Development of Iowa Pavement Analysis Techniques (IPAT)

Final Report
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16. Abstract

Recent federal legislation requires state highway agencies (SHA) and local road agencies to utilize performance-based approaches in their pavement management decision-making processes. The use of a remaining service life (RSL) model would be one such performance-based approach that could facilitate the pavement management decision-making process.

This study developed a Microsoft Excel macro and Visual Basic for Applications (VBA)-based Iowa Pavement Analysis Techniques (IPAT) automation tool that Iowa county engineers can use to estimate the project- and network-level pavement performance and RSL. To address this aim, statistics and artificial neural network (ANN)-based pavement performance and RSL models were developed using pavement structural features, traffic, construction history, and pavement performance records obtained from the Iowa Department of Transportation (DOT) Pavement Management Information System (PMIS) and the Iowa county agencies' database. The accuracy of models was evaluated using real database representing Iowa county pavement systems.

The IPAT tool provides a series of options for four pavement types representing Iowa county pavement systems—jointed plain concrete pavement (JPCP), asphalt concrete (AC) pavement, AC over JPCP, and portland cement concrete (PCC) overlay—to estimate RSL through different approaches based on various conditions and distress data availability from an individual county. As part of data processing, the concept of developing an Iowa historical performance databank (HPD) was introduced and demonstrated by using raw data collected from county pavements. In addition, the feasibility of integrating preservation and rehabilitation techniques for RSL predictions using ANN models was investigated to evaluate the effects of treatments on RSL of pavements.

The IPAT tool is expected to be used as part of performance-based pavement management strategies and to significantly help decision-makers facilitating maintenance and rehabilitation decisions for better prioritization and allocation of resources.

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EXECUTIVE SUMMARY

More than 20% of the secondary roads in Iowa are paved and hard-surfaced, with about 30% of statewide road projects slated for surfacing roadways with hot-mixed asphalt (HMA) and portland cement concrete (PCC). Given that paved and hard-surfaced roadways, which deliver access to public and private property throughout a county require continual maintenance and reconstruction, these roadways play a critical role in the jobs of Iowa county engineers.

Iowa county engineers can operate their road systems by inventorying their records and inspecting them to perform preventive maintenance and rehabilitation. Such an inventory includes pavement history, pavement structural design features, pavement condition measures, traffic volume information, and material properties, but the lack of a reliable tool to estimate future pavement performance has resulted in counties encountering challenges to estimating remaining service life (RSL), i.e., when a pavement will reach and how long it will remain in a particular condition before its next rehabilitation. Accurate RSL estimations could facilitate maintenance and rehabilitation decisions to provide better prioritization and allocation of resources.

The primary objective of this study was to develop an Iowa Pavement Analysis Techniques (IPAT) tool (using Microsoft Excel, macro, and Visual Basic for Applications [VBA]) to help engineers predict performance and RSL of Iowa county pavement systems for four pavement types—jointed plain concrete pavement (JPCP), asphalt concrete (AC) pavement, AC over JPCP, and PCC overlay at the project- and network-levels.

The IPAT tool takes into account traffic capacities, equivalent single-axle load (ESAL) or annual average daily traffic (AADT), and design lifetime (based on layer ages, properties, slab thickness, and prior surface treatments). The IPAT tool uses a navigation panel (main tool) that can launch 56 sub-tools utilizing statistical- and artificial intelligence (AI)-based models to predict pavement performance and RSL.

A detailed step-by-step methodology for developing pavement performance and RSL prediction models was established and deployed using real pavement performance data obtained from the Iowa Department of Transportation (DOT) Pavement Management Information System (PMIS) database. The developed models were evaluated and improved using available data specifically related to Iowa county pavement systems. As an aspect of preparing such data, the concept of an Iowa historical performance databank (i.e., HPD) was introduced and demonstrated using raw data obtained from Lee County.

To develop RSL models, project- and network-level pavement performance models were initially developed using two approaches: a statistically (or mathematically) defined approach and an AI-based approach using artificial neural network (ANN) techniques. Although both approaches can be utilized for predicting pavement performance and RSL at both project and network levels, the research team recommends using the statistics-based models for project-level predictions and the ANN-based models for network-level predictions. This is because the ANN-based models were developed using aggregated data from statewide pavement systems and the statistics-based models were developed using individual pavement section data, and this difference increases the capability of ANN models to capture various scenarios throughout the network system. On the other hand, since statistics-based performance models require very few data for analysis, they can be extensively used when only a few details on pavement condition or structural and traffic data are available for the given pavement sections of interest. Another benefit of the ANN approach is that the fields will be automatically refined as engineers add more data through the user interface in the IPAT tool and have the most recent and more accurate pavement performance predictions for decision-making.

To estimate RSL, the user provides threshold limits for various pavement performance indicators, including the international roughness index (IRI) for the statistics-based models, and rutting, percent cracking, and IRI for ANN-based models. The Federal Highway Administration (FHWA)-specified threshold limits could be utilized and assigned as default threshold limit values for use by the IPAT tool. The feasibility of integrating preservation and rehabilitation techniques for RSL predictions using ANN models was also investigated to evaluate the effects of treatments on pavement RSL.

The key findings from this study and recommendations for implementation are as follows:

- Statistics-based models provide high accuracy in IRI or pavement condition index (PCI) predictions when there is only a single pavement deterioration trend, as for a project-level pavement system. Sigmoidal equations have mainly been used in statistical model development, because: (1) they have a low initial slope that increases with time, and (2) they follow a trend in which pavement condition always gets worse and damage becomes irreversible, and such behavior makes these models mimic pavement deterioration behavior observed in field studies.

- ANN-based models, depending on the pavement type, provide high accuracy in IRI, rutting, and percent cracking predictions when there are many pavement sections with a variety of traffic volumes, thicknesses, and other various deterioration trends, as in a network-level system.

- The feasibility study for integrating pavement treatment techniques into pavement RSL models that was conducted highlights some challenges in the data collection phase that require specific parameters to be defined before predicting post-treatment performance and RSL. These parameters include preservation and rehabilitation treatment triggers, recovery percentages in performance, expected treatment service life, and pavement RSL extension based on the pavement type and treatment type.

- The IPAT tool developed in this study is a user-friendly tool that provides flexibility in launching different types of tools based on pavement type and data available from local agencies. The statistics- and AI-based approaches have been successfully utilized to help estimate pavement performance and RSL in facilitating decision-making and managing county pavement systems.

