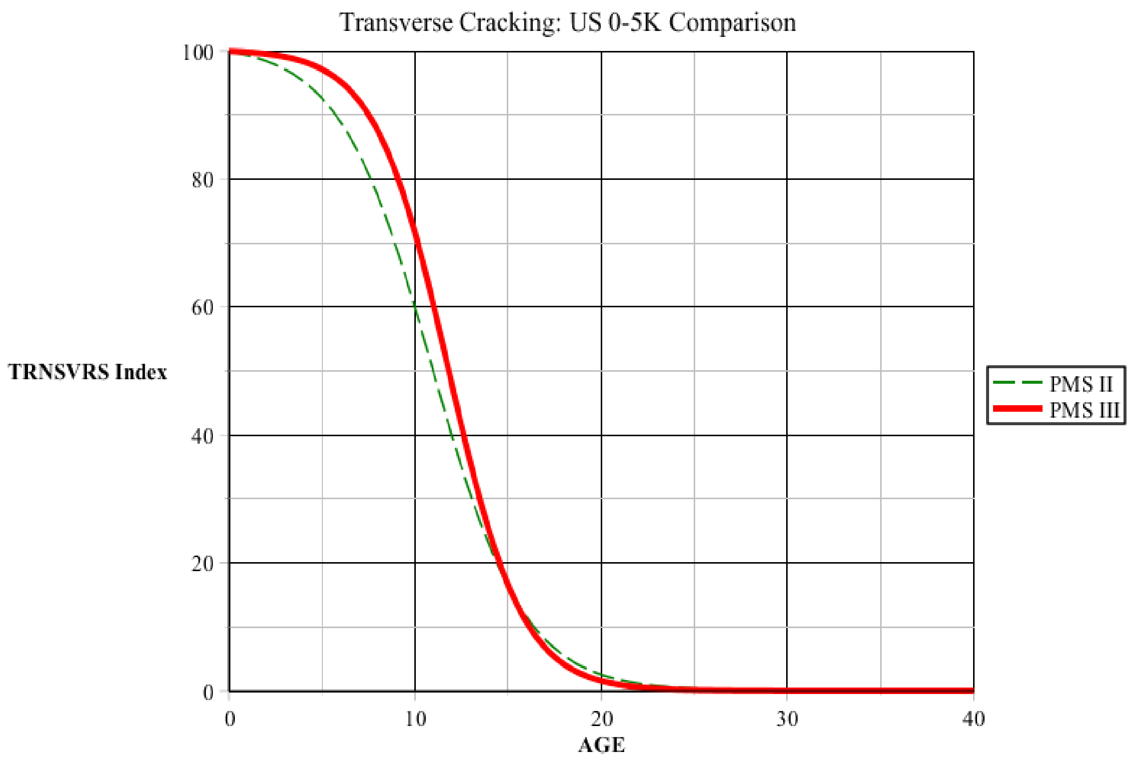

FIGURE 45: Transverse cracking – US 0-5K comparison

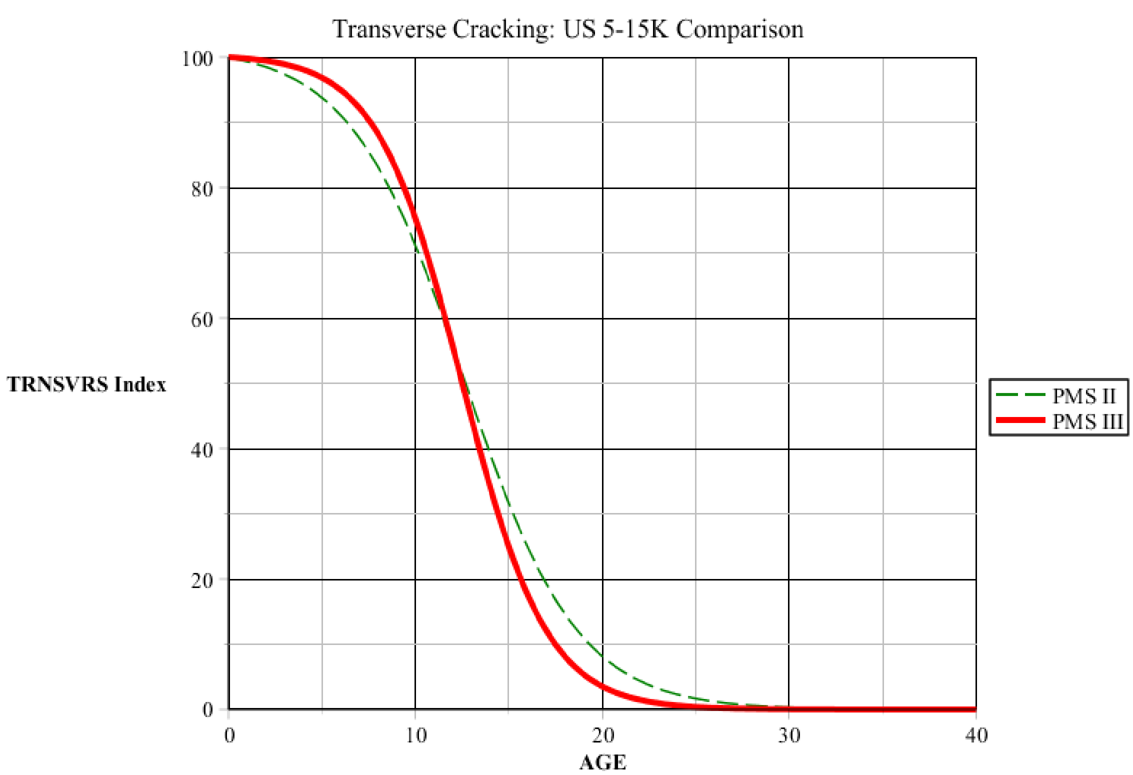

FIGURE 46: Transverse cracking – US 5-15K comparison

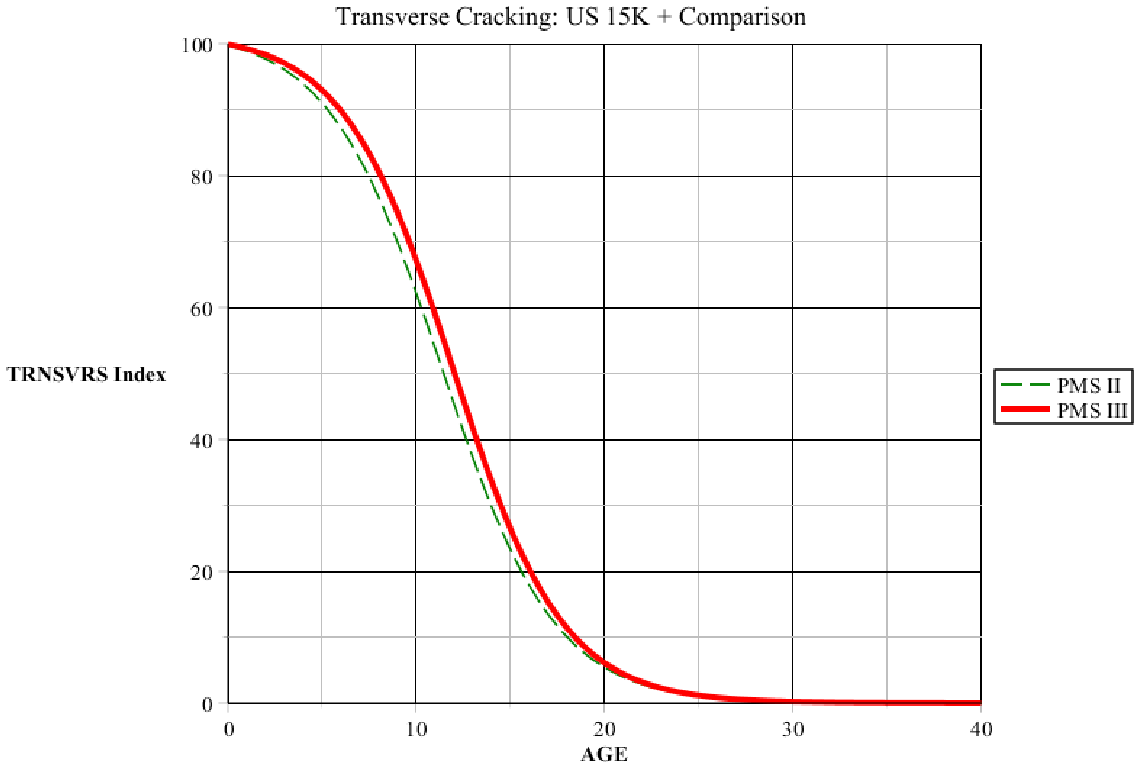

FIGURE 47: Transverse cracking – US 15K + comparison

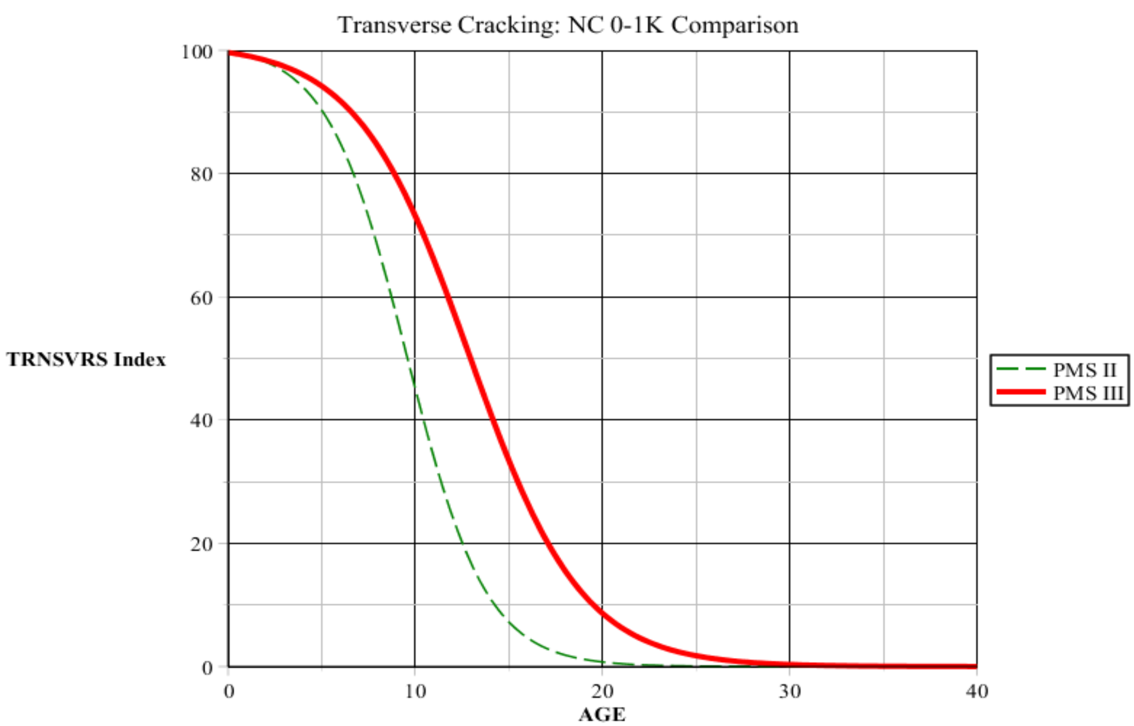

FIGURE 48: Transverse cracking – NC 0-1K comparison

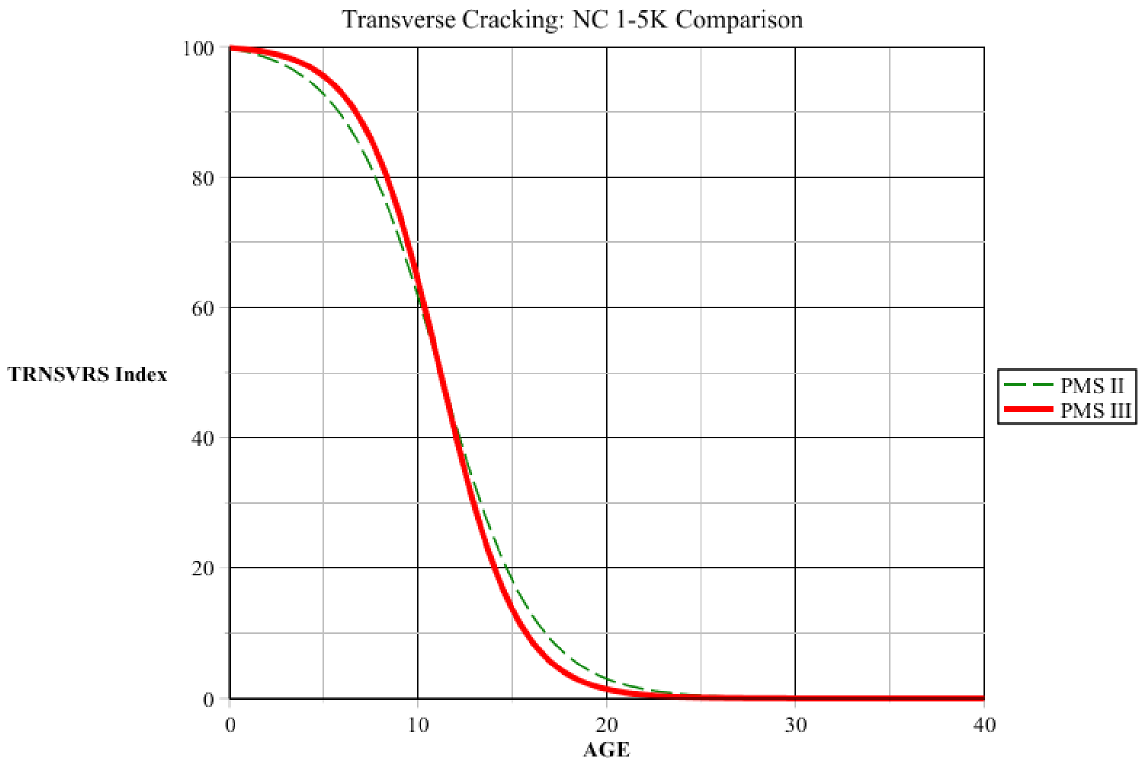

FIGURE 49: Transverse cracking – NC 1-5K comparison

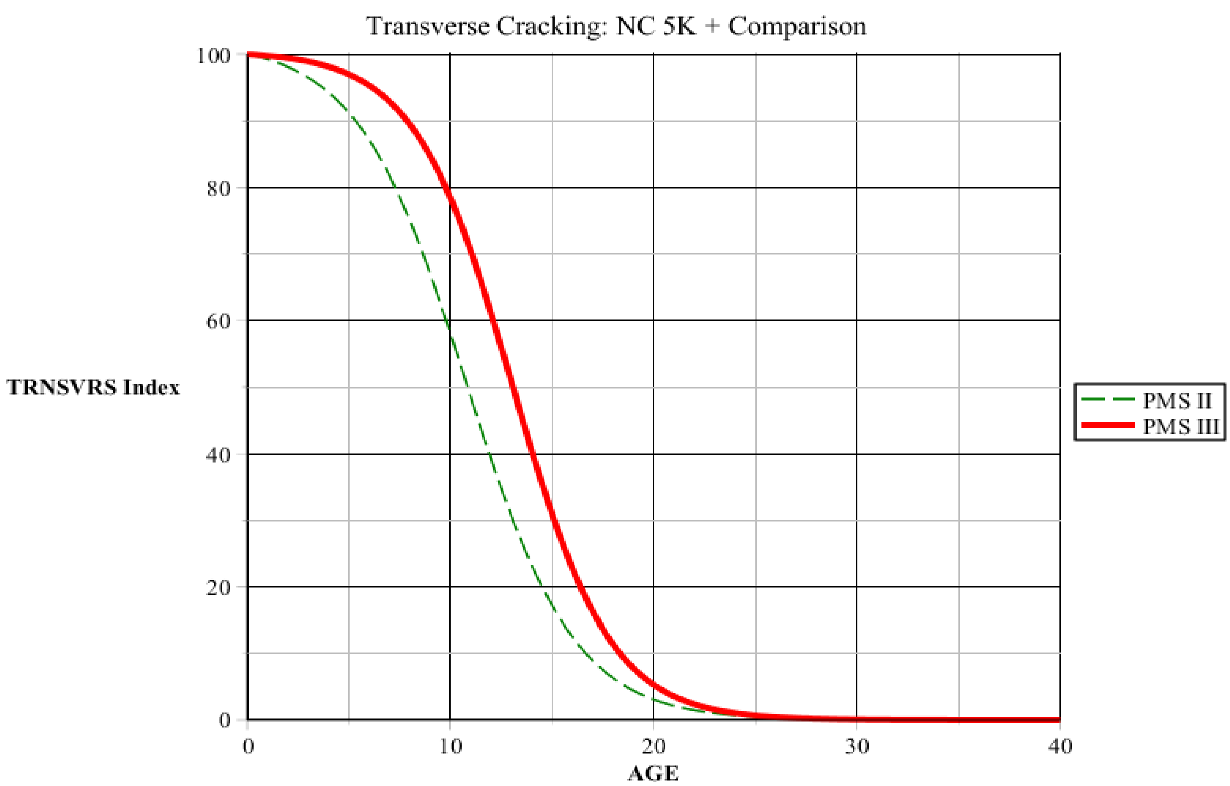

FIGURE 50: Transverse cracking – NC 5K + comparison

5.1.3 Longitudinal Cracking Comparison

Longitudinal cracking models developed in this research presented higher deterioration rates compared to PMS II as shown in Figures 51 - 53. However, as shown in Figures 54 - 57, US roadways with traffic exceeding 15,000 vehicles per day and all NC roadway family models developed in this research presented higher deterioration rates until year ten of service life. After year ten of service life for these roadway families, deterioration rates were less significant than that of PMS II. As shown in Table 21, there is a statistical difference in 6 out of 7 (85.7%) models at 95% confidence.

TABLE 21: Longitudinal cracking confidence intervals

Model Family	95% C.I. for b variable	PMS II b variable
LNGTDNL Interstate	(14.85,15.96)	16.57
LNGTDNL US 0-5K	(13.57,14.24)	14.47
LNGTDNL US 5-15K	(13.44,13.80)	15.32
LNGTDNL US 15K +	(12.29,13.15)	12.18
LNGTDNL NC 0-1K	(13.52,14.58)	12.36
LNGTDNL NC 1-5K	(13.15,13.71)	13.76
LNGTDNL NC 5K +	(13.79,14.12)	13.97*
* denotes no statistical difference between models		

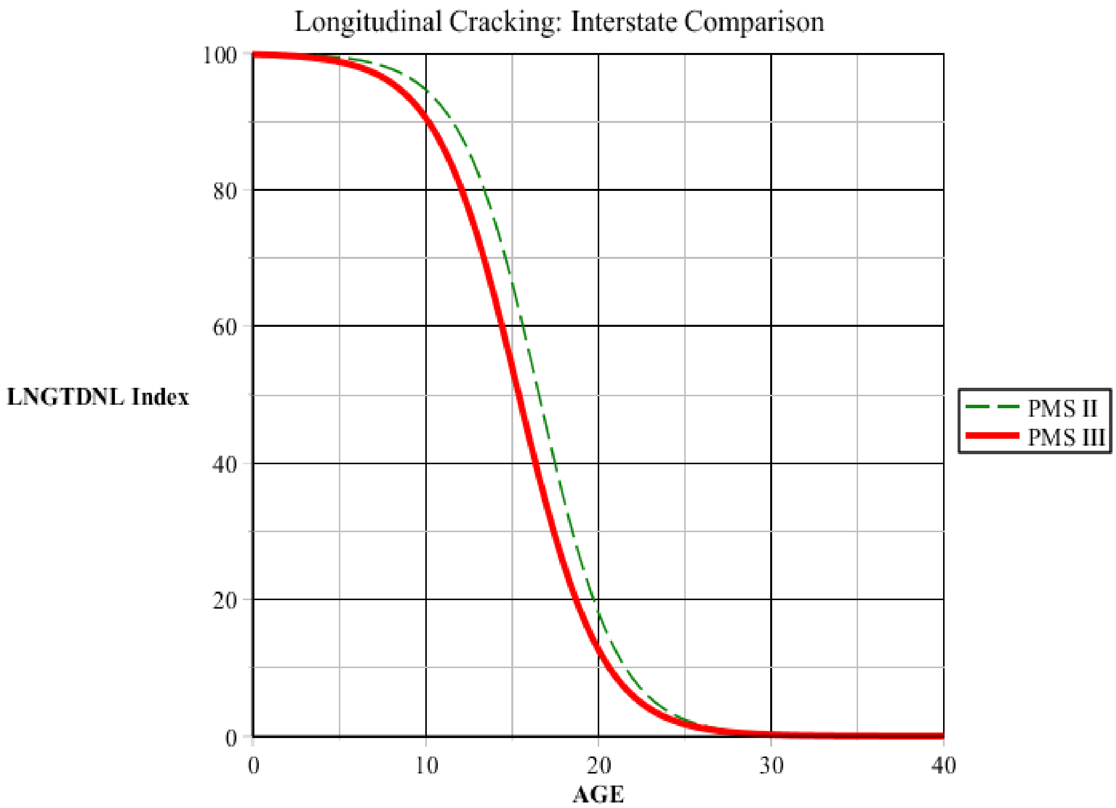

FIGURE 51: Longitudinal cracking – Interstate comparison

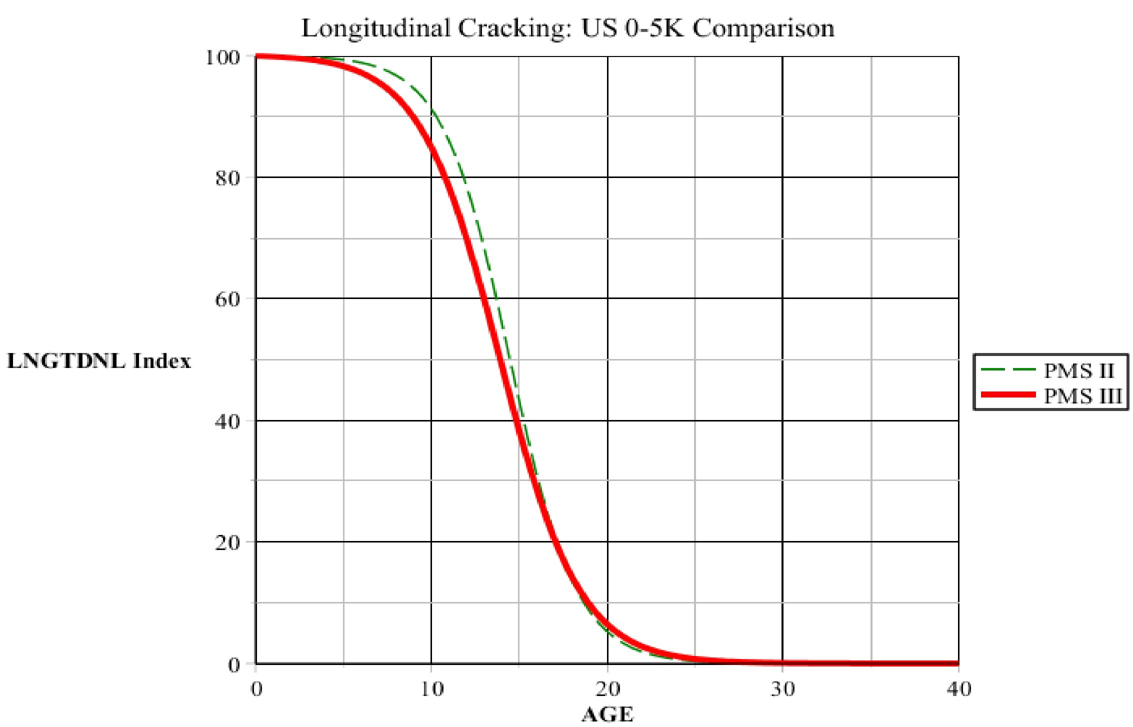

FIGURE 52: Longitudinal cracking – US 0-5K comparison

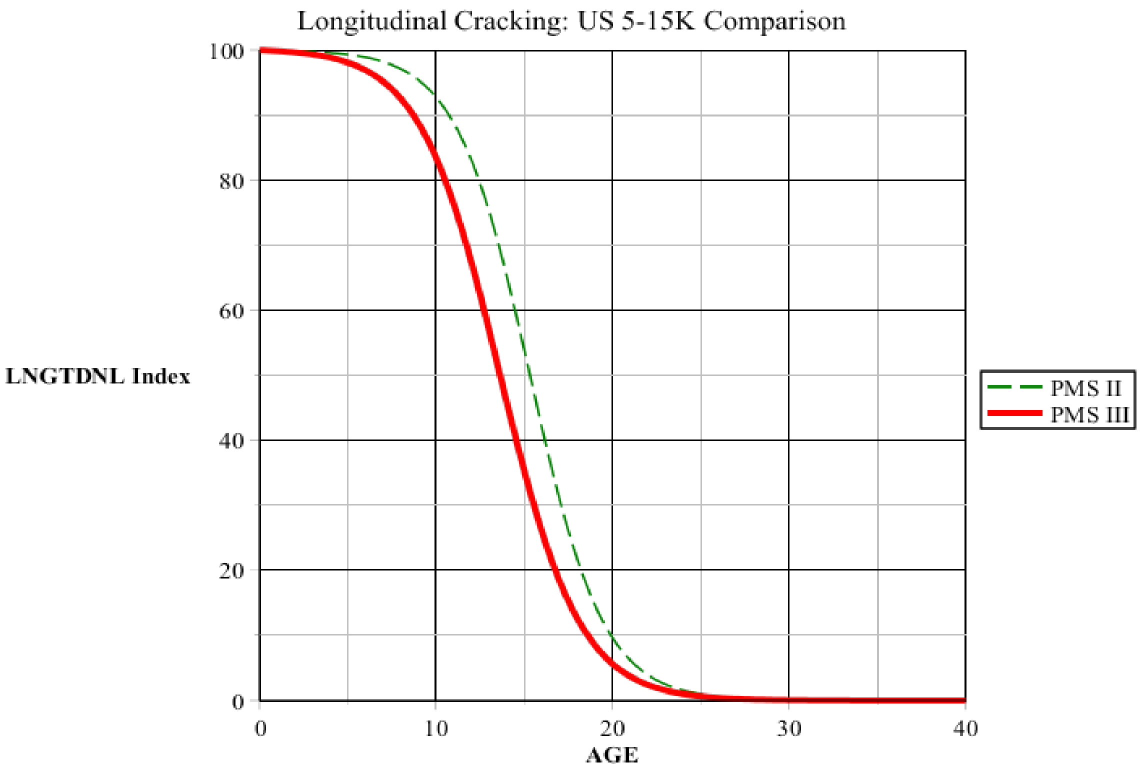

FIGURE 53: Longitudinal cracking – US 5-15K comparison

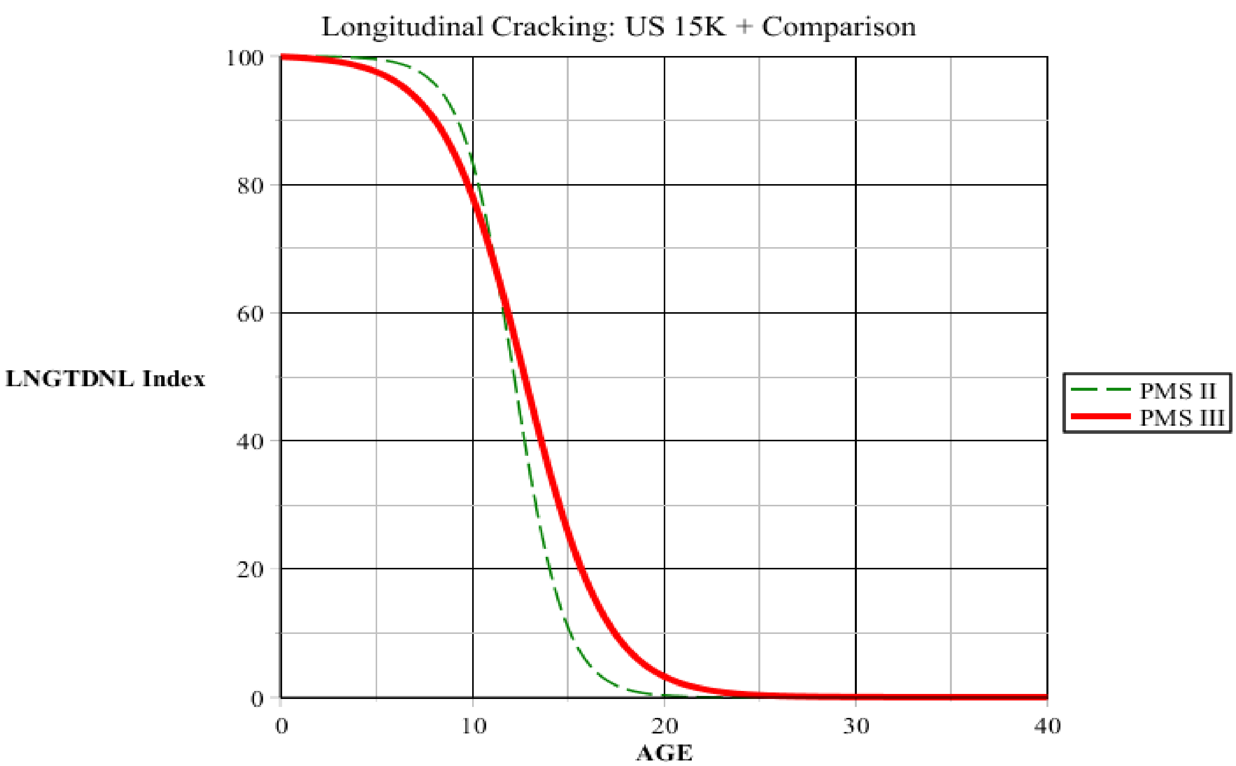

FIGURE 54: Longitudinal cracking – US 15K + comparison

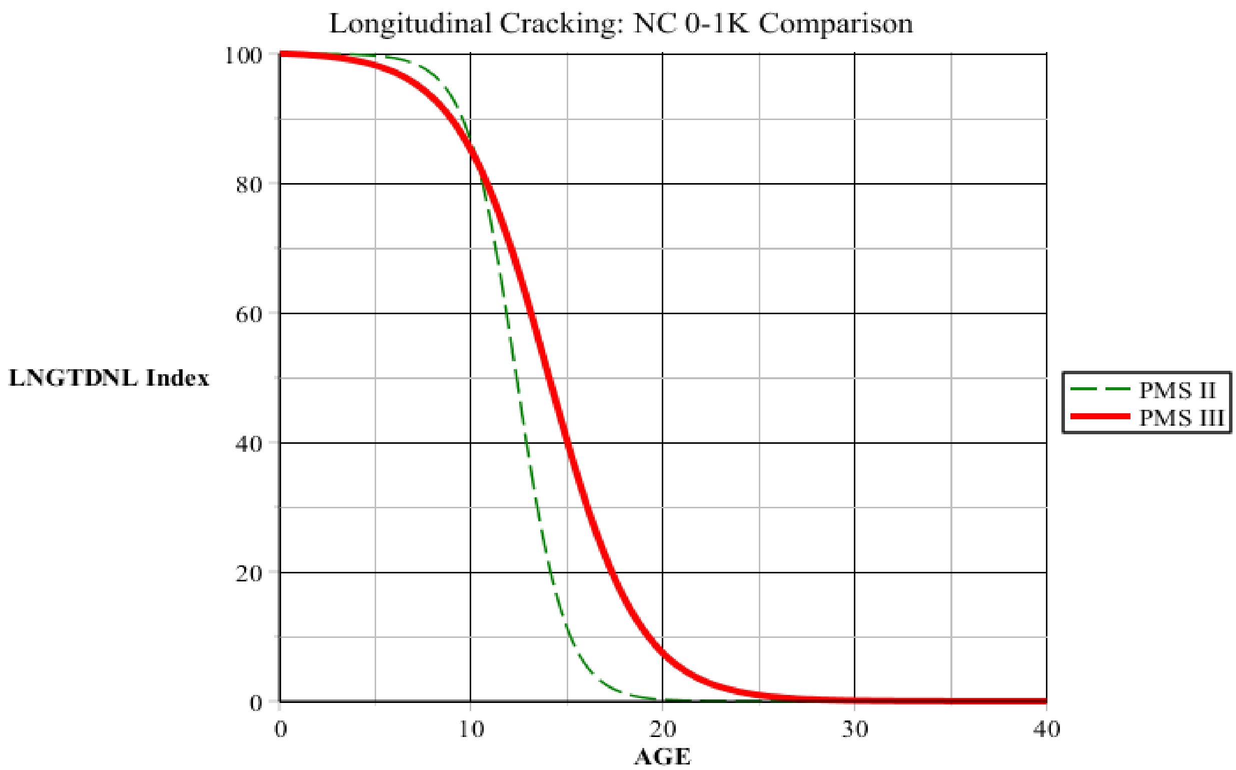

FIGURE 55: Longitudinal cracking – NC 0-1K comparison

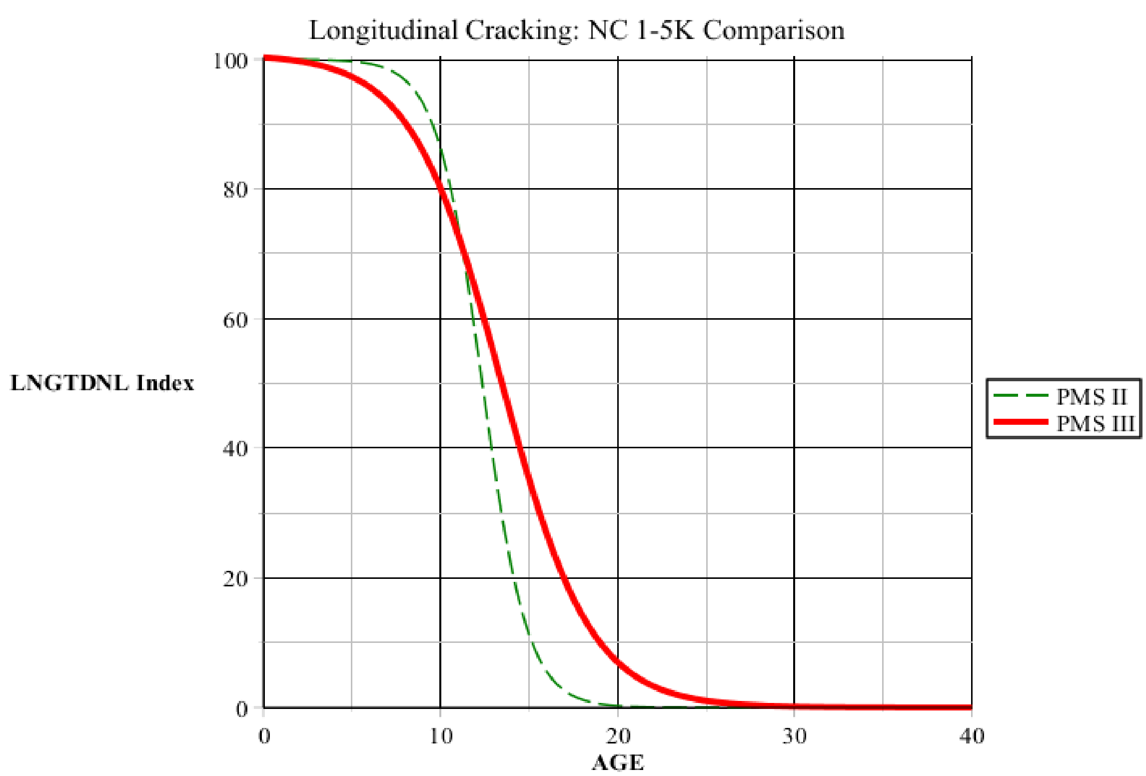

FIGURE 56: Longitudinal cracking – NC 1-5K comparison

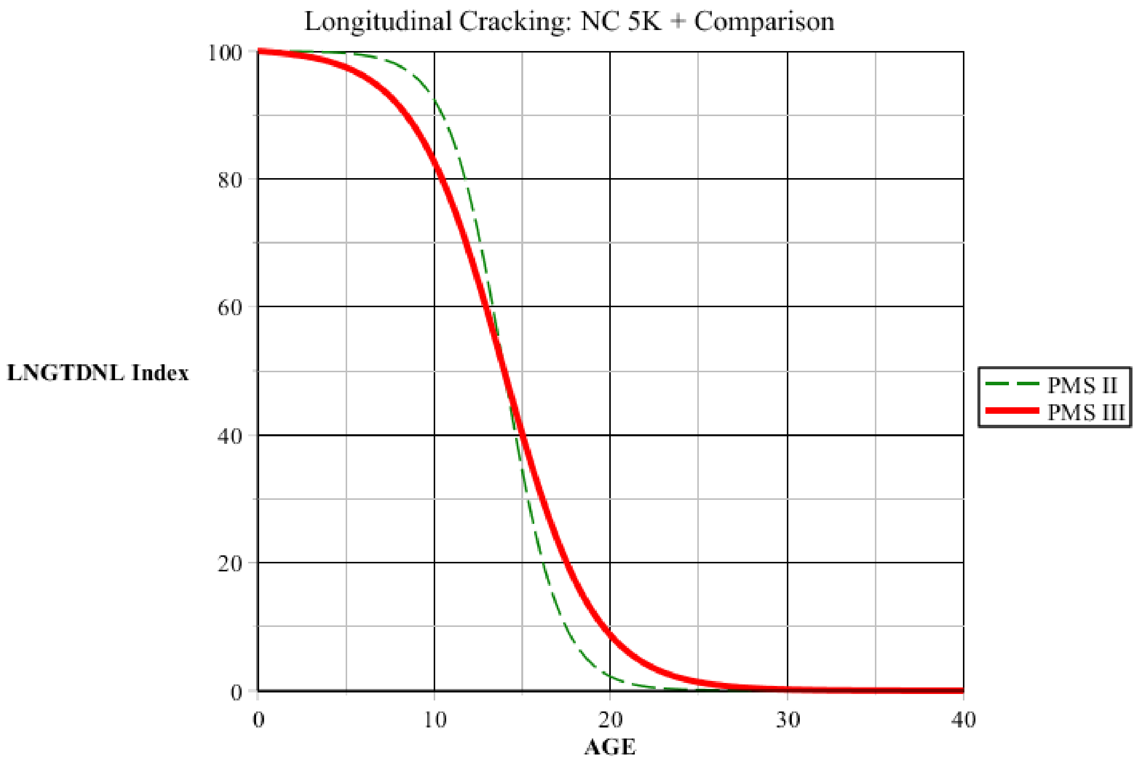

FIGURE 57: Longitudinal cracking – NC 5K + comparison

5.1.4 Longitudinal Lane Joint Cracking Comparison

With the exception of NC roadways with traffic of 0 – 1,000 vehicles per day and NC roadways exceeding 5,000 vehicles per day, longitudinal lane joint cracking models developed in this research presented significantly higher rates of deterioration than that of PMS II as sown in Figures 58 - 61. Models developed for NC roadways with traffic of 0 – 1,000 vehicles per day and NC roadways exceeding 5,000 vehicles per day presented a lower deterioration rate than that of PMS II as shown in Figures 62 and 64. As shown in Table 22 there was a statistical difference at 95% confidence in 7 out of 7 (100%) models.