- The Microsoft Excel-based IPAT tool could be integrated into Iowa county pavement asset management procedures consisting of five recommended steps: (1) data collection, (2) data processing, (3) data analysis, (4) data management, and (5) data-driven decision-making. Future research directions for fully implementing the recommended steps in Iowa county pavement asset management practices to fulfill county engineer needs were identified and recommended for the next phase of this study. These research directions, categorized into five topics related to each of the steps include: (1) implementing low-cost data collection tools for local road agencies, (2) automating or semi-automating data processing, (3) fully integrating maintenance/preservation/rehabilitation activities into the IPAT tool, (4) integrating the IPAT tool into the geographic information system (GIS) platform and/or software and developing a smartphone application version of IPAT tool as an official app under the Iowa County Engineers Association Service Bureau (ICEASB) AppSuite for better data management practices, and (5) developing multi-objective optimized RSL models for assisting in better decision-making.

CHAPTER 1. INTRODUCTION

Problem Statement

Many state transportation and local road agencies measure road conditions to evaluate the need for pavement preservation or rehabilitation. Remaining service life (RSL) is defined as the time until either a road condition index reaches its threshold limit or until the next rehabilitation or reconstruction event is required (Elkins et al. 2013a, Elkins et al. 2013b). Compared to a conventional condition index, RSL is easier to understand and provides insight by converting condition measures to an operational performance measure that indicates how well or how long the road will continue serving the public (Mack and Sullivan 2014).

The Moving Ahead for Progress in the 21st Century (MAP-21) Act is a milestone for the US economy and the nation's surface transportation program (FHWA 2012). It contains three major provisions (section 1203 §150, section 1106 §119, and section 1202 §135) that, when combined, require states to develop a far-reaching performance-based management program for pavements and roads. The American Association of State Highway and Transportation Officials (AASHTO) Standing Committee on Performance Management (SCOPM) Task Force on Performance Measure Development, Coordination, and Reporting produced several recommendations for defining national-level performance measures and target setting for pavements, including the international roughness index (IRI) and the pavement structural health index (PSHI) (AASHTO 2012, AASHTO 2013). However, since such condition measurements have no time element that tells how long a pavement will remain in a particular condition or how pavement performance may change over time, pavement engineers have new need for a tool that can tell when preservation and rehabilitation are required for given road sections.

Iowa has 19,166 miles of paved and hard-surface secondary roads. Iowa county engineers have the capability to inspect these pavements at any time, and the data they acquire includes pavement history (related to construction, maintenance, and rehabilitation), pavement structural design features, pavement condition measures, traffic volume information, and material properties. While collecting and using these data to develop RSL models for Iowa county pavement systems would be challenging, it could facilitate better decision-making in managing county road assets.

Another challenge is to create tools that could enable county engineers to more easily estimate RSL. Since two pavements under identical conditions can have significantly different RSL values, there is a need to predict future pavement condition trends for more than just pavement surface conditions, with original equivalent single-axle load (ESAL) capacity and design lifetime (based on layer ages, properties, slab thickness, and prior surface treatments) factors that should be taken into consideration.

Research Objectives and Scope

The primary objective of this study is to develop an Iowa Pavement Analysis Techniques (IPAT) tool for Iowa county pavement management and decision-making. Specific objectives established to achieve this primary objective were as follows:

- Find the best way to model a pavement's lifetime and make predictions as to when it will reach the end of its service lifetime (arrive at minimum service level)
- Take into consideration available data such as pavement history and structure, materials, traffic, truck volumes, etc., for model development
- Absorb and integrate condition data from multiple sources, such as the Iowa Department of Transportation (DOT) Pavement Management Information System (PMIS), Iowa Pavement Management Program (IPMP), engineering field assessments, and inspector team distress evaluations
- Compute an RSL value for every paved segment and provide a mile versus RSL tally
- Develop methodology to support predictive and consequence analysis

Report Organization

This report consists of seven chapters and three appendices as follows:

- Chapter 1 provides an introduction, including the problem statement, research needs, and objectives.

- Chapter 2 presents a review of the RSL concept, including its advantages, and discussions on the general relationship of RSL to pavement condition measures.

- Chapter 3 describes a detailed step-by-step methodology for development of a framework for pavement performance and RSL prediction models using real pavement performance data obtained from the Iowa DOT PMIS database. To develop RSL models, both statistical- (or mathematical-) and artificial neural network (ANN)-based pavement performance models were initially developed. Using pavement performance models for various pavement performance indicators (IRI for project-level models, and rutting, percent cracking, and IRI for network-level models) along with the Federal Highway Administration (FHWA)-specified threshold limits for these pavement performance indicators. RSL models for three pavement types are described—jointed plain concrete pavements (JPCPs) representing rigid pavement systems, asphalt concrete (AC) pavements representing flexible pavement systems, and AC over JPCP representing composite pavement systems in Iowa. These RSL models will significantly assist engineers in their decision-making processes. Predictions of impact on pavement performance are also evaluated.

- Chapter 4 describes a detailed step-by-step methodology for development of a framework for an Iowa county pavement historical performance databank (HPD), with a detailed description of data summarization and improvements in pavement performance and RSL prediction models using real pavement performance data obtained from the Iowa DOT and Iowa county engineer's offices. Based on the approaches in Chapter 3, the statistical- and ANN-based models developed using the PMIS database were validated using the HPD in this chapter for

JPCPs and AC pavements. The models were repeatedly improved with new input parameters until highly accurate pavement performance predictions for county pavements were achieved. RSL models were then developed for JPCP and AC pavement models.

- Chapter 5 presents an ANN-based model developed using county portland cement concrete (PCC) overlays or concrete overlays obtained from previous research in the Iowa Highway Research Board (IHRB) Project TR-698 (Gross et al. 2017) to predict IRI and estimate RSL of county PCC overlays.

- Chapter 6 discusses the feasibility of integrating preservation and rehabilitation techniques for RSL predictions using ANN models to evaluate the effects of treatments on RSL of pavements. Excel-based tools employing ANN models, which have not cooperated with the current version of the IPAT tool developed through this study, are introduced and discussed for such feasibility.

- Chapter 7 presents the IPAT tool by describing the interface of the main navigating tool and providing flowcharts describing the various analysis steps for all types of pavement analysis, including JPCP, AC, AC over JPCP, and PCC overlays.

- Chapter 8 presents the overall research conclusions made from the entire study, including detailed findings from studies conducted for each type of pavement system.

- Chapter 9 summarizes the recommendations for implementation and future research directions suggested by this study.

- Appendix A offers a step-by-step detailed standard procedure to illustrate how an Iowa HPD concept could be developed. This document, together with the application of methods used by the Iowa DOT PMIS for primary roads, delineates procedures for creating and processing raw data for pavements and guidelines for developing an accurate database for Iowa secondary roads referred to in Chapter 4.

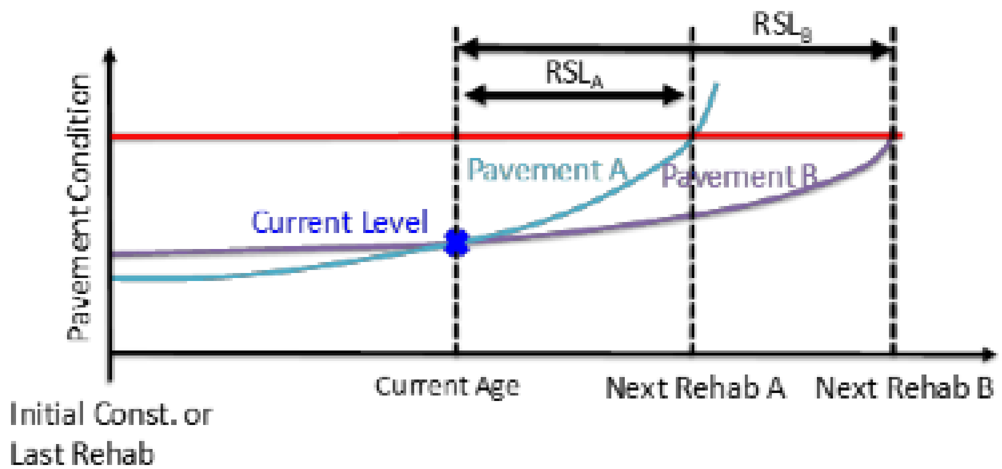
- Appendix B presents prototype analysis tools for preservation and rehabilitation techniques to be integrated into pavement performance and RSL prediction models referred to in Chapter 6.

- Appendix C provides examples of MATLAB software source code for developing ANN models and scripts for the Visual Basic for Applications (VBA) and macro-based Excel-based IPAT tool.

In addition, as part of this project, the research team also developed a user guide on how to use the VBA- and macro-based IPAT tool described in Chapter 7.

CHAPTER 2. REVIEW OF RSL CONCEPT

In general, there are two definitions for RSL: the time remaining until a condition index threshold limit is reached and the time remaining until the next rehabilitation or reconstruction event is scheduled to occur (called remaining service interval [RSI] to distinguish it from the first definition) (Elkins et al. 2013a, Elkins et al. 2013b, Mack and Sullivan 2014). In contrast to RSL, a condition measurement reflects only the current condition of the road network and has no time element that tells how long a pavement would be expected to remain in a given condition or how its performance will change over time (Figure 1).



Reproduced from Mack and Sullivan 2014

Figure 1. Pavement condition vs. age and rehabilitation

The multiple advantages of using RSL have been reported in the literature (Mack and Sullivan 2014), and key positive RSL features include the following:

- Provides the time (in years) before rehabilitation is required for any given road section
- Easy to understand (especially by the public)
- Can be a multi-conditional measure developed from any type of functional and/or structural data
- Allows agencies to distinguish between two road sections having the same current condition (i.e., the same current IRI)
- Provides deeper insight by converting condition measures into an operational performance measure that predicts how well or how long a road will continue serving the public
- Can be an ideal tool to address the transportation planning and performance management criteria requirements of the MAP-21 legislation

The definition of RSL by different DOTs and transportation agencies may differ because factors affecting future conditions of pavement network might vary by state while playing an essential role in decision-making, life-cycle cost analysis (LCCA), planning, and budget allocations. As examples, the Minnesota DOT (MnDOT) considers the RSL to be the estimated time until the next major rehabilitation (Kumar et al. 2018), while the Michigan DOT (MDOT) outlines the RSL using the Michigan ride-quality index, with the assumption of no remaining life represented by an index of 50. The Louisiana DOT and Development (LADOTD), using the most common definition used by other state agencies, refers to RSL as the time period between construction date and major rehabilitation date. More examples are presented in Table 1.

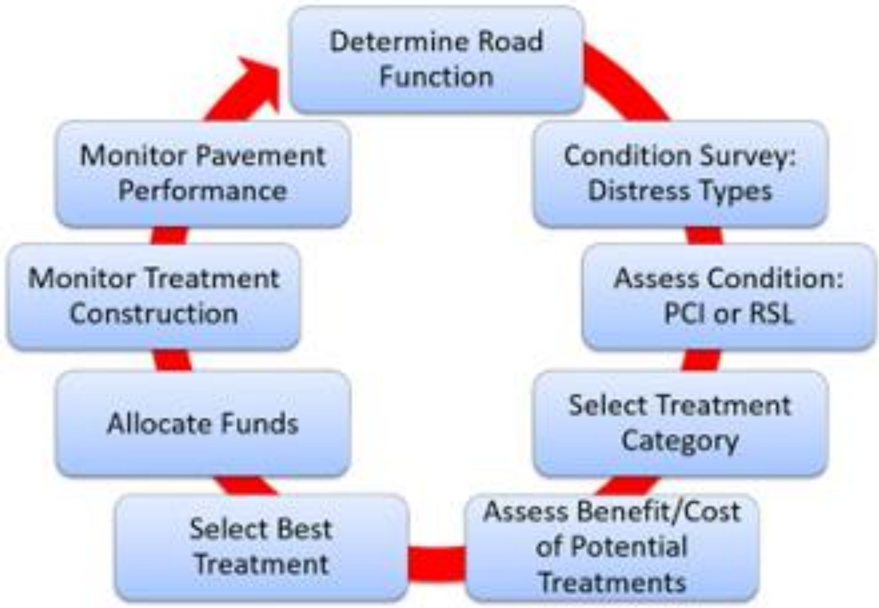
Table 1. RSL definitions used by different state agencies

State	State abbreviation	How do you define service life for concrete and asphalt pavements?
British Columbia	BC	Service life: years until end-of-life rehabilitation. We get approximately 15 to 20 years out of asphalt pavement, dependent on traffic and environment. (Design life is 20 years.) End of life occurs with an overlay or mill-and-fill or hot in-place recycling. Pavement condition indices (PCIs) are used but not as rehabilitation triggers.
Arizona	AR	Service life: overall condition or structural adequacy of the pavement structure. In asphalt, indicators include excessive rutting, fatigue cracking, and excessive cracking. In concrete, indicators entail excessive faulting and cracking and pavement texture. Overall capacity and user safety can also affect service assessments.
Florida	FL	Service life: the typical time between rehabilitation projects.
Iowa	IA	Not defined, per se. Pavements are assessed by PCI values on a 100-point scale; below 40 requires major rehabilitation or reconstruction.
Kansas	KS	Service life: the period during which pavement structure can be effectively and economically rehabilitated and kept in service.
Maryland	MD	Service life: the length of time until first rehabilitation. Rehabs are overlays or major repair that improves structural capacity; after rehab, pavement begins a new service life. Preventive or reactive treatments that add no structure—such as patching, crack sealing, diamond grinding—do not end service life. Reconstruction is rare, reserved for realignments, traffic volume improvements, utility improvements, and such.
Minnesota	MN	Service life: the time, in years, until pavement reaches a present pavement serviceability rating (PSR) of 2.5.
Mississippi	MS	Service life: for design purposes, defined in years (Editor’s note: from construction until overlay, or from overlay to next overlay or end-of-life.)
Missouri	MO	Service life: used interchangeably with design life, JPCP and deep-strength hot-mixed asphalt (HMA) for new pavements only; anticipate 45 years with interim maintenance and rehabilitation.