TABLE 22: Longitudinal lane joint cracking confidence intervals

Model Family	95% C.I. for b variable	PMS II b variable
LNGTDNL_JNT Interstate	(13.05,13.31)	18.76
LNGTDNL_JNT US 0-5K	(13.01,13.47)	13.50
LNGTDNL_JNT US 5-15K	(12.38,12.59)	15.93
LNGTDNL_JNT US 15K +	(13.11,13.34)	21.51
LNGTDNL_JNT NC 0-1K	(18.75,18.94)	16.71
LNGTDNL_JNT NC 1-5K	(15.65,16.30)	17.46
LNGTDNL_JNT NC 5K +	(14.78,14.85)	13.87

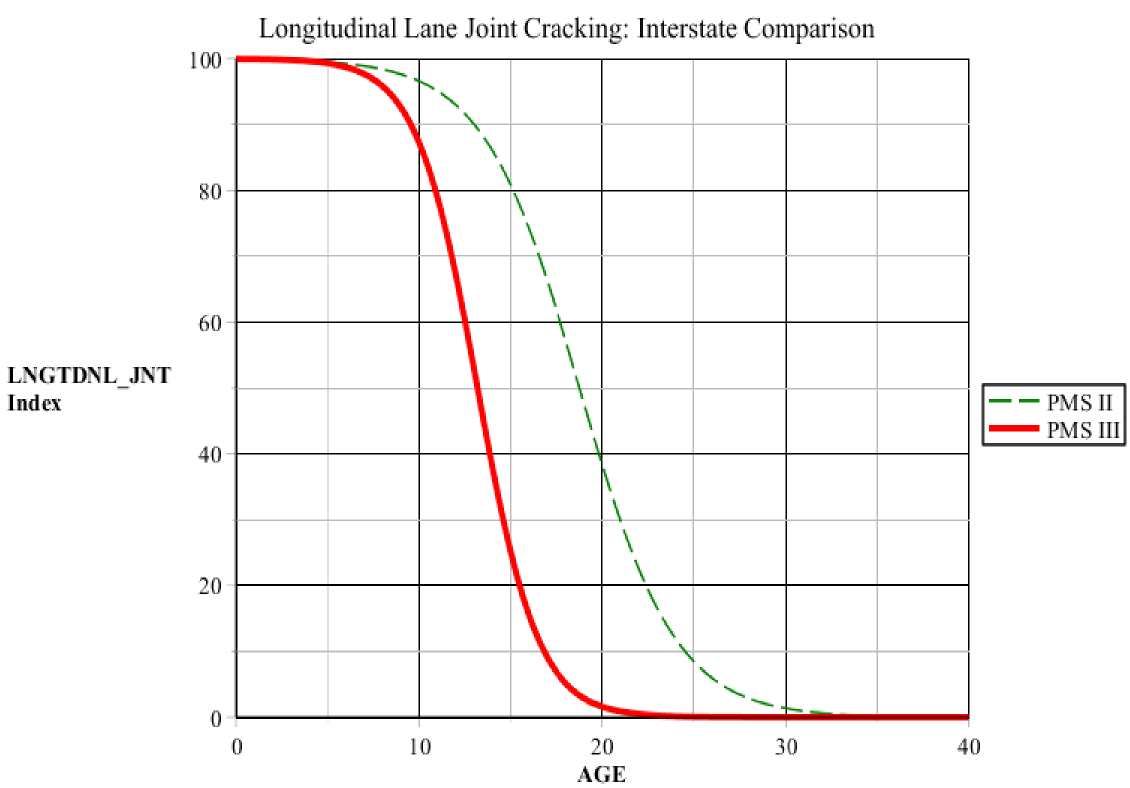

FIGURE 58: Longitudinal lane joint cracking – Interstate comparison

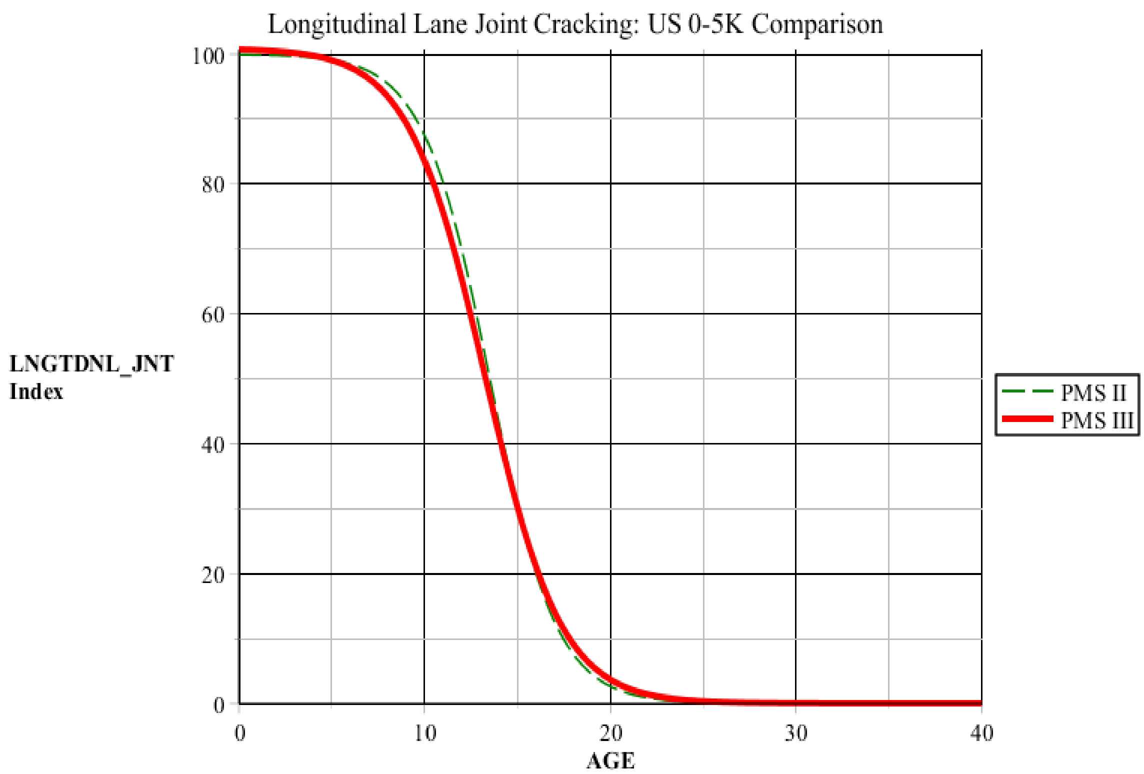

FIGURE 59: Longitudinal lane joint cracking – US 0-5K comparison

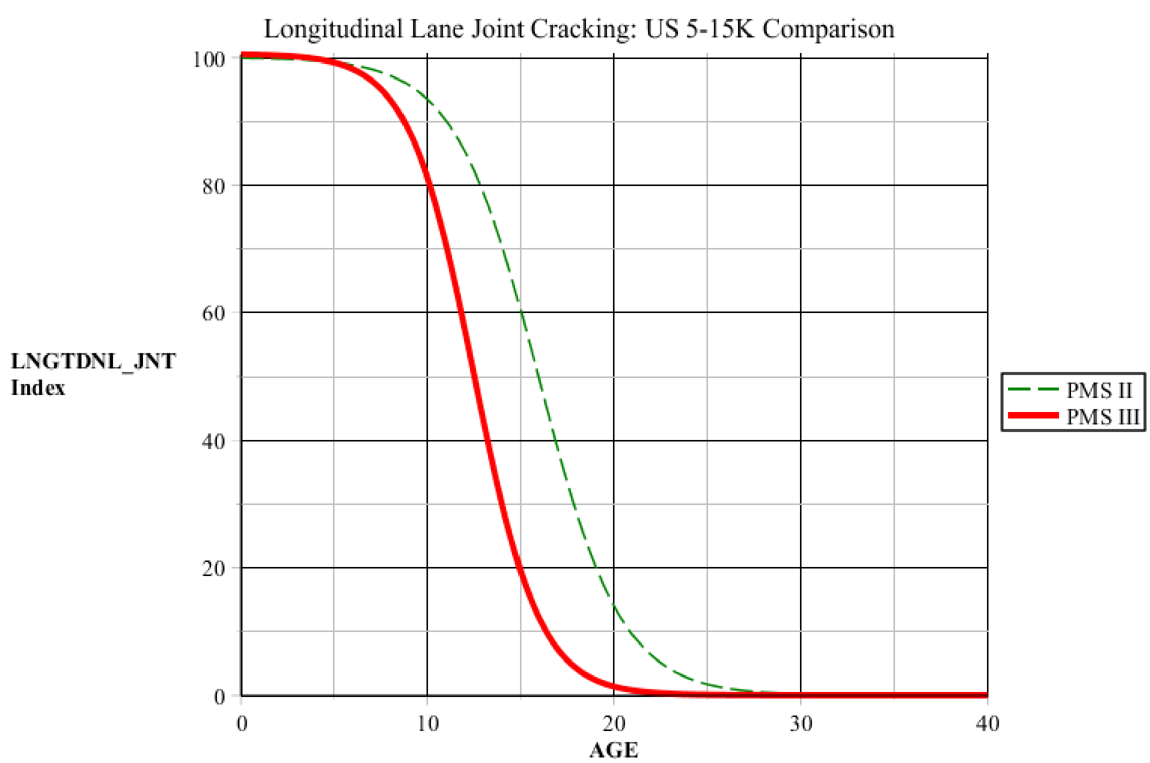

FIGURE 60: Longitudinal lane joint cracking – US 5-15K comparison

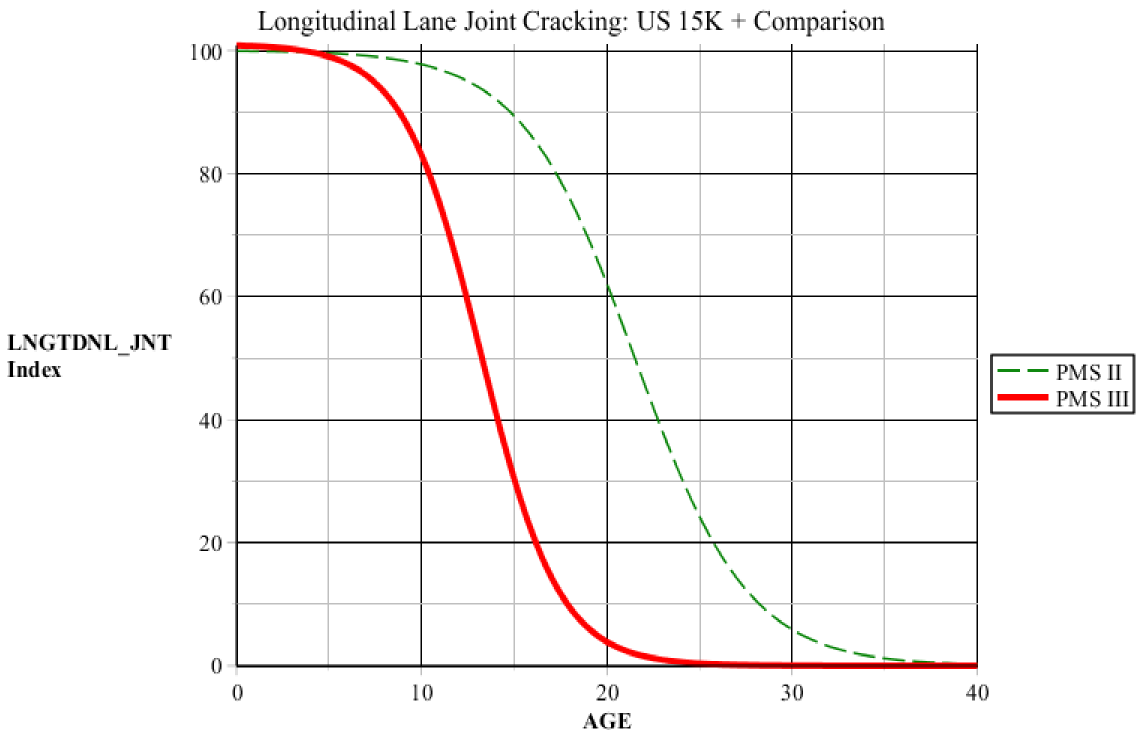

FIGURE 61: Longitudinal lane joint cracking – US 15K + comparison

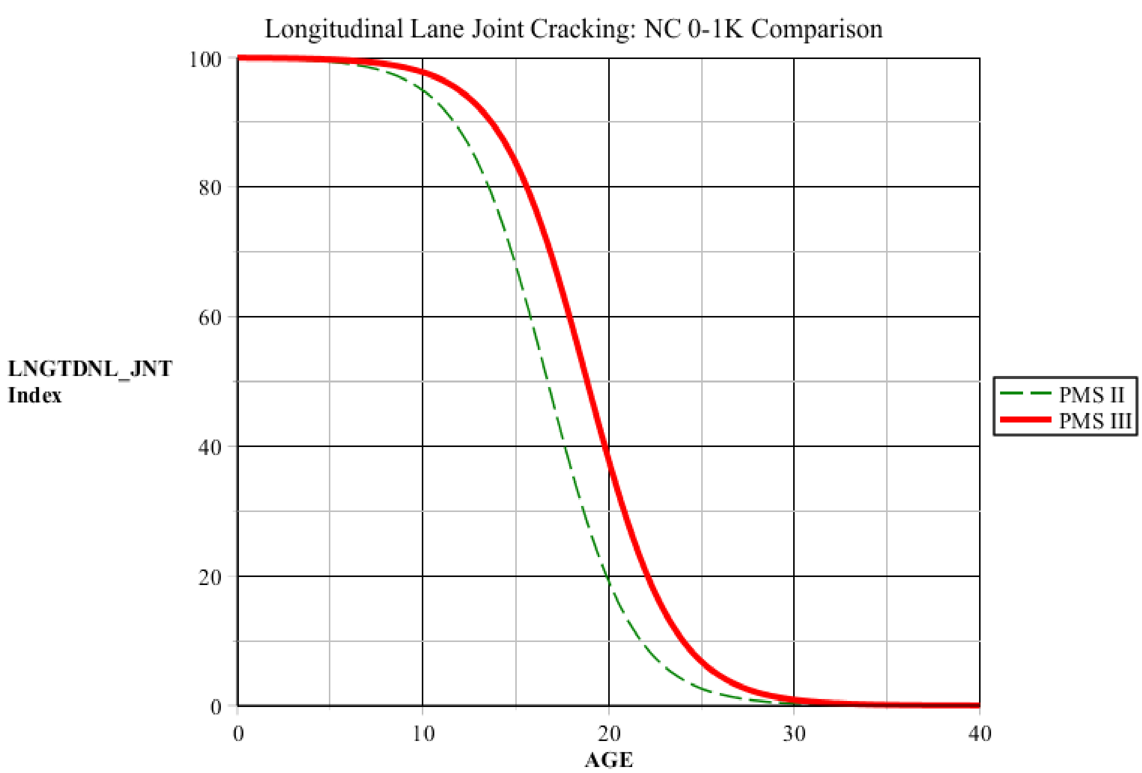

FIGURE 62: Longitudinal lane joint cracking – NC 0-1K comparison

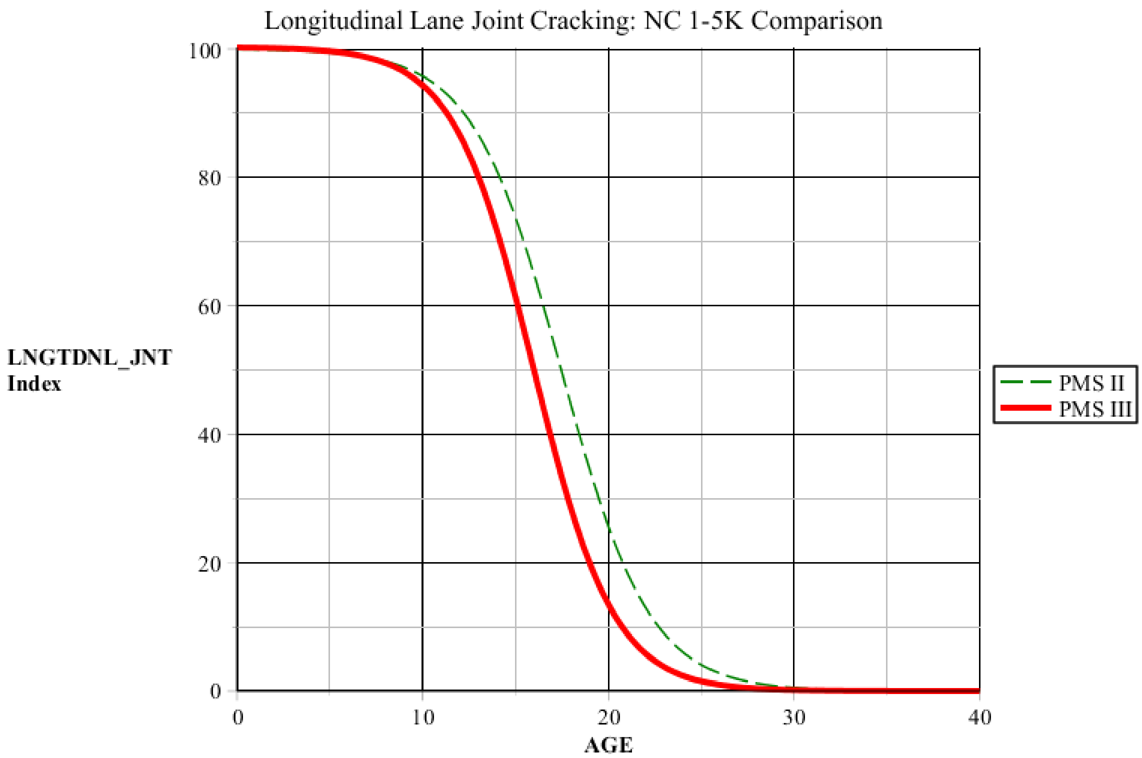

FIGURE 63: Longitudinal lane joint cracking – NC 1-5K comparison

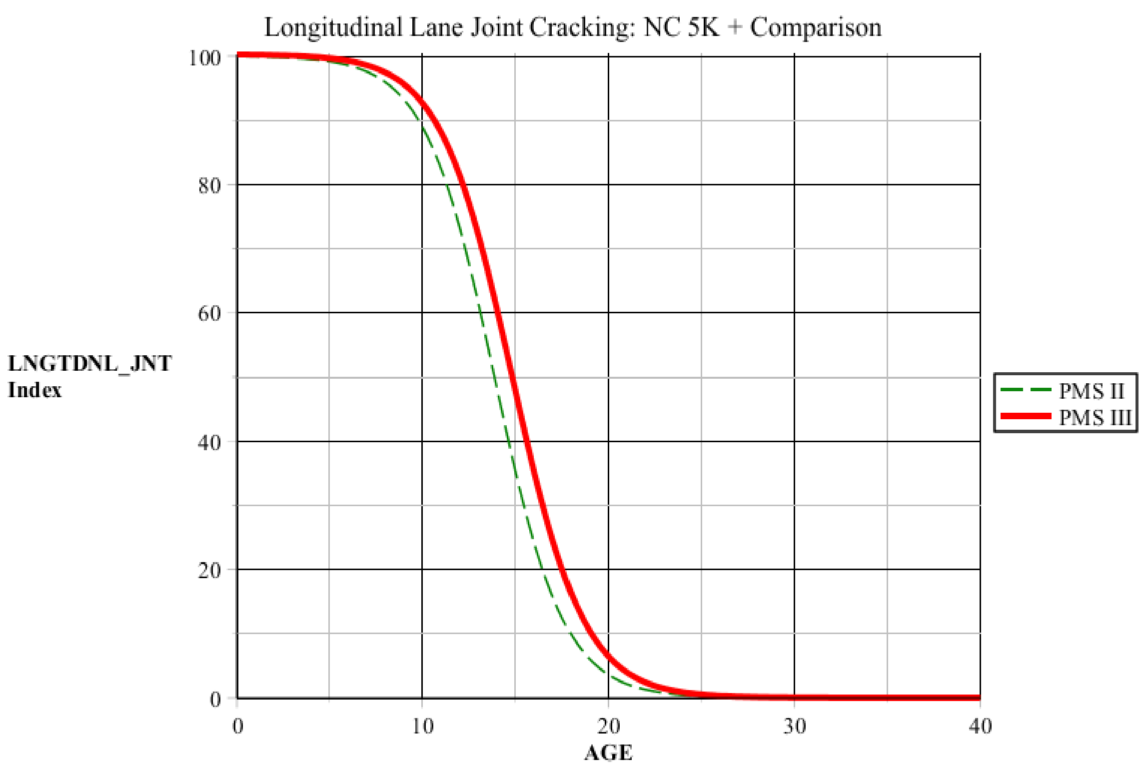

FIGURE 64: Longitudinal lane joint cracking – NC 5K + comparison

5.1.5 Raveling Comparison

With the exception of the interstate family, shown in Figure 65, raveling models developed in this research presented significantly higher rates of deterioration as shown in Figures 66 - 71. The interstate model developed in this research was consistent fairly consistent to the model developed in PMS II. However, this model presented a slightly less deterioration rate after year 15 of service life. As shown in Table 23, at 95% confidence it was concluded that 7 out of 7 (100%) models had a statistical difference in raveling predications.

TABLE 23: Raveling confidence intervals

Model Family	95% C.I. for b variable	PMS II b variable
RVL Interstate	(17.15,18.12)	17.10
RVL US 0-5K	(15.30,15.72)	30.41
RVL US 5-15K	(14.71,15.10)	22.59
RVL US 15K +	(13.41,13.98)	20.95
RVL NC 0-1K	(14.93,15.89)	16.45
RVL NC 1-5K	(14.06,14.48)	22.64
RVL NC 5K +	(12.23,12.61)	21.18
* denotes no statistical difference between models		

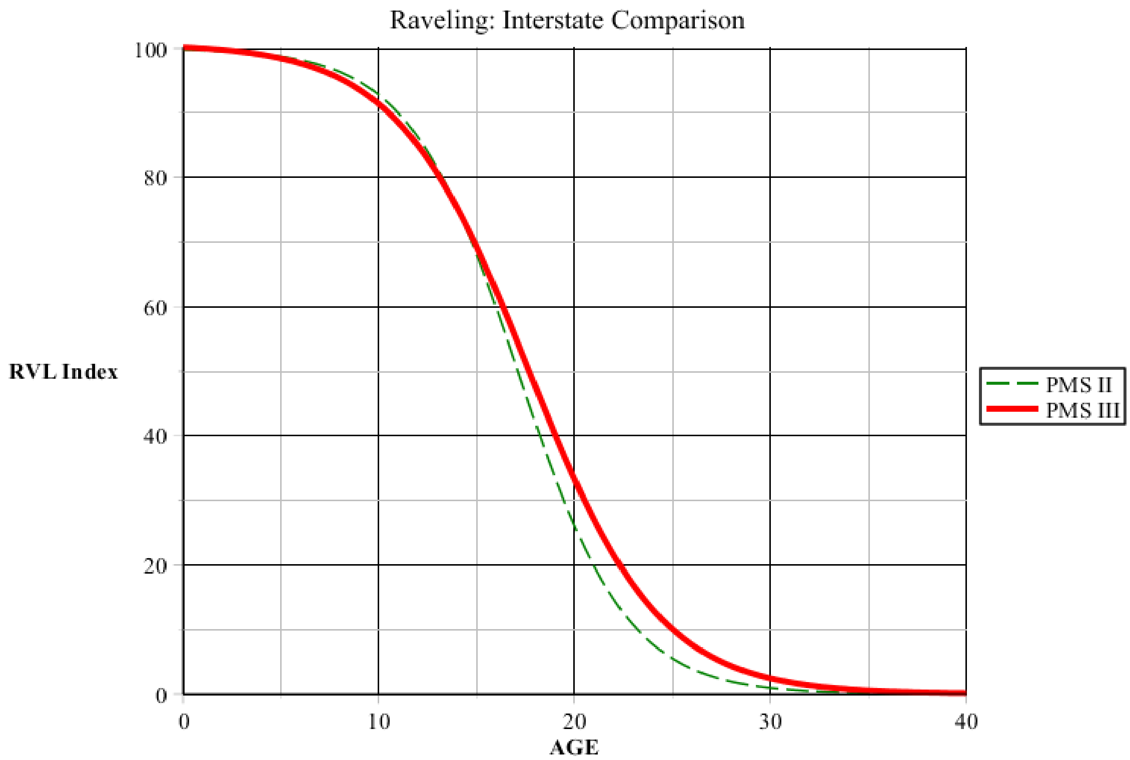

FIGURE 65: Raveling – Interstate comparison

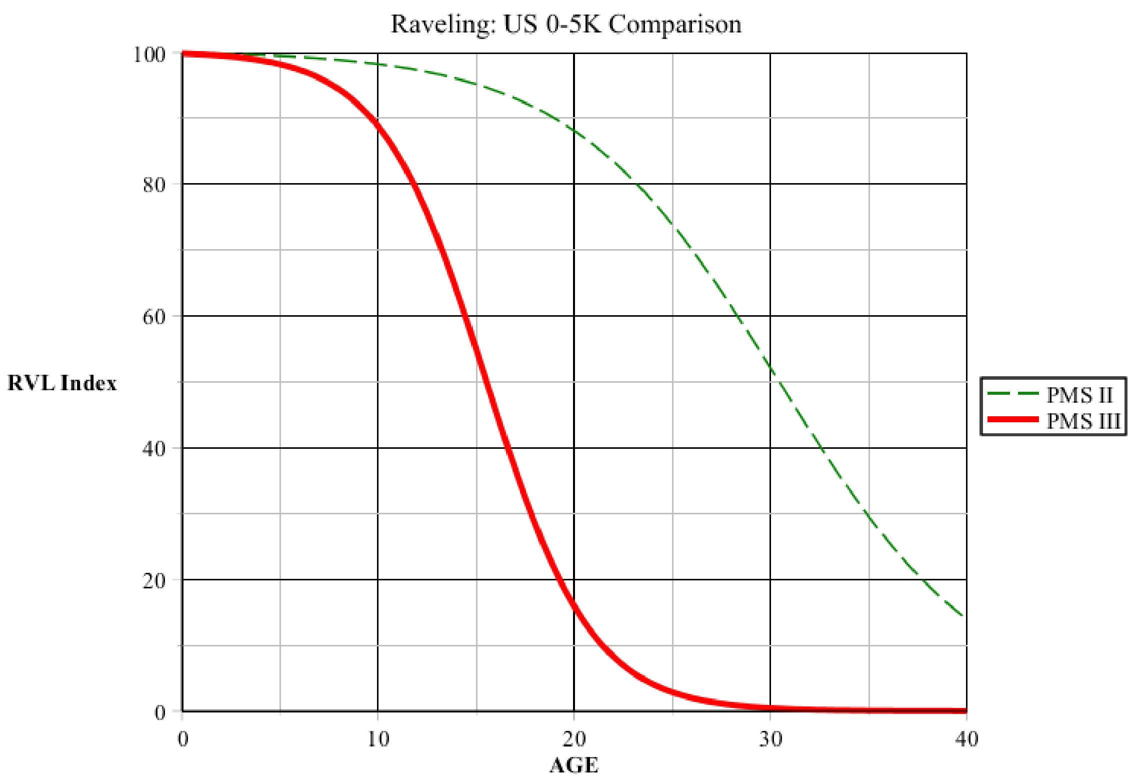

FIGURE 66: Raveling – US 0-5K comparison

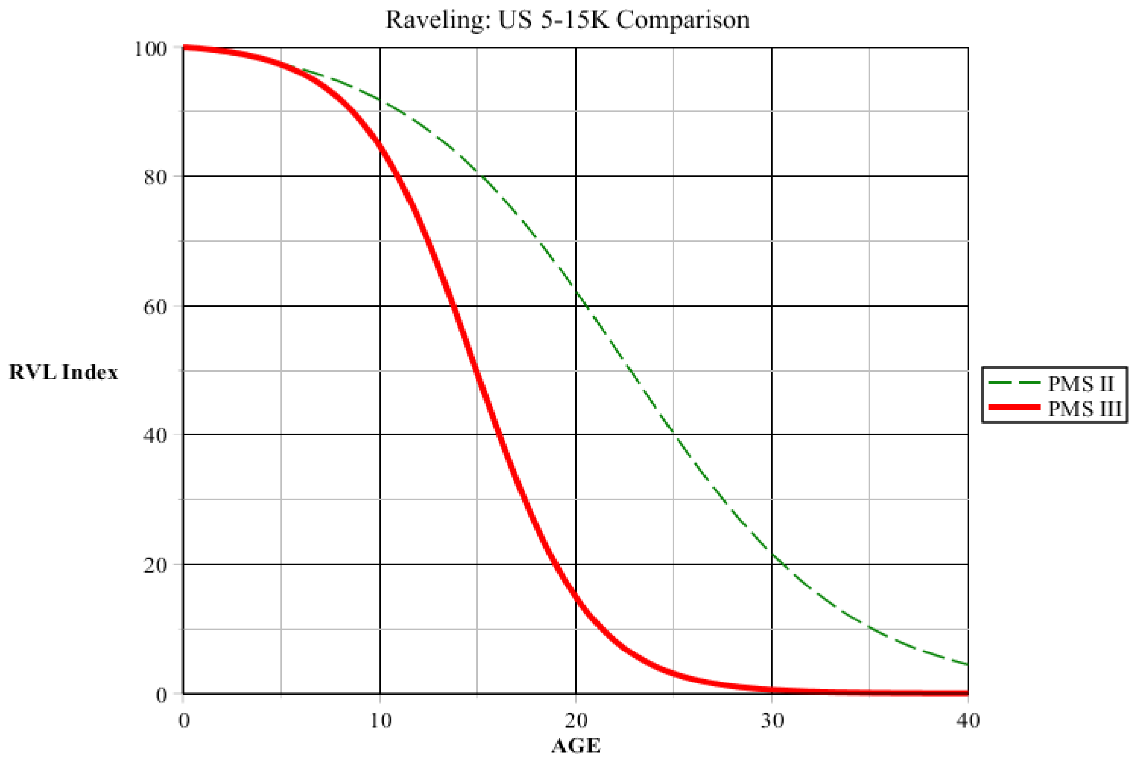

FIGURE 67: Raveling – US 5-15K comparison

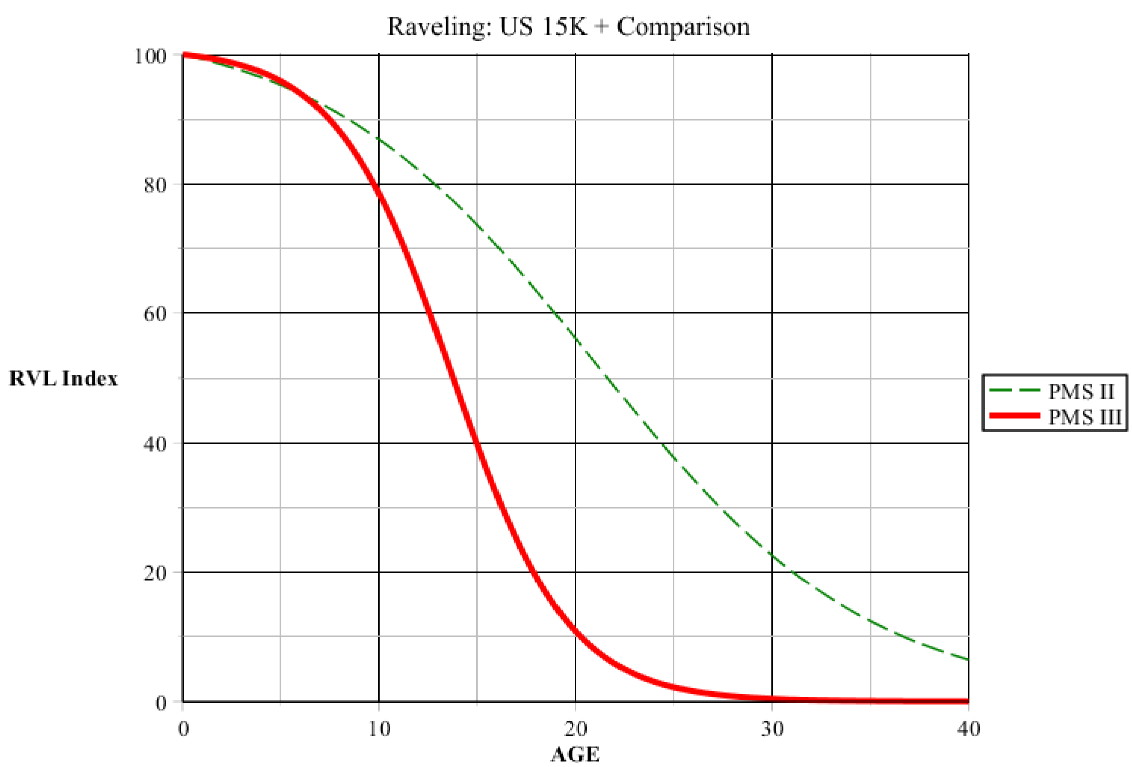

FIGURE 68: Raveling – US 15K + comparison

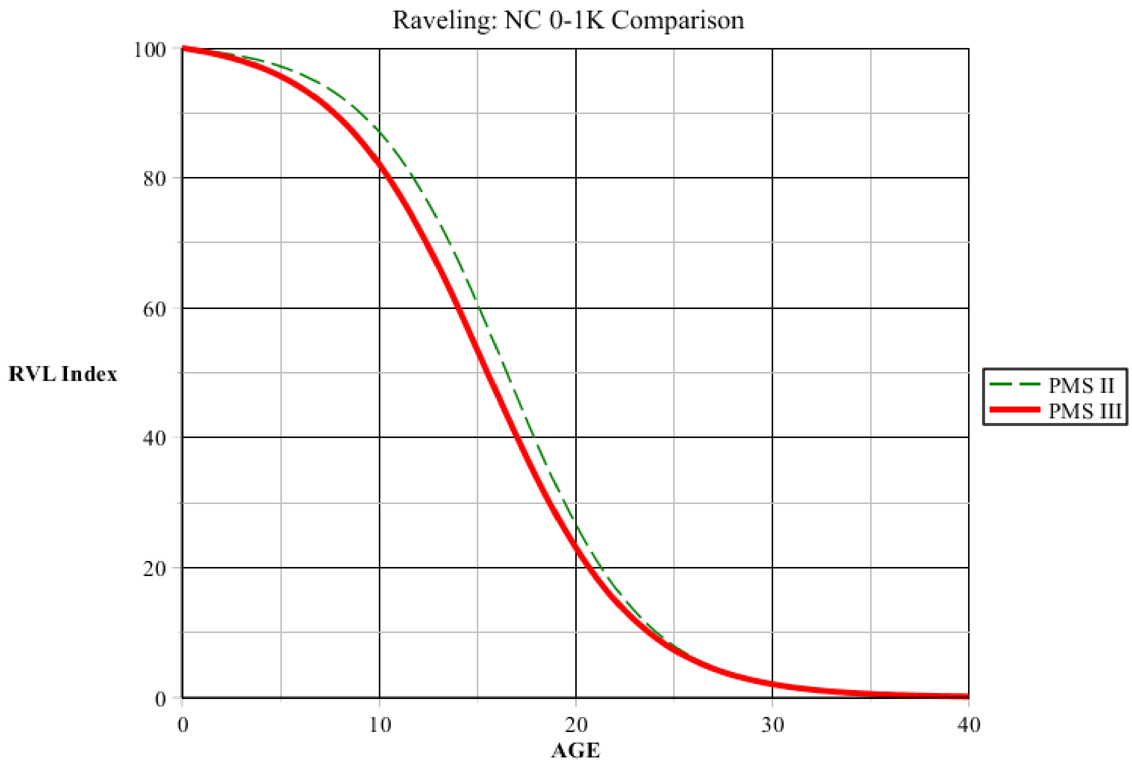

FIGURE 69: Raveling – NC 0-1K comparison

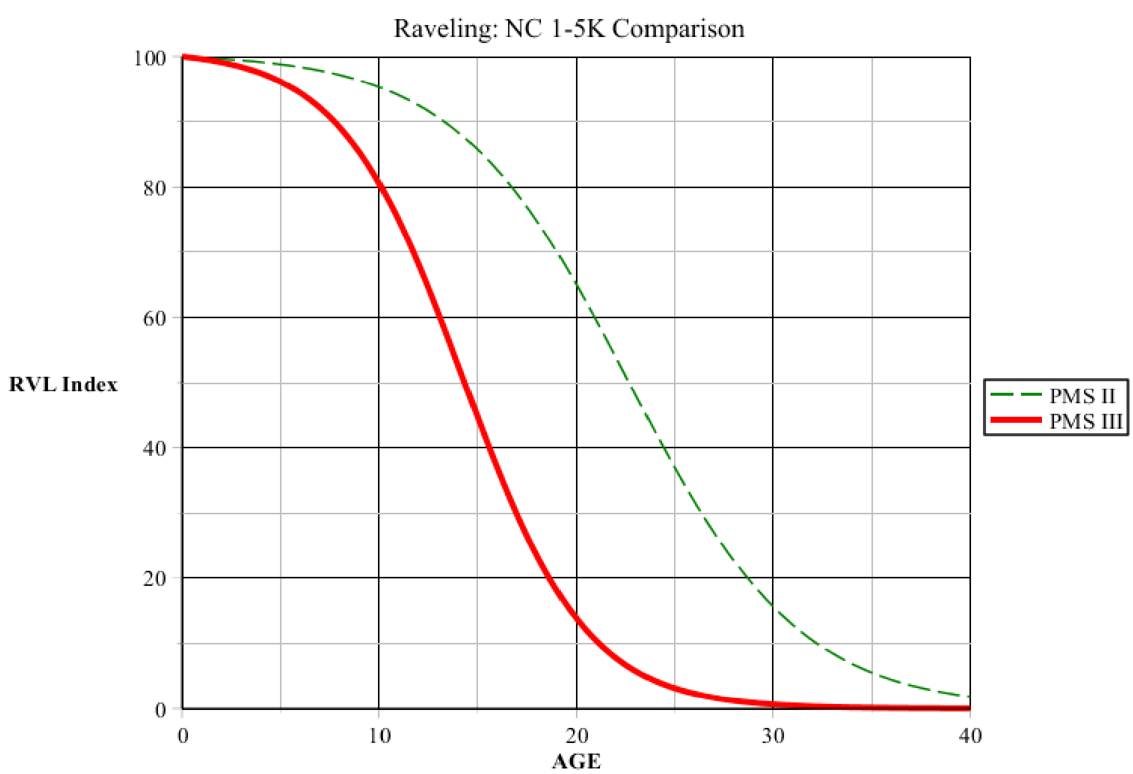

FIGURE 70: Raveling – NC 1-5K comparison

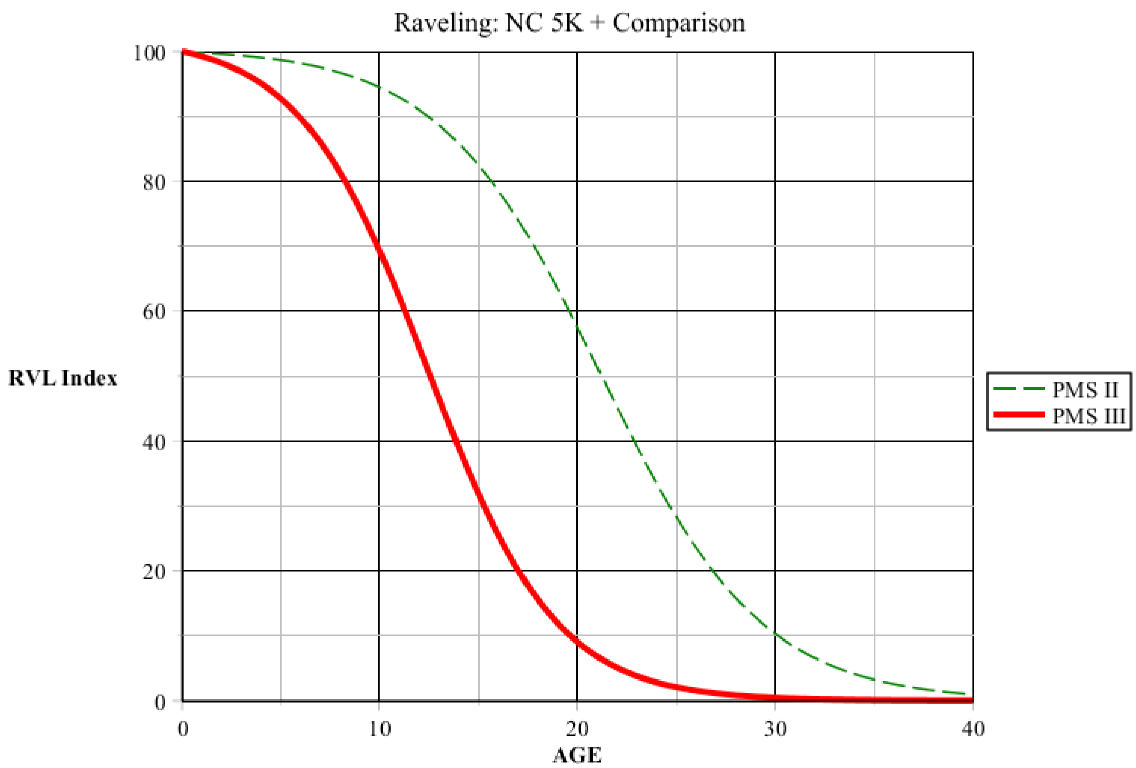

FIGURE 71: Raveling – NC 5K + comparison

5.1.6 Rutting Comparison

As shown in Figures 72 – 78, rutting models developed in this research were very consistent to rutting models developed in PMS II. Rutting models for both US roadways with traffic of 5,000 – 15,000 vehicles per day and NC roadways with traffic of 0 – 1,000 vehicles per day presented the same deterioration curve for PMS II and this research. The interstate family model developed in this research presented a slightly lower rate of deterioration and a majority of US and NC models presented a slightly higher rate of deterioration. However, the differences between these models were not significant, indicating that the change in NCDOT's raw data processing algorithm did not effect this distress type. As shown in Table 24, there was a statistical difference at 95% confidence in 5 out of 7 (71.4%) models.

TABLE 24: Rutting confidence intervals

Model Family	**95% C.I. for b variable**	**PMS II b variable**
RUT Interstate	(0.88,0.95)	0.99
RUT US 0-5K	(0.98,1.01)	0.94
RUT US 5-15K	(1.01,1.03)	1.02*
RUT US 15K +	(0.96,1.01)	0.95
RUT NC 0-1K	(0.96,1.04)	1.00*
RUT NC 1-5K	(1.00,1.04)	0.94
RUT NC 5K +	(1.00,1.03)	0.94
* denotes no statistical difference between models		