State	State abbreviation	How do you define service life for concrete and asphalt pavements?
New Mexico	NM	Service life: in the project-level management program, defined as the time from when a section of pavement first enters service to the point its condition is such that the useful performance period has ended. We use 5 performance indices for asphalt pavement and 4 others for rigid pavement. Service life: in design, we estimate the number of cumulative ESALs for the design years in question via a design serviceability index of 2.5 for high volume, 2.0 for low. Rehabs designed for 10-year ESAL projections; new construction for 20-year.
New York	NY	Service life: the length of time treatment is effective, or life of pavement or overlay until rehabilitation is required. When rehab required, a pavement is scored a 5 on a scale of 10
Rhode Island	RI	Service life (or performance period): the time between successive reconstructions.
South Dakota	SD	We don't use this concept.
Utah	UT	Utah uses three terms regarding pavement life. RSL: estimated number of years from any given date (usually last survey date) for a pavement section to accumulate distress points equal to a threshold value (pavement distress value beyond which pavement considered failed). Design life: planned number of years from construction to structural failure from fatigue. For flexible pavement, we design for 20 years; for rigid, 40. Pavement life: number of years from original construction to complete reconstruction; we use a "pavement life strategy" for each family of pavements, recognizing pavement life may extend well beyond design life and may require multiple rehabilitation treatments over a lifetime.
Virginia	VA	Service life: VaDOT currently uses a combination index of pavement age and visual rating of surface distresses, load-related and not. VaDOT anticipates moving to an automated measure of structural adequacy.

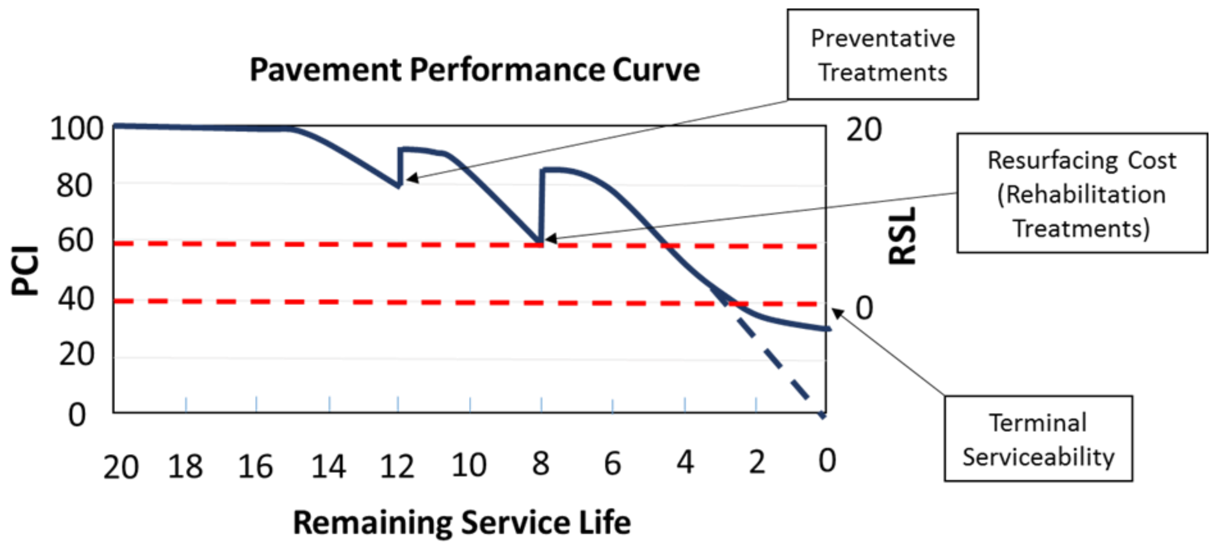
Source: Adapted from McLawhorn 2004

Conventionally, pavement condition and service time/traffic are the two key factors used to determine the necessity for pavement preservation and rehabilitation. Preventive triggers and rehabilitation triggers are always specified along with specific pavement conditions, and optimal timing for preservation and rehabilitation occurs when a pavement condition reaches such a trigger (threshold). Figure 2 depicts the typical project selection process for pavement preservation and rehabilitation, while Figure 3 shows the general relationship between PCI and RSL (Bolling 2008).



Adapted from Bolling 2008

Figure 2. Typical project selection process for pavement preservation and rehabilitation



Bolling 2008

Figure 3. General relationship between PCI and RSL

Most developed pavement RSL prediction models utilize pavement performance (i.e., distress and IRI) predictions using categorization of pavement RSL prediction models based on failure type (Witczak 1978, Vepa et al. 1996), including functional failure-based approaches, structural failure-based approaches, or both. Empirical models (mainly using statistical approaches) and mechanistic-based models (mainly using engineering principles) are two main types of performance models (Elkins et al. 2013a, Elkins et al. 2013b), and comparisons of the pros and cons of these approaches are presented in Table 2.

Table 2. Approaches measuring and estimating RSL

Class	Common approaches	Pros	Cons
Mechanical	• Fatigue test • Punch-out failures • Falling weight deflectometer (FWD)	• No traffic data or historical conditions are needed • Suitable for project-level management • Simple to assess the mechanical status of various pavements • The operation is done in a standard manner	• Pavement is damaged by destructive tests • Pricy equipment • Non-destructive test with back-calculation has low accuracy • Location and traffic effects on the accuracy of estimation • The influences of the effective parameters cannot be easily forecasted • Low suitability for management at a network-level
Empirical	• Life table • Cox proportional hazards • Neural network • Nomograph • Regression • Kaplan–Meier • Failure time theory	• If historical data are available, this approach is cheaper than another approach • The effects of the effective parameters can be predicted • It is relatively simple to do and merge with pavement management systems	• Need enough historical data • Accuracy of estimation is very much a function of data quality and model format • Comprehensive experience and field knowledge are needed for the specification of the format

Source: Yu 2005

Most mechanistic-based models use statistical methods for calibration, and some of the empirical models incorporate engineering principles. In addition, many models using a mechanistic-based approach, e.g., FWD measurements and back-calculated layer moduli and some mechanistic-based distress prediction models (Elkins et al. 2013a, Elkins et al. 2013b). Table 3 summarizes the related literature survey that uses different methods developed for use at the project level to estimate the RSL of pavements.

Table 3. Pavement RSL prediction models survey summary

Model	Type	Note	Reference
Life table survivor curves	Empirical	Developed for pavements built each year from 1903 to 1937 in 46 states; the probability versus time interval graph formed a survival curve; RSL was estimated by extrapolating the survival curve to 0% survival	Winfrey and Howell 1968
AASHTO empirical pavement design guides	Empirical	These methods use two basic empirical design equations (one for flexible and the other for rigid pavements) that relate the number of traffic loadings (expressed in terms of 18 kip [40 kN] ESALs) to pavement structural capacity, subgrade support properties, pavement serviceability changes, and reliability considerations; step 1: determine the total number of 18 kip ESAL applications that the pavement structure can support until it reaches the terminal serviceability level of interest; step 2: calculate the remaining ESAL loadings by subtracting the number of ESALs applied to the pavement so far from the total number of ESALs (determined from step 1); step 3: estimate RSL trough dividing the remaining ESAL loadings by the ESAL rate per year	AASHTO 1986, AASHTO 1993
Failure time theory	Empirical	The basis of the failure time theory requires that the underlying functional form of the parametric failure distribution be assumed a priori; this allows for estimation of the coefficients of those parameters and in effect dictates the influential factors; this may not be feasible when the underlying functional form does not match any known parametric statistical distribution	Prozzi and Madanat 2000
Cox PH model	Empirical	A semi-parametric model that does not require the survival time distribution to be known and can evaluate the effects of influential factors on pavement service life; it can take censored (i.e., incomplete) data into account; a pavement is considered to have reached the end of its useable life either if it is rehabilitated or if its condition falls below a specified criterion	Yu 2005

Model	Type	Note	Reference
Kaplan-Meier survival analysis (Product limit estimator method)	Empirical	A statistical technique used to generate tables and plots of survivor or hazard functions for time-to-event data; advantages of the method are that it accounts for censored data (i.e., incomplete), losses from the sample, and non-uniform time intervals between observations; pavements must be grouped into families that have similar characteristics, traffic loadings, and environments; a separate survivor curve has to be generated for each factor of interest	Balla 2010
Pavement health track (PHT) analysis tool	Mechanistic-based	Models based on use of default level 3 Mechanistic-Empirical Pavement Design Guide (MEPDG) inputs along with the Highway Performance Monitoring System (HPMS) data are used to predict changes in multiple pavement condition measures adjusted for currently observed levels; pavement health is defined as the time in age or load application from initial construction or reconstruction to the first major rehabilitation as warranted by pavement ride and structural conditions	O'Toole et al. 2013
Correlation analysis	Mechanistic-based	Statistical regression model developed by using PCI and FWD measurement to evaluate pavement condition and RSL; the required data to predict RSL includes road information, traffic data, and deflection data; PCI values can help determine selection of treatment time and predict RSL; a correlation coefficient of 0.88 has been found for the relationship between PCI and RSL	Setyawan et al. 2015
Artificial intelligence (AI)-based particle filter method (Optimized support vector machine [SVM])	Empirical	By using thickness of each pavement layer and temperature of asphalt surface in the presented AI-based model, the RSL of the pavement is predicted; the performance of support vector regression (SVR) depends on its parameters based on the weight of particles; the model was trained until the best weights were introduced; this model's advantage was it was proposed to be used as an alternative to heavy FWD testing in case of availability of weather and pavement thickness information	Karballaeezadeh et al. 2019a

Model	Type	Note	Reference
AI-based machine learning techniques	Empirical	Three models were developed using SVR, SVM optimized by fruit fly optimization algorithm (SVR-FOA), and gene expression programming (GEP) methods to predict RSL based on PCI; among these methods, the GEP method has been found to have the highest accuracy in RSL prediction	Karballaeezadeh et al. 2019b, Nabipour et al. 2019

CHAPTER 3. DEVELOPMENT OF PAVEMENT PERFORMANCE AND RSL PREDICTION MODELS

Description of Overall Approaches and Data Preparation

In this study, a detailed step-by-step methodology in the development of a framework for measuring project- and network-level pavement performance and RSL prediction models is described using real pavement performance data obtained from the Iowa DOT PMIS database. Project- and network-level pavement performance models are developed using two approaches: a statistically (or mathematically) defined approach primarily used for project-level modeling and analysis and an AI-based approach using ANN primarily used for network-level modeling and analysis. Network-level pavement performance models using statistical and AI-based approaches are also described. The same input parameters are used in both approaches to evaluate their relative success in network-level pavement performance modeling.

Microsoft Excel-based automation tools have been developed for both project- and network-level pavement performance modeling and analysis to facilitate pavement performance and RSL model development, make future pavement performance predictions, and estimate RSL for any given road section. These tools, which use real pavement performance data to produce realistic future condition predictions, can be easily incorporated into pavement management processes to help engineers make better informed performance-based pavement infrastructure planning decisions.

Figure 4 depicts the pavement performance and RSL model development stages followed in this study.

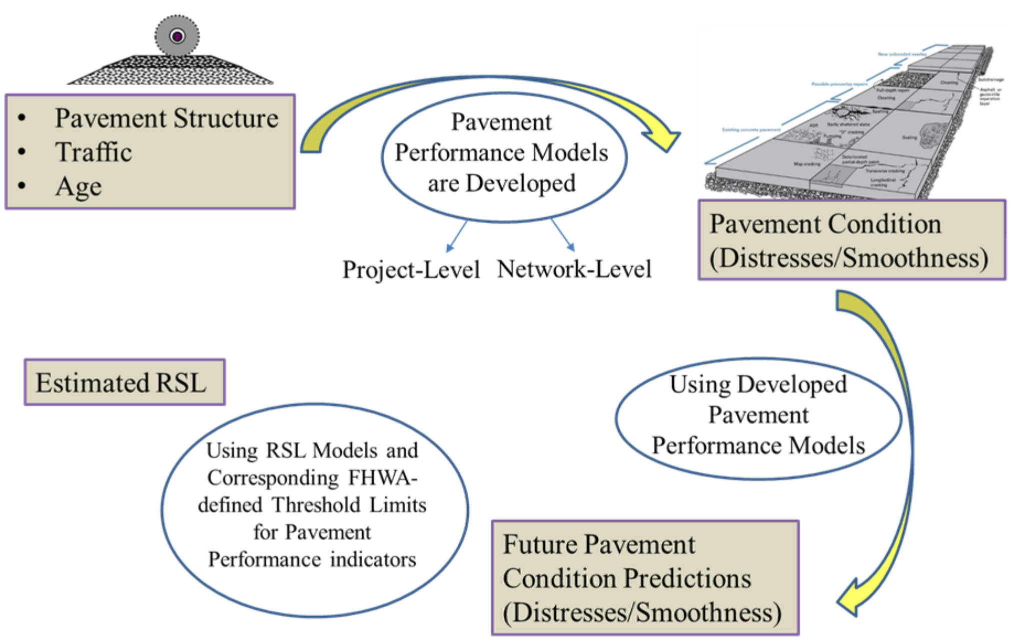


Figure 4. Pavement performance and RSL model development stages

Initially, project- and network-level pavement performance models were developed using two approaches: a statistically (or mathematically) defined approach for project-level use and an AI-based approach for network-level pavement management, with both performance models developed for the Iowa JPCP, AC pavement, and AC over JPCP systems considered in this chapter. They were also developed for the Iowa PCC overlays described in a later chapter. Project-level pavement performance models were developed for each pavement section of each pavement type, while network-level pavement performance models were developed to provide a pavement performance indicator or a condition matrix (i.e., distresses and IRI) for each pavement type.