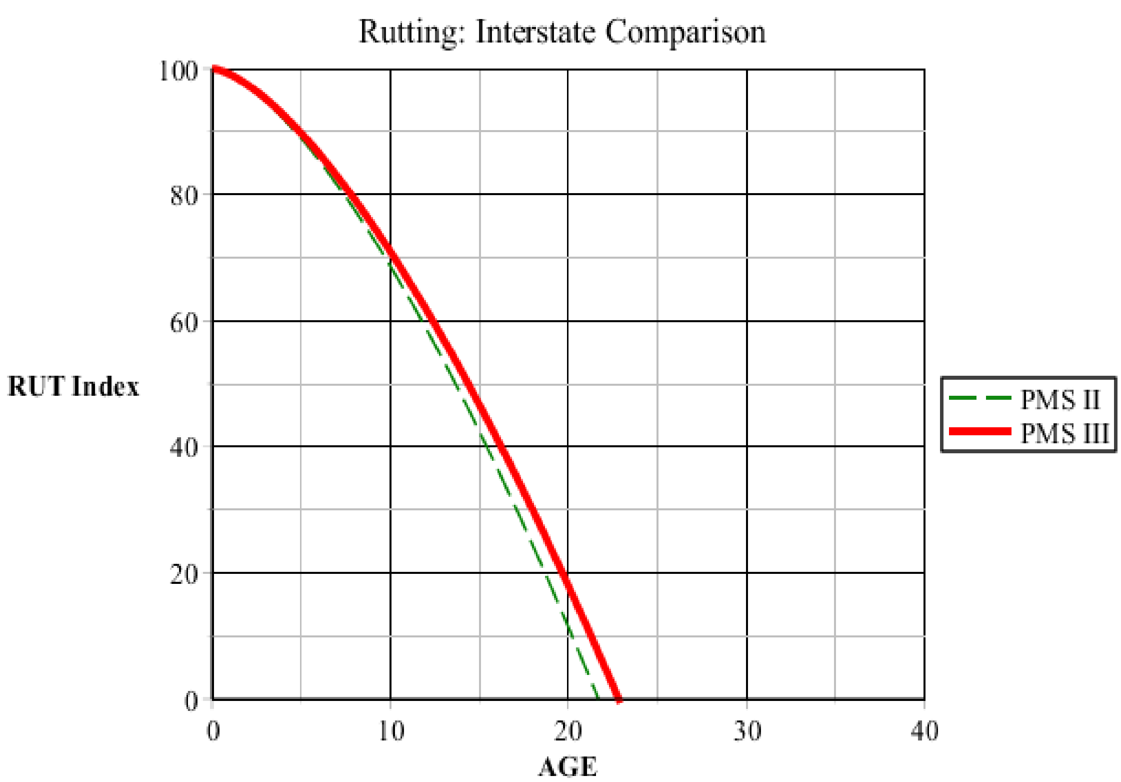

FIGURE 72: Rutting – Interstate comparison

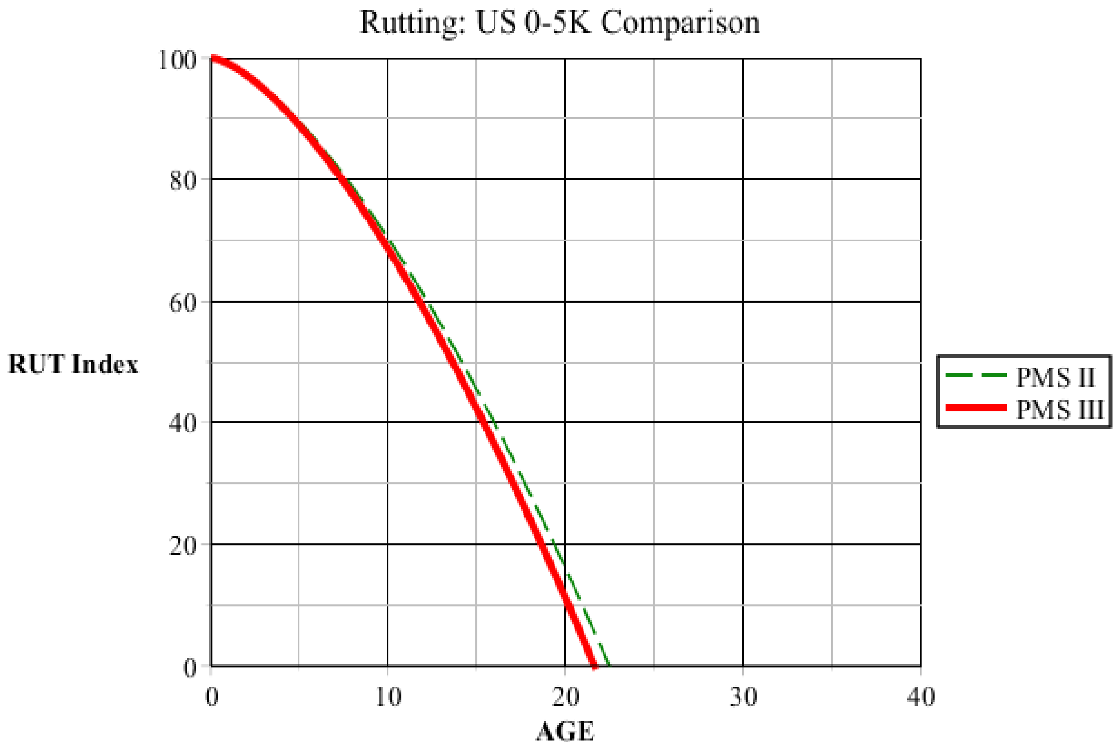

FIGURE 73: Rutting – US 0-5K comparison

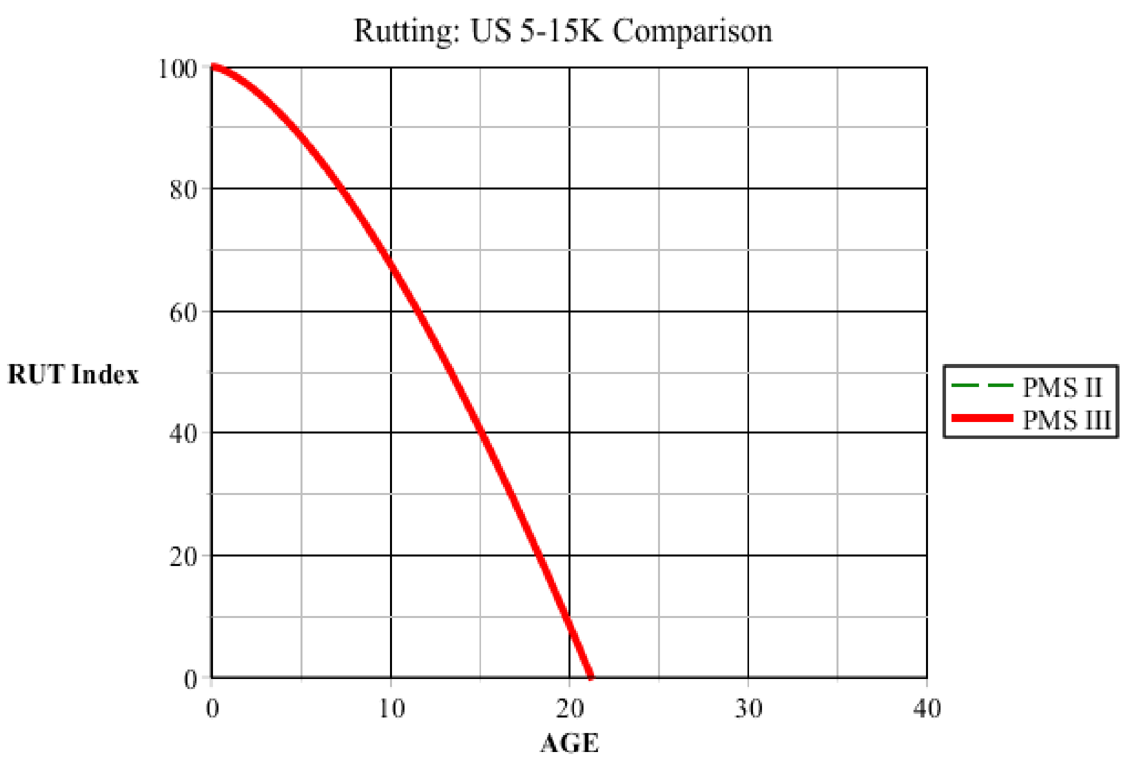

FIGURE 74: Rutting – US 5-15K comparison

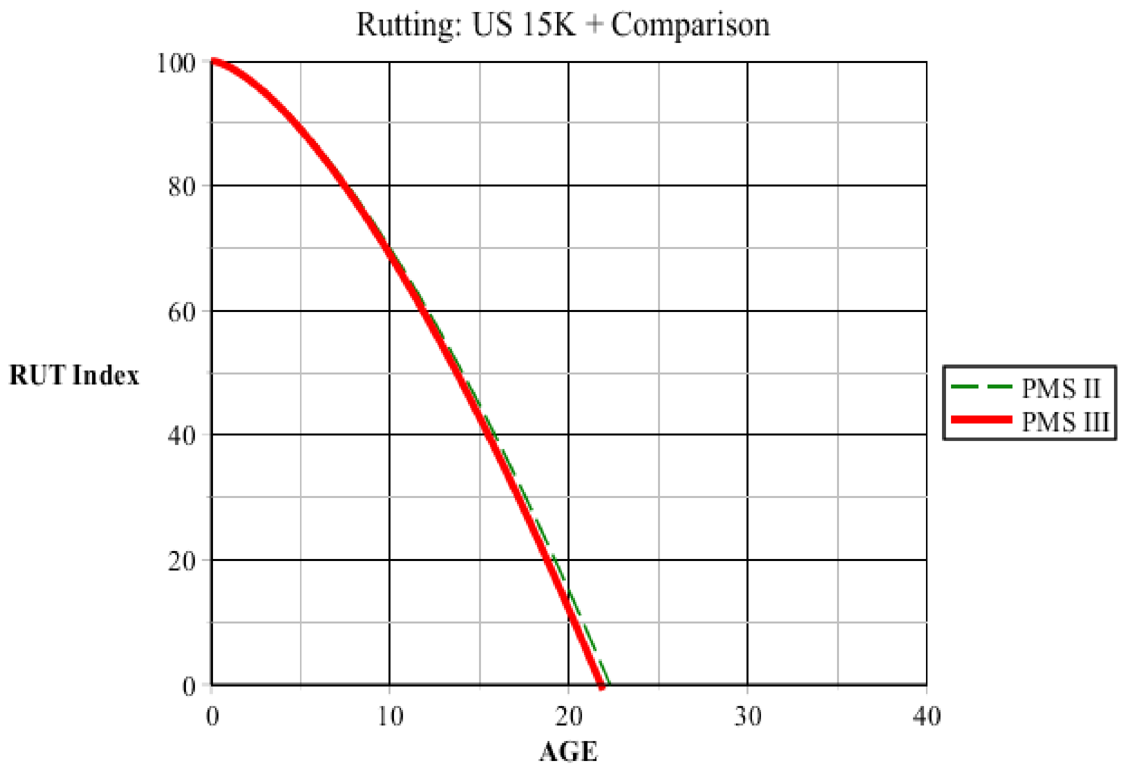

FIGURE 75: Rutting – US 15K + comparison

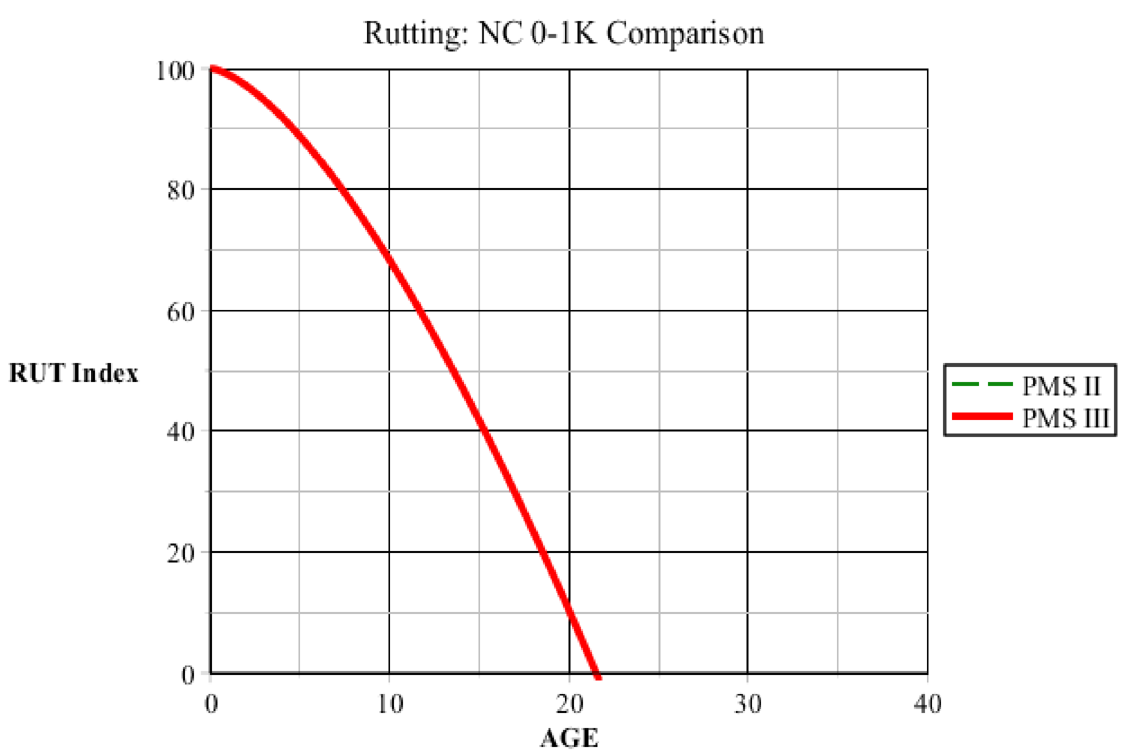

FIGURE 76: Rutting – NC 0-1K comparison

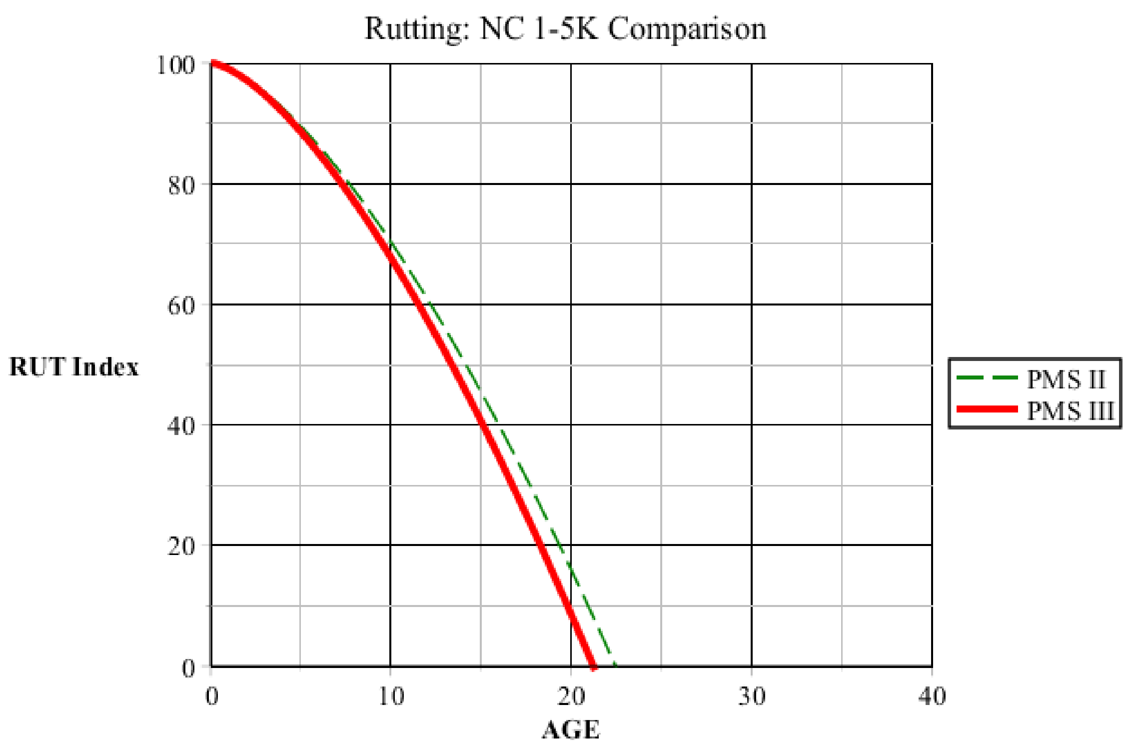

FIGURE 77: Rutting – NC 1-5K comparison

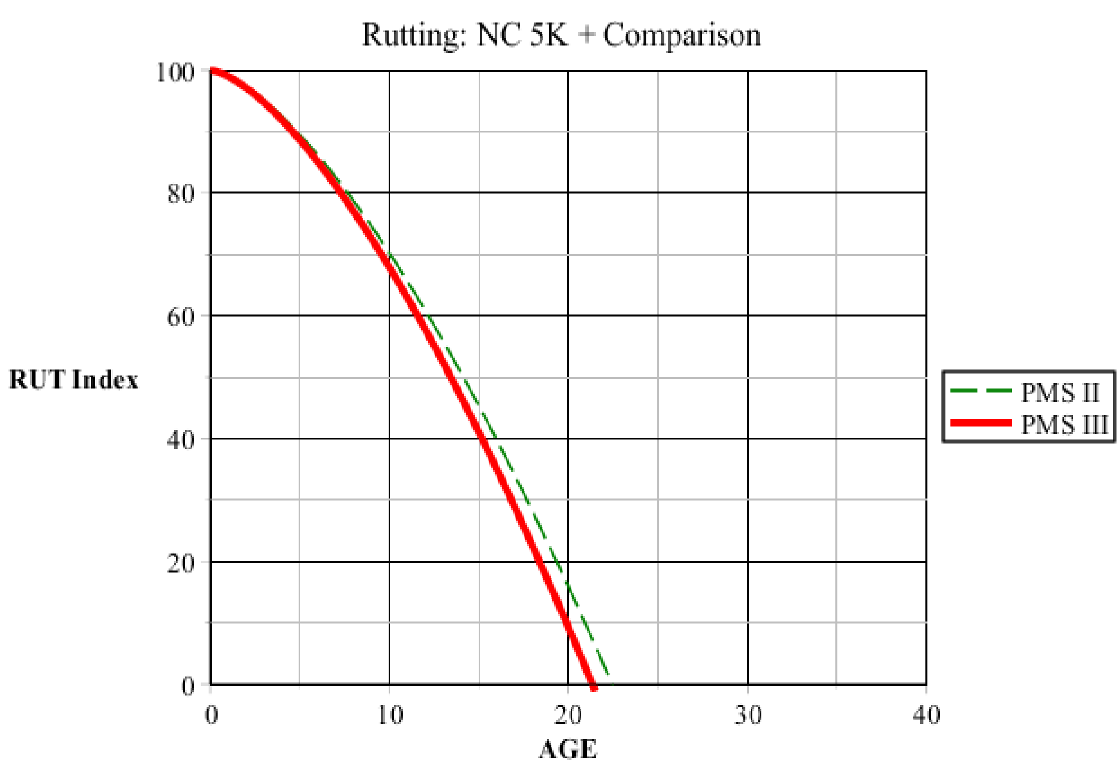

FIGURE 78: Rutting – NC 5K + comparison

5.1.7 Patching (Non-Wheel Path) Comparison

The non-wheel path patching comparison graphs are shown in Figures 79 – 85. With the exception of the interstate family model, which presented a lower rate of deterioration, overall non-wheel path models developed in this research show higher deterioration rates for US and NC roadway families compared to PMS II. As shown in Table 25, there was a statistical difference at 95% confidence in 7 out of 7 (100%) models.

TABLE 25: Patching (non-wheel path) confidence intervals

Model Family	95% C.I. for b variable	PMS II b variable
NWP Interstate	(20.20,21.35)	18.77
NWP US 0-5K	(19.38,20.06)	21.86
NWP US 5-15K	(19.99,20.88)	24.41
NWP US 15K +	(17.42,18.16)	22.45
NWP NC 0-1K	(18.90,20.37)	24.24
NWP NC 1-5K	(18.16,18.75)	21.04
NWP NC 5K +	(18.34,19.00)	21.31

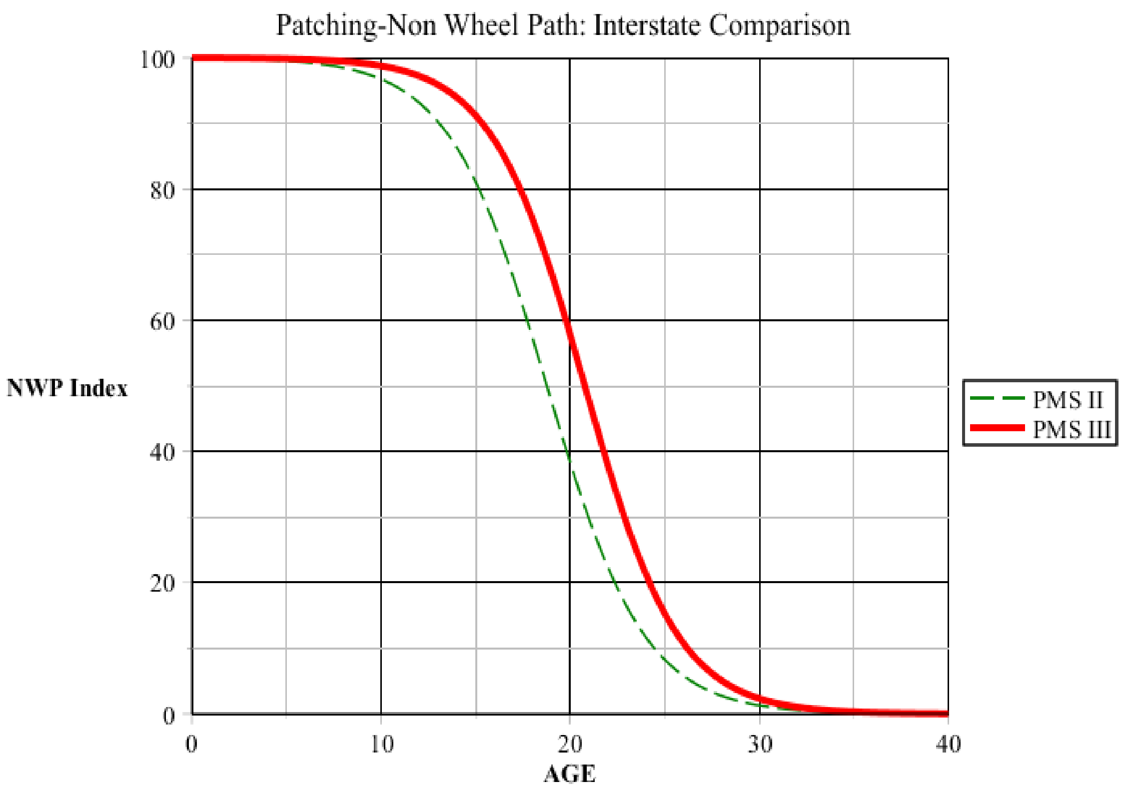

FIGURE 79: Patching (non-wheel path) – Interstate comparison

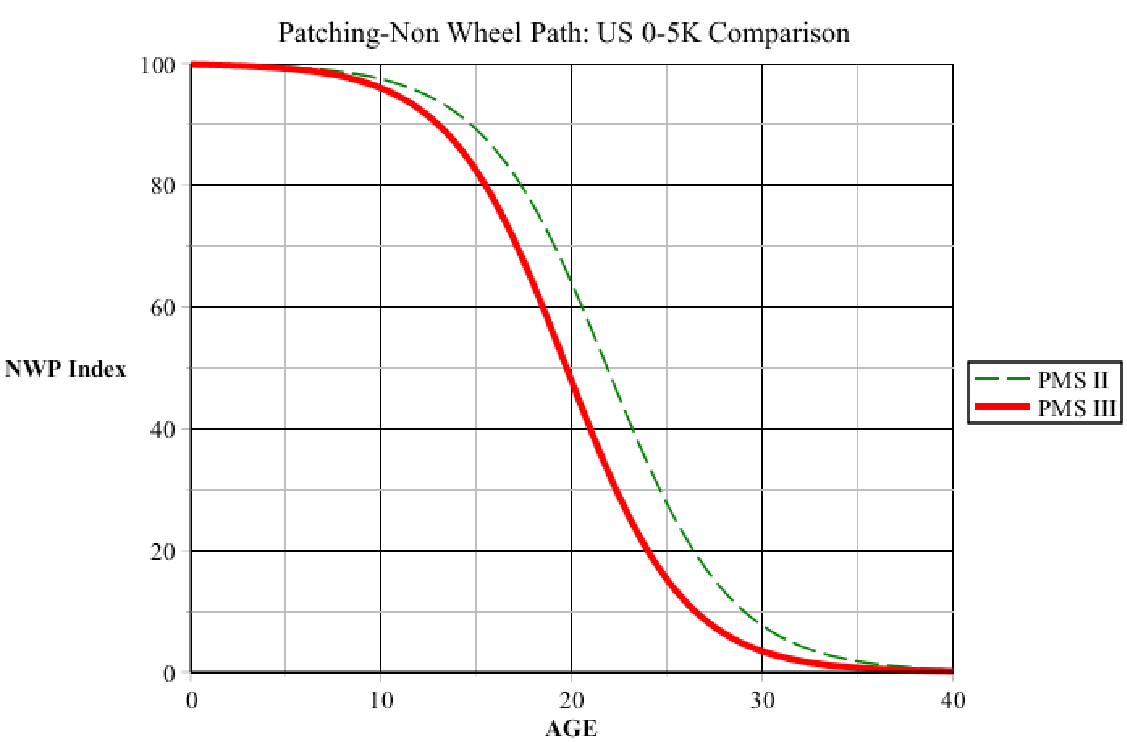

FIGURE 80: Patching (non-wheel path) – US 0-5K comparison

FIGURE 81: Patching (non-wheel path) – US 5-15K comparison

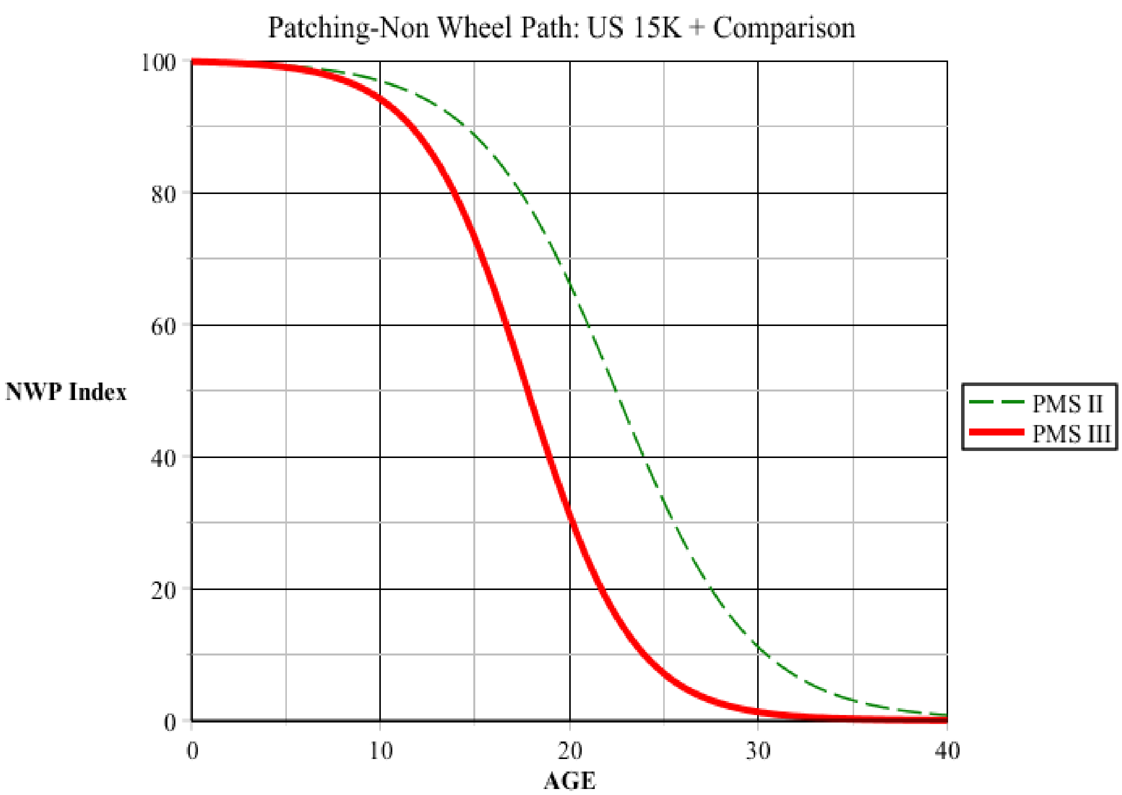

FIGURE 82: Patching (non-wheel path) – US 15K + comparison

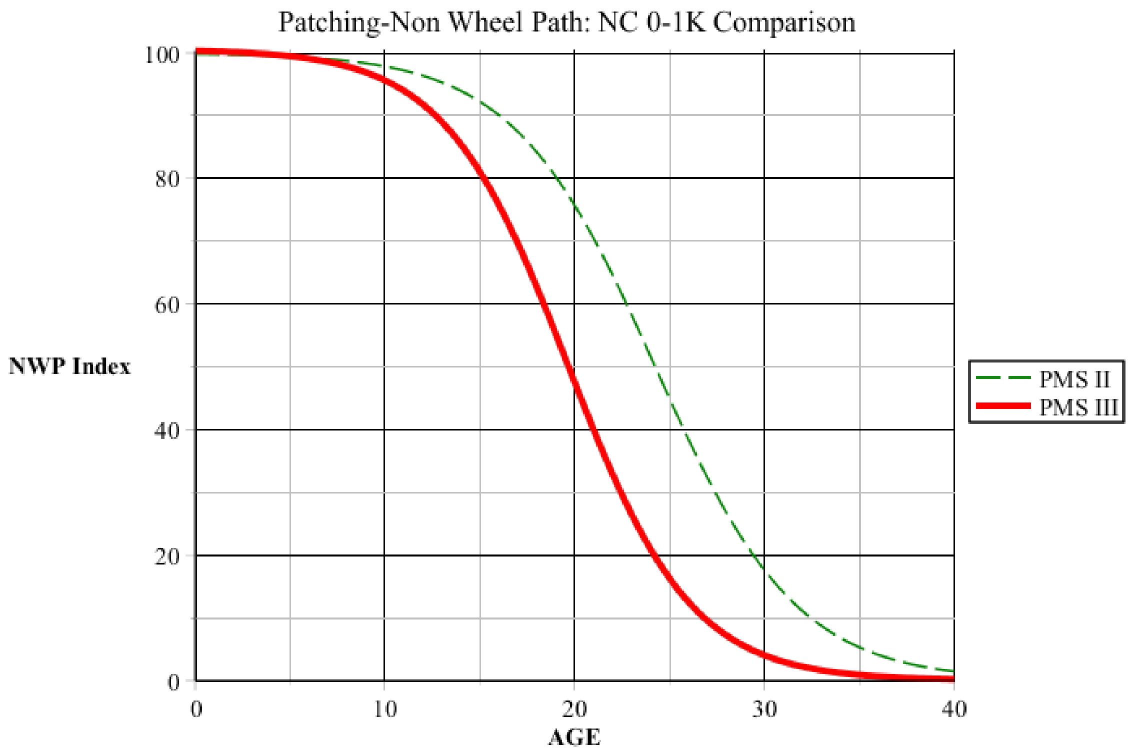

FIGURE 83: Patching (non-wheel path) – NC 0-1K comparison

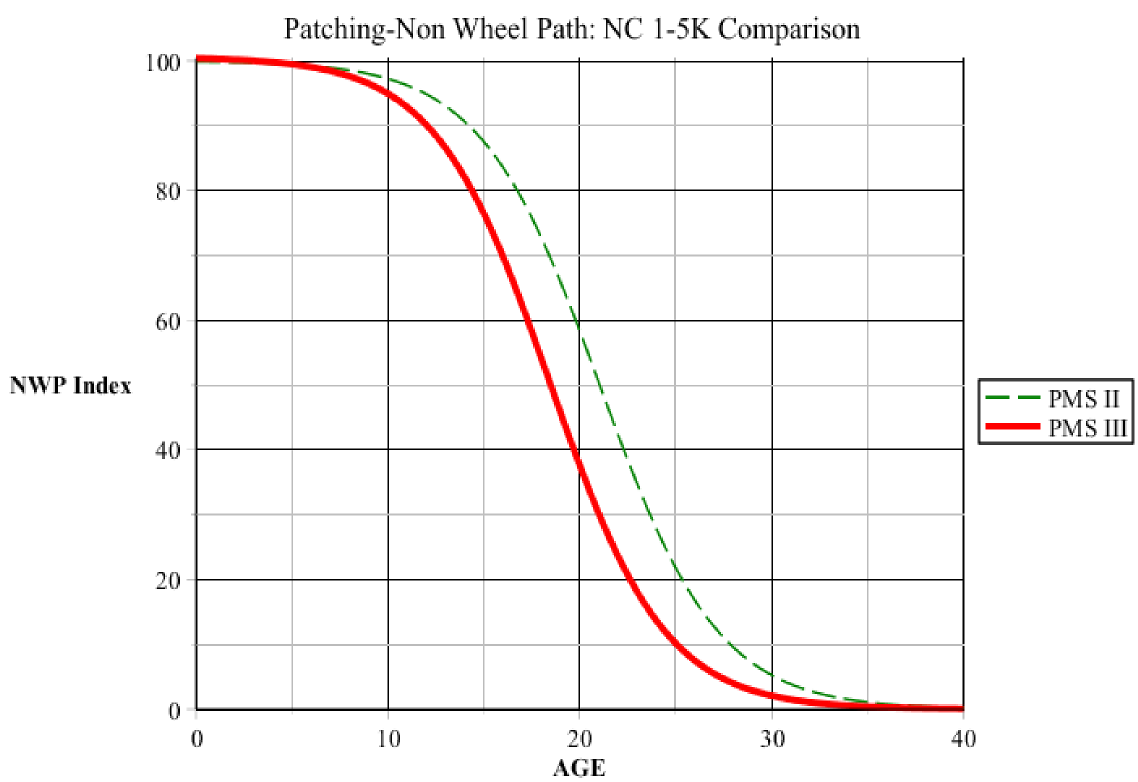

FIGURE 84: Patching (non-wheel path) – NC 1-5K comparison

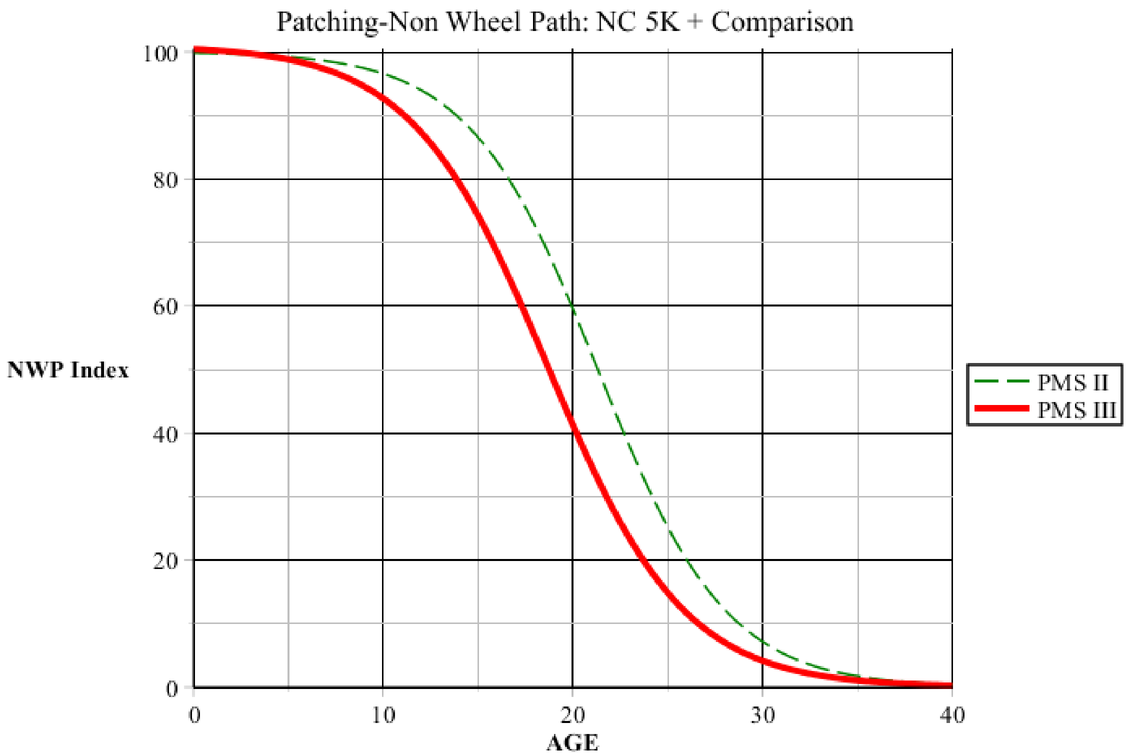

FIGURE 85: Patching (non-wheel path) – NC 5K + comparison

5.1.8 Patching (Wheel Path) Comparison

Wheel path patching comparison models are shown in Figures 86 - 92. As shown in Figure 86, the interstate model developed for this research presented lower a deterioration rate than the model developed in PMS II. This was also the same case for the model developed for US roadways with traffic ranging from 0 – 5,000 vehicles per day. As shown in Figure 88, the model developed for US roadways with traffic ranging from 5,000 – 15,000 vehicles per day presented an initially higher rate of deterioration compared to PMS II. However, after year 17 of service life, this model shows less of a deterioration rate compared to PMS II. This was also the same case for the model developed for NC roadways with traffic ranging from 1,000 – 5,000 vehicles per day. The remainder of the models (US 15K plus, NC 0-1K, and NC 5K plus), present higher deterioration rates throughout the entire service life compared to PMS II. As shown in Table 26, there was a statistical difference at 95% confidence in 6 out of 7 (85.7%) models.

TABLE 26: Patching (wheel path) confidence intervals

Model Family	95% C.I. for b variable	PMS II b variable
WP Interstate	(17.10,18.58)	14.67
WP US 0-5K	(21.44,22.21)	18.14
WP US 5-15K	(18.97,19.67)	18.81
WP US 15K +	(18.03,18.77)	20.50
WP NC 0-1K	(17.27,18.23)	20.07
WP NC 1-5K	(17.89,18.63)	18.00*
WP NC 5K +	(16.12,16.79)	18.39
* denotes no statistical difference between models		

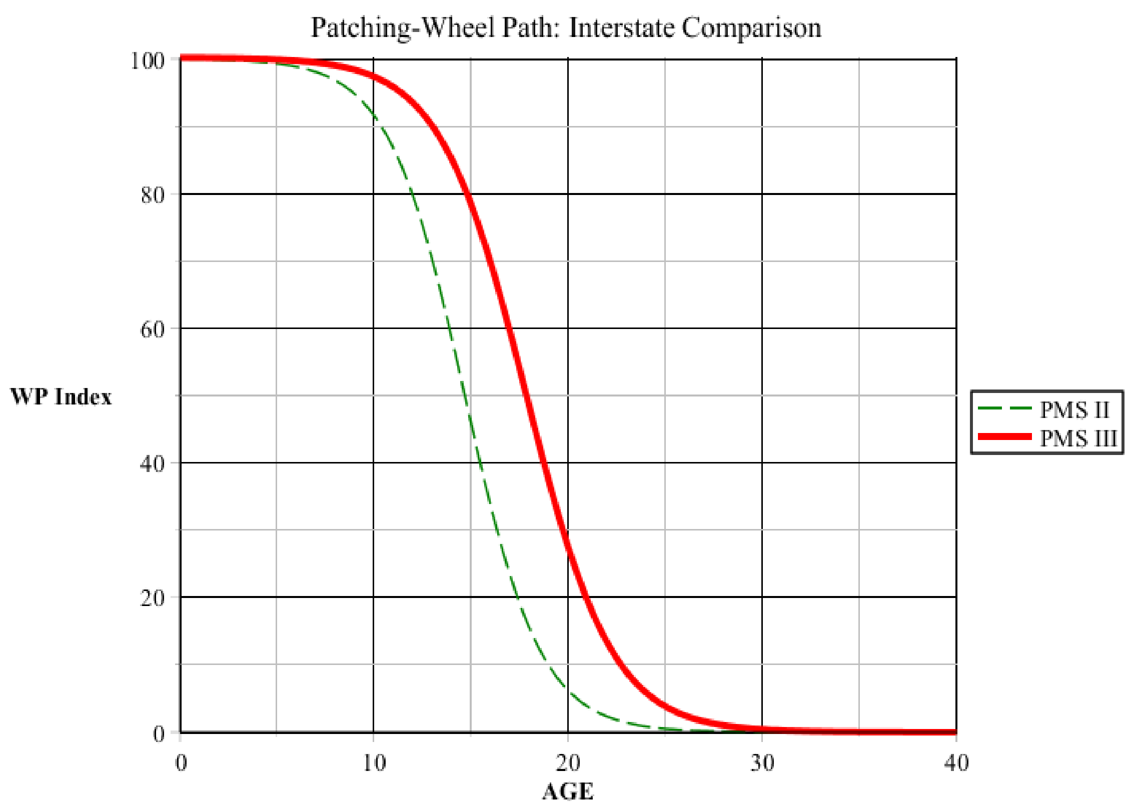

FIGURE 86: Patching (wheel path) – Interstate comparison

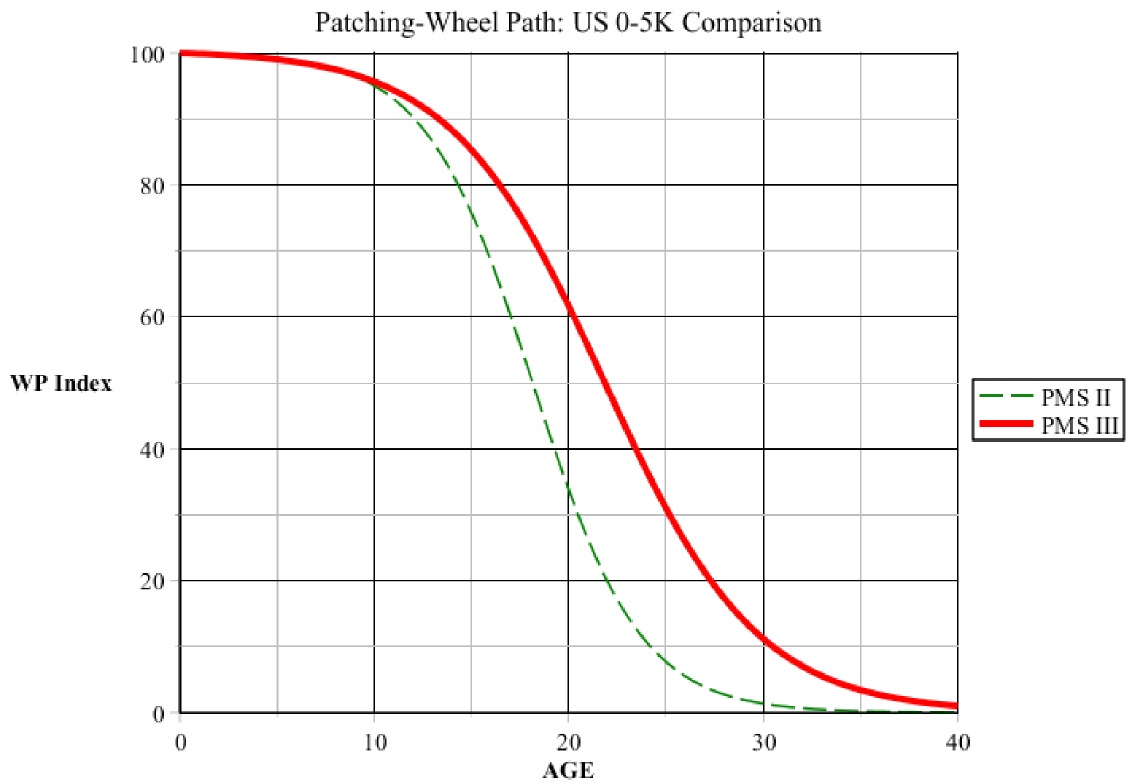

FIGURE 87: Patching (wheel path) – US 0-5K comparison

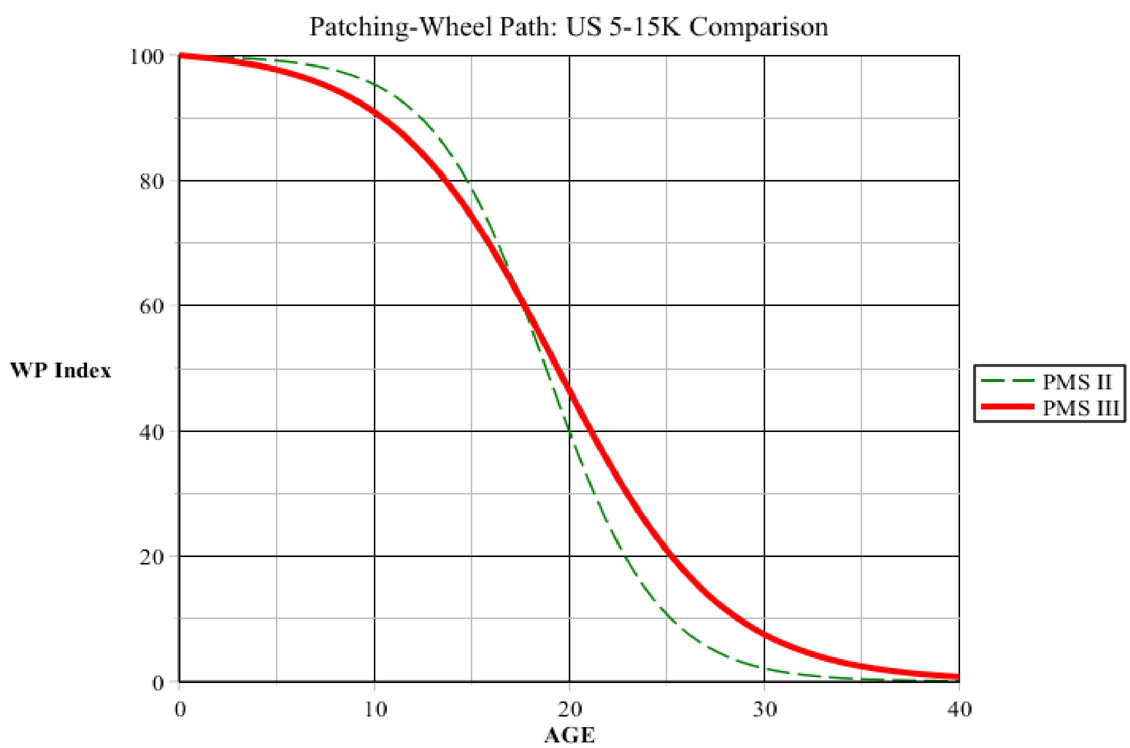

FIGURE 88: Patching (wheel path) – US 5-15K comparison

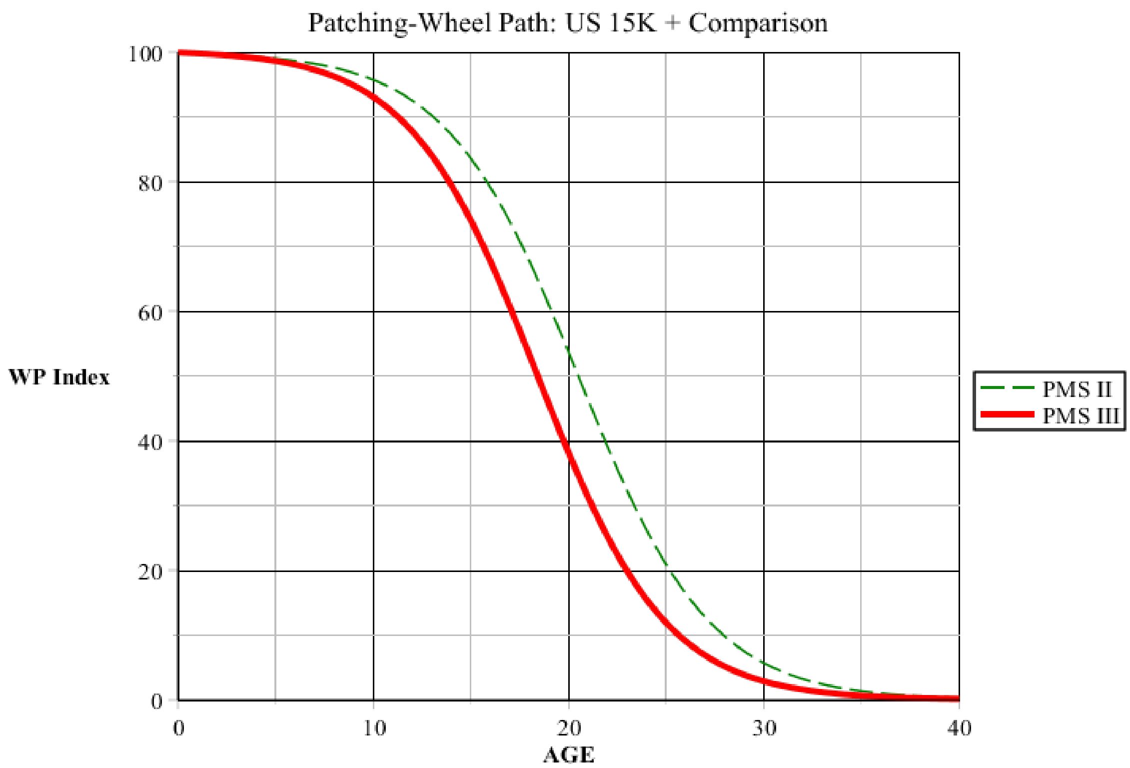

FIGURE 89: Patching (wheel path) – US 15K + comparison

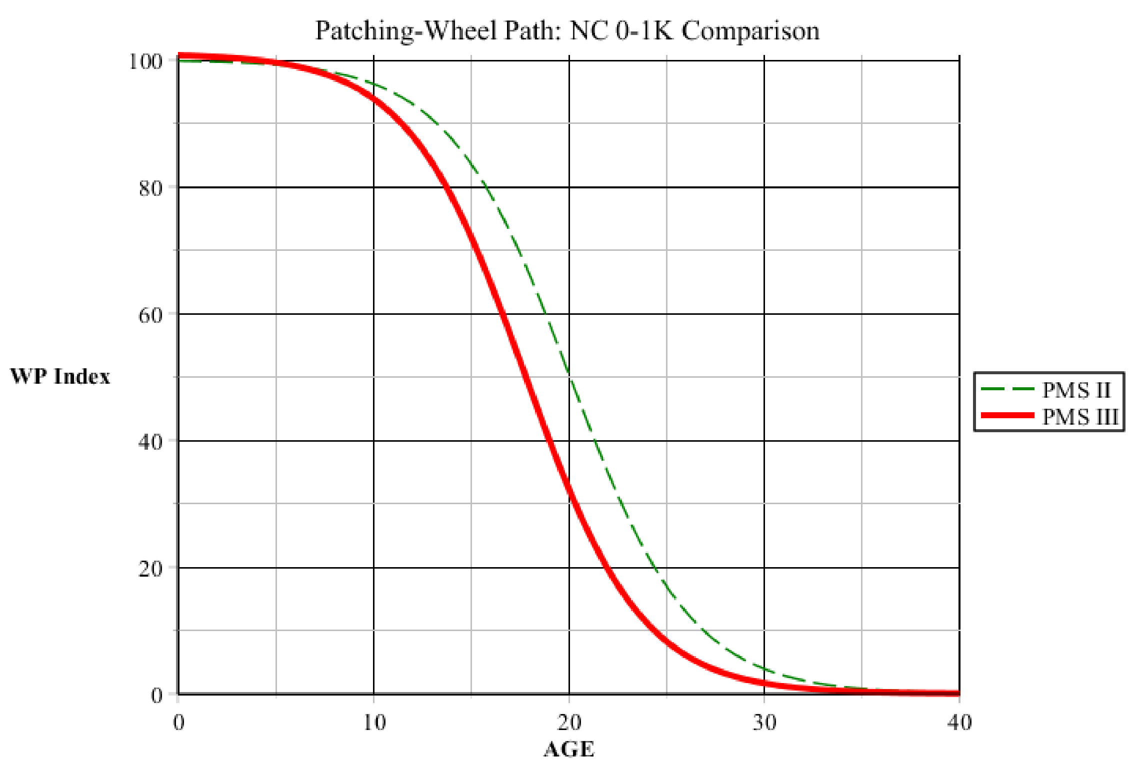

FIGURE 90: Patching (wheel path) – NC 0-1K comparison

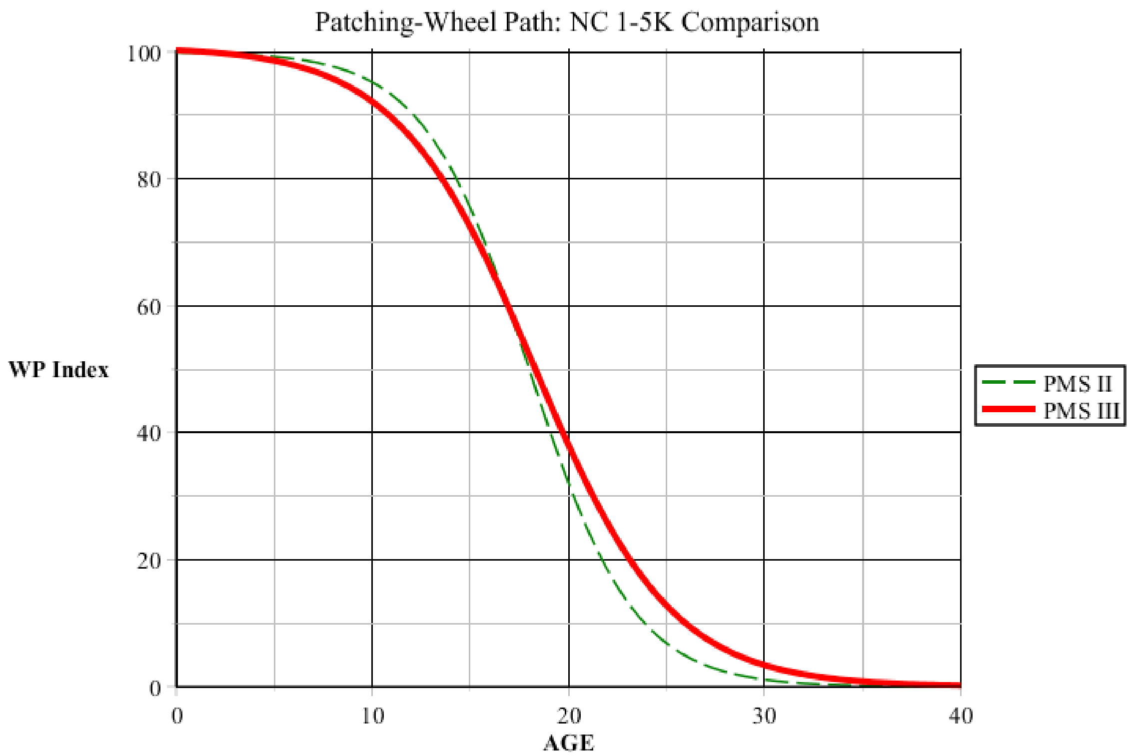

FIGURE 91: Patching (wheel path) – NC 1-5K comparison

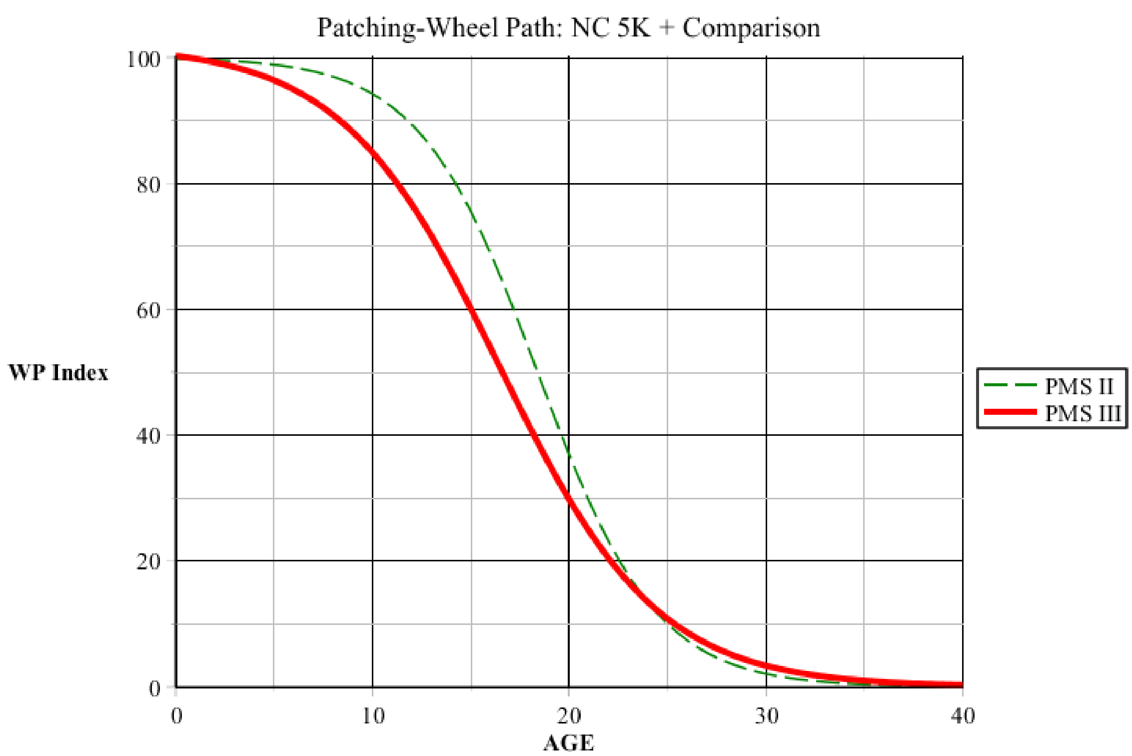

FIGURE 92: Patching (wheel path) – NC 5K + comparison

5.2 Performance Model Comparison

Performance models were compared between phase one, two and three of NCDOT's PMS. Phase one (PMS I) implemented manual data to develop performance models while phase two (PMS II) implemented automated data from 2012 and 2013 and phase three (PMS III) implemented automated data from 2014. Although the data collection method was different for the first phase of NCDOT's PMS, the overall deterioration trends should be similar.