Once pavement performance models were developed for the four pavement types, RSLs for the pavement sections were calculated using threshold limits for various performance indicators. Based on the FHWA's Final Rule (effective February 17, 2017) regarding the implementation of the performance management requirements of MAP-21 and the Fixing America's Surface Transportation (FAST) Act (HR 4348 2012, Visintine et al. 2018), determination of pavement condition is required to be based on the following metrics: IRI, percent cracking, rutting, and faulting (Table 4).

Table 4. Pavement condition rating thresholds determined by the FHWA

Condition metric	Performance level	Threshold
IRI (in./mi) (AC, JPCP, AC over JPCP, PCC overlay)	Good	<95
	Fair	95–170
	Poor	>170
Percent cracking (AC, AC over JPCP)	Good	<5%
	Fair	5%–20%
	Poor	>20%
Percent slab cracked (JPCP)	Good	<5%
	Fair	5%–15%
	Poor	>15%
Rutting (in.) (AC, AC over JPCP)	Good	<0.20
	Fair	0.20–0.40
	Poor	>0.40

Source: Visintine et al. 2018

IRI was used as the construction trigger for the rehabilitation decision-making process in project-level RSL calculations, and rutting, percent cracking, and IRI were used as construction triggers for the rehabilitation decision-making process in network-level RSL calculations. RSL was determined based on the year when future performance predictions reach the poor condition threshold for the corresponding condition metric (defined in Table 4).

MAP-21 mandates all state highway agencies (SHAs) to develop state asset management plans, and in response to this mandate, all SHAs have already developed their plans as of June 30,

2019. As stated in its transportation asset management plan (TAMP), the Iowa DOT uses PCI as the pavement condition metric for tracking and communicating the overall condition of its pavements (Iowa DOT 2019). The U.S. Army Corps of Engineers first developed PCI in the 1980s, after which the American Public Works Association (APWA) and the U.S. Department of Defense (DOD) adopted it to quantify pavement condition (ASTM 2009). A PCI rating scale was standardized in ASTM D6433 (ASTM 2009), Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys, where pavement sections with a PCI value of 85% and above were rated to be in good condition, and those with 25%–40% were rated to be in very poor condition (Table 5). Furthermore, based on the rating system, pavement sections with PCI values between 20%–25% were rated in severe condition, while those with PCI values less than 10% were rated as failed (Table 5).

Table 5. Pavement condition corresponding to PCI rating scale

Pavement condition	Standard PCI rating scale
Good	100
Satisfactory	85
Fair	70
Poor	55
Very Poor	40
Serious	25
Failed	<10

Source: Adapted from ASTM 2009

PCI accounts for ride quality and the amount of cracking, faulting, and rutting on pavements. The Iowa DOT categorizes the condition of its pavements as good, fair, or poor, and uses different PCI threshold values for each condition category based on the roadway type (Table 6) (Iowa DOT 2019).

Table 6. Iowa DOT PCI thresholds

Condition metric	Performance level	Interstate	Non-interstate NHS	Non-NHS
PCI	Good	76–100	71–100	71–100
	Fair	51–75	46–70	41–70
	Poor	0–50	0–45	0–40

Source: Iowa DOT 2019

Although asset management plans had already been developed by SHAs, in almost all cases they exclude local roads, and asset management roadmaps for local roads are still in development in many states. No literature has been found to provide statewide PCI-based construction triggers for county roads (Saha and Ksaibati 2016). In examining an analysis of PCI's relationship with IRI, the results of a study showed that a road segment could be classified as fair with PCI while good with IRI. An exponential regression equation was provided with IRI and PCI, with a line-of-equality coefficient of determination (R^2) value of 59% and a correlation coefficient value (r) of -0.768, that showed that PCI may have a strong but opposite impact on IRI value (Hasibuan and Surbakti 2019). Another study conducted on 62 samples presented an overall range of IRI and the predicted PCI using power regression models, seen in Table 7, that resulted in an R^2 value of 59% and 66%, respectively, with strong linear dependence of variations in PCI on IRI (Park et al. 2007).

Table 7. Overall range of IRI and the predicted PCI

Pavement quality	PCI	IRI, in./mile (m/km)
Excellent	100	0.727 (46.06)
Very Good	85	1.055 (66.85)
Good	70	1.650 (104.54)
Fair	55	2.870 (181.84)
Poor	40	5.947 (376.80)
Very Poor	25	17.50 (1,108.80)
Failed	10	>20 (>1,267.20)

Source: Adapted from Park et al. 2007

The IPMP also provides a PCI scale, as presented in Table 8.

Table 8. PCI scale by IPMP

Performance level	PCI
Excellent	80–100
Good	60–80
Fair	40–60
Poor	20–40
Very Poor	0–20

Source: Nlenanya 2017

Based on a literature review, a PCI value of 40% could be used as a threshold value for Iowa county roads, because: (1) this is consistent with Iowa DOT's non-NHS poor-condition threshold, (2) it corresponds to the very poor PCI threshold in ASTM D6433, and (3) it is very similar to some counties' PCI construction triggers, as explained in the preceding paragraphs, provided that local road agencies reach a consensus on this value. For demonstration purposes, as part of this report, a PCI value of 40% was used as the rehabilitation trigger.