5.2.1 Interstate Asphalt Roadway Performance Comparison

Figure 94 displays the interstate PCR comparison between each NCDOT PMS phase. With the comparison of each model, it is evident that for this family the various PCR curves are fairly consistent in practical terms. Overall the PCR model developed in this research presents an initially lower rate of deterioration during the service life of 0 to 10 years. After year 10, the deterioration rate for PMS III is higher than that of PMS I and PMS II. Table 27 displays the confidence interval for this roadway family. At 95% confidence it is evident that there is a statistically significant difference between models developed in this study compared to models developed in previous studies. Both *b* variables for PMS I and PMS II fell outside the upper bound of the confidence interval. This indicates that the interstate model developed in this study presents a higher deterioration rate and less service life until maintenance is needed for this particular group of asphalt pavements.

TABLE 27: Interstate PCR confidence interval

Model Family	**95% C.I. for b variable**	**PMS I b variable**	**PMS II b variable**
PCR Interstate	(11.58,12.29)	12.41	12.68

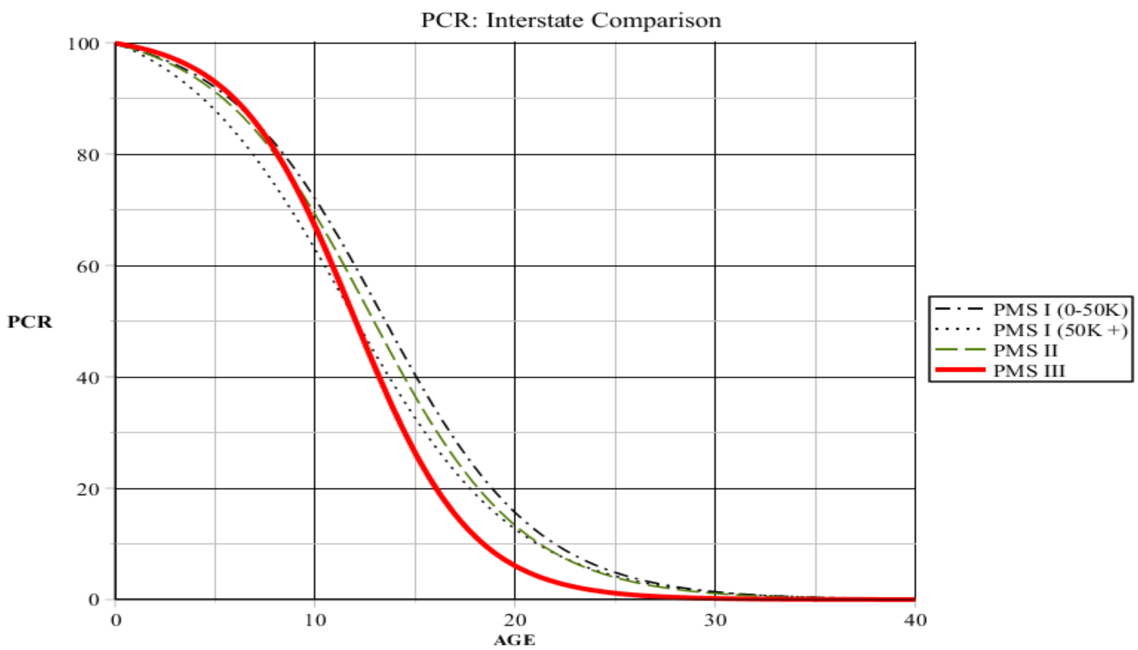

FIGURE 93: PCR – Interstate comparison

5.2.2 US Asphalt Roadway Performance Comparison

Figures 94 - 96 display the US roadway PCR comparisons between each NCDOT PMS phase. As shown in Figure 94, the US model developed for roadways with traffic of 0 – 5,000 vehicles per day presents less of a deterioration rate for years 0 to 10 compared to PMS I. After year 10, the deterioration rate is slightly higher compared to PMS I. Compared to PMS II, the US 0 – 5K model developed in this research presents a significantly higher deterioration rate throughout the service life.

As shown in Figure 95, the US model developed for roadways with traffic of 5,000 – 15,000 vehicles per day presents a lower deterioration rate for years 0 to 8 compared to both PMS I and PMS II. After year 8, the deterioration rate is higher compared to PMS II. It is not until year 14 that the deterioration rate is higher for this model compared to PMS I.

As shown in Figure 96, the US model developed for roadways with traffic greater than 15,000 vehicles per day presents less of a deterioration rate for years 0 to 7 compared to PMS I and PMS II. After year 7, the deterioration rate increases for this model and by year 10 the PCR deteriorates at a much faster rate compared to PMS I and PMS II.

Table 28 displays the confidence intervals for the US family models. With the exception of the US 0-5K model, all *b* variables for both PMS I and PMS II fell outside the confidence intervals for models developed in this study. This indicates that there is a statistical difference between models at 95% confidence. For the US 0-5K model, the PMS I *b* variable fell within the 95% confidence interval, indicating that there was no difference in performance predictions between the model developed in this study and the model developed in phase one.

TABLE 28: US PCR confidence intervals

Model Family	95% C.I. for b variable	PMS I b variable	PMS II b variable
PCR US 0-5K	(10.56,11.13)	10.70*	14.57
PCR US 5-15K	(11.96,12.35)	10.68	14.23
PCR US 15K +	(10.78,11.41)	12.61	14.23
* denotes no statistical difference between models			

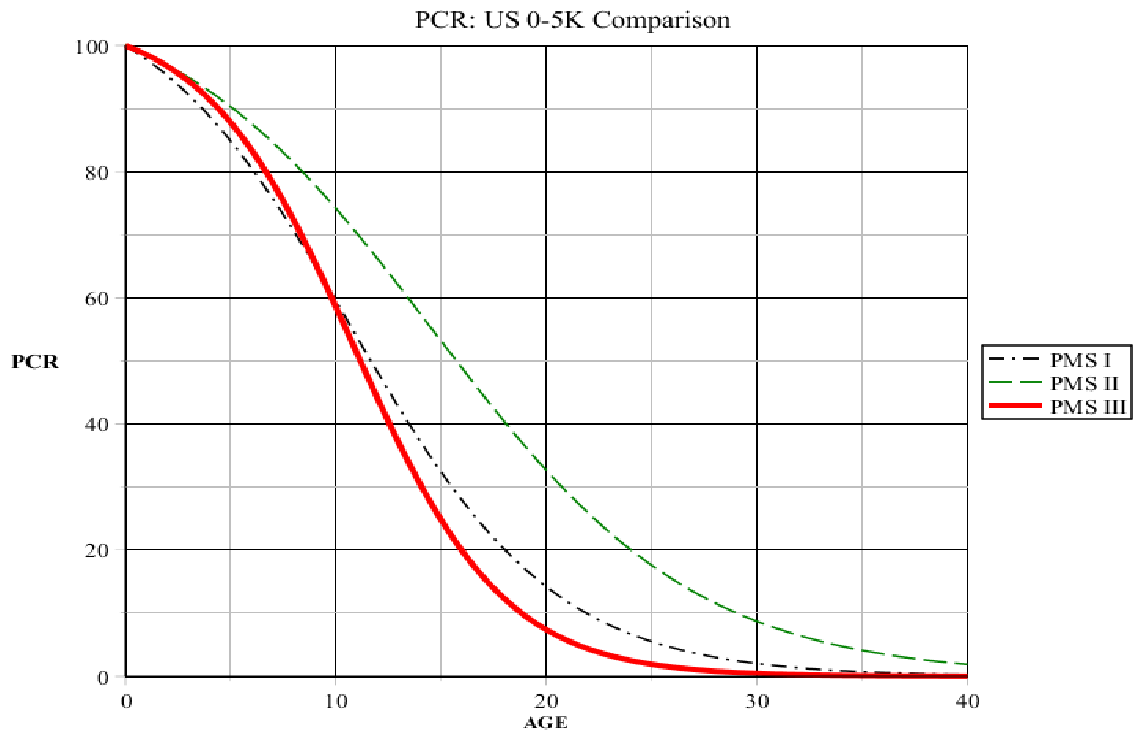

FIGURE 94: PCR – US 0-5K comparison

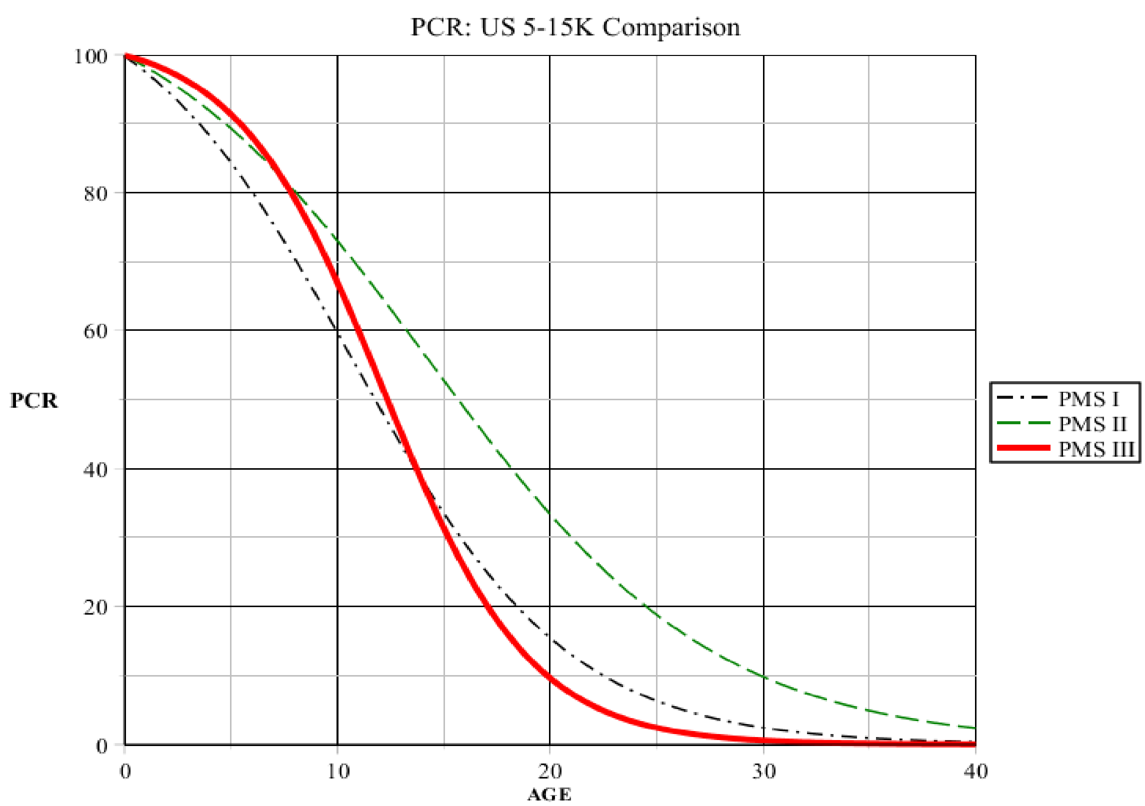

FIGURE 95: PCR – US 5-15K comparison

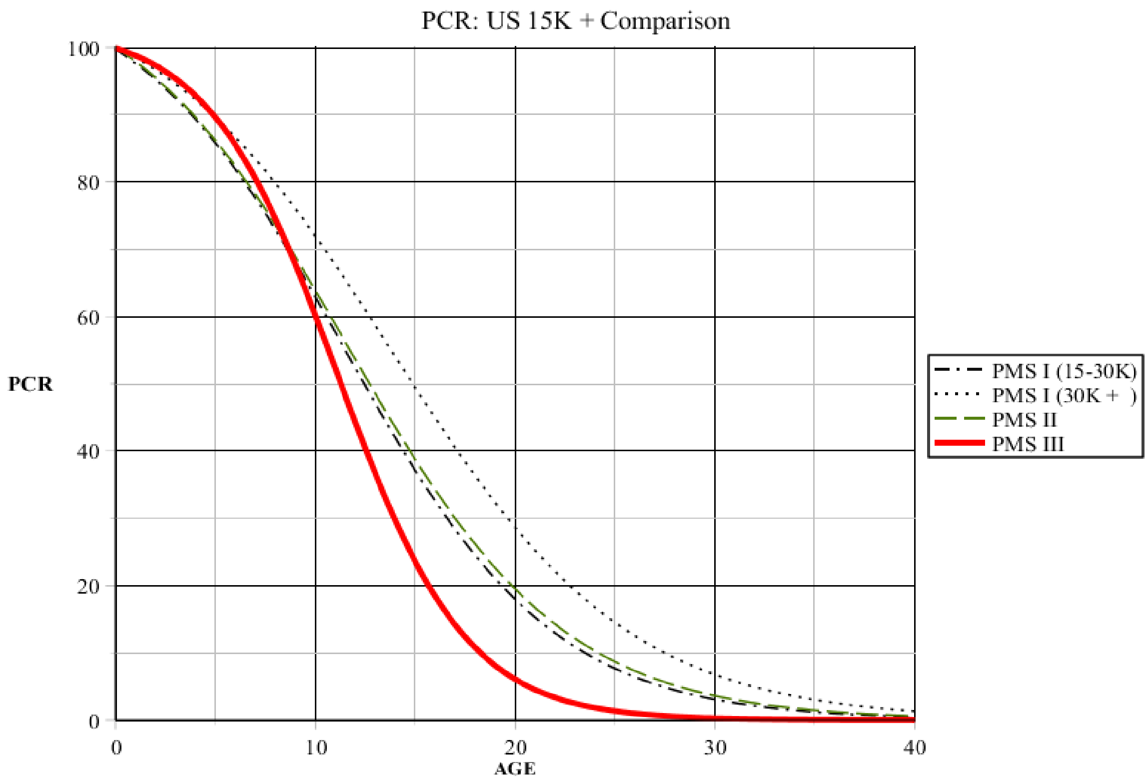

FIGURE 96: PCR – US 15K + comparison

5.2.3 NC Asphalt Roadway Performance Comparison

Figures 103 - 105 display the NC roadway PCR comparisons between each NCDOT PMS phase. As shown in Figure 103, the NC model developed for roadways with traffic of 0 – 1,000 vehicles per day presents a slightly less deterioration rate for years 0 to 10 compared to PMS I and PMS II models. After year 10, the deterioration rate is slightly higher compared to PMS I and PMS II.

As shown in Figure 104, the NC model developed for roadways with traffic of 1,000 – 5,000 vehicles per day presents a lower deterioration rate for years 0 to 8 compared to both PMS I and PMS II. After year 8, the deterioration rate is higher compared to PMS II. It is not until year 14 that the deterioration rate is higher for this model compared to PMS I.

As shown in Figure 105, the NC model developed for roadways with traffic greater than 5,000 vehicles per day presents less of a deterioration rate for years 0 to 7 compared to PMS I and PMS II. After year 7, the deterioration rate increases for this model compared to PMS II. Compared to PMS I, the model developed in this research is fairly consistent. However, after year 16 this model shows slightly higher deterioration compared to PMS I. As shown in Table 29, there was a statistical difference between all NC family PCR models at 95% confidence. Compared to PMS II *b* variables, the models developed in this study have smaller *b* values. This indicates that delaying maintenance reduces service life which is a practical conclusion to what actually happens when maintenance on roadways is delayed.

TABLE 29: NC PCR confidence intervals

Model Family	95% C.I. for b variable	PMS I b variable	PMS II b variable
PCR NC 0-1K	(11.55,12.22)	11.52	12.30
PCR NC 1-5K	(11.71,12.12)	11.14	13.58
PCR NC 5K +	(11.95,12.45)	10.88	13.51

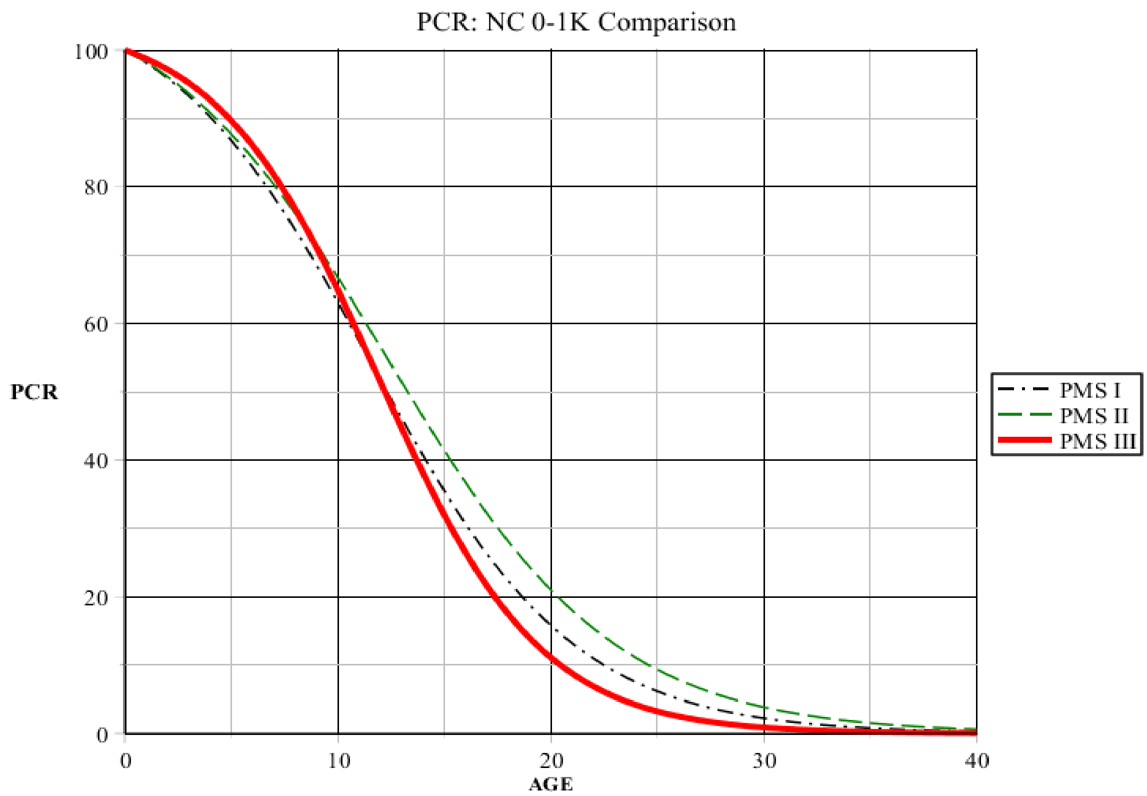

FIGURE 97: PCR – NC 0-1K comparison

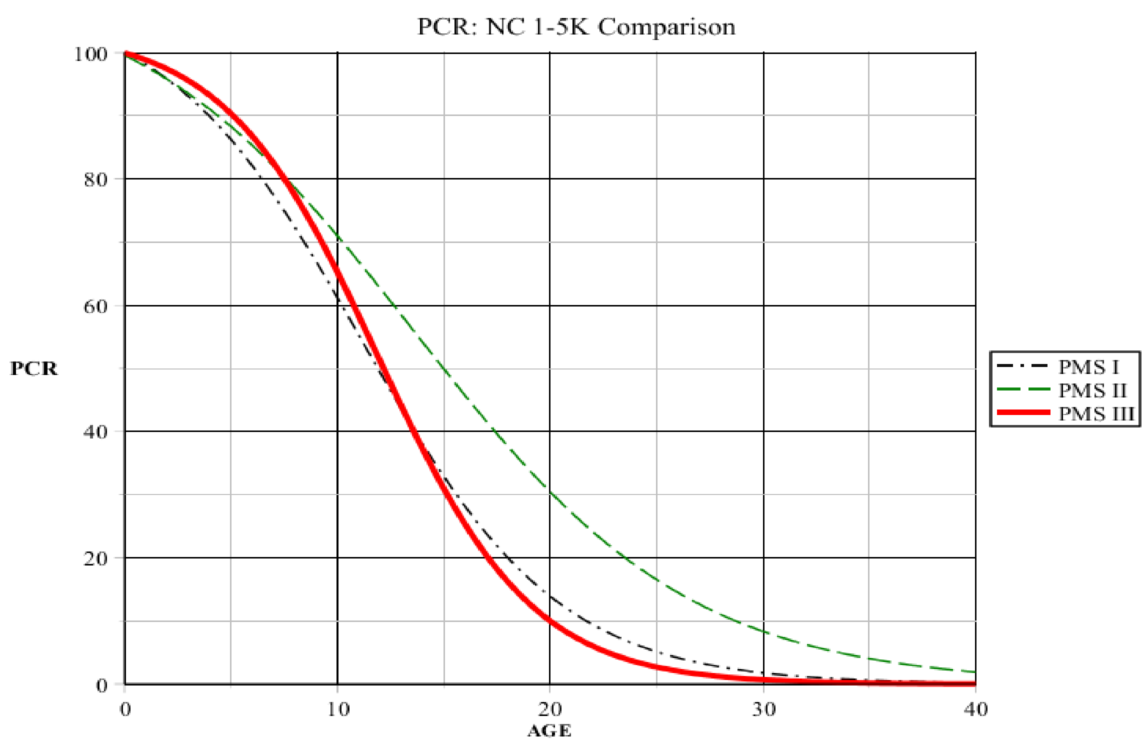

FIGURE 98: PCR – NC 1-5K comparison

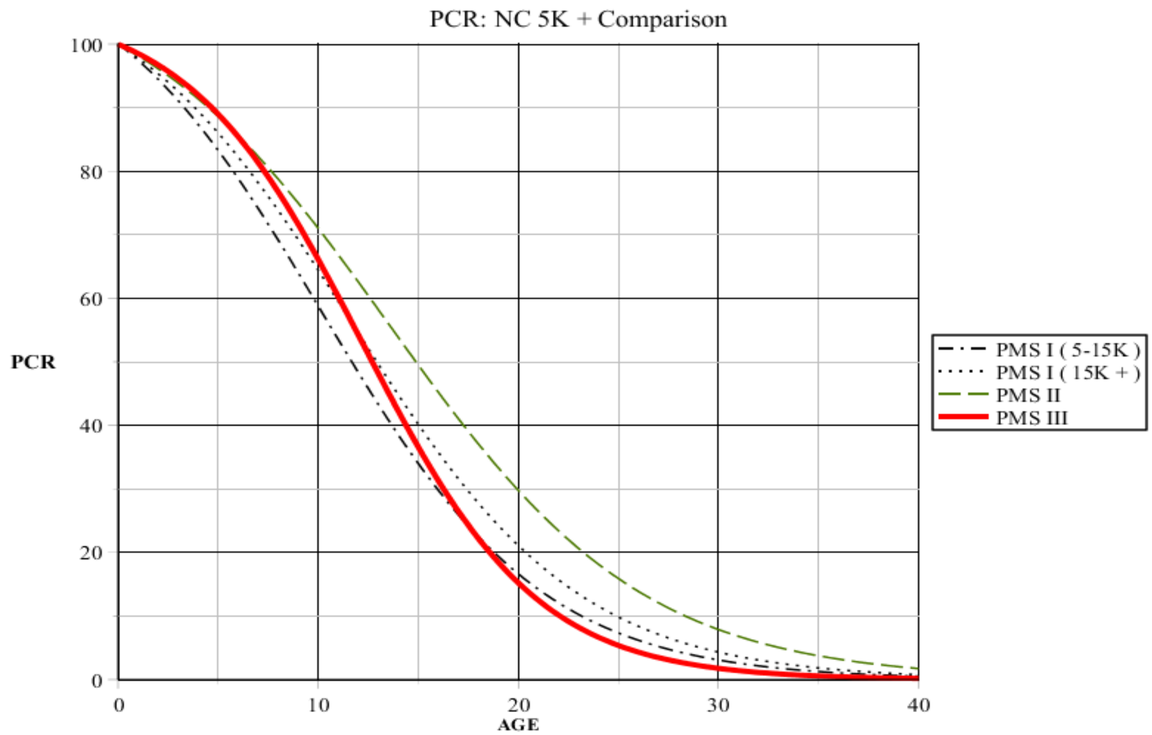

FIGURE 99: PCR – NC 5K + comparison

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

For this research, distress and performance models were developed for asphalt roadways, maintenance trigger points were calculated, and a systematic method of evaluating and validating models was proposed. Distress indices were developed for eight different distress types using the MAE process defined in section 3.4.2. A composite performance index was developed using the AHP method defined in section 3.4.7. Once distress and composite performance indices were developed, their deterioration over time was modeled using sigmoidal regression analysis defined in section 3.4.4. To calculate maintenance trigger points for each distress type and PCR threshold, an algebraic substitution method was implemented by using the AHP pairwise comparisons and the PCR equation developed in section 4.2. Once new asphalt models were developed, an evaluation was performed by visually comparing these models to previously developed models.

6.1 Conclusions

A systematic method of developing distress and performance models was carried out in this study by incorporating previous research methodologies (Chen et al, 2013 and Dye, 2014). Using updated asphalt condition data provided by the NCDOT, a methodology for evaluating and validating newly developed distress and performance models has been proposed in this study.

6.1.1 Distress and Performance Indices

The first step was to merge three different databases provided by the NCDOT. The databases consisted of a 1) a pavement condition database 2) a maintenance and construction history database and 3) a traffic usage database. A data merging process, explained in section 3.3 was carried out to develop a central database that contained pavement condition data with a corresponding age and average annual daily traffic value. Data was subdivided into three classification families consisting of Interstate, US, and NC roadways. The US and NC roadways were further divided into three different families based on traffic usage. This family modeling approach was used because these roadway families are considered to perform similarly.

Once the data merging process was carried out, the second step was to calculate distress indices for each asphalt distress type collected by the NCDOT. The NCDOT observes most distress types in three severity levels consisting of low, moderate, and high. The distress types consisting of wheel path patching, non-wheel path patching, and longitudinal lane joint cracking were observed exclusively as low severity levels. For longitudinal cracking low and high severities were observed. Rutting was observed as the maximum average without regards to any severity level. The remaining distress types were observed as low, moderate, and high severities. Raw data for each distress and type and severity level was then normalized and the 98th percentile was calculated for distress type and asphalt roadway family. As explained in section 3.4.2, the 98th percentile of each severity level was averaged and used in NCDOT's MAE process to calculate a distress index that combines each distress severity into an overall index ranging from 0 to 100. A distress index of 100 indicates that no distress is present and a distress index of 0 indicates that high amounts of a specific distress is present.

A composite performance index, PCR, was developed by using the AHP method to determine each distress type's weight factor. Distress deduction points were calculated for each distress type and averaged as indicated in section 3.4.7. These deduction points were incorporated into a pairwise comparison matrix and the AHP method was carried out by squaring this matrix and calculating the eigenvalues or weight factors. A consistency index and consistency ratio was then calculated to ensure pairwise comparisons were appropriate. Once weight factors were determined, the PCR equation was developed as indicated in section 4.2.

6.1.2 Distress and Performance Models

The non-linear sigmoidal model form was used to develop both distress and performance models. Initial estimates of model coefficients a, b, and c were obtained using the process shown in section 3.4.5. The final distress and performance models were developed in TableCurve® as indicated in section 3.4.6. A data cleaning process had to be utilized in the development of these distress and performance models due to the large number of outliers and the fact that a pavements age is not reset in NCDOT's database after it received maintenance, rehabilitation, or reconstruction. Since a pavements age is not reset after it has received maintenance, there were no obvious declining trends in pavement performance over time. This issue should be addressed in future research to more accurately predict pavement performance over time and increase the efficiency and effectiveness of a PMS.

6.1.3 Maintenance Trigger Points

Maintenance, rehabilitation, and reconstruction trigger points were developed for each asphalt distress type. The PCR equation developed in section 4.2 and the NCDOT PCR threshold values of 80, 60, and 30 were used to calculate each distress types trigger point. These trigger point values only takes into consideration that the distress type occurs by itself and no other distress is present. Trigger points were developed by algebraically manipulating the PCR equation, substituting each distress's relative importance, and solving for the trigger point that enables the PCR to equal the threshold amounts of 80, 60, and 30. As shown in Table 19 in section 4.4, the trigger point values for alligator cracking were substantially higher than the other various distress types trigger point values. For the PCR threshold of 80 the trigger point value for alligator cracking was 121.1. Since the alligator cracking index is on a scale of 0 to 100, this would continuously trigger a maintenance activity, even if the roadway was newly built. This issue should be addressed in further research to quantify an appropriate trigger point for alligator cracking.

6.1.4 Distress and Performance Model Comparison

Distress models were compared between phases two and three of NCDOT's pavement management system research. Phase two consisted of automated data from years 2012 and 2013. Phase three consisted of this research project and used data from 2014. Since NCDOT's raw data processing algorithm changed beginning in 2014, data for phase three was considered more suitable. With the visual comparison of each distress model it was found that were substantial differences between a majority of the distress types. A 95% confidence interval was calculated for the *b* coefficient of distress models developed in this study to determine if there was a statistical difference between models. The *b* variable of

PMS II was analyzed to determine if it fell within the 95% confidence interval. If the coefficient did not fall within the confidence interval it was determined that there was a statistical difference between data used to develop these models. Table 20 displays the results of the confidence interval comparison. It was determined that out of the 56 family models, only 7 models (ALGTR US 5-15K, TRNSVRS US 5-15K, TRNSVRS NC 1-5K, LNGTDNL NC 5K+, WP NC 1-5K, RUT US 5-15K, and RUT NC 0-1K) were not statistically different from PMS II models. This reveals that 12.5% of models showed no statistical difference compared to models developed with previous data. This concludes that 87.5% of models developed in this study were statistically different than models developed in previous research with an outdated raw data processing algorithm.

Performance models were compared between all three phases of NCDOT's pavement management system research. Phase one consisted of manual data, however the PCR curves between each of the three phases should be consistent. With the comparison of each performance model it was found that the performance models developed with 2014 data were more consistent with the models developed with manual data. There were substantial differences between the performance models developed in phase two of NCDOT's research. To statistically determine the differences between models, a 95% confidence interval was calculated for the estimated *b* variable of the models developed in this study. It was found that out of 14 comparisons there was only 1 model (US 0-5K) for PMS I that was not statistically different. This concludes that 92.9% or 13 out of 14 model comparisons were statistically different. Comparing this research to PMS II, it was determined that all of PMS II *b* variables fell outside the upper bound of the confidence interval. This indicates that asphalt roadway models developed in PMS II overall delay maintenance compared to models developed in this study. This is likely to be due to the change in NCDOT's raw data processing algorithm. Comparing this research to PMS I it was determined that most of PMS I *b* variables fell outside the lower bound of the confidence interval. This indicates that in PMS I roadway prediction models showed higher deterioration rates and a reduced service life compared to PMS III models.

Overall, the PCR models developed in this study cross NCDOT's rehabilitation threshold around the service life of 10-15 years. This is typical for most asphalt pavements in North Carolina as a rehabilitation strategy is usually implemented every 15 years for most roadways. The models developed in this study are considered robust because they promote a responsive PMS that indicates a negative impact of network level performance if maintenance is delayed.

6.2 Recommendations

There are a total of three recommendations based on the results of this study. It is recommended that distress and performance models be updated when at least three years' worth data is available. Since the raw data processing algorithm changed beginning in 2014, it is crucial that when similar data is available, the process conducted in this study be repeated to better predict pavement performance. Also, three years' worth of consistent data would allow for pavement age to be reset when there is a significant increase in the PCR over a roadway section's performance history. If maintenance activities can be more appropriately identified and the pavement age reset to reflect a maintenance strategy such as preventative maintenance, rehabilitation, and reconstruction, prediction models that take into consideration a SHAs maintenance program could be developed.

The second recommendation is to use the comparisons between PMS II and PMS III to improve crack analyzing algorithms that are used to classify the extent of distress on roadways. The results of this research indicate that in practical terms the models and predictions of the raveling distress are not significant. This could be due to the fact that this is not a cracking distress type and data for this distress is collected using a profile system to determine maximum rutting averages. There were large discrepancies between a majority of PMS II and PMS III distress models. Further research should be conducted to determine how the changes to the data collectors crack analyzer effects data quality and pavement performance predictions.

The final recommendation is to further research asphalt distress weight factors and maintenance trigger point values. The weight factor for alligator cracking was substantially higher than the other distress types observed by the NCDOT. This is thought to be the reason why the trigger point values for alligator cracking was greater than 100. More appropriate weight factors would potentially solve this issue. It is recommended that future research be conducted to determine if the amount of variables used to calculate the PCR index can be combined into one distress index. For example, non-wheel path patching and wheel path patching can be combined into an overall patching index that represents all patching on an asphalt pavement section. The resulting effect on distress weight factors could potentially reduce the substantially high maintenance trigger points calculated in this research. Another method of reducing the alligator cracking trigger points is to develop a new deduction point system for the automated data collection system to determine distress importance and distress weight factors. This would potentially eliminate the issue of alligator cracking being substantially more important or over weighted compared to other distress types.

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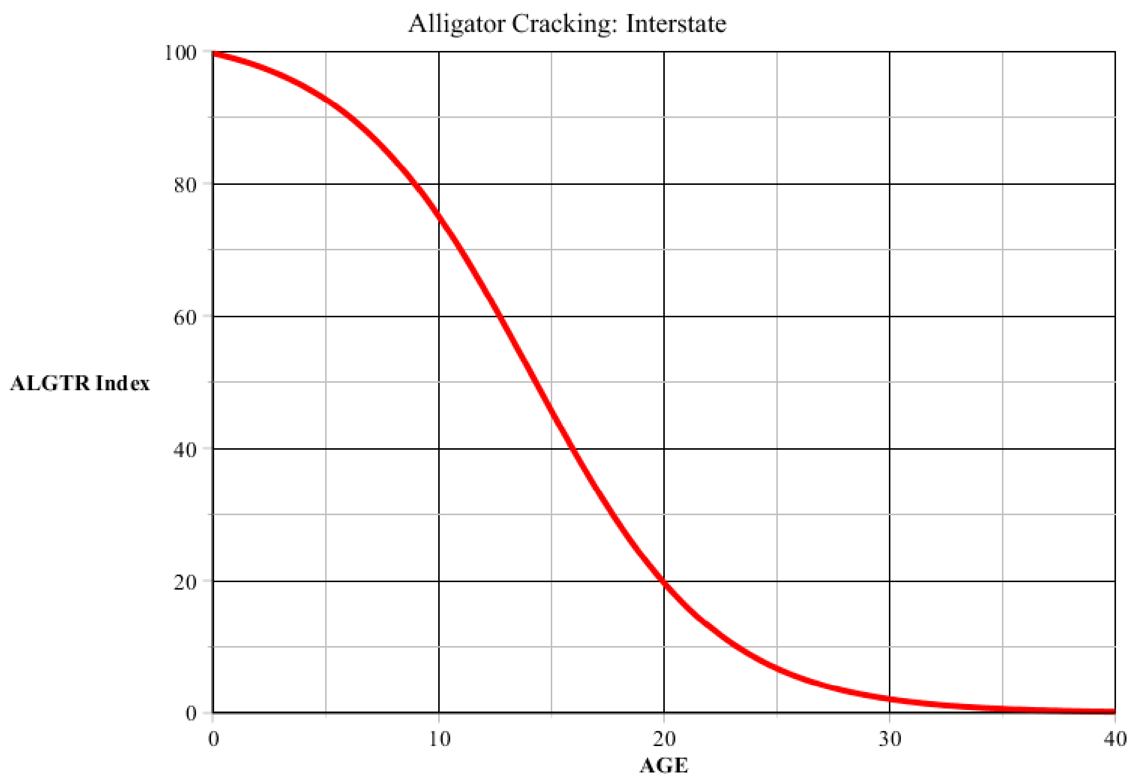
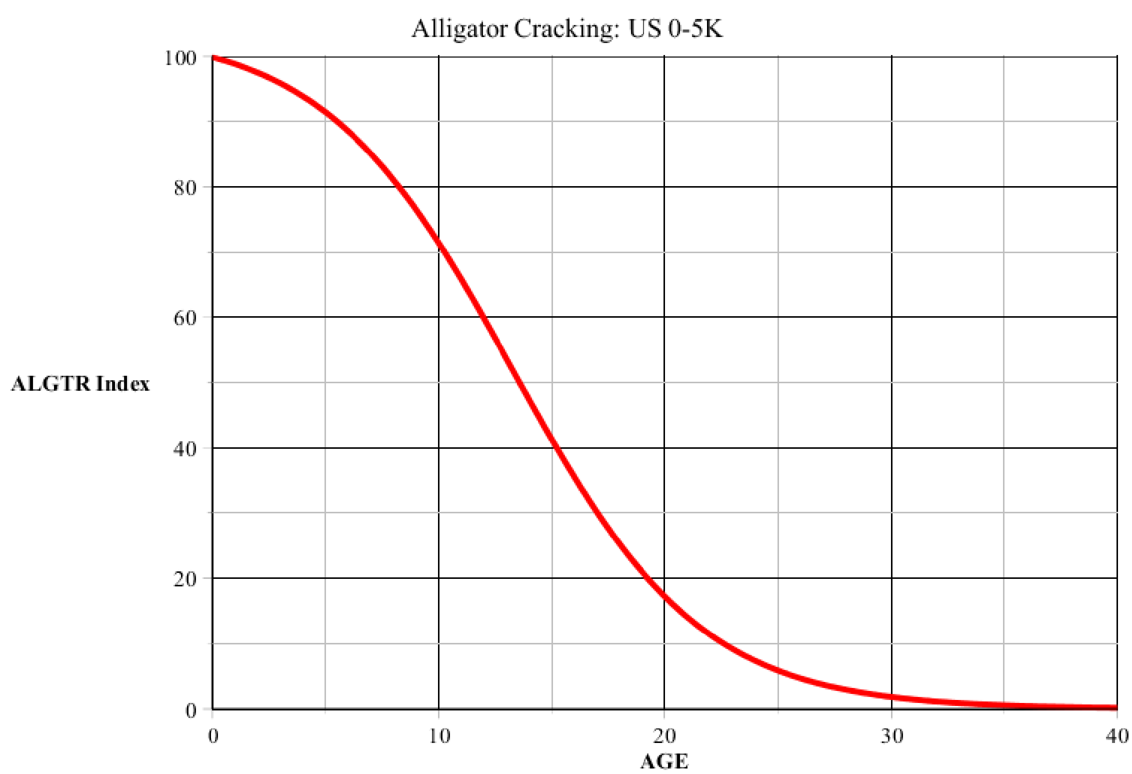
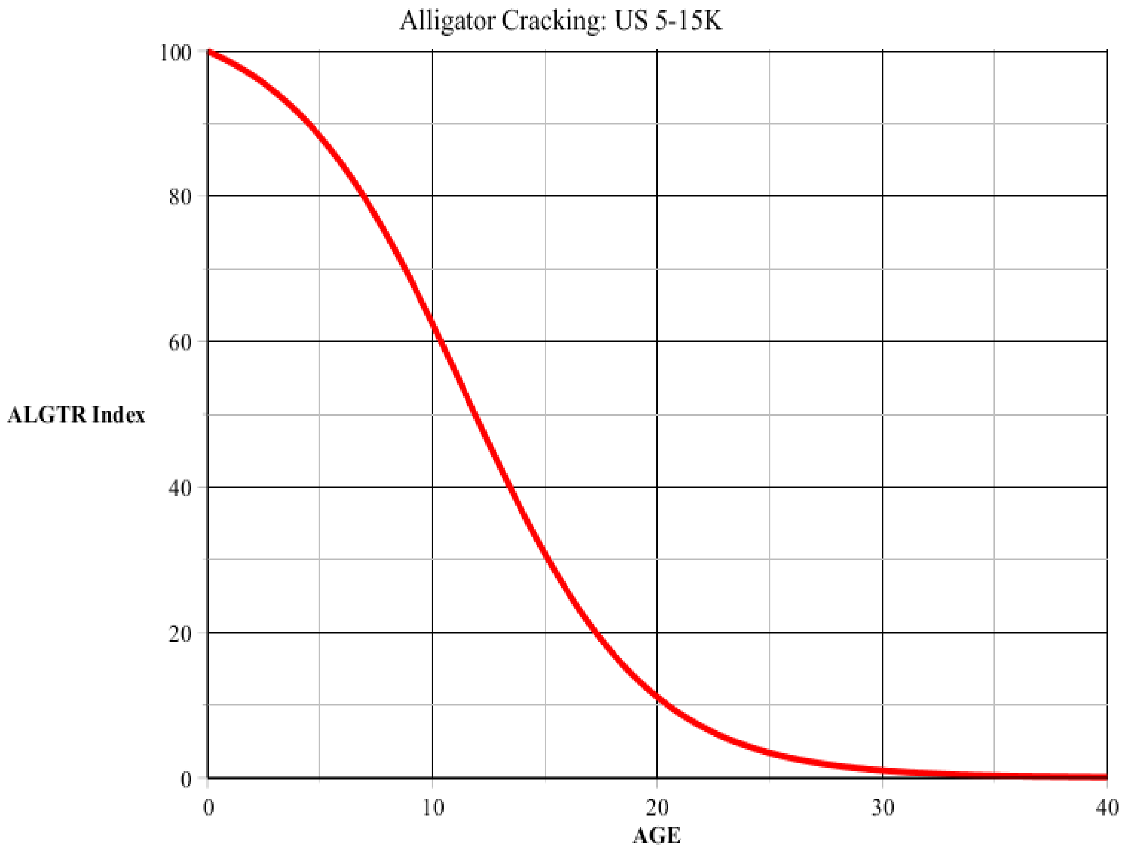
APPENDIX A: ALLIGATOR CRACKING MODELS