The success of the pavement performance prediction models in mimicking measured pavement performance indicators was quantified using R^2 (equation 1), an absolute average error (AAE) (equation 2), and standard error of the estimates (SEE) (equation 3). Higher R^2 and lower AAE and SEE values are indicators of the model prediction accuracy. The three equations are given as follows:

$$R^2 = 1 - \frac{\sum_{j=1}^{n}\left(y_j^{measured} - y_j^{predicted}\right)^2}{\sum_{j=1}^{n}\left(y_j^{measured} - y_{mean}^{measured}\right)^2} \quad \textbf{(1)}$$

$$AAE = \frac{\sum_{j=1}^{n}\left|y_j^{measured} - y_j^{predicted}\right|}{n} \quad \textbf{(2)}$$

$$SEE = \sqrt{\frac{\sum_{j=1}^{n}\left(y_j^{measured} - y_j^{predicted}\right)^2}{n}} \quad \textbf{(3)}$$

where,

- n = Data set size
- j = Case number in the data set
- $y^{measured}$ = Measured IRI or calculated PCI value
- $y^{prediction}$ = Model predictions for IRI and PCI

Statistics-Based Pavement Performance Model Development and Accuracy Evaluations

A statistically (or mathematically) defined sigmoid pavement deterioration curve-based approach was used in this study for project-level pavement performance model development. Sigmoidal equations have been most particularly used in statistical model development, because: (1) they have a low initial slope and an increasing slope with time, and (2) they follow a trend in which pavement condition always gets worse, and damage is irreversible, and both these features cause such models to mimic pavement deterioration behavior observed in field studies (Chen and Mastin 2016, Beckley 2016, Ercisli 2015). Since sigmoidal equations have been found to successfully model pavement deterioration when there is a single pavement deterioration trend (project-level), a sigmoidal equation for each pavement section in each pavement type was optimized so that each equation had different coefficients. IRI and PCI were used as performance indicators in project-level pavement performance models.

Equation 4 is the generalized sigmoidal equation used for IRI calculation, given as follows:

$$IRI = C_1 + \frac{C_2}{1+e^{(C_3+C_4\times age)}} \quad \textbf{(4)}$$

where, *C1*, *C2*, *C3*, and *C4* are coefficients that represent contributions of different input parameters.

Equation 5 is the generalized sigmoidal equation used for PCI calculation, given as follows:

$$PCI = \frac{100}{1+e^{(\mathrm{D}+\mathrm{C}\times age)}} \quad \textbf{(5)}$$

where, *C* and *D* are coefficients that represent contributions of different input parameters.

Sigmoidal curves were fitted to measured IRI/PCI values by minimizing the square of differences value between measured and predicted IRI/PCI values. The fitting process was carried out by manipulating prediction coefficients (equation 4 and equation 5) to produce minimum error. Figure 5 through Figure 7 show examples of IRI prediction models for JPCP, flexible, and composite (AC over JPCP) pavement types, respectively. Using these models, future IRI predictions can be calculated for these pavement types.

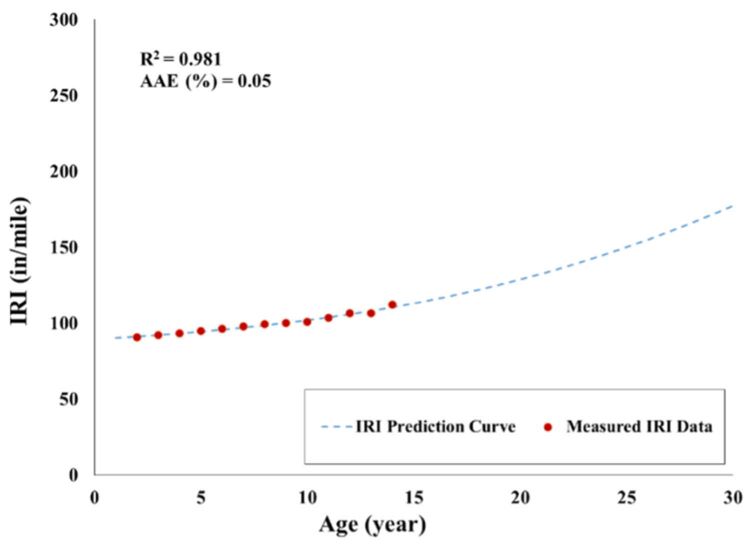


Figure 5. IRI prediction model example for JPCP

The prediction model is based on the measured IRI data given in the following equation:

$$IRI = 80.30 + \frac{307.34}{1 + e^{(3.48 - 0.09 \times age)}}$$

The section used as the example in Figure 5 is on US 18, from milepost 208.94 to 211.75, westbound, with an annual average daily truck traffic (AADTT) of 2,104, and it was constructed in 2000.

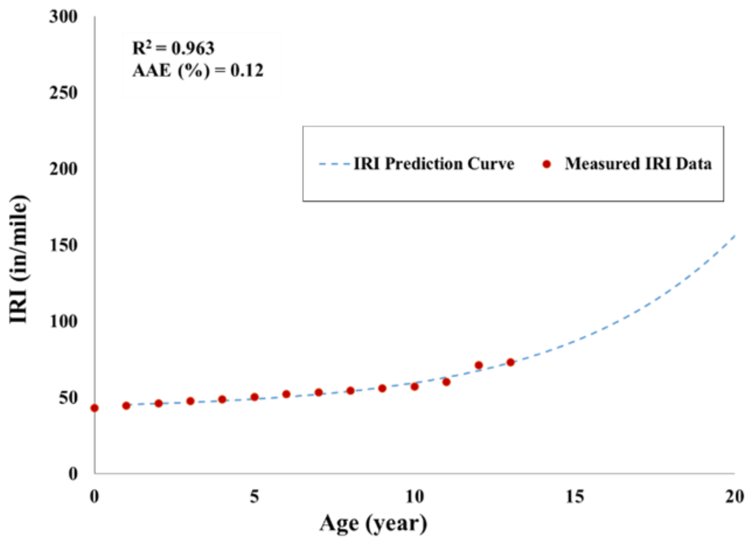


Figure 6. IRI prediction model for flexible pavement

The prediction model is based on the measured IRI data given in the following equation:

$$IRI = 42.24 + \frac{4335.36}{1 + e^{(7.42 - 0.19 \times age)}}$$

The section used as the example in Figure 6 is on US 61, from milepost 167.95 to 174.74, northbound, with an AADTT of 1,154, and it was constructed in 1999.

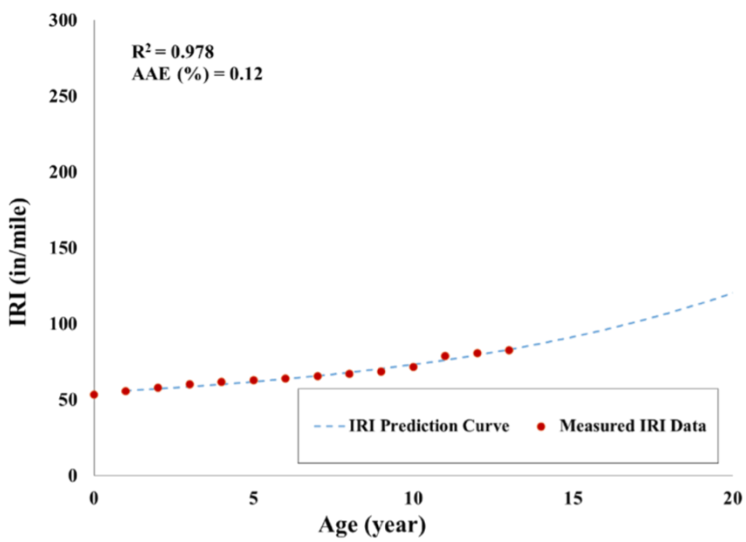


Figure 7. IRI prediction model for composite pavement (AC over JPCP)

The prediction model is based on the measured IRI data given in the following equation:

$$IRI = 44.07 + \frac{1197.96}{1 + e^{(4.70 - 0.10 \times age)}}$$

The section used as the example in Figure 7 is on US 30, from milepost 310.08 to 318.84, westbound, with an AADTT of 1,264, and it was restored in 2000.