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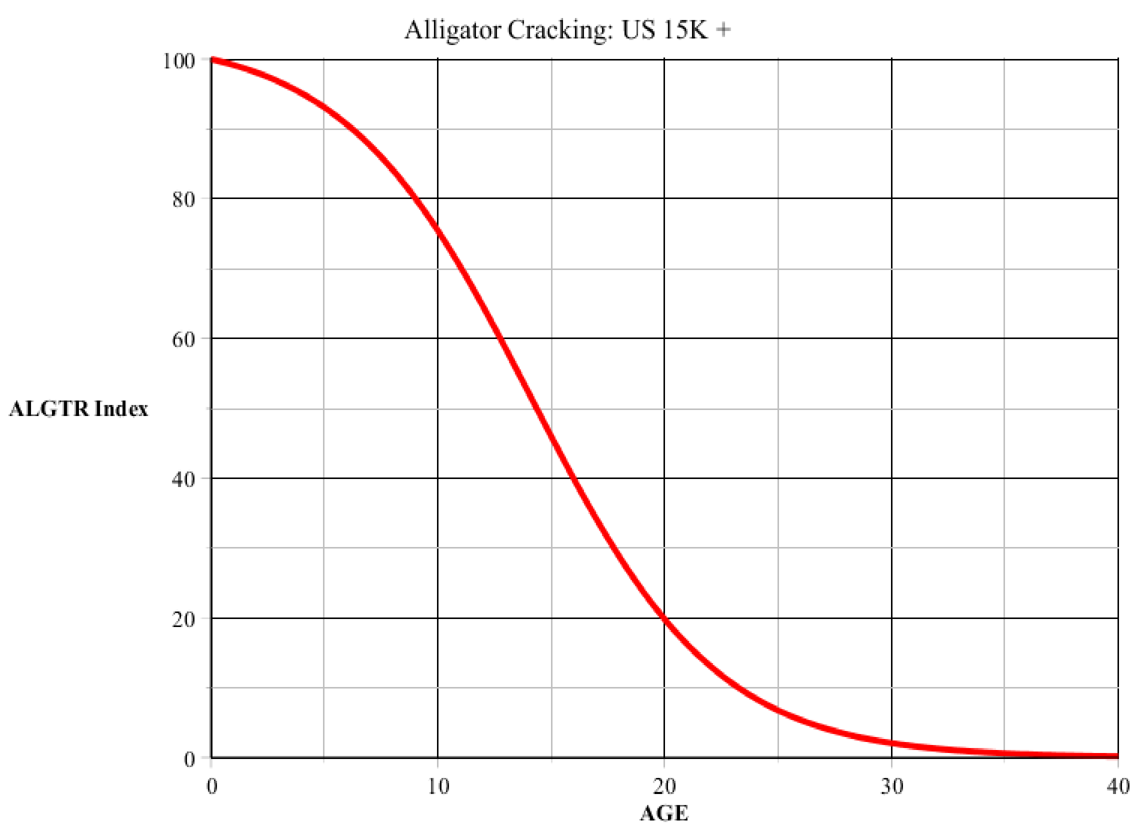
60
40
20
0
0
10
20
30
40
AGE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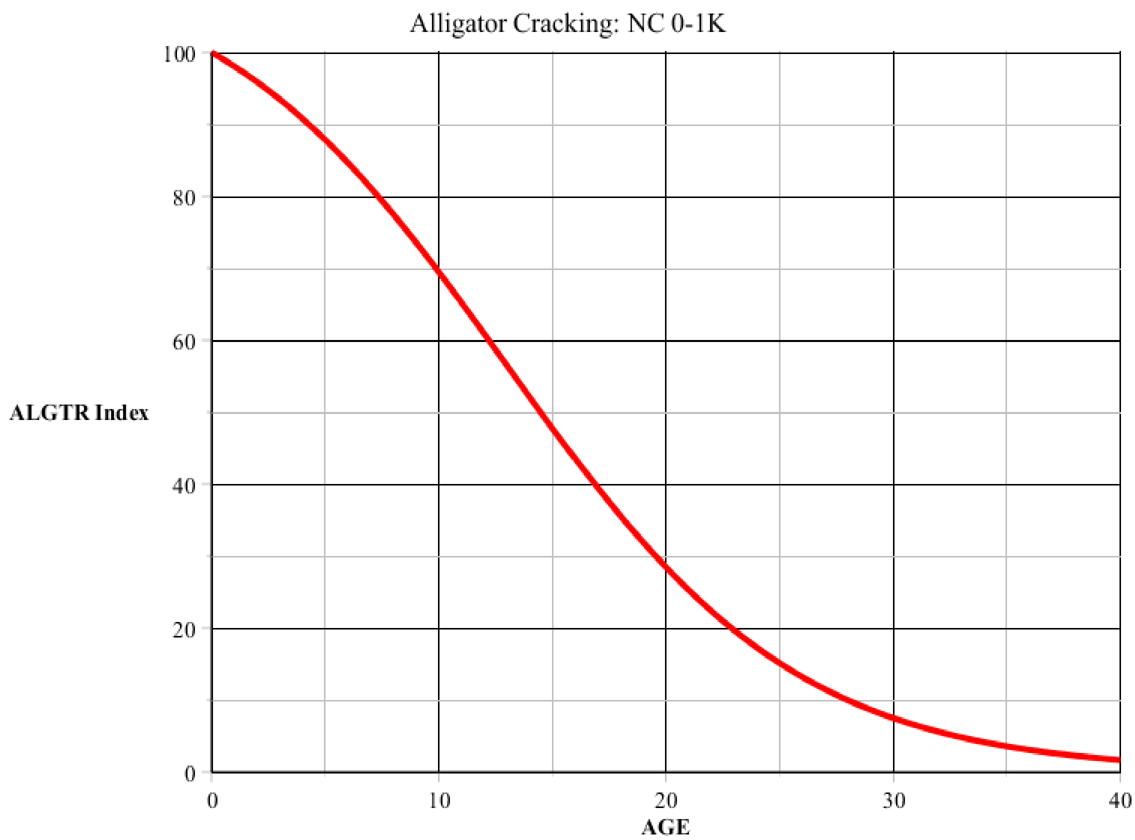
60
40
20
0
0
10
20
30
40
AGE



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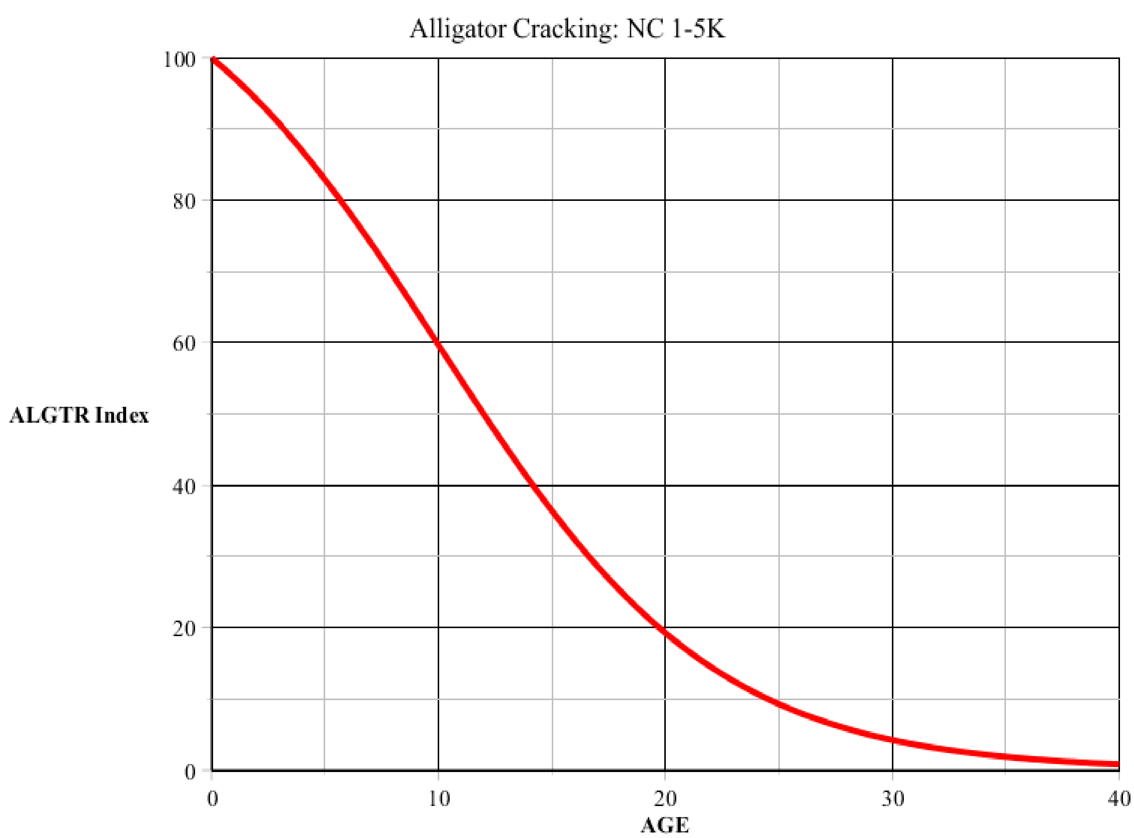
100
80
60
40
20
0
0
10
20
30
40
AGE



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60
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20
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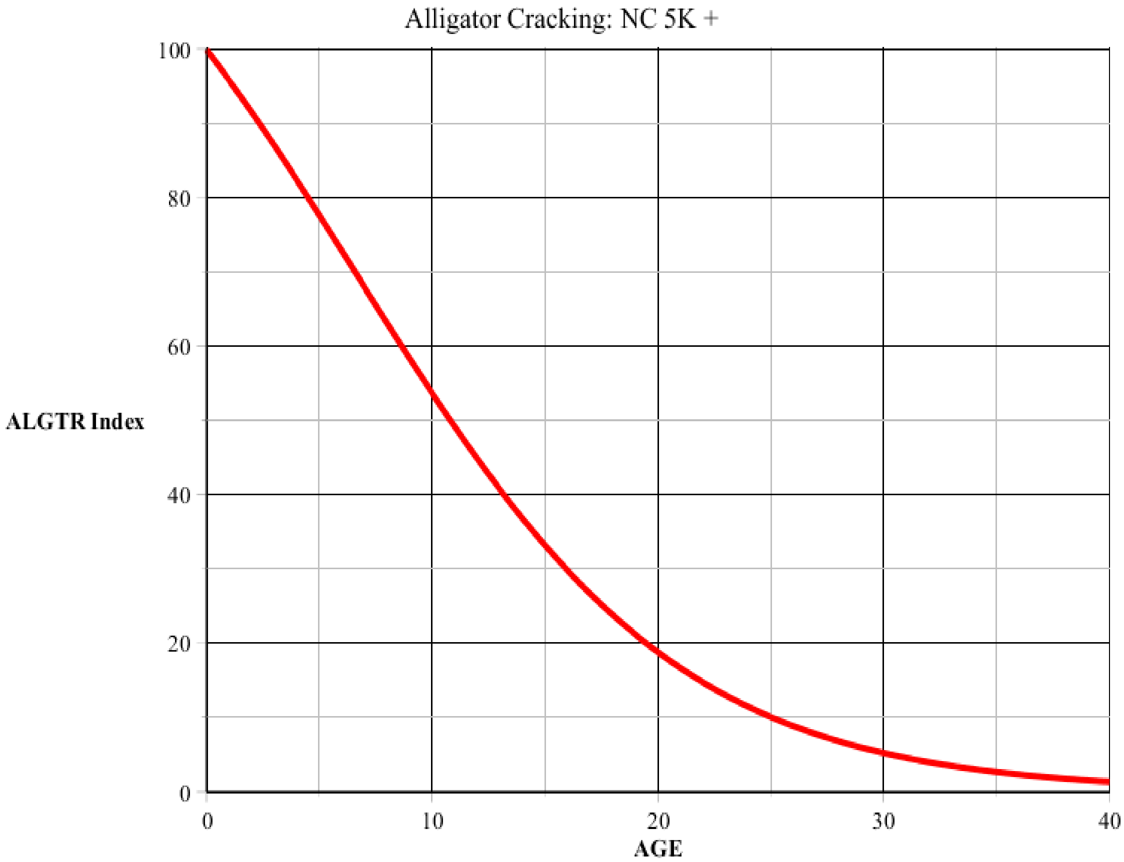
10
20
30
40
AGE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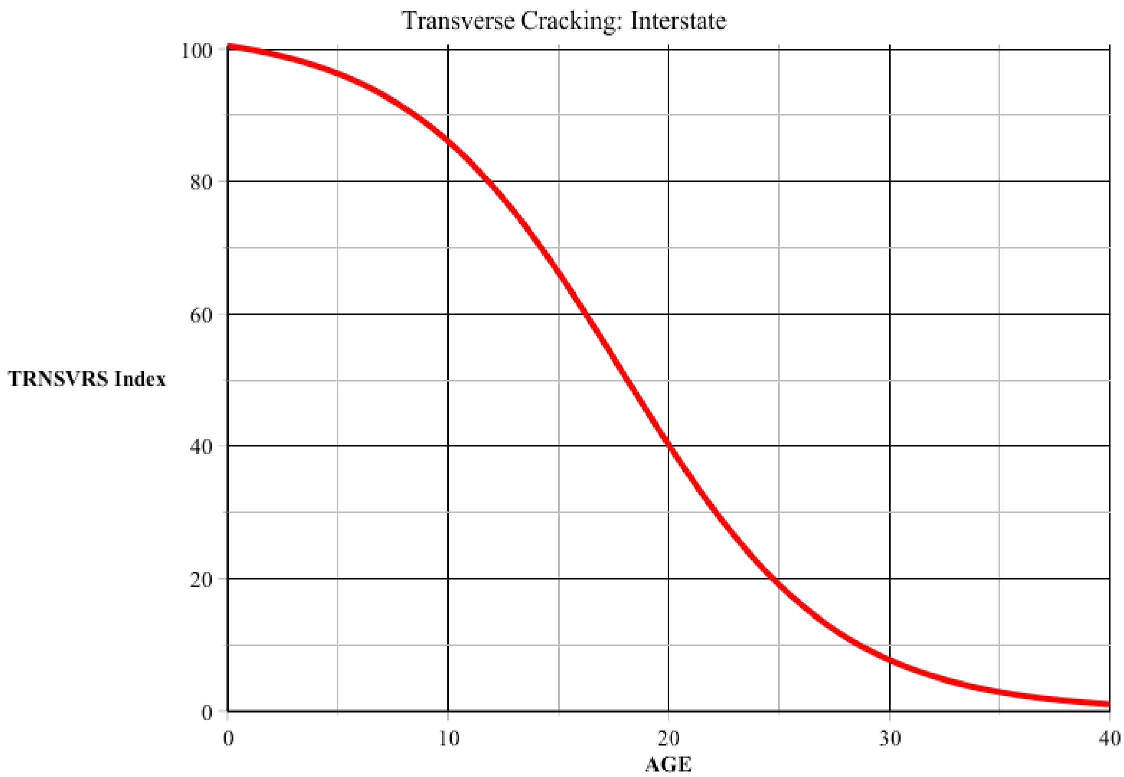
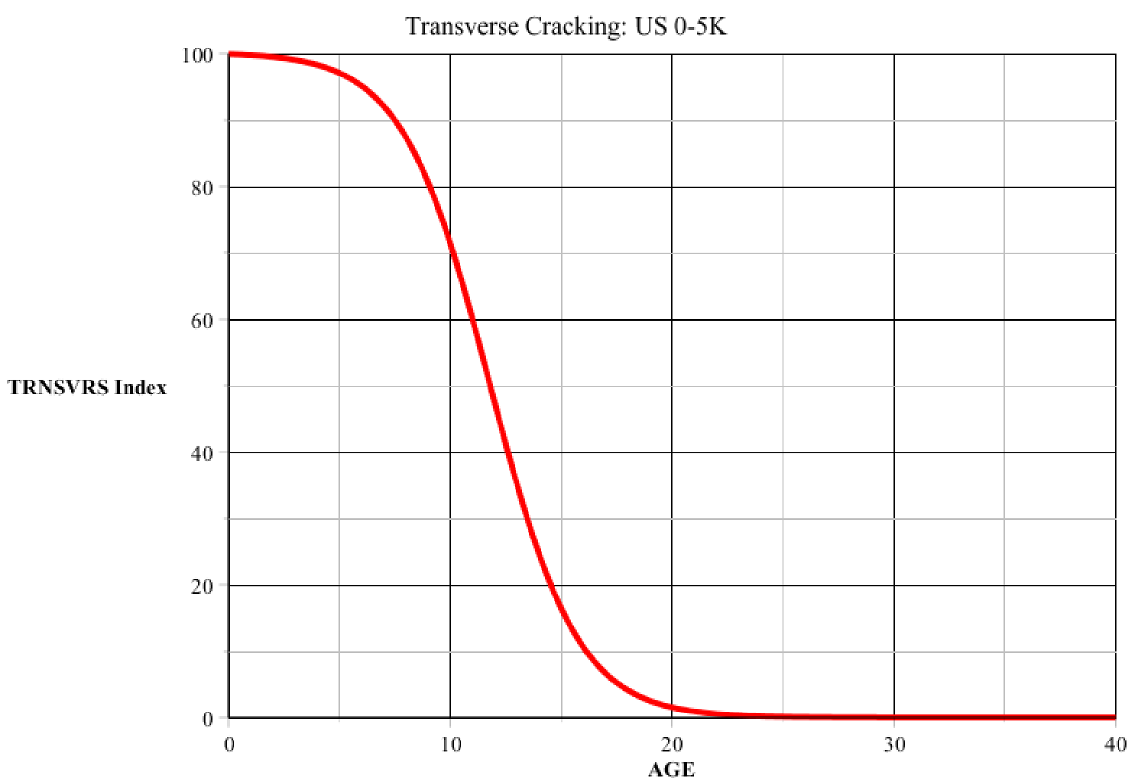
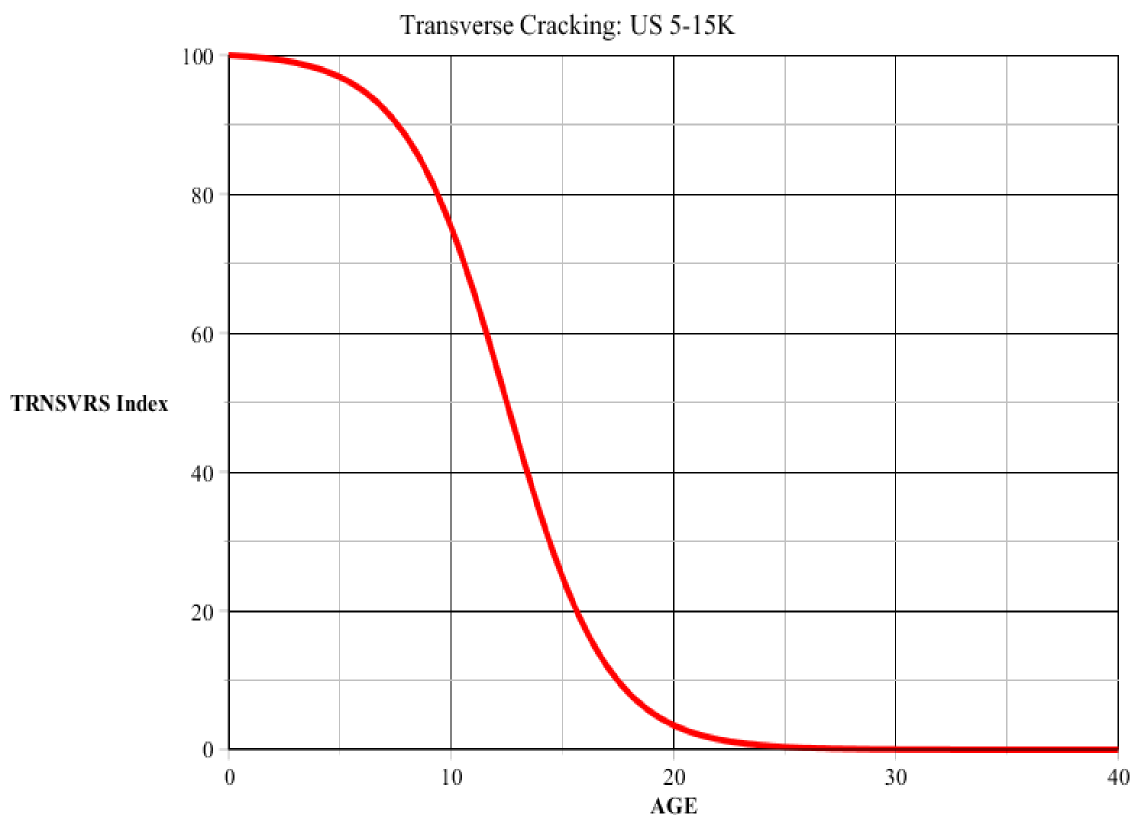
30
40
AGE

APPENDIX B: TRANSVERSE CRACKING MODELS



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60
40
20
0
TRNSVRS Index
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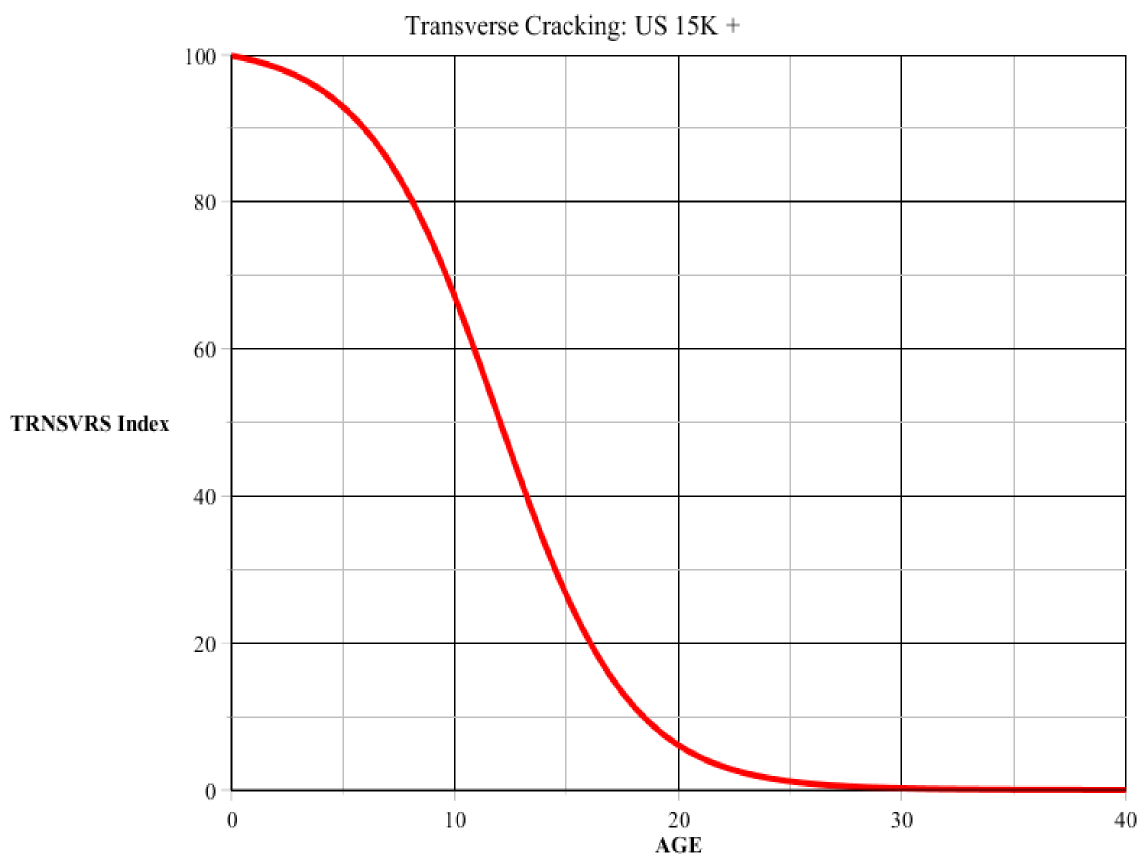
10
20
30
40
AGE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60
40
20
0
TRNSVRS Index
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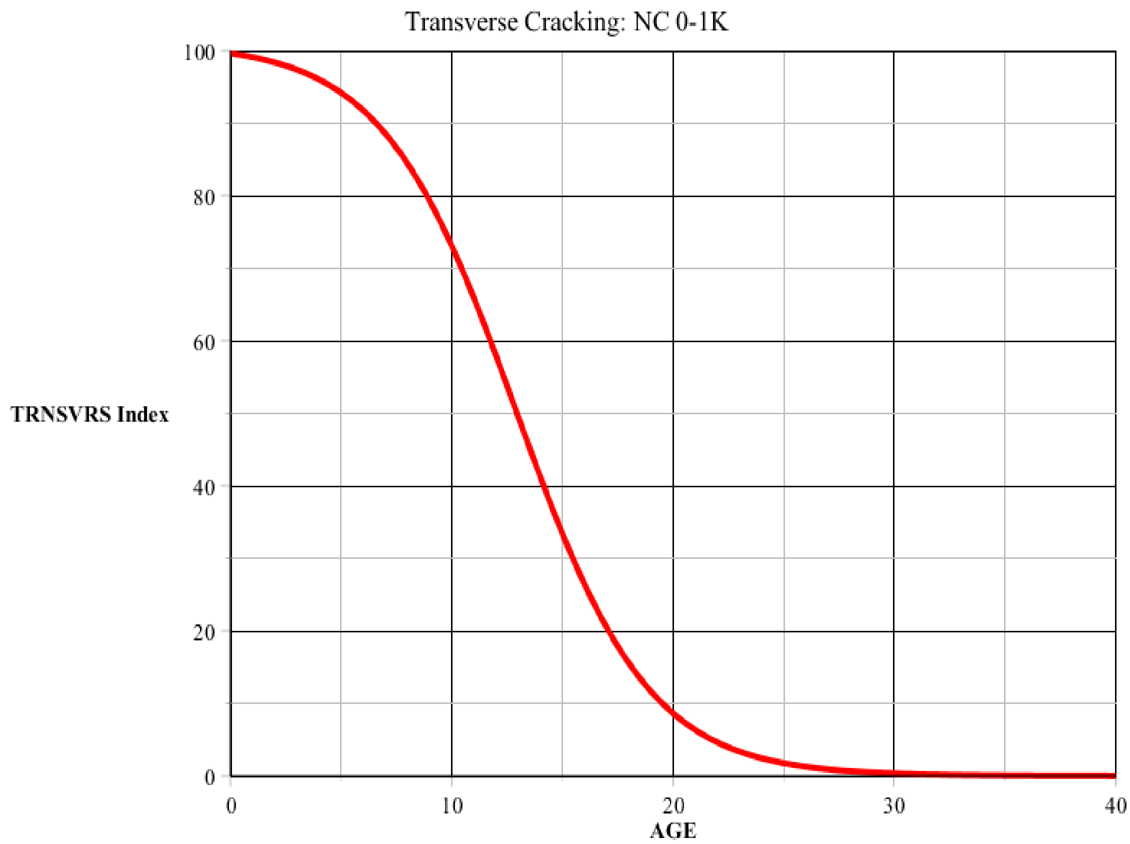
10
20
30
40
AGE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100
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60
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20
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TRNSVRS Index
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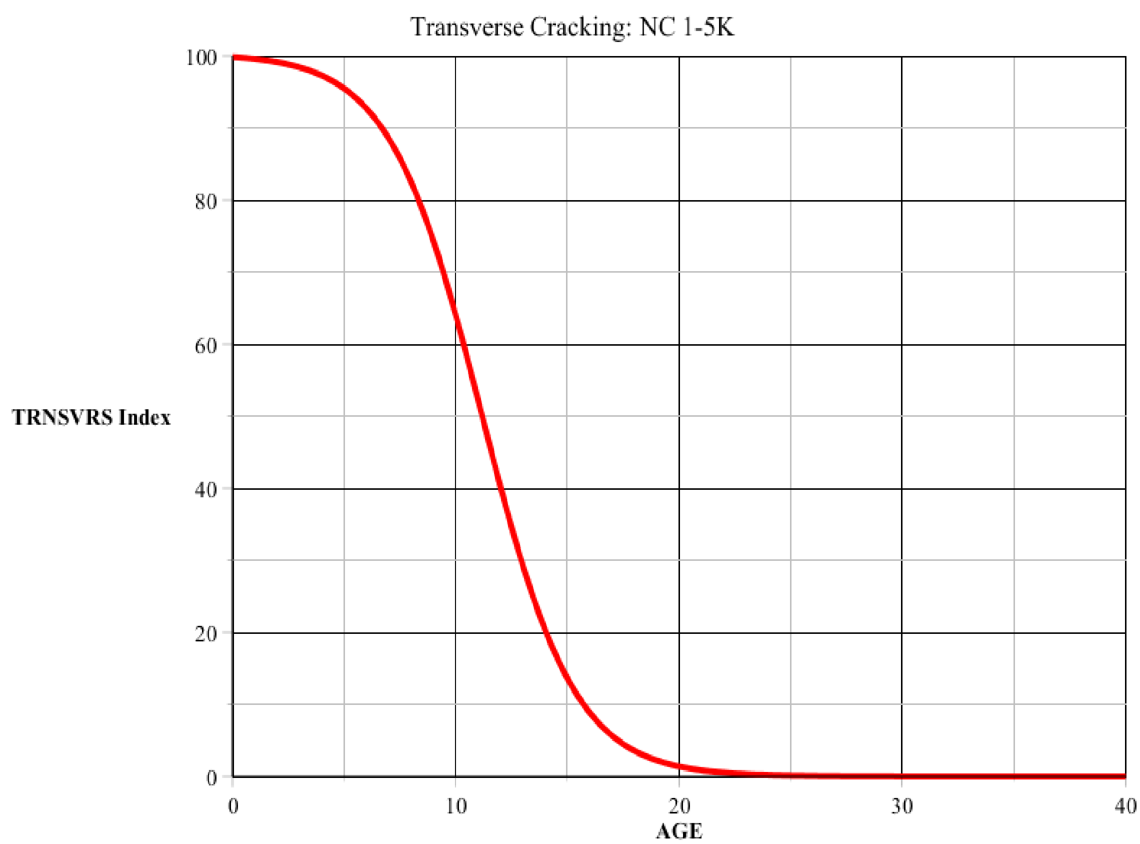
10
20
30
40
AGE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TRNSVRS Index
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40
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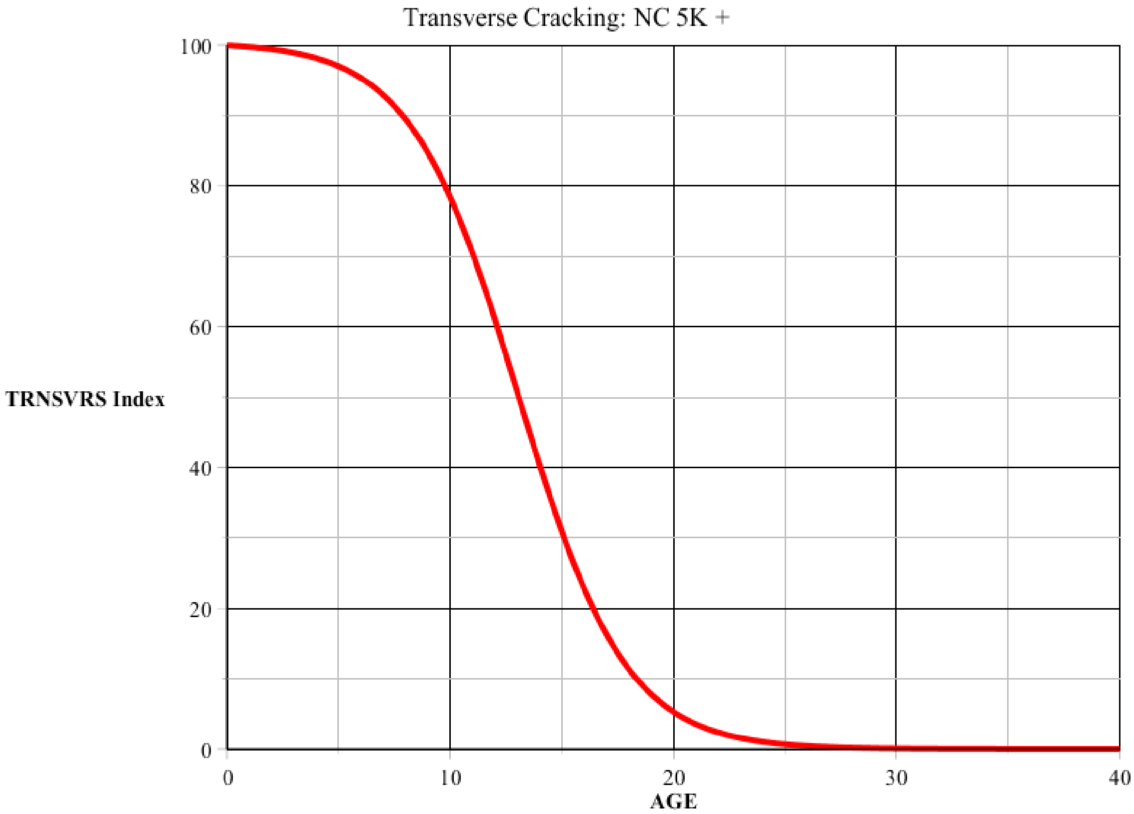
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10
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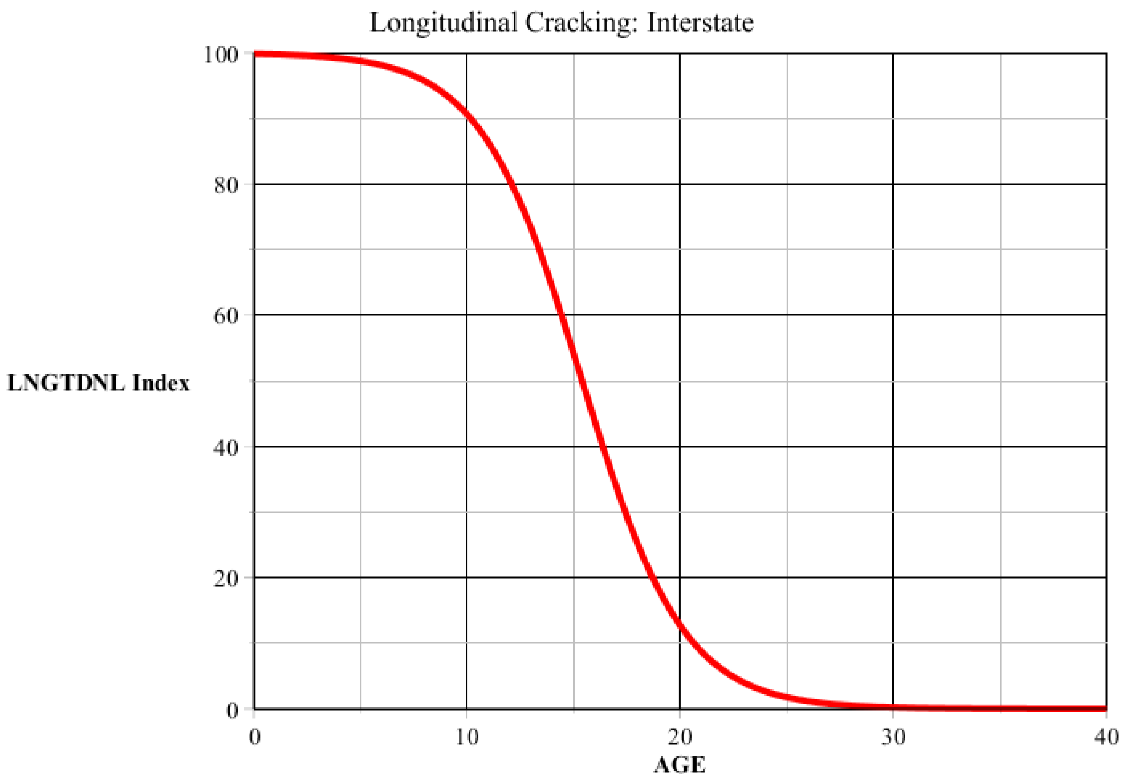
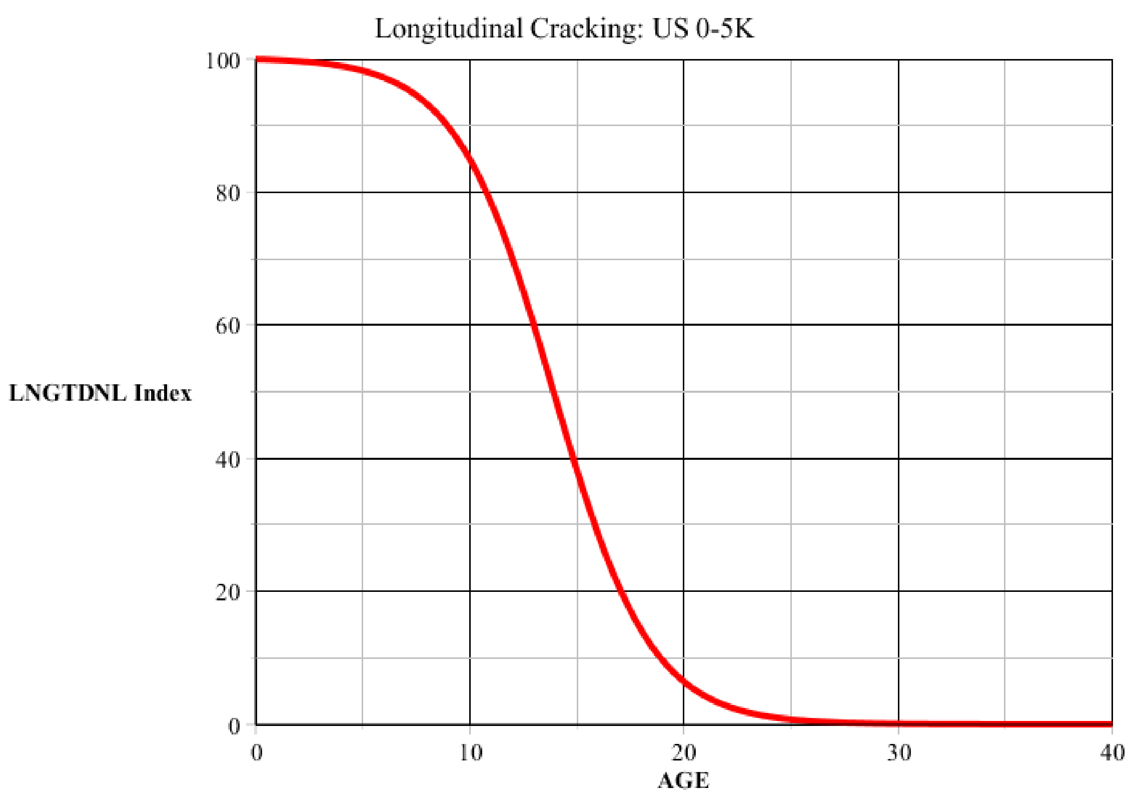
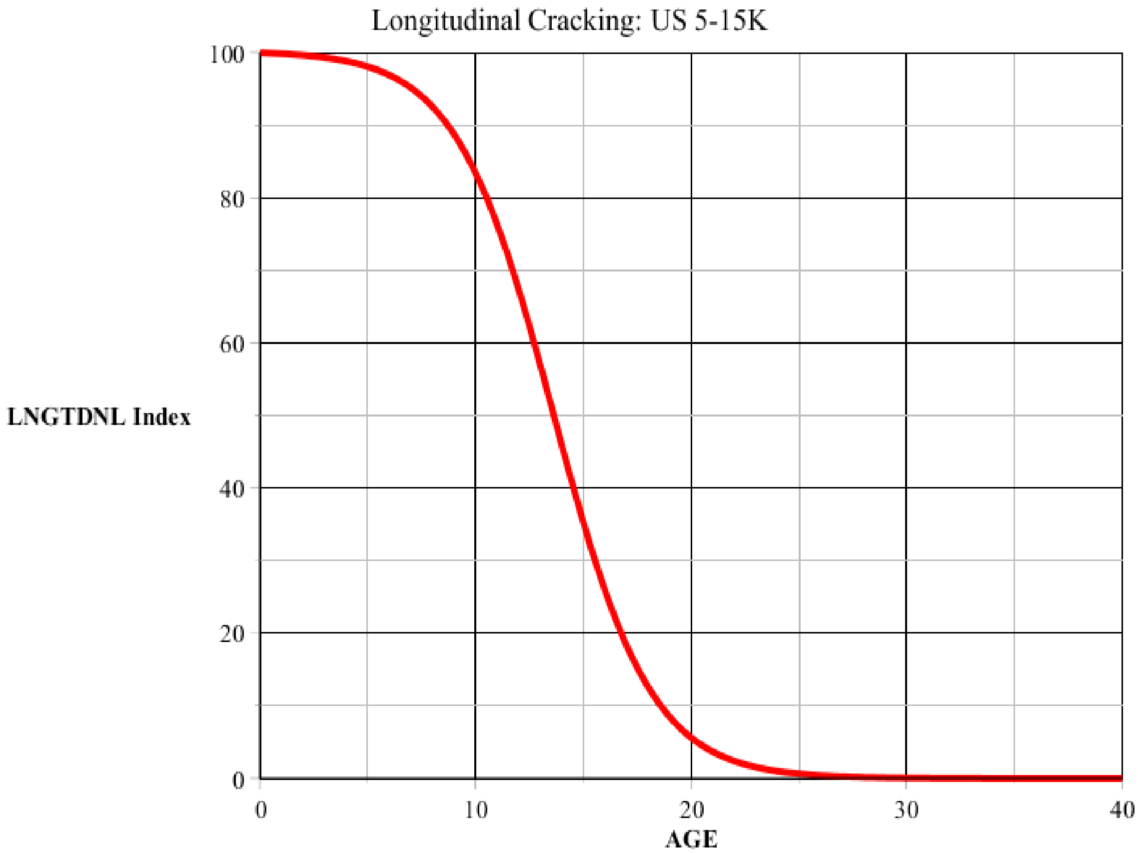
30
40
AGE

APPENDIX C: LONGITUDINAL CRACKING MODELS



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LNGTDNL Index
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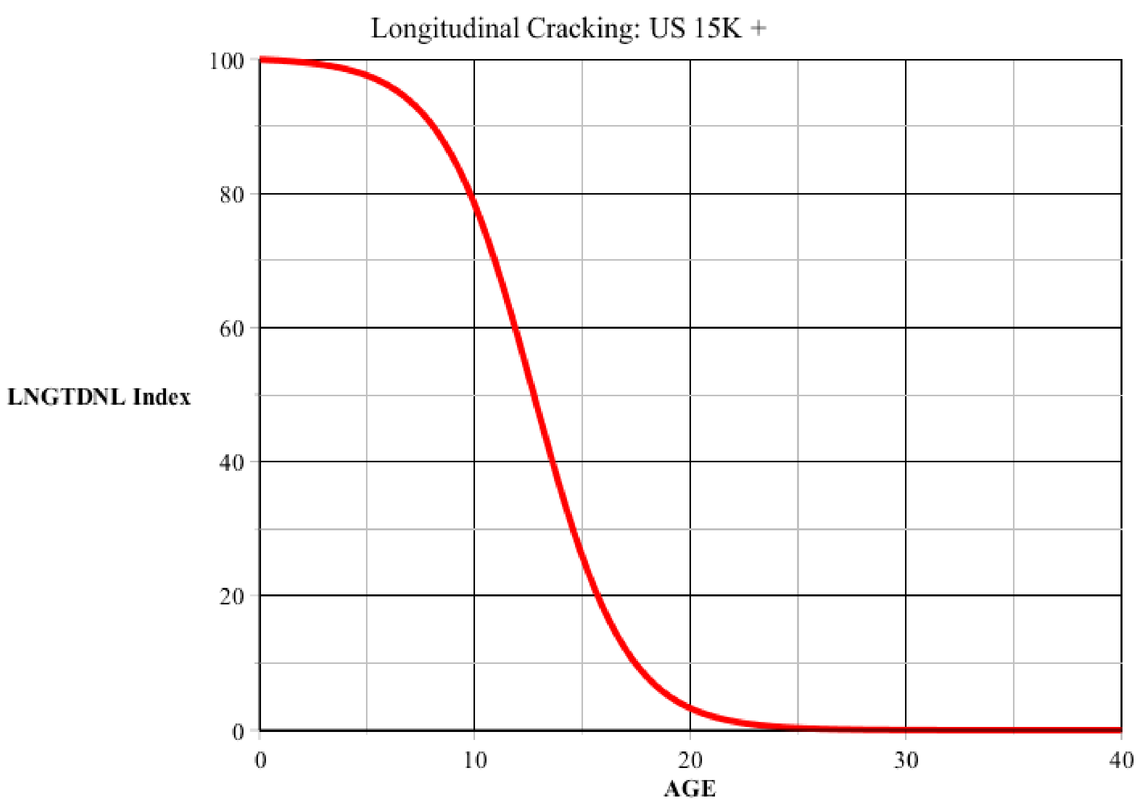
60
40
20
0
0
10
20
30
40
AGE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40
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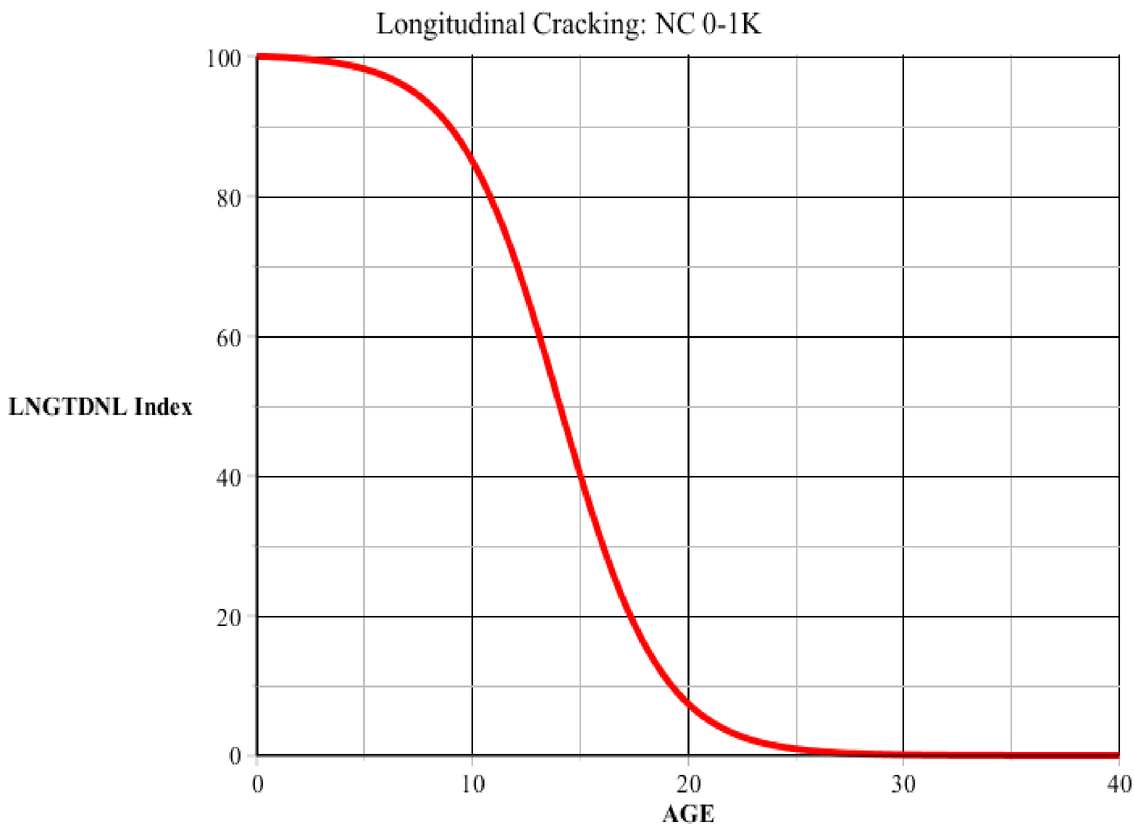
10
20
30
40
AGE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60
40
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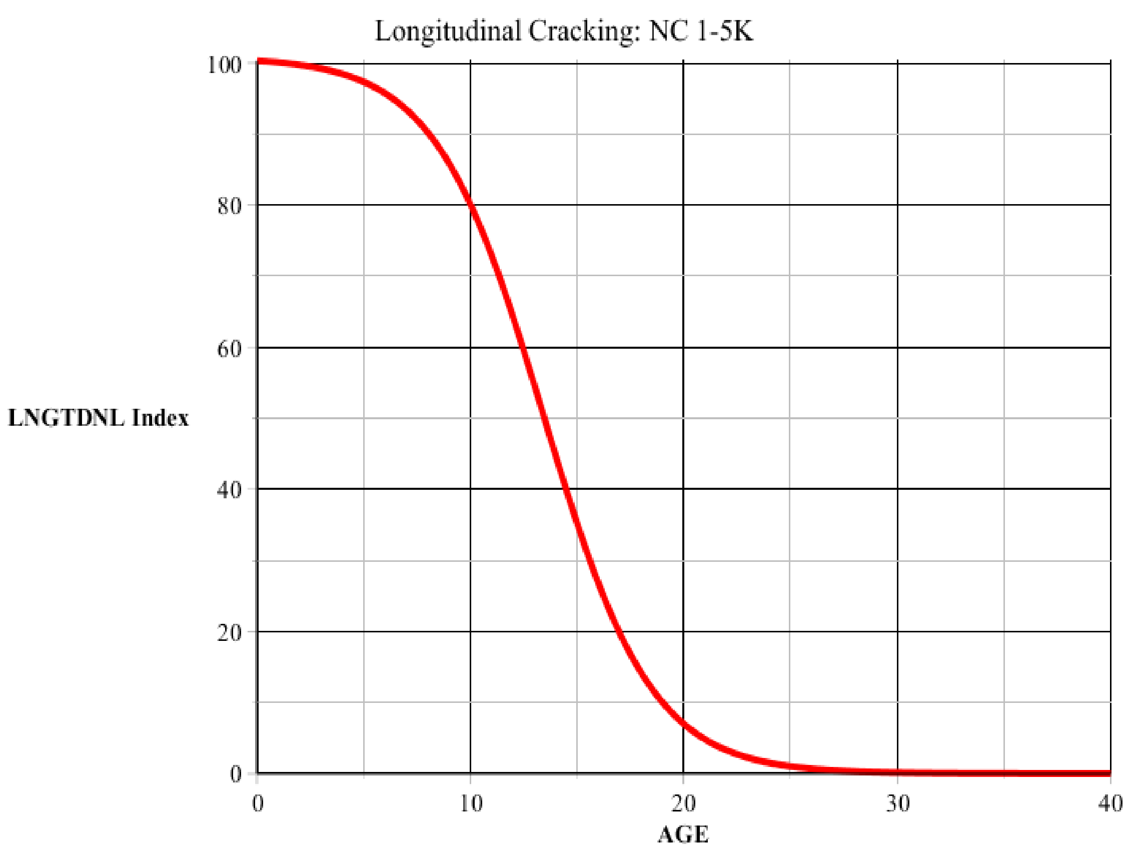
10
20
30
40
AGE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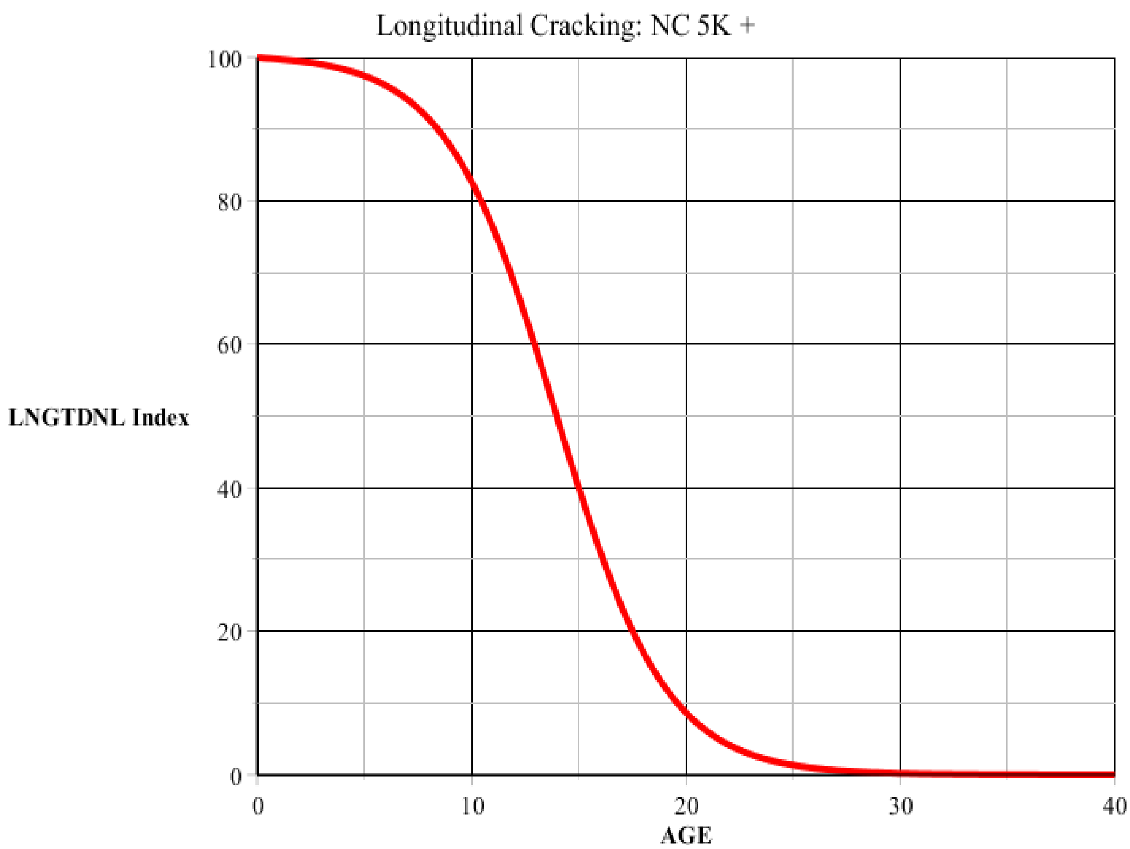
60
40
20
0
0
10
20
30
40
AGE


Longitudinal Cracking: NC 5K +
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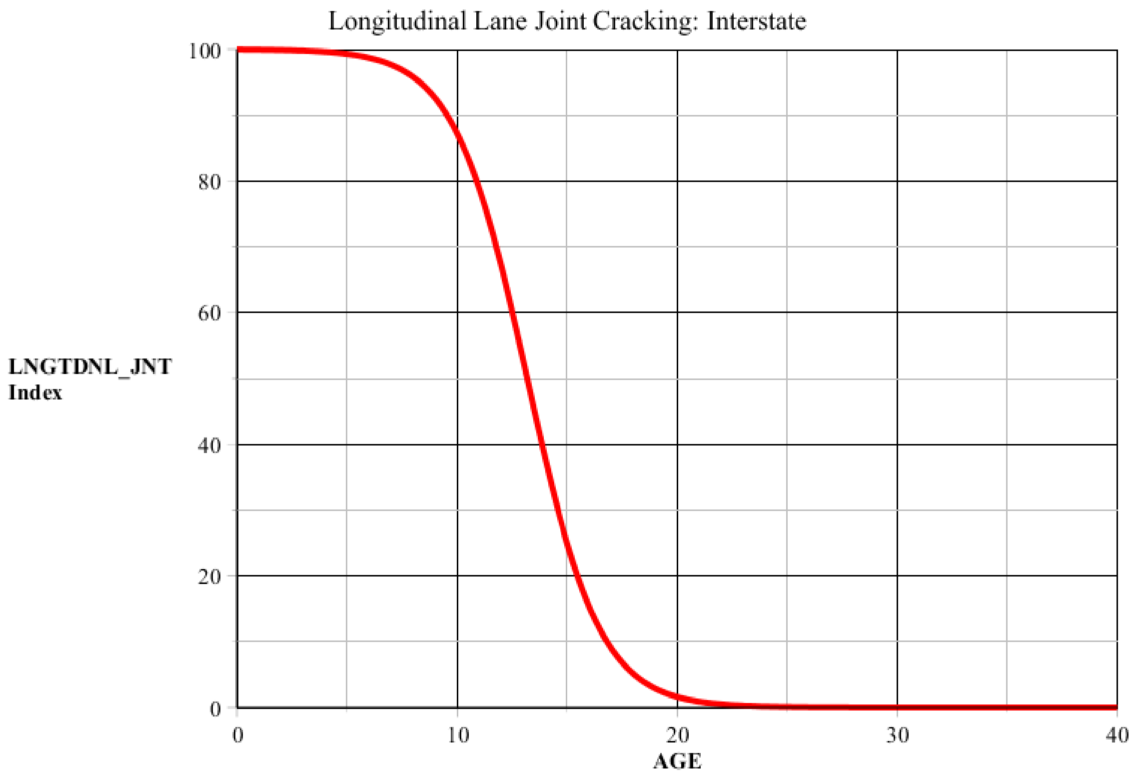
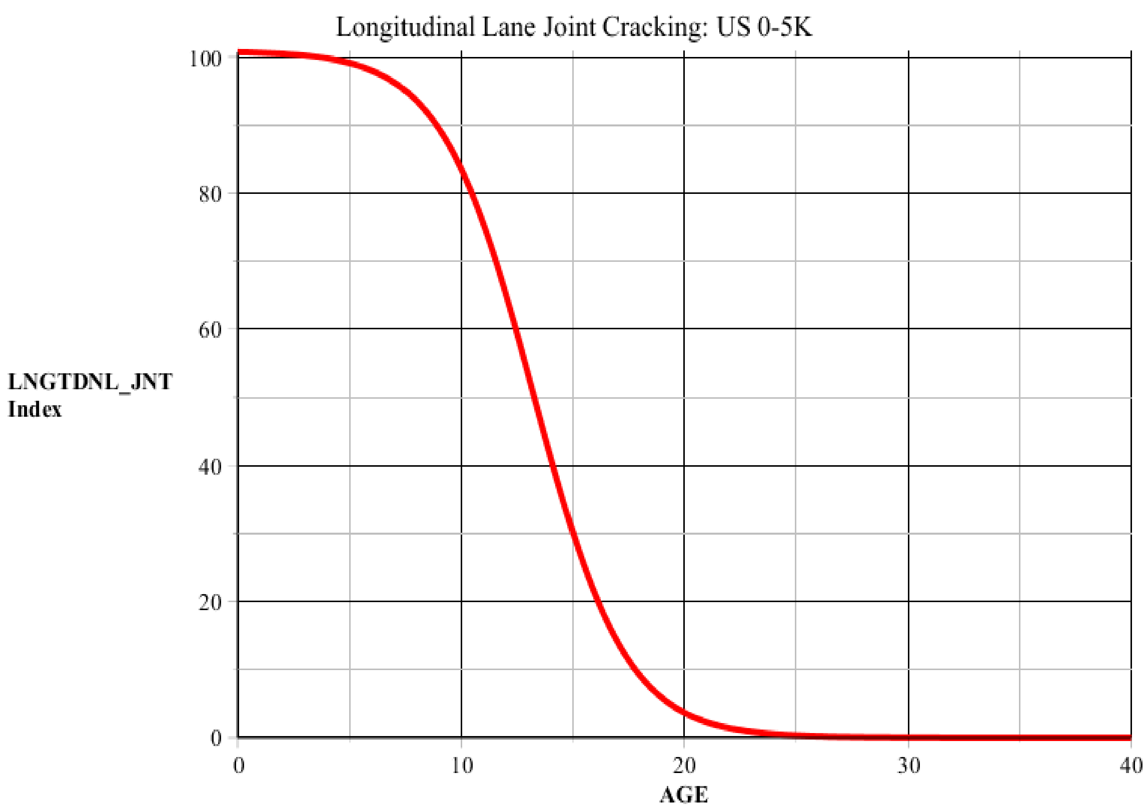
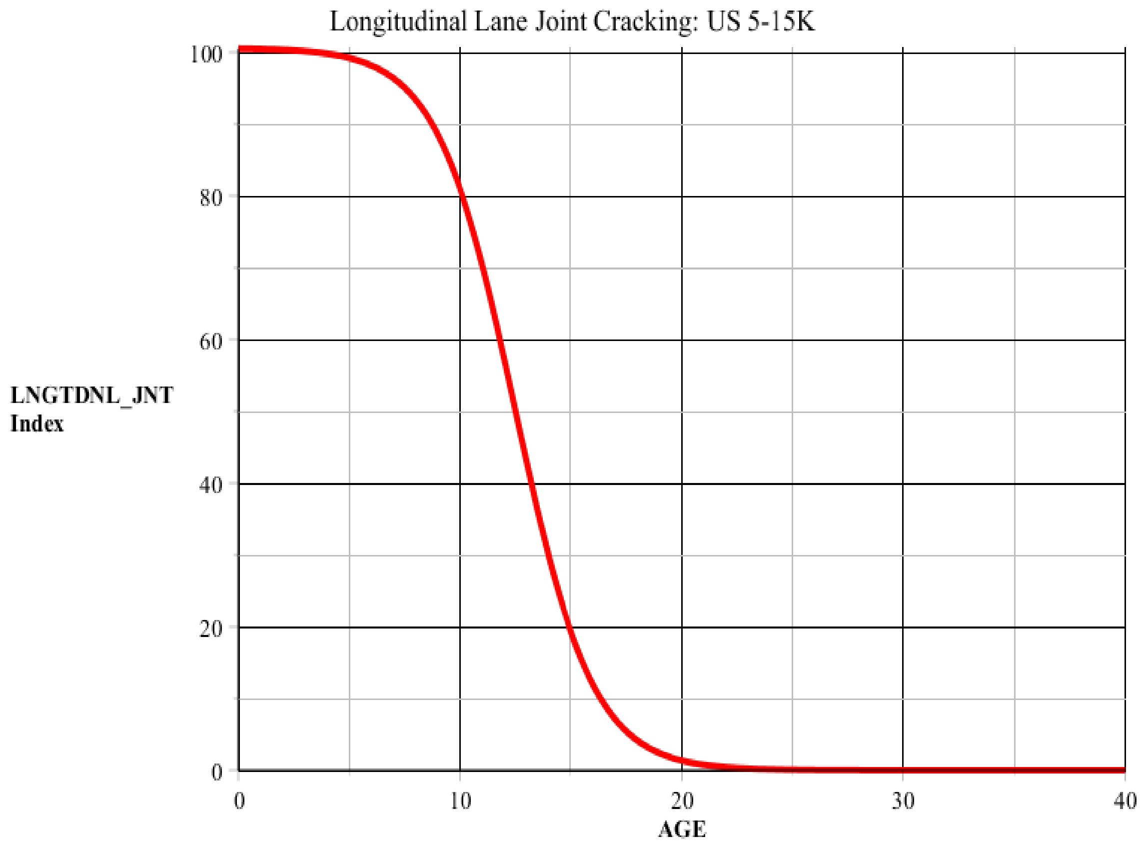
60
40
20
0
0
10
20
30
40
AGE

APPENDIX D: LONGITUDINAL LANE JOINT MODELS



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LNGTDNL_JNT
Index
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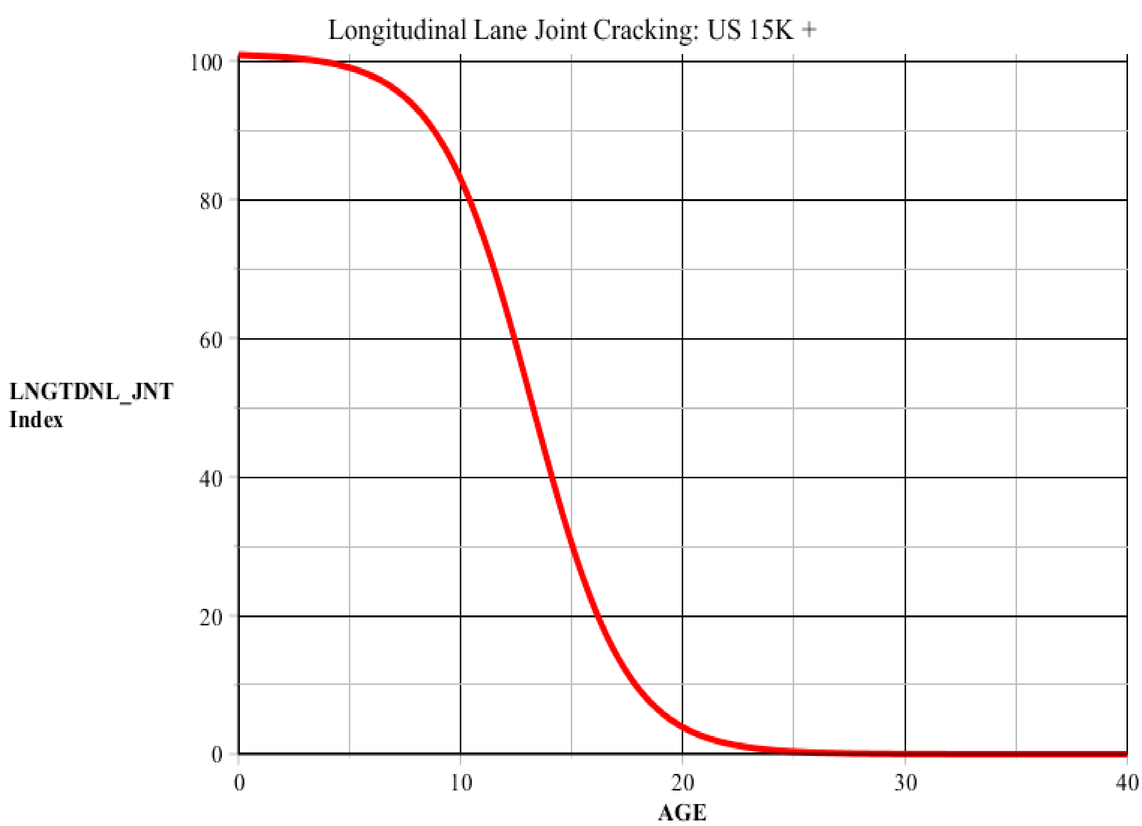
80
60
40
20
0
0
10
20
30
40
AGE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40
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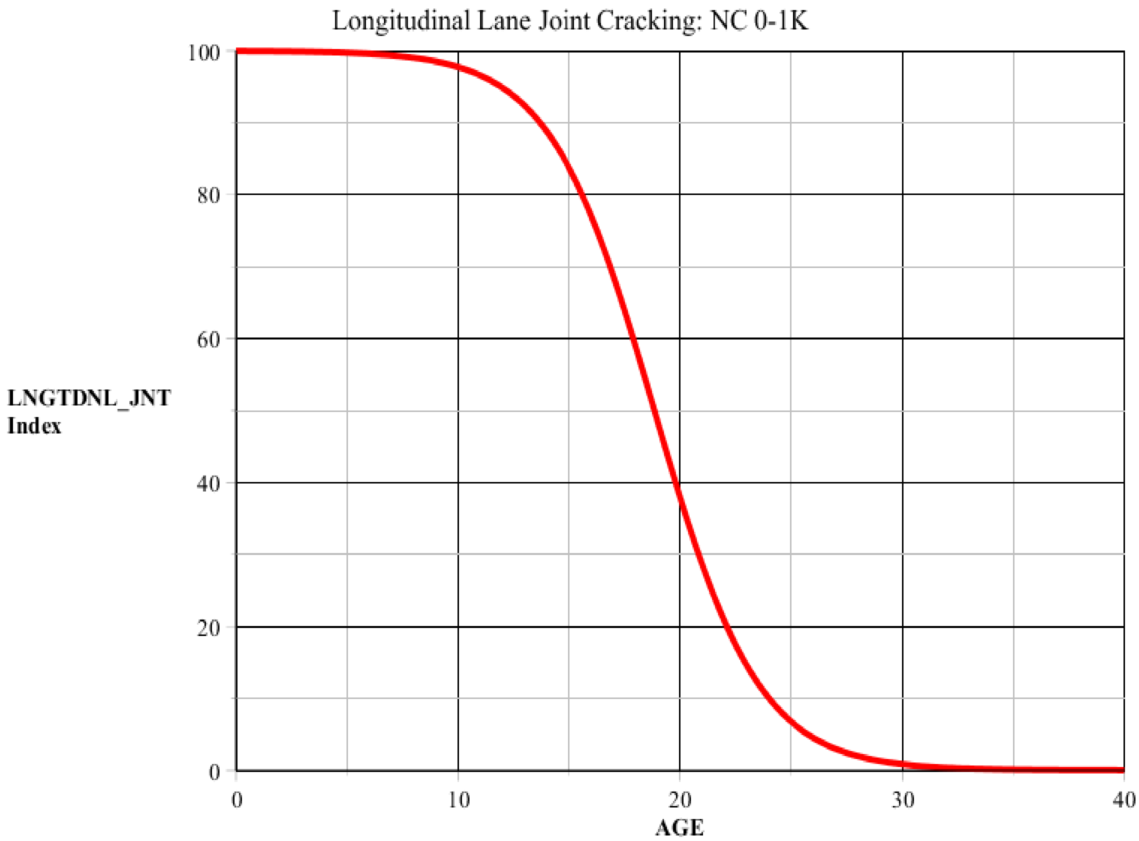
20
30
40
AGE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AGE
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10
20
30
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100
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60
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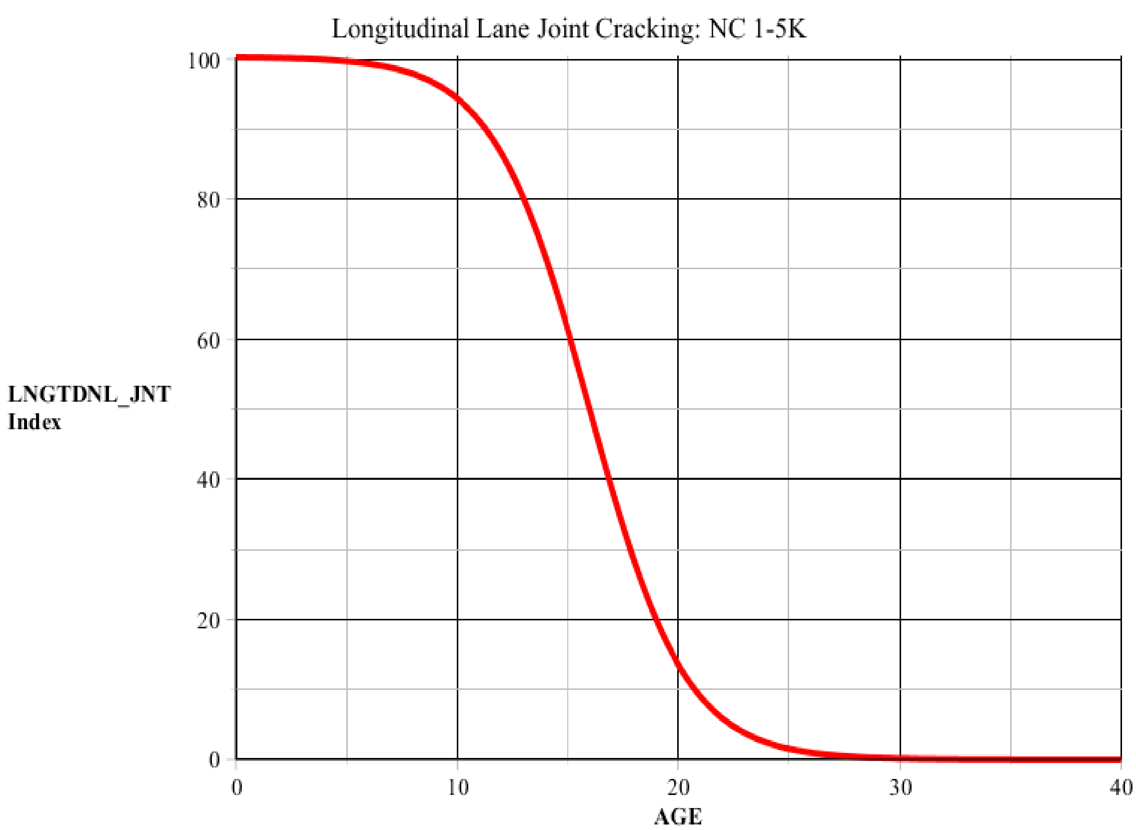
20
0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AGE
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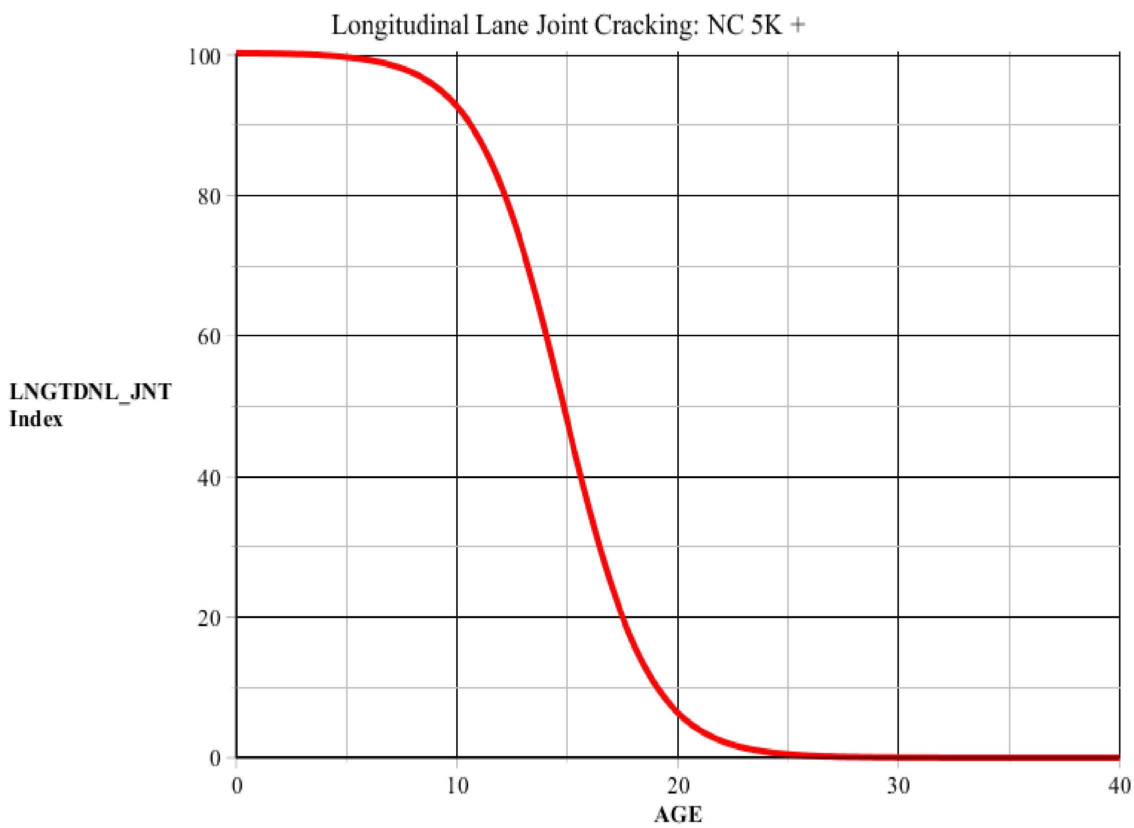
10
20
30
40
100
80
60
40
20
0


Longitudinal Lane Joint Cracking: NC 5K +
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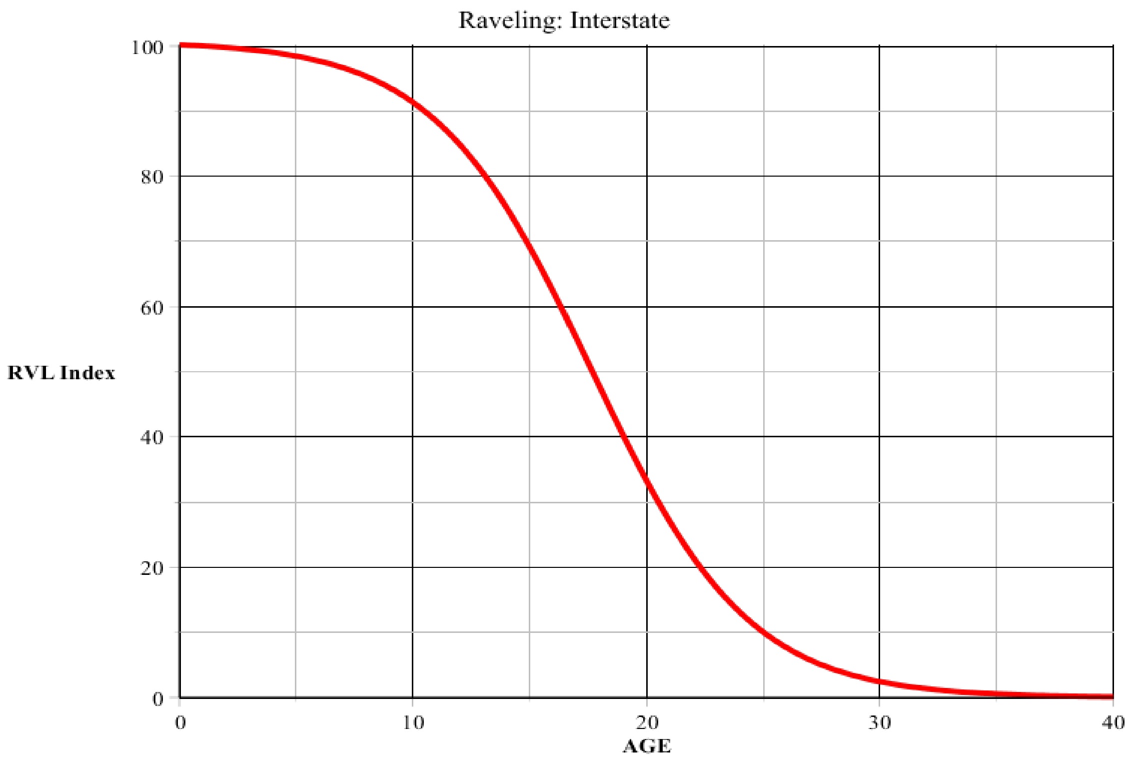
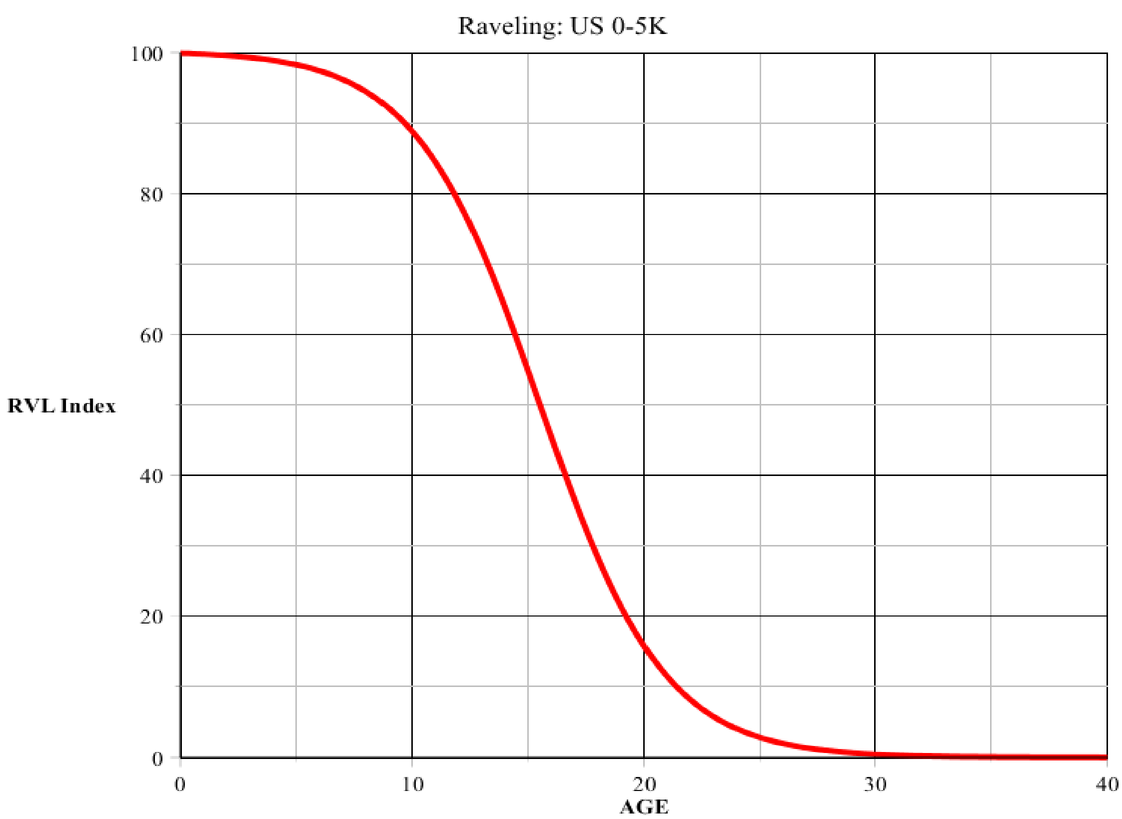
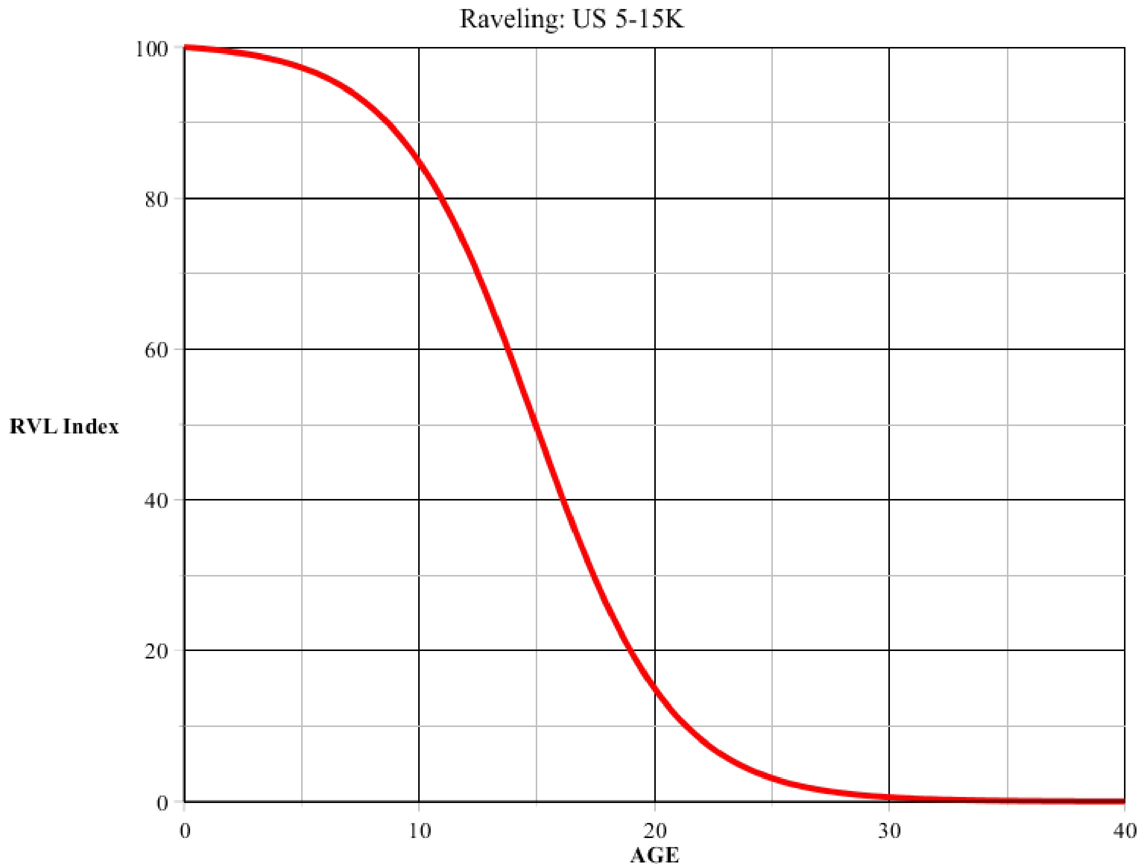
80
60
40
20
0
0
10
20
30
40
AGE

APPENDIX E: RAVELING MODELS



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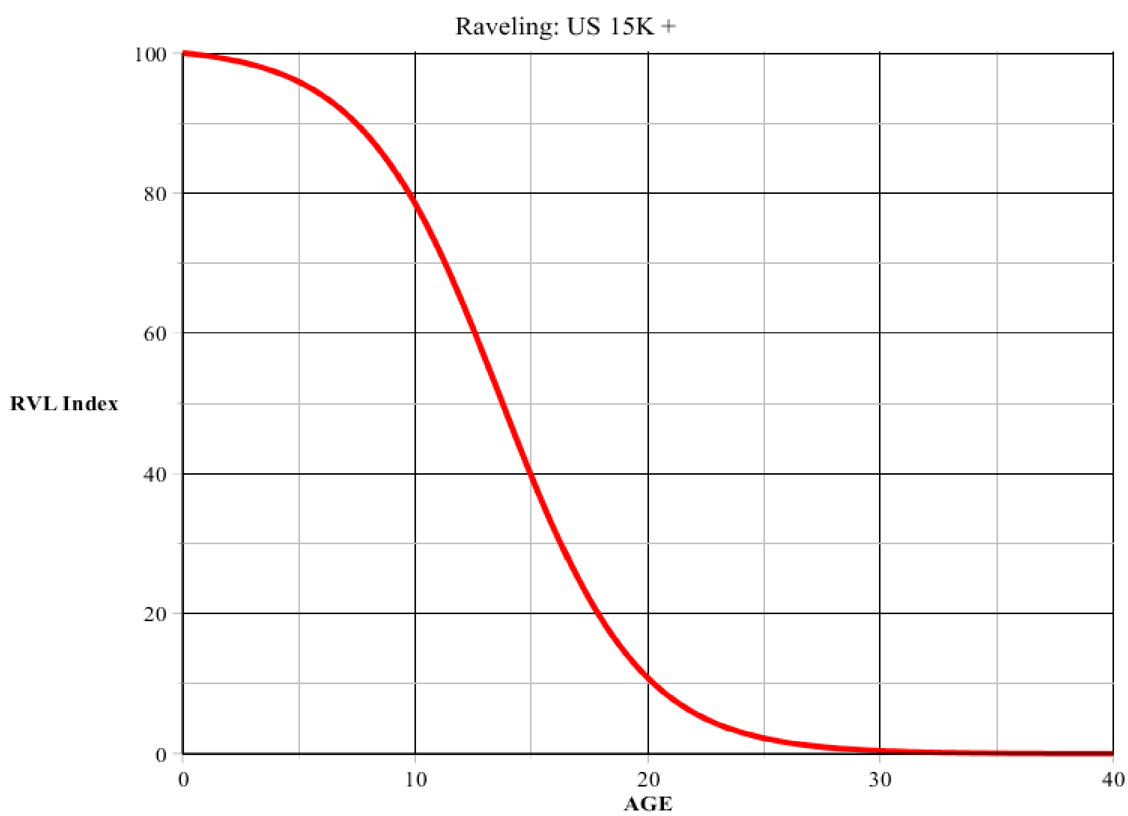
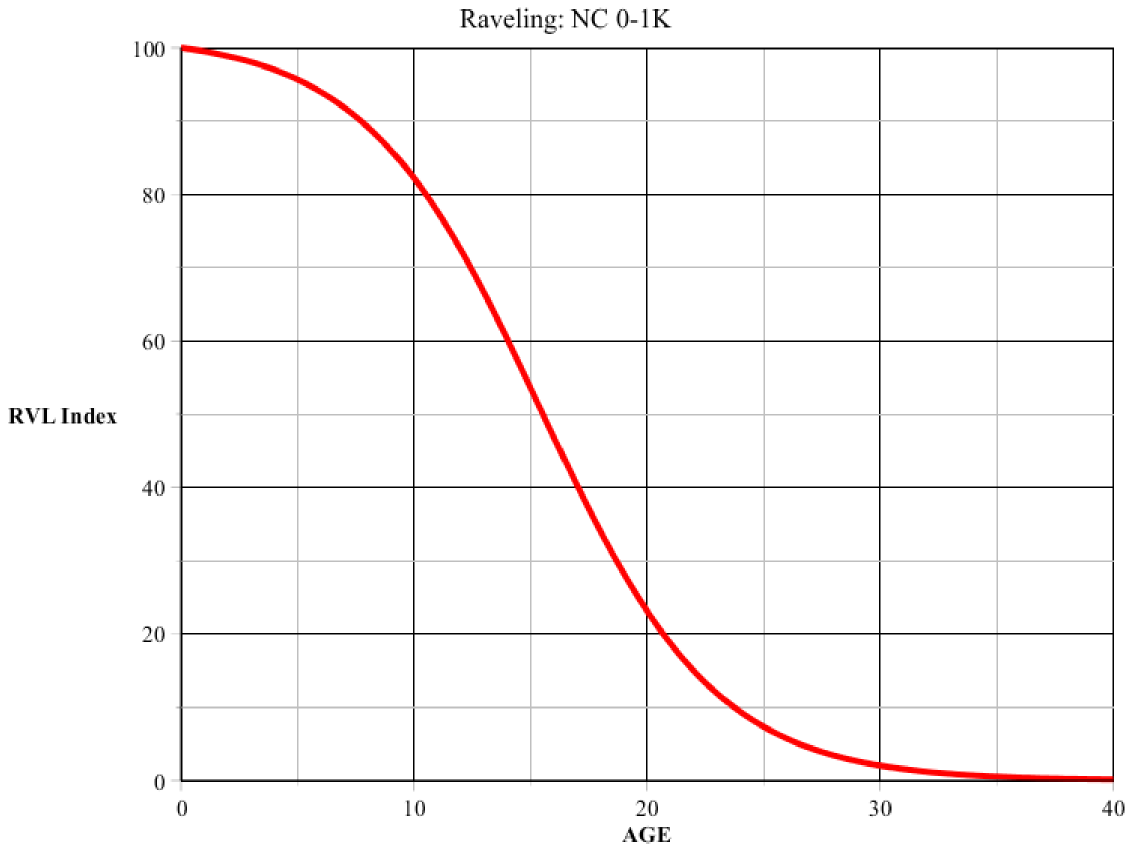
RVL Index
100
80
60
40
20
0
0
10
20
30
40
AGE


Raveling: US 15K +
RVL Index
100
80
60
40
20
0
0
10
20
30
40
AGE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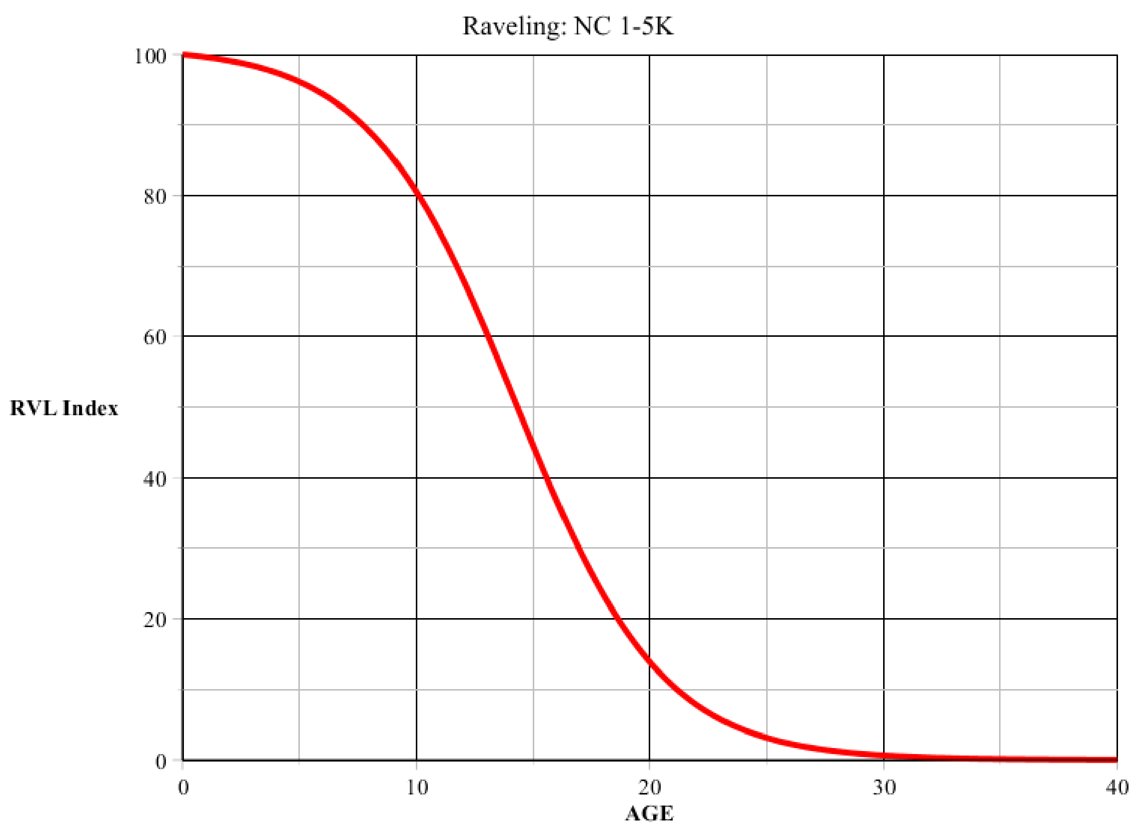
100
80
60
40
20
0
RVL Index
0
10
20
30
40
AGE


Raveling: NC 1-5K
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80
60
40
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RVL Index
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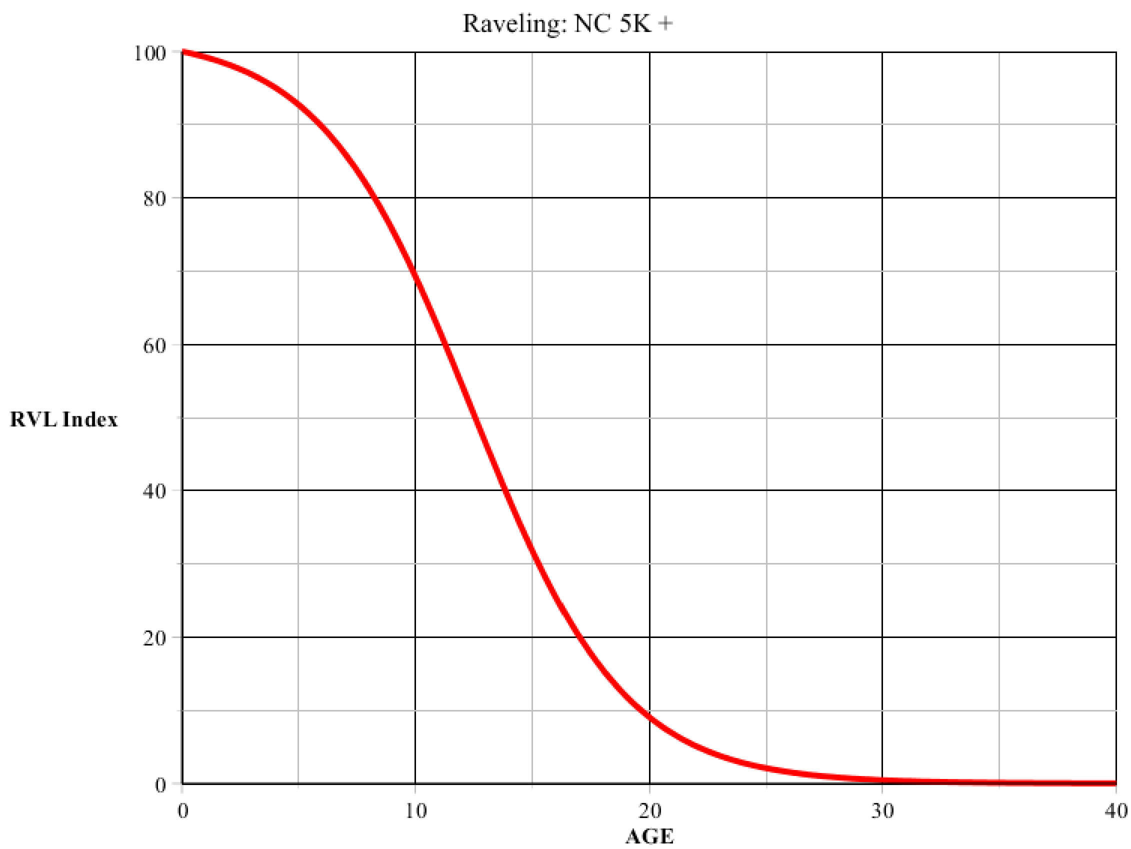
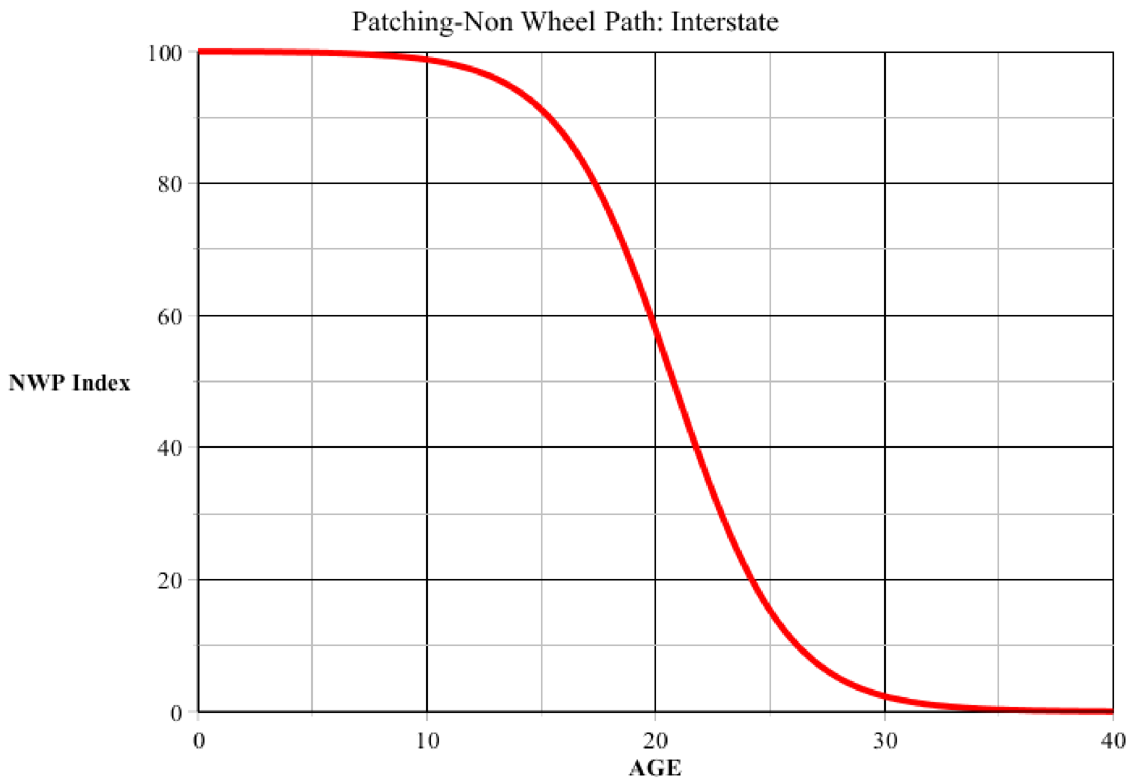
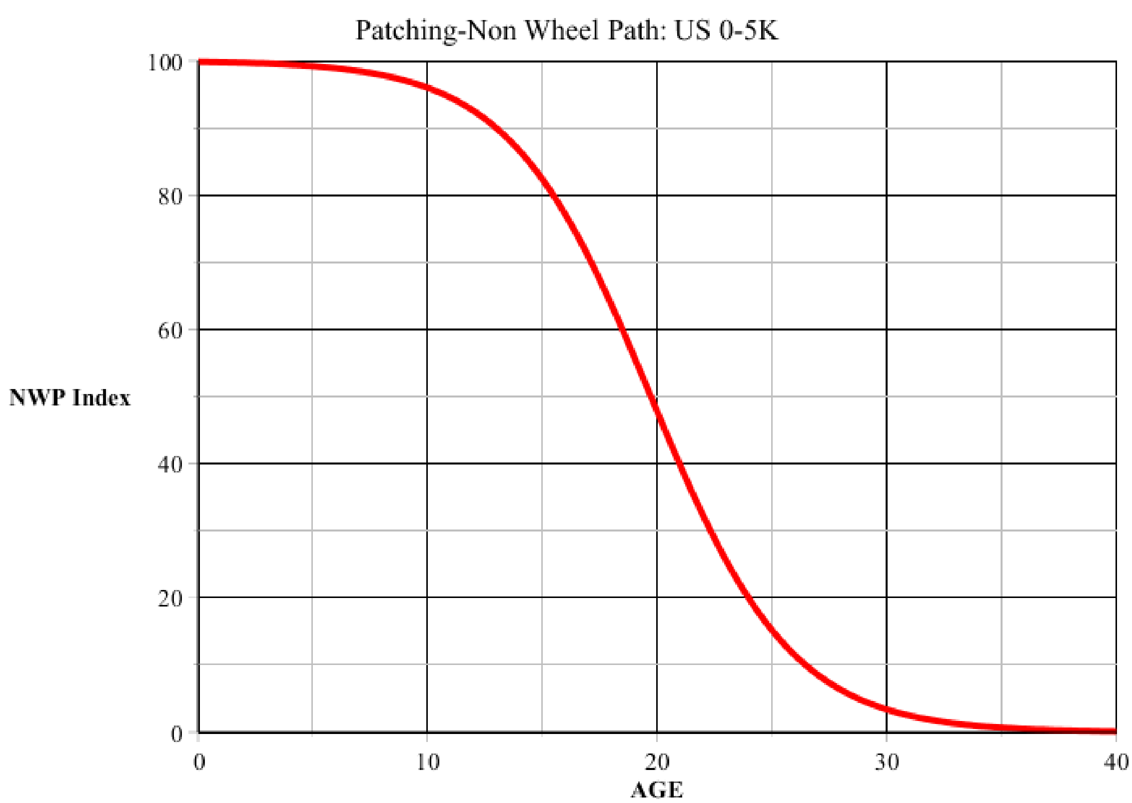
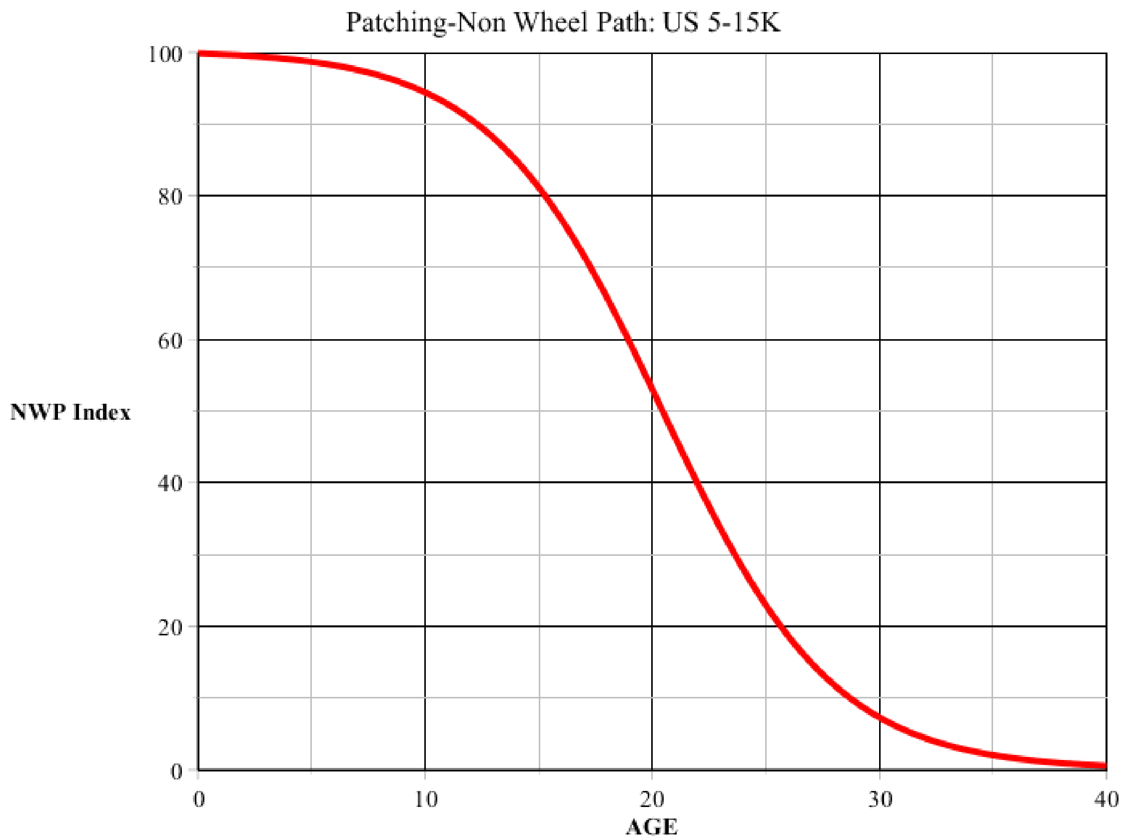
10
20
30
40
AGE

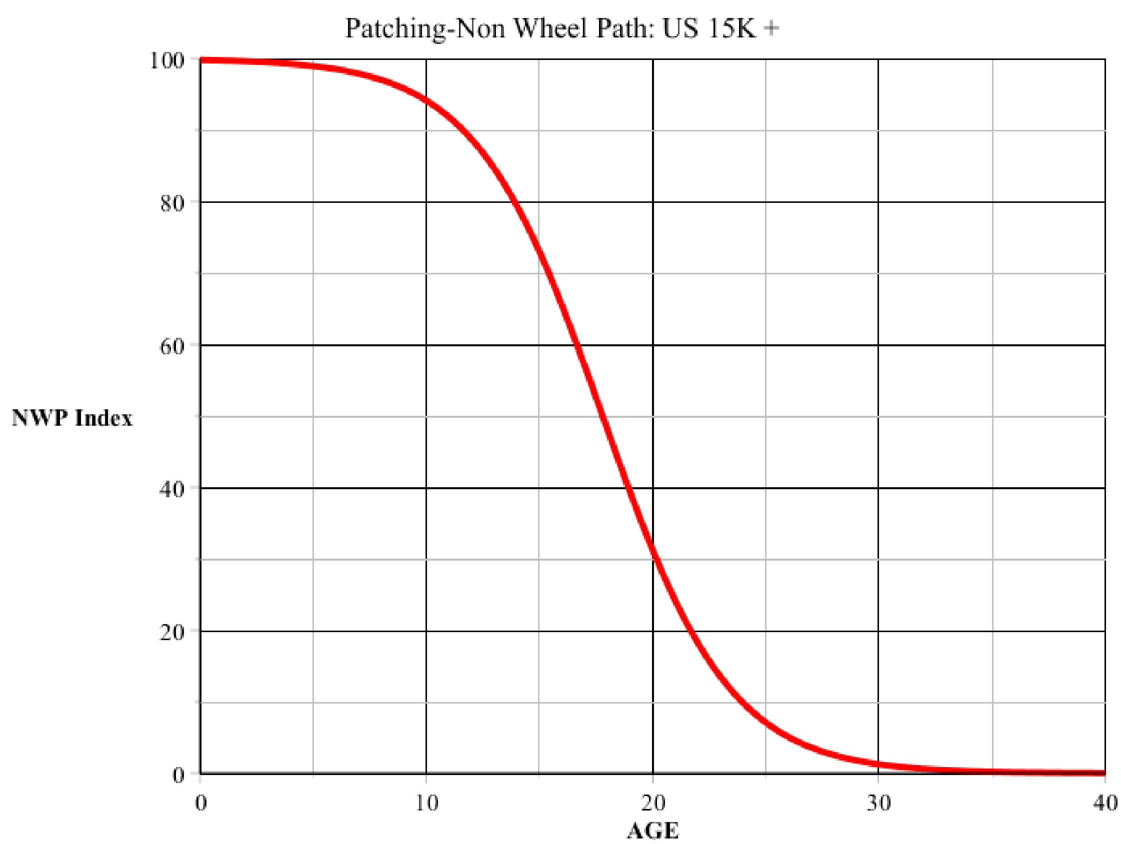

Raveling: NC 5K +
RVL Index
100
80
60
40
20
0
0
10
20
30
40
AGE

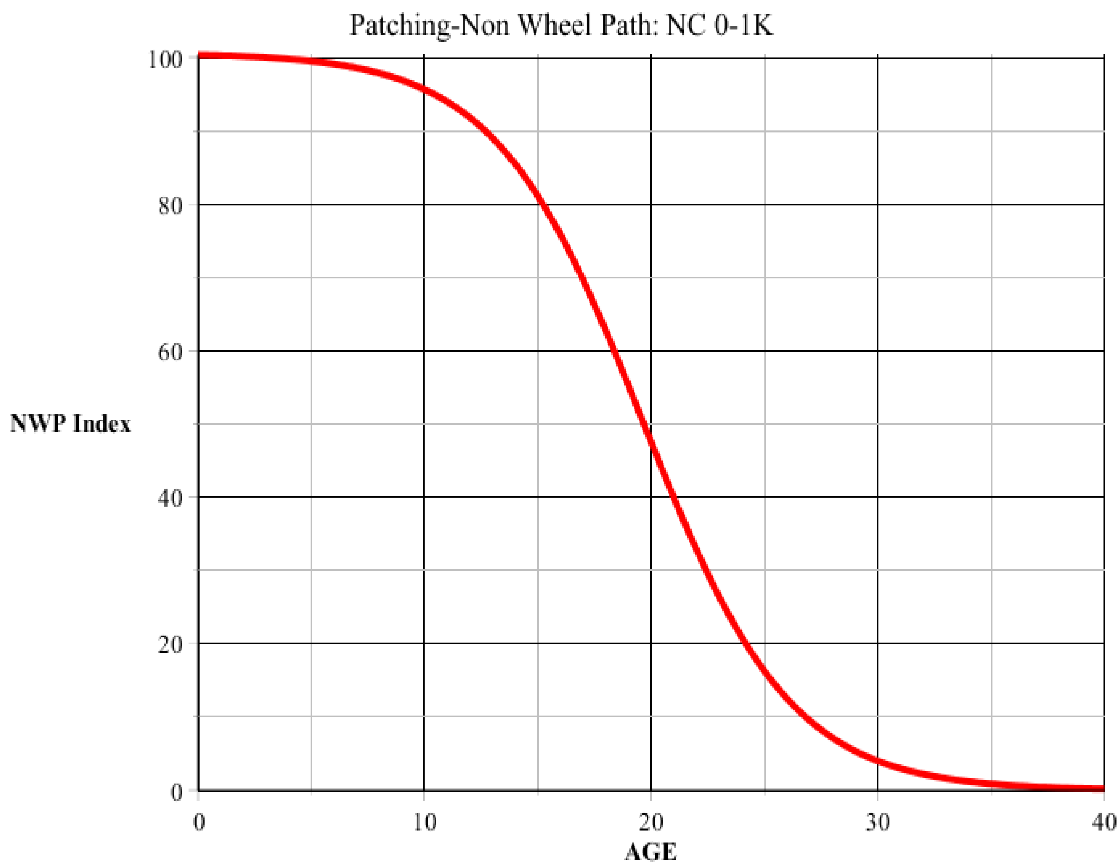
APPENDIX F: PATCHING (NON-WHEEL PATH) MODELS

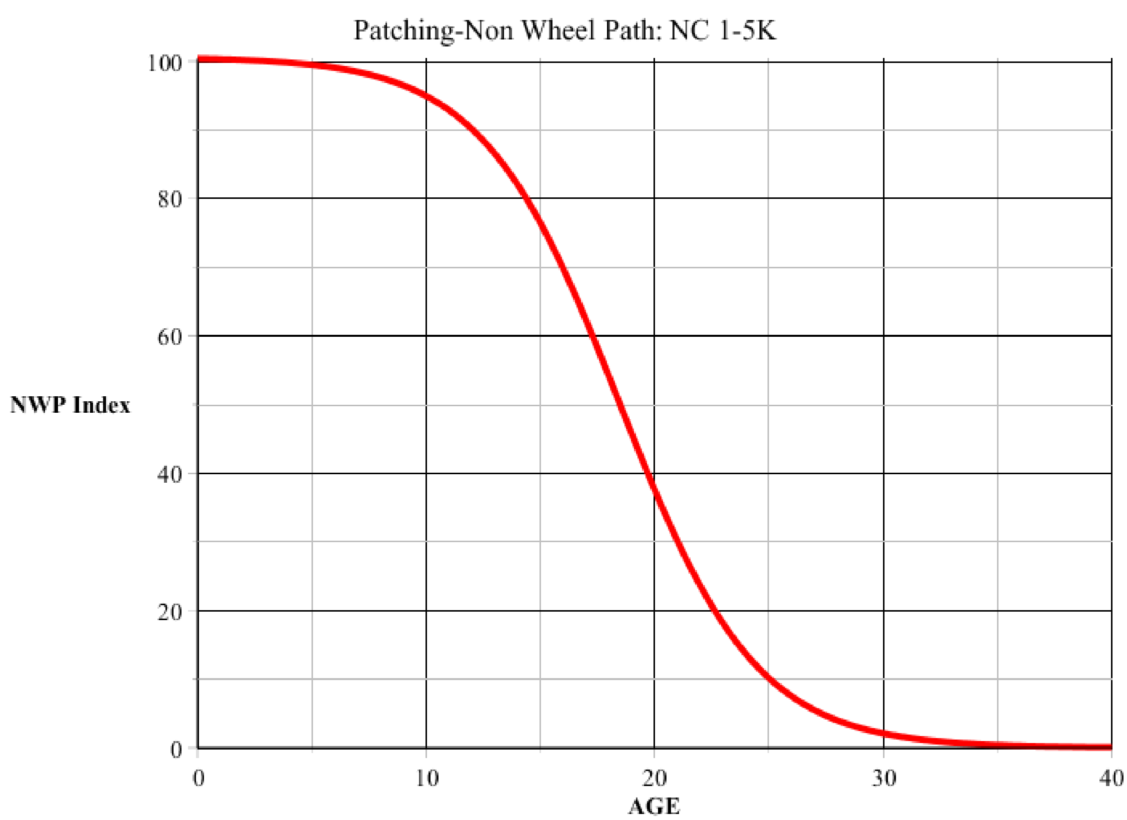


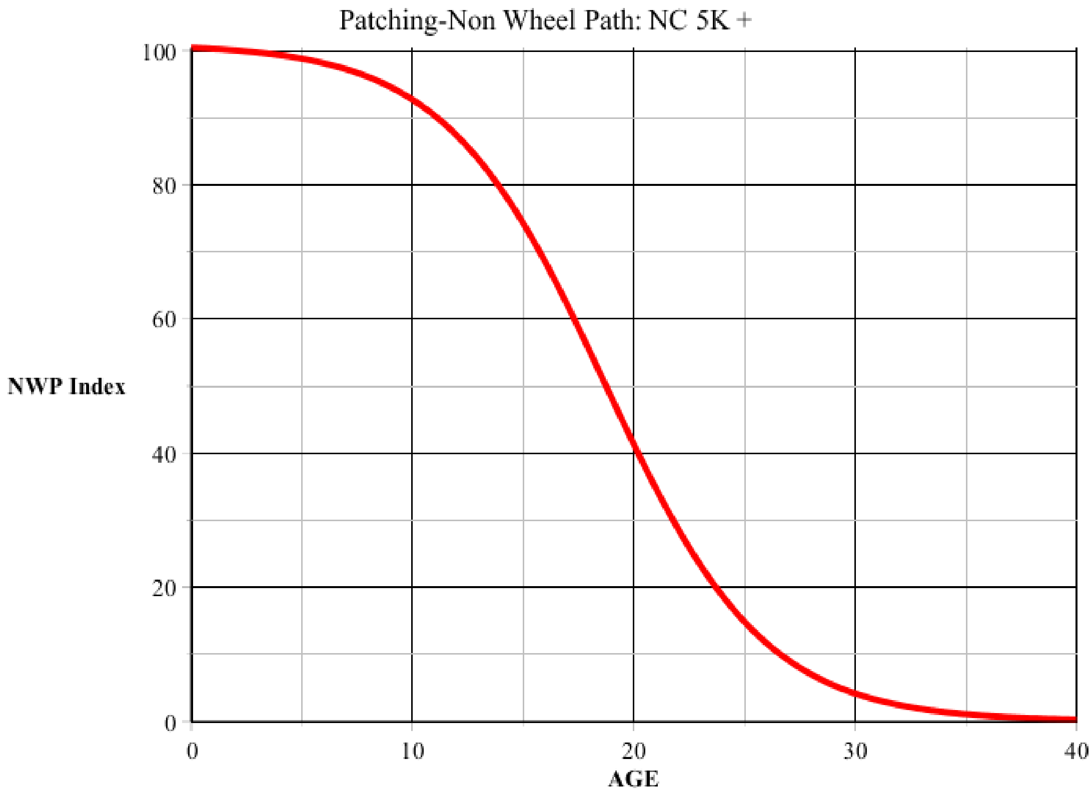



Patching-Non Wheel Path: US 5-15K
NWP Index
AGE
0
20
40
60
80
100
0
10
20
30
40

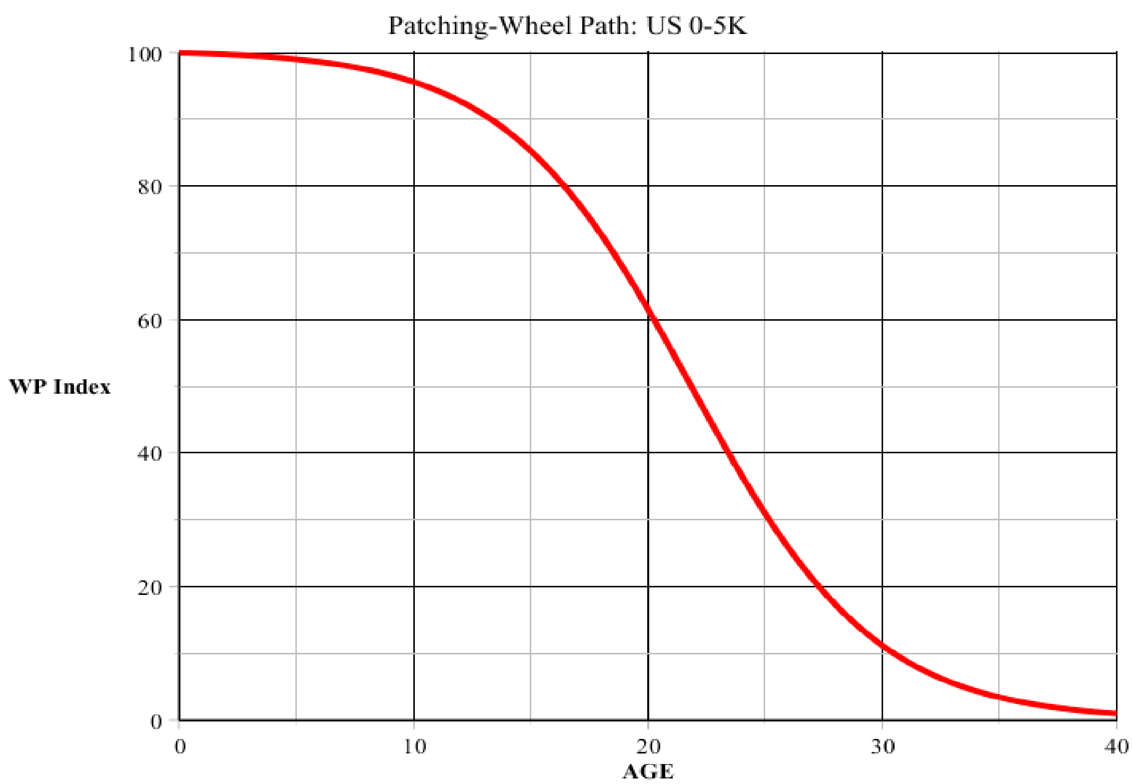

Patching-Non Wheel Path: US 15K +
NWP Index
AGE
0
20
40
60
80
100
0
10
20
30
40

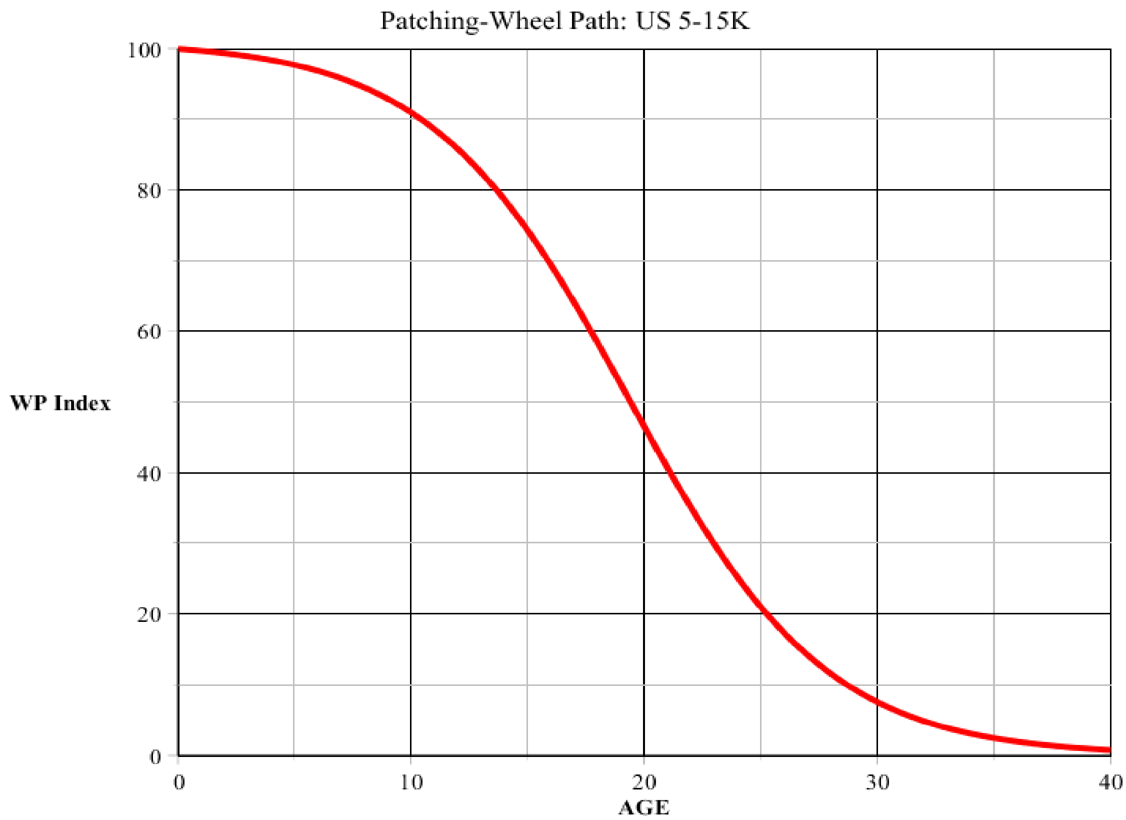

Patching-Non Wheel Path: NC 0-1K
NWP Index
100
80
60
40
20
0
0
10
20
30
40
AGE


Patching-Non Wheel Path: NC 1-5K
NWP Index
100
80
60
40
20
0
0
10
20
30
40
AGE

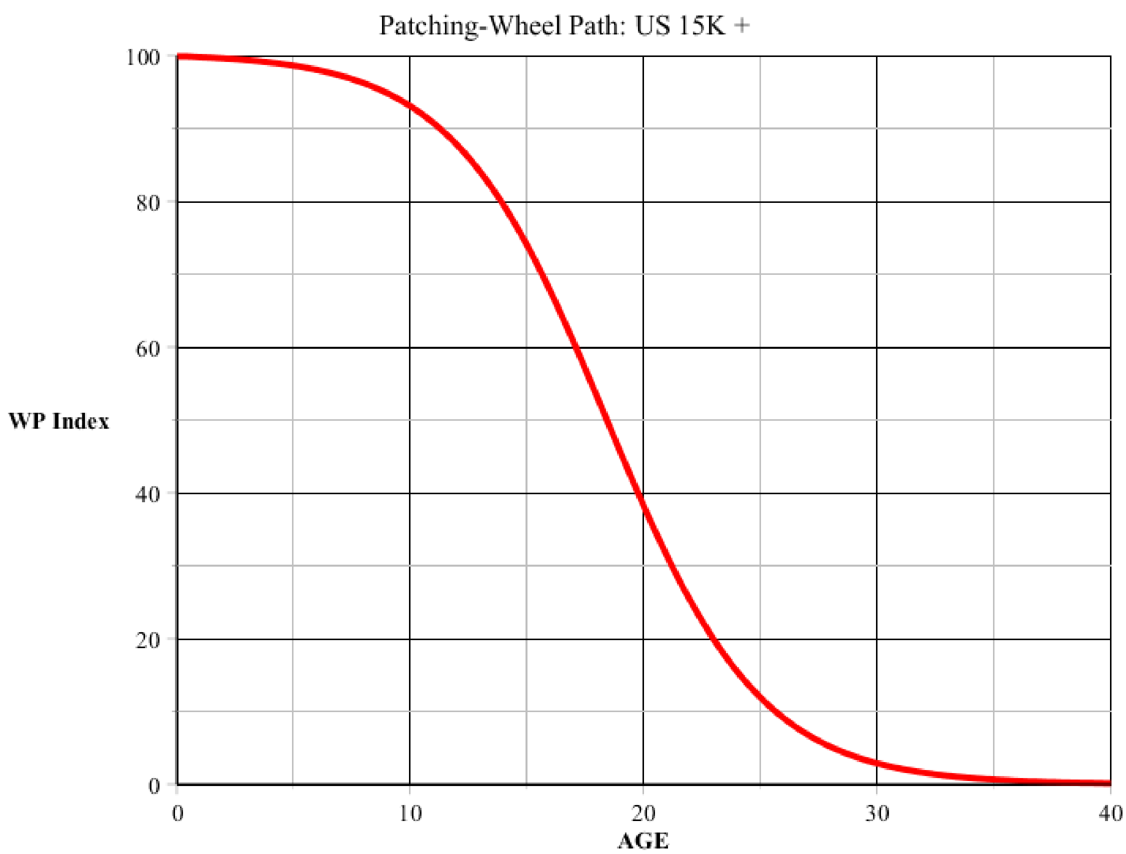

Patching-Non Wheel Path: NC 5K +
NWP Index
100
80
60
40
20
0
0
10
20
30
40
AGE

APPENDIX G: PATCHING (WHEEL PATH) MODELS

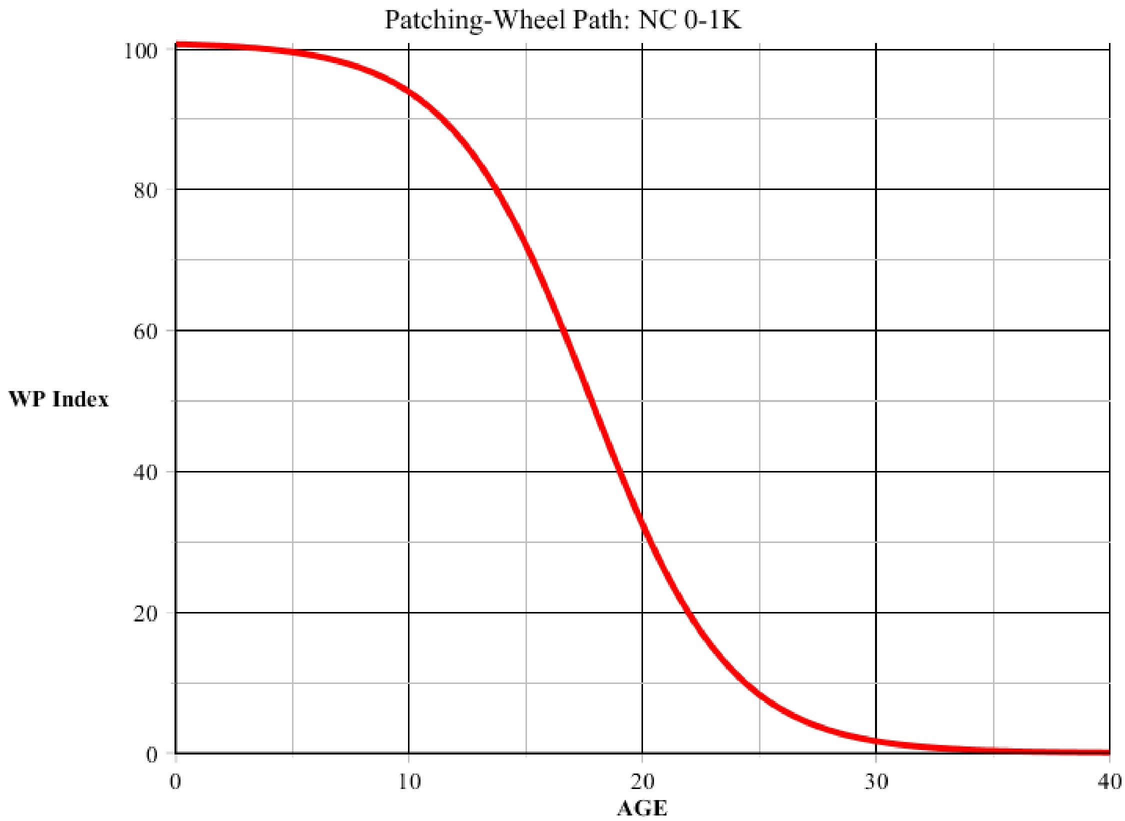


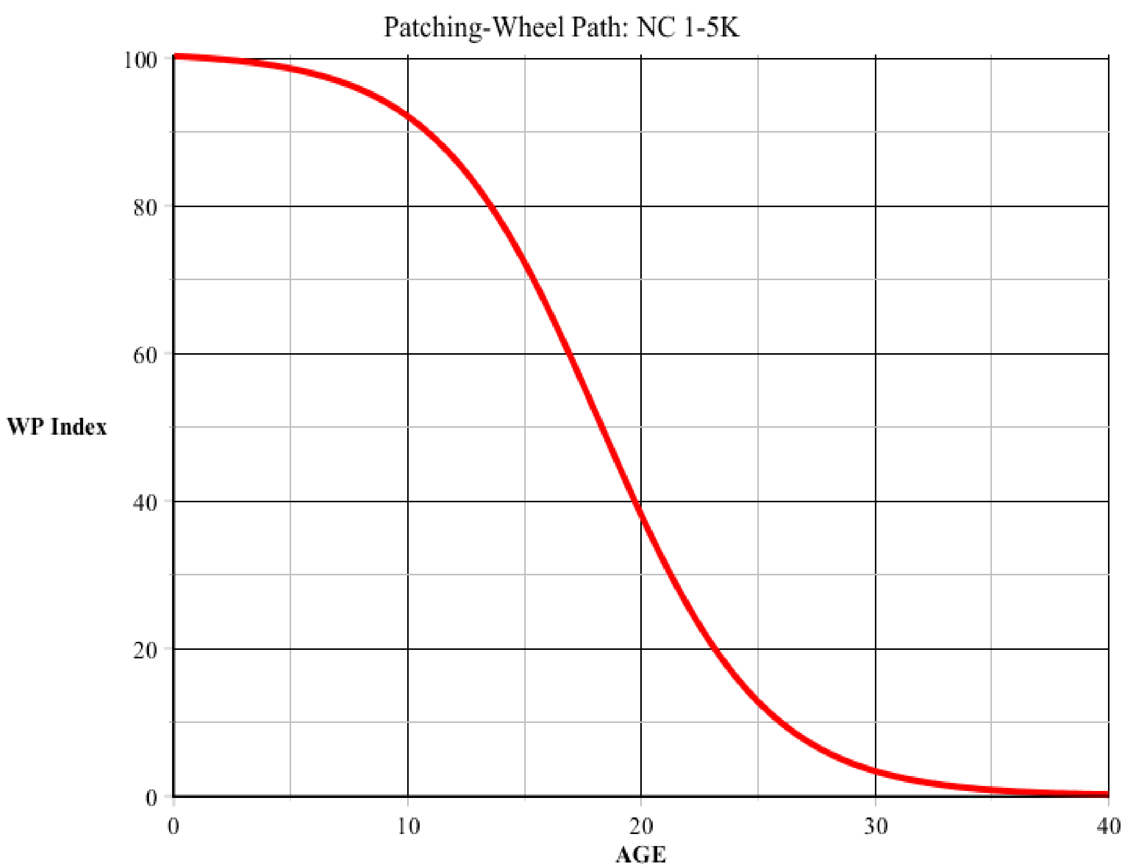


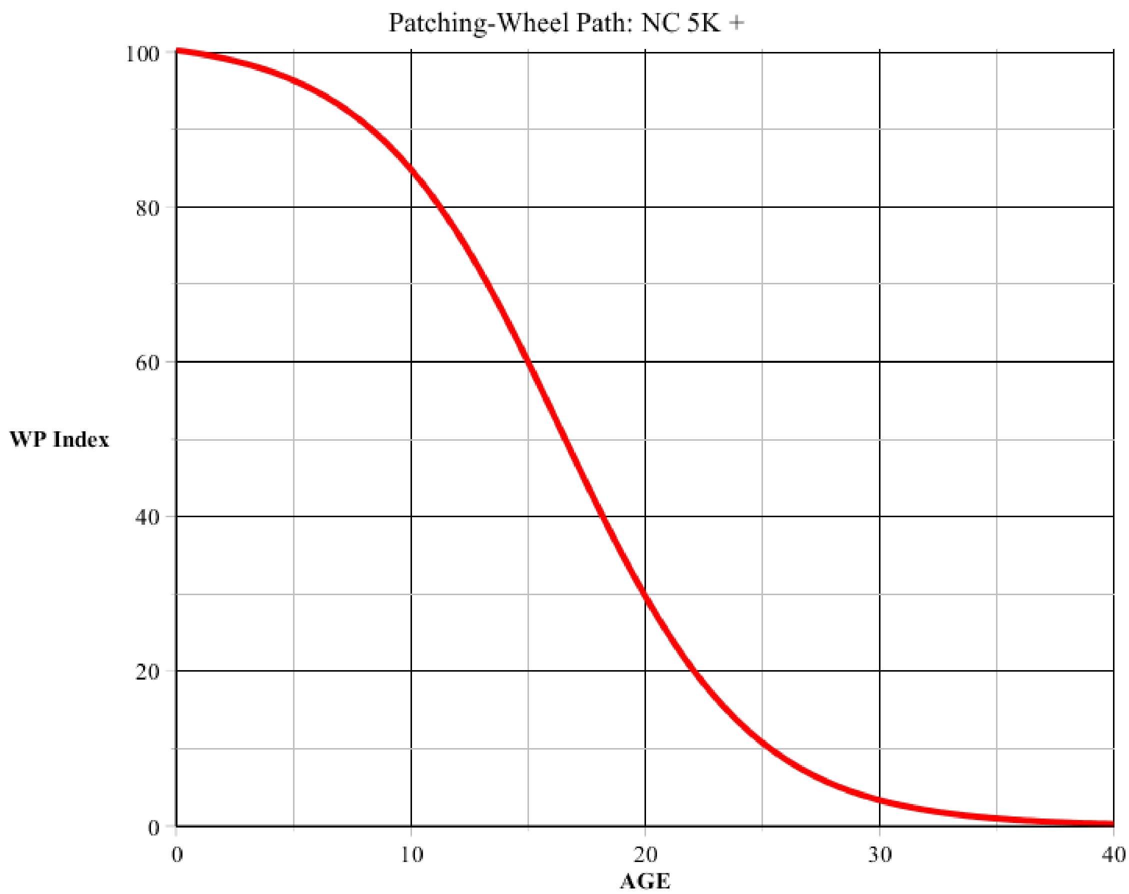
Patching-Wheel Path: US 5-15K
100
80
60
WP Index
40
20
0
0
10
20
30
40
AGE



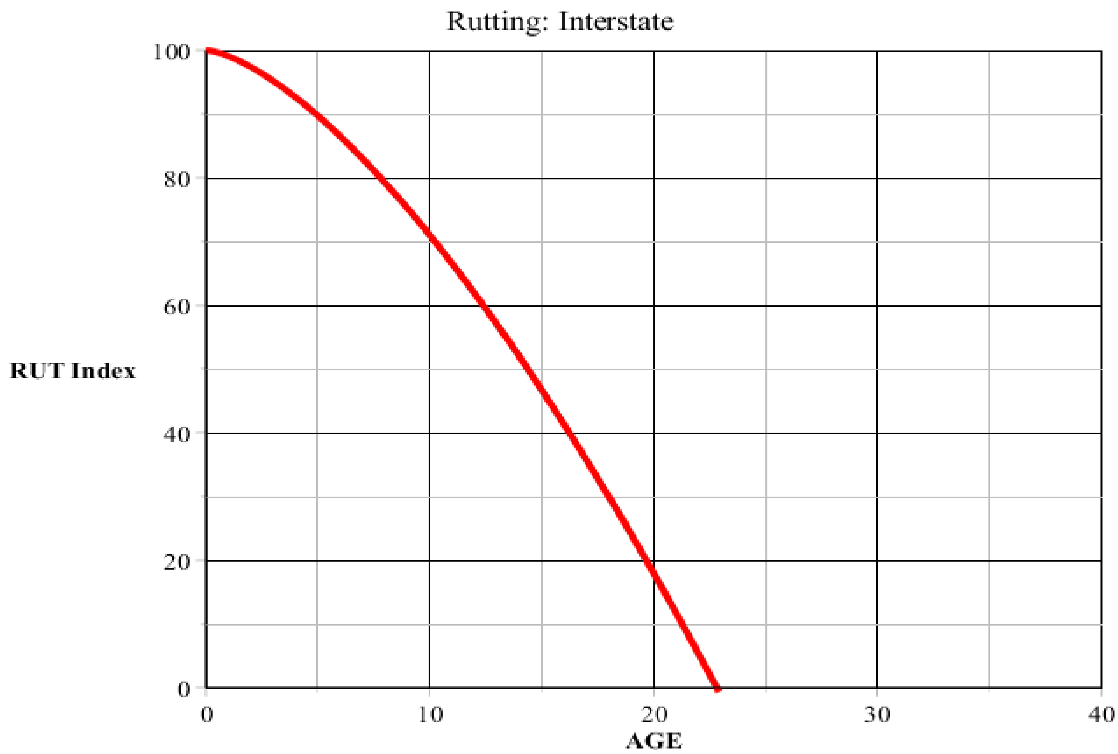
Patching-Wheel Path: US 15K +
100
80
60
WP Index
40
20
0
0
10
20
30
40
AGE

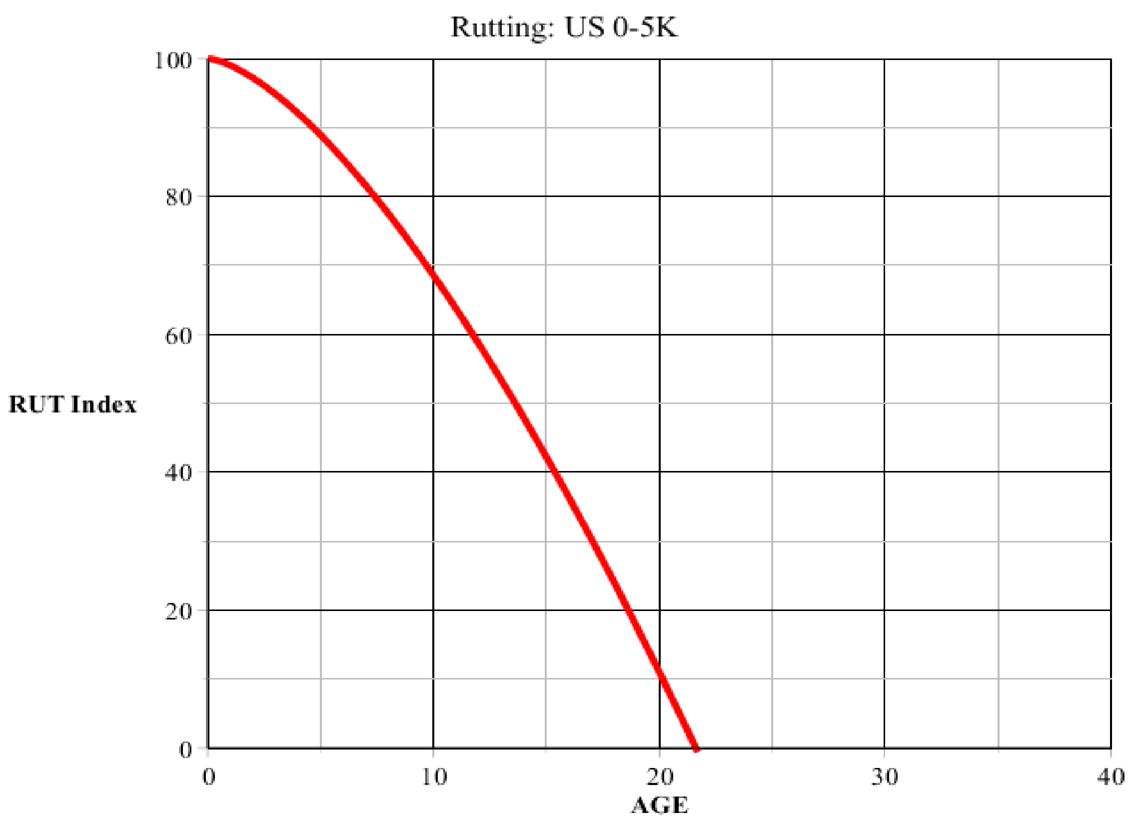

Patching-Wheel Path: NC 0-1K
WP Index
AGE
0
10
20
30
40
100
80
60
40
20
0

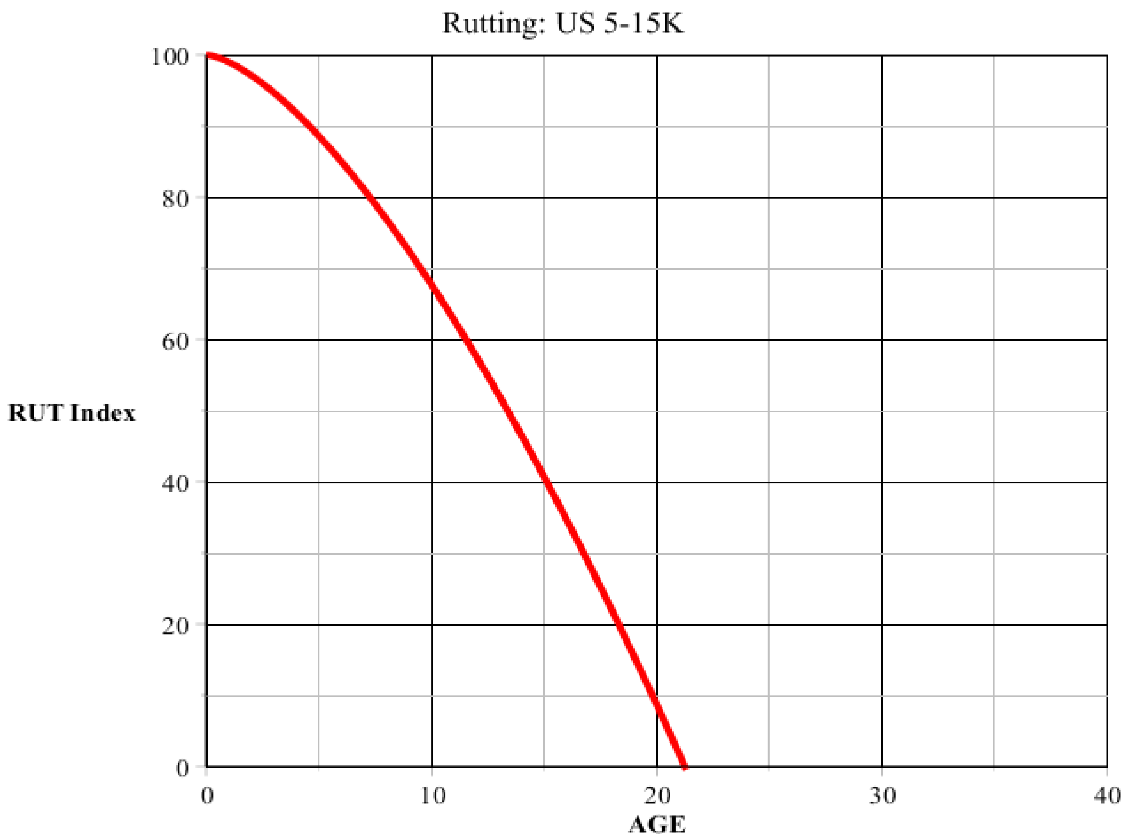

Patching-Wheel Path: NC 1-5K
WP Index
AGE
0
10
20
30
40
100
80
60
40
20
0

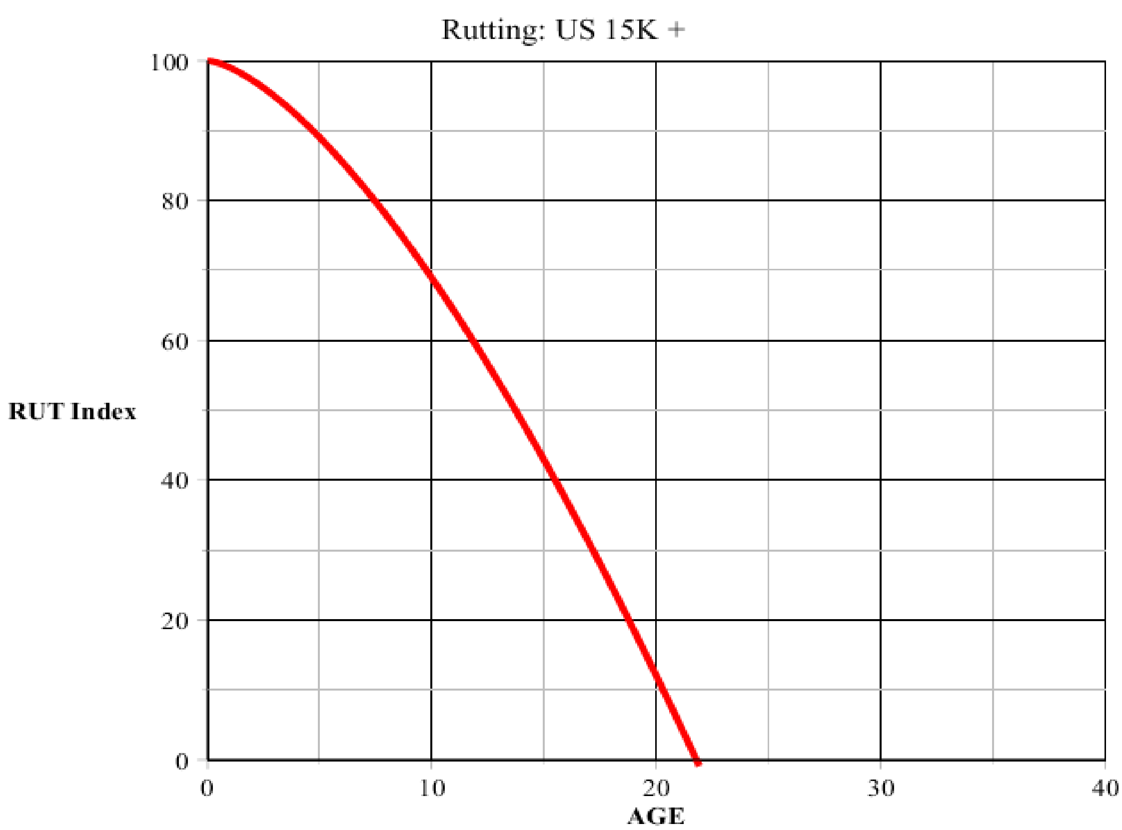

Patching-Wheel Path: NC 5K +
100
80
60
40
20
0
WP Index
0
10
20
30
40
AGE

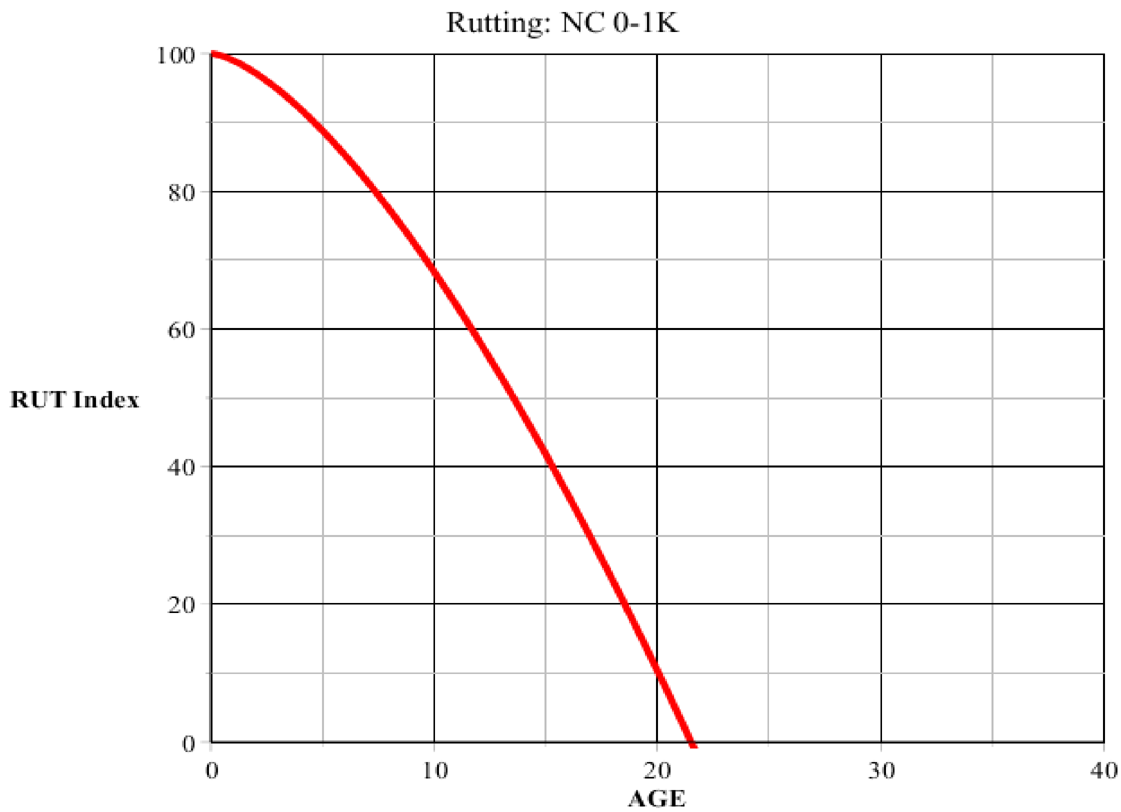
APPENDIX H: RUTTING MODELS

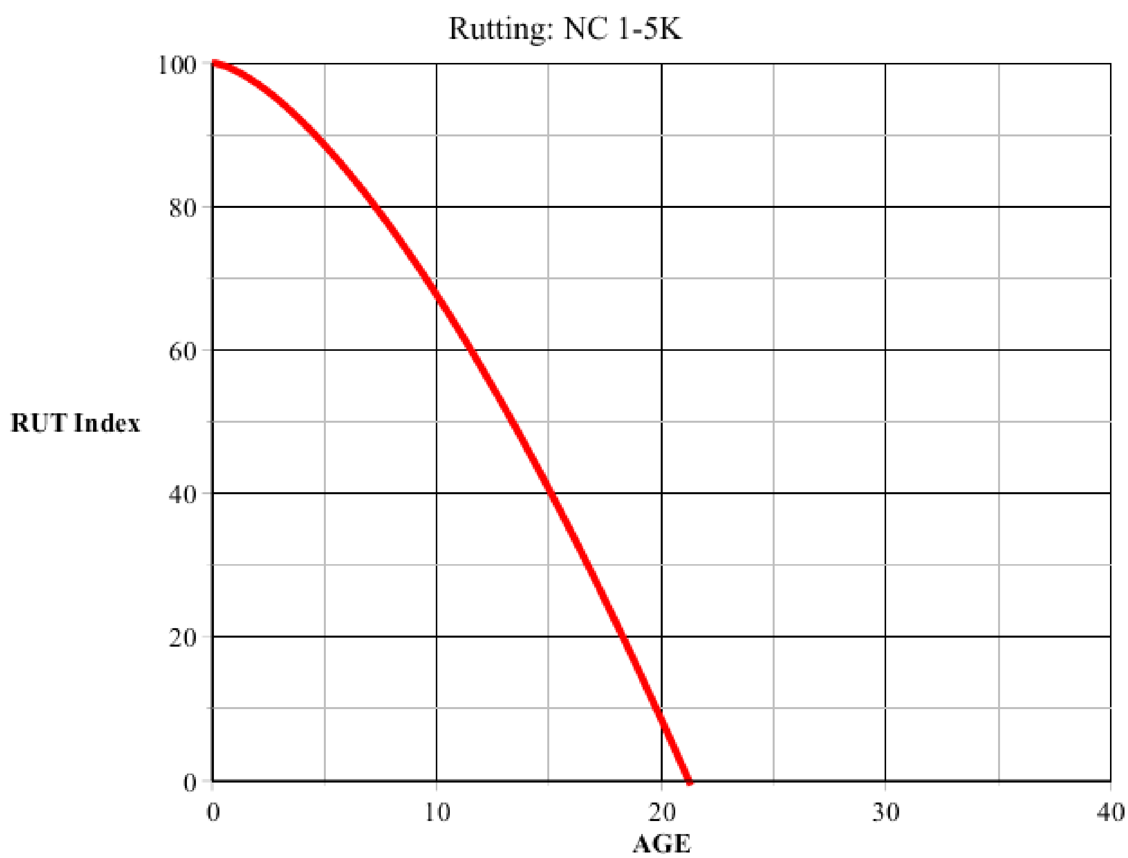


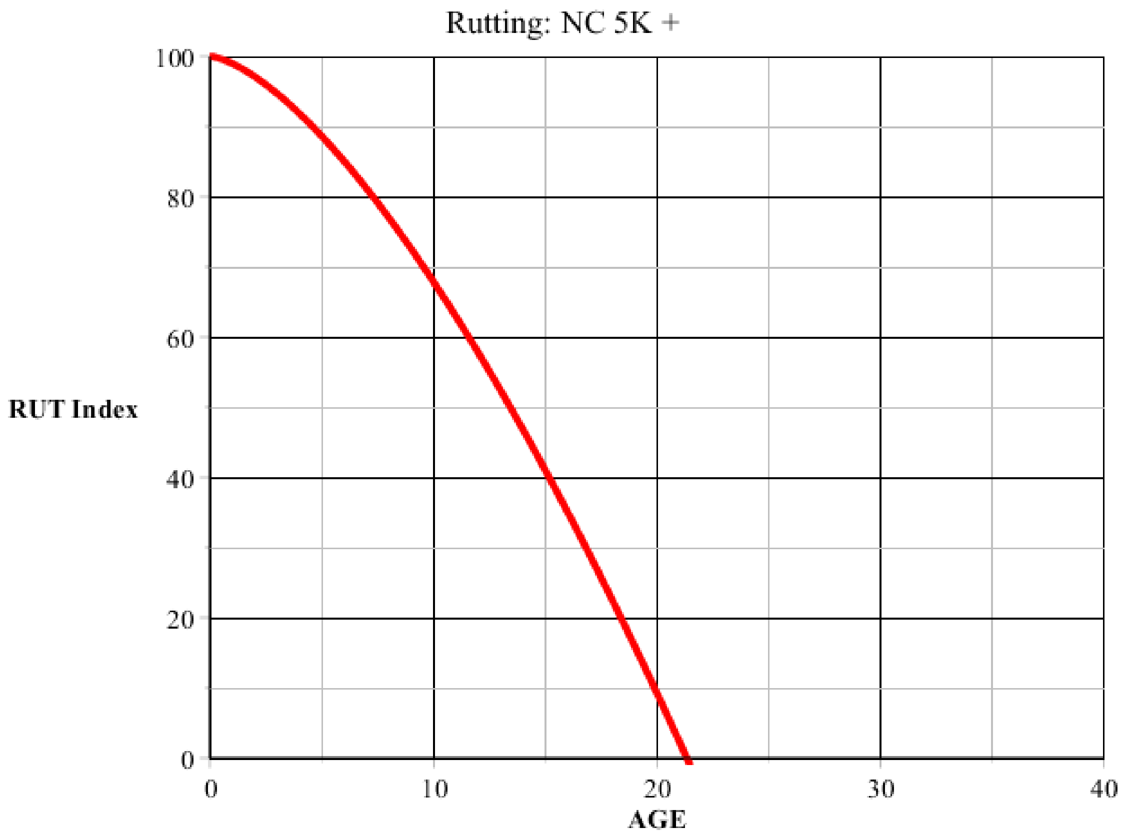



Rutting: US 5-15K
RUT Index
100
80
60
40
20
0
0
10
20
30
40
AGE

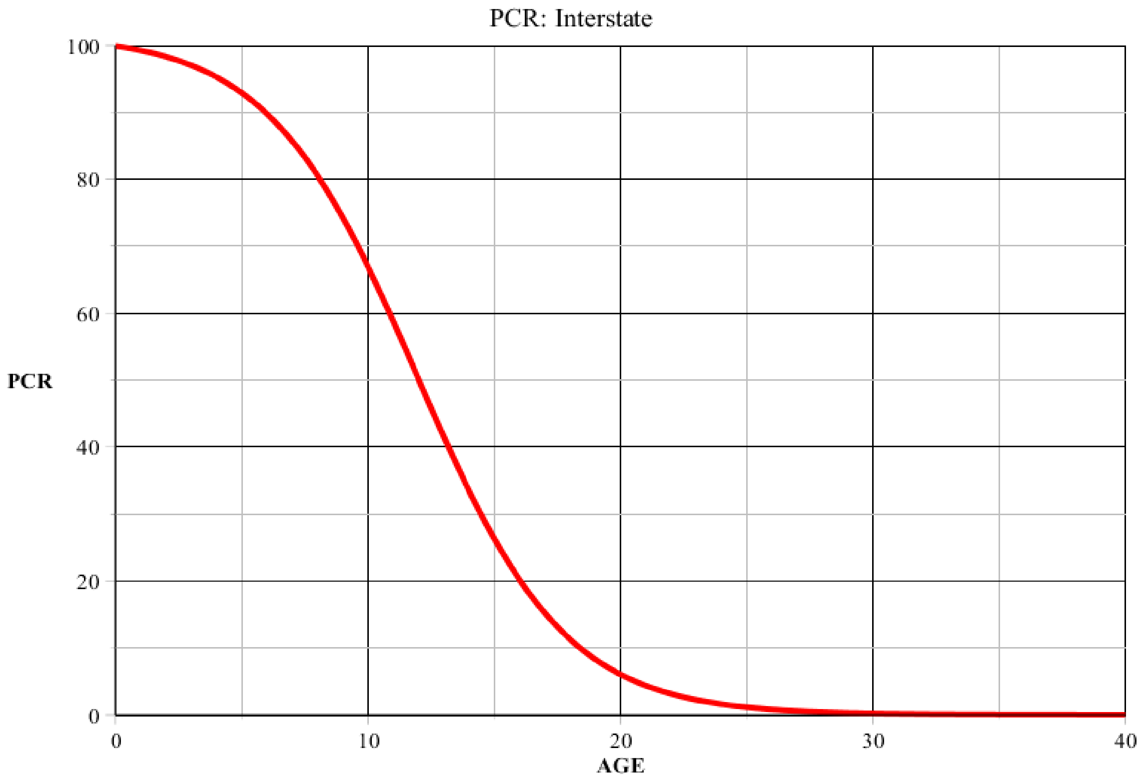

Rutting: US 15K +
RUT Index
100
80
60
40
20
0
0
10
20
30
40
AGE

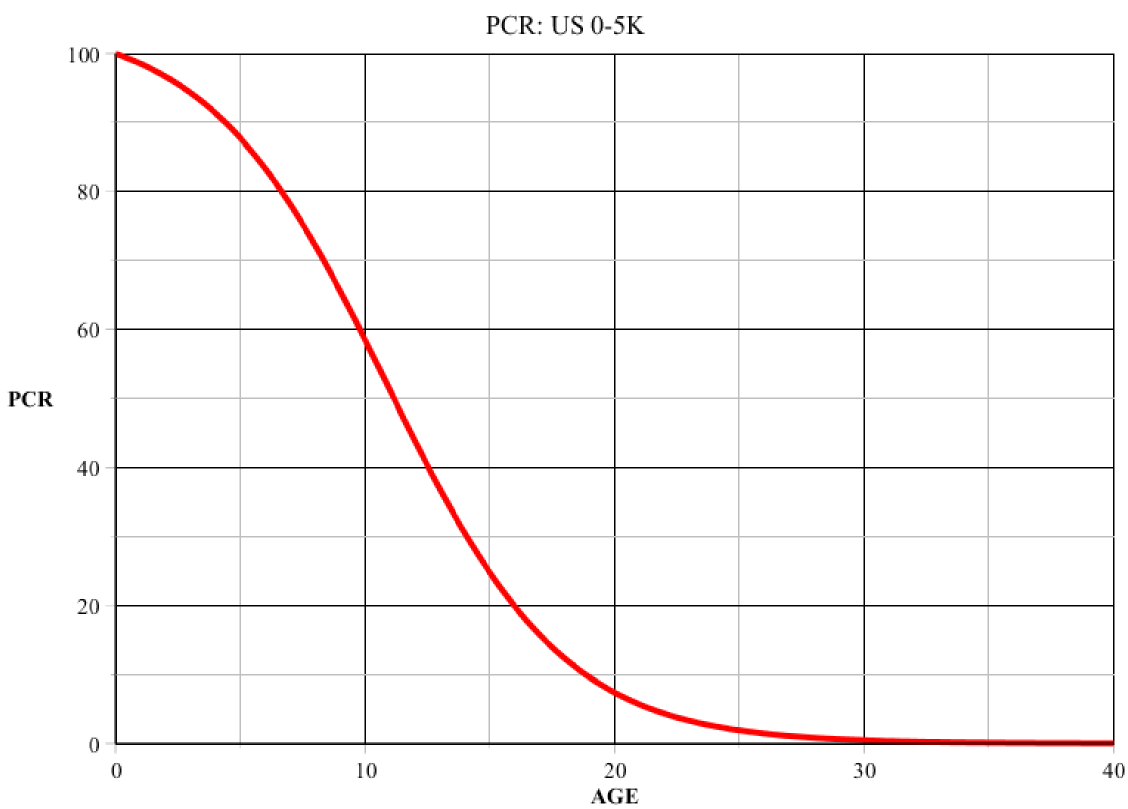

Rutting: NC 0-1K
RUT Index
100
80
60
40
20
0
0
10
20
30
40
AGE

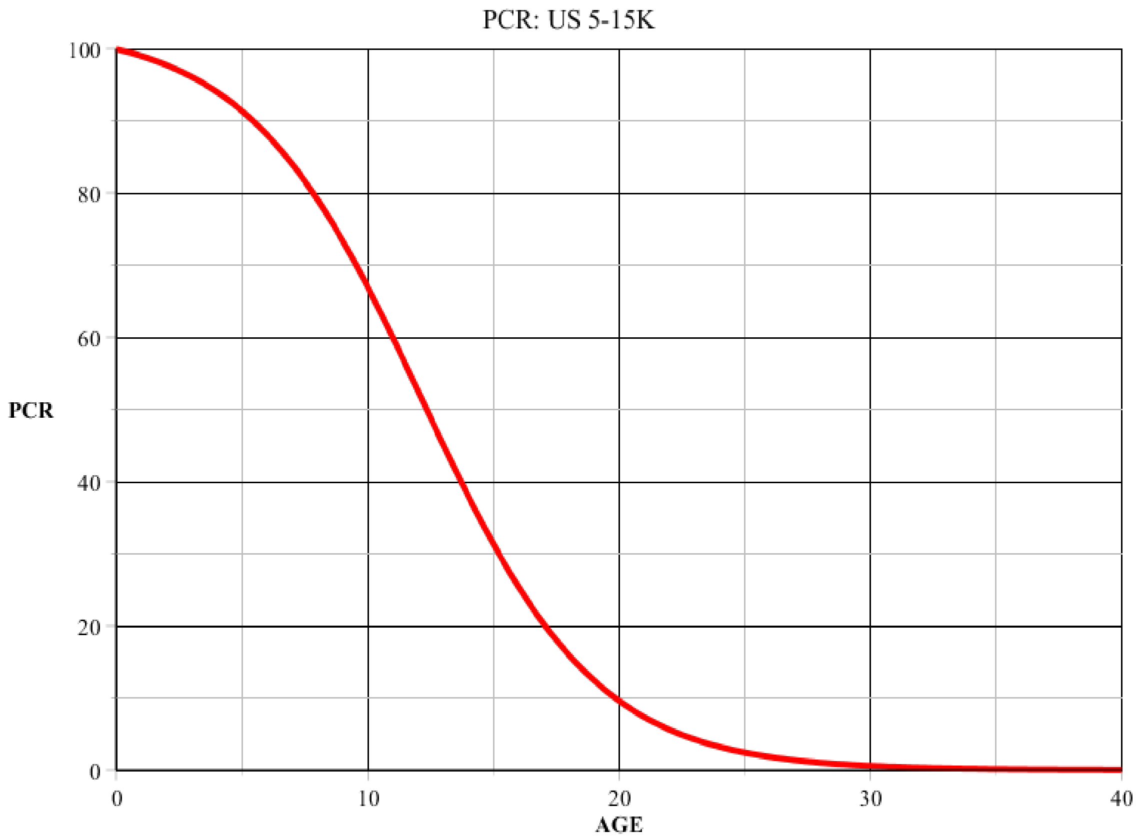

Rutting: NC 1-5K
RUT Index
100
80
60
40
20
0
0
10
20
30
40
AGE

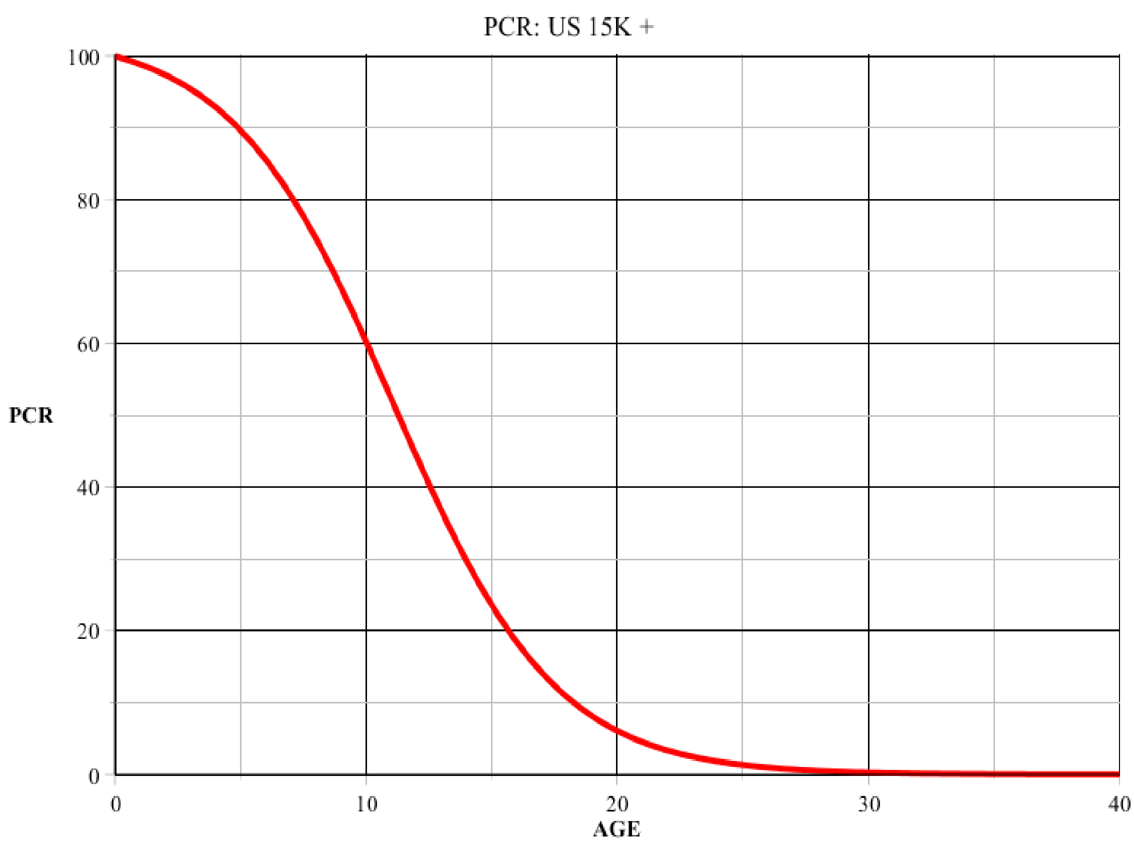

Rutting: NC 5K +
RUT Index
100
80
60
40
20
0
0
10
20
30
40
AGE

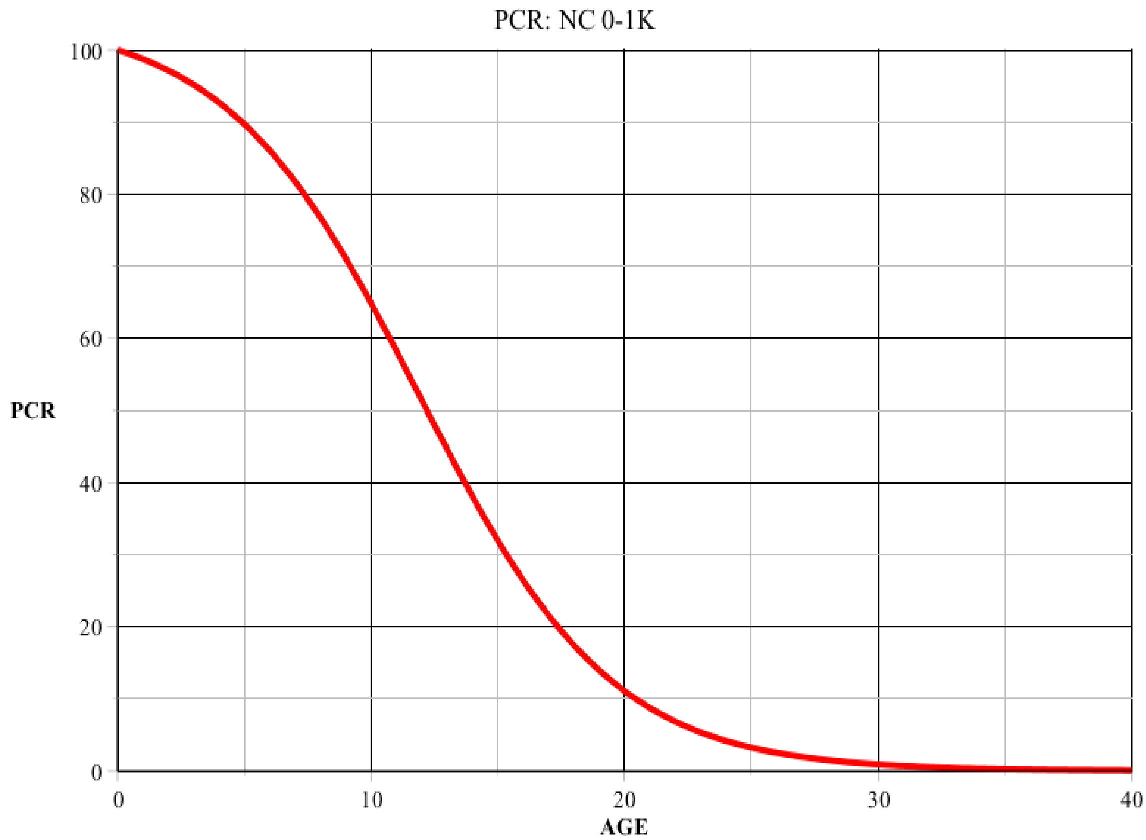
APPENDIX I: PCR MODELS

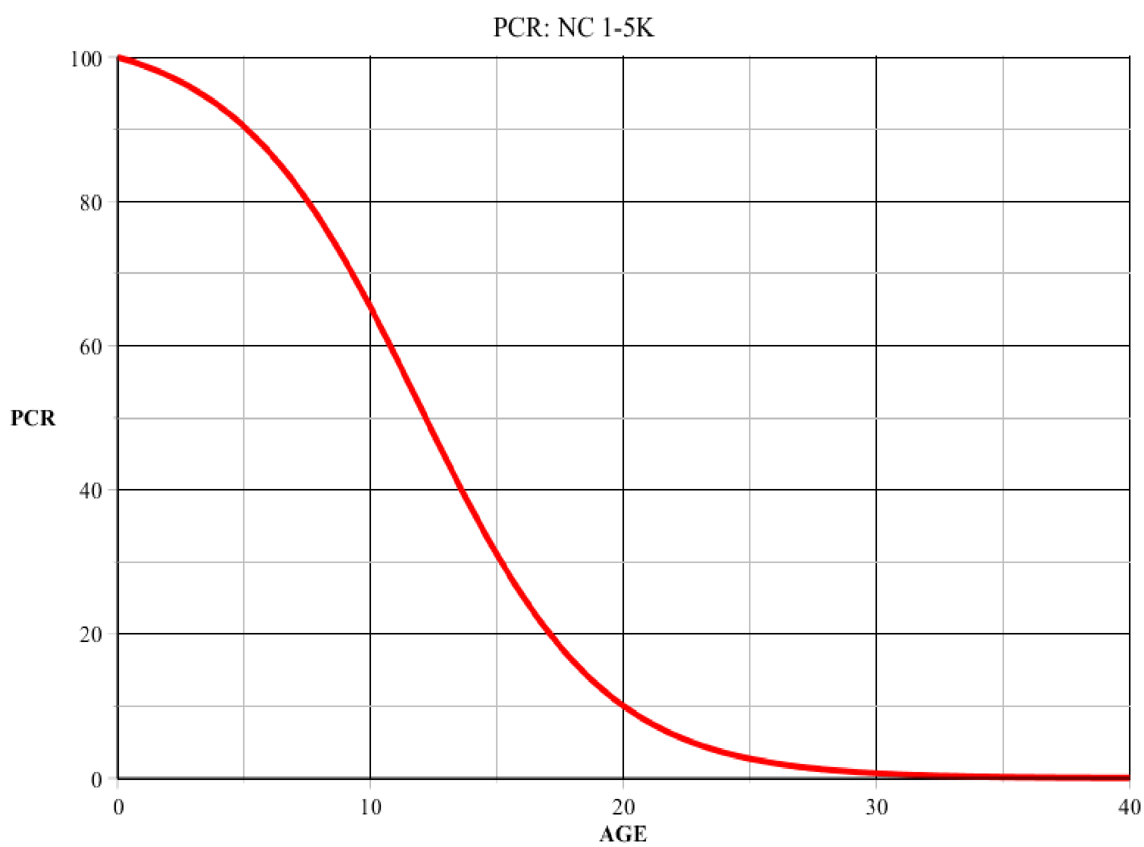


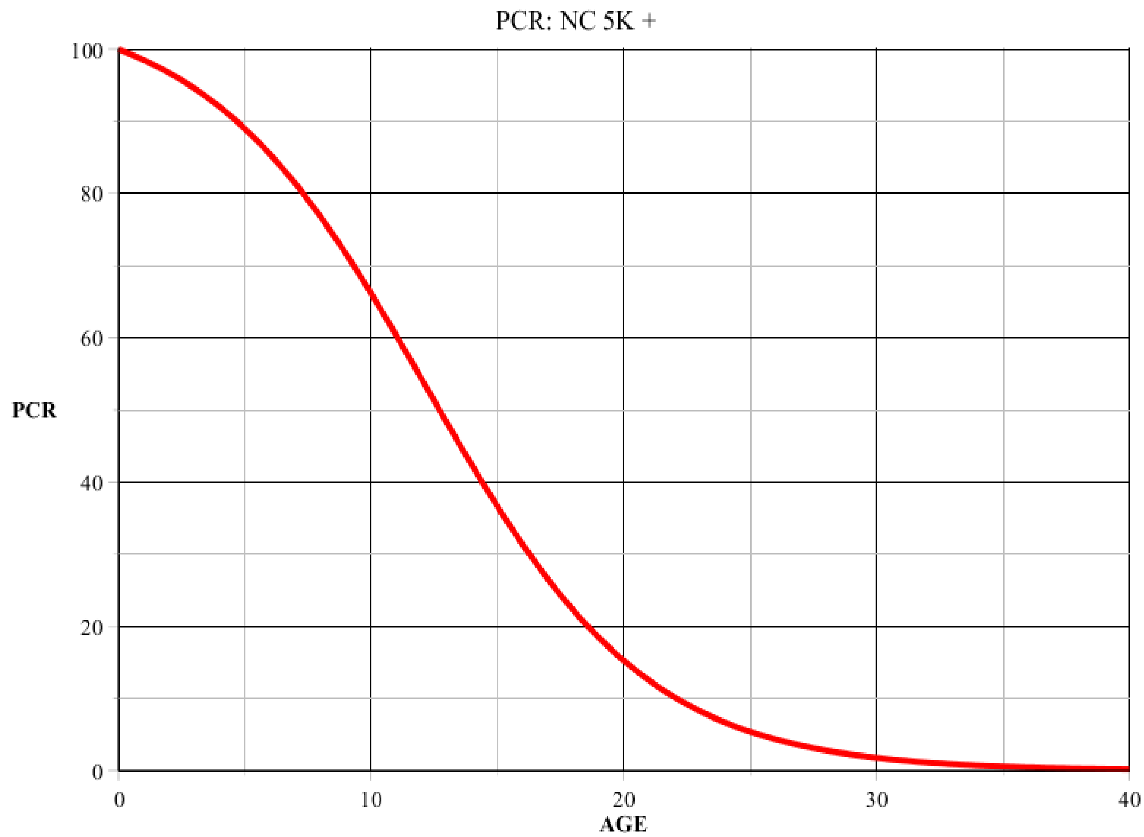



PCR: US 5-15K
100
80
60
40
20
0
PCR
0
10
20
30
40
AGE


PCR: US 15K +
100
80
60
40
20
0
PCR
0
10
20
30
40
AGE


PCR: NC 0-1K
PCR
AGE
100
80
60
40
20
0
0
10
20
30
40


PCR: NC 1-5K
PCR
AGE
100
80
60
40
20
0
0
10
20
30
40


PCR: NC 5K +
PCR
AGE
100
80
60
40
20
0
0
10
20
30
40