As part of this study, a Microsoft Excel macro-based automation tool was developed for automatically updating and improving pavement performance prediction models as more data were added into the model development data set. Figure 8 presents the calculation steps and capabilities of this automation tool.

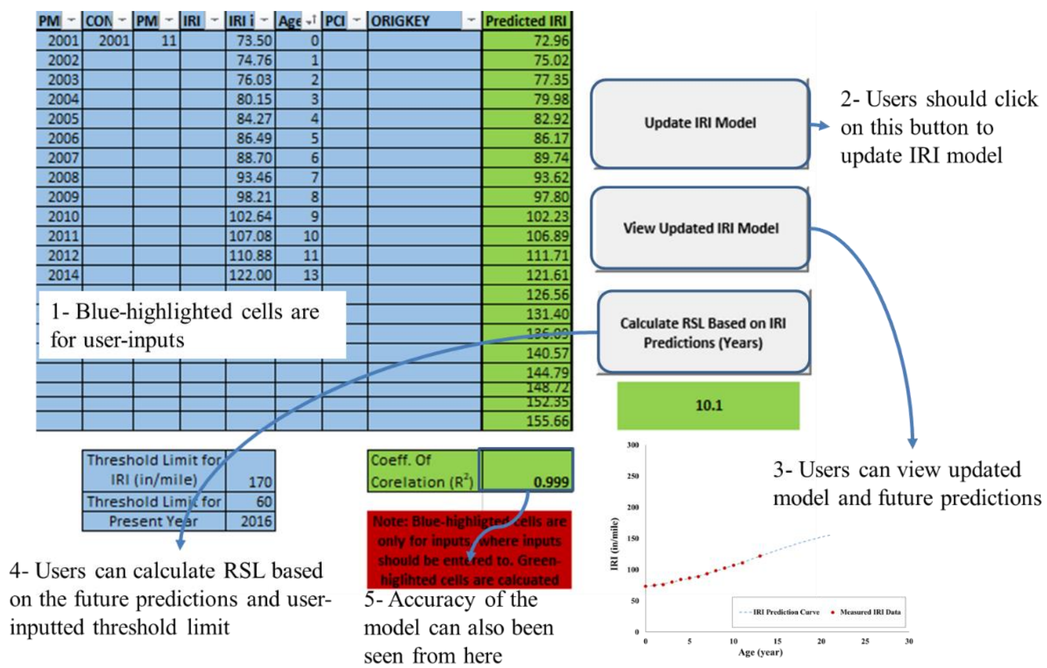


Figure 8. Project-level "tunable" pavement performance prediction automation tool

The benefit of this tool is that as engineers add more data into the model development data set, they will be able to automatically refine performance prediction models and make decisions using the most recent and more accurate pavement performance models. Another benefit of using this tool is that pavement performance prediction models can be developed using very few data points.

Figure 9 shows an example of IRI prediction model changes as more measured IRI data points are used in model development for an AC pavement section.

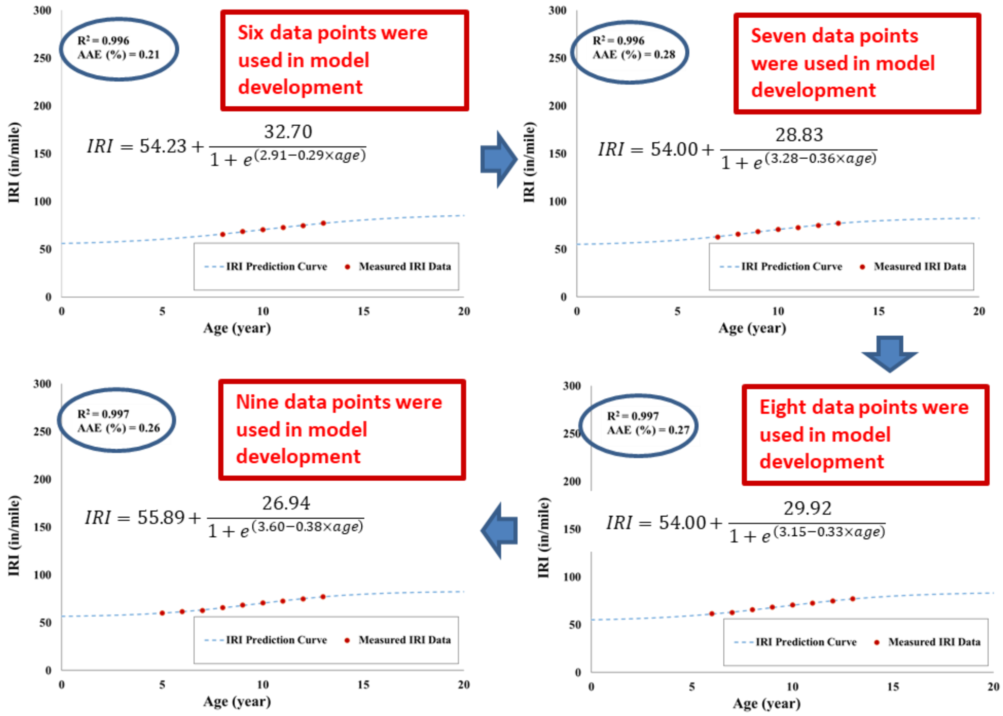


Figure 9. IRI model changes as more data points are added into the data set as an example for an AC pavement section

The section used in Figure 9 is on Iowa 3, from milepost 039.09 to 044.12, eastbound, with an AADTT of 500, and it was constructed in 1999.

As shown in this figure, as more data are added to the model development data set, prediction equations change slightly, and model accuracy increases. Note that the PCI prediction model and its calculation steps look similar to the IRI prediction model and calculation processes seen in Figure 8 and Figure 9.

Statistics-Based Pavement RSL Model Development and Results

Once pavement performance models have been developed for pavement sections, as discussed in the previous section, RSLs for these pavement sections can be calculated using threshold limits for the pavement performance indicators. In this study, IRI was used as a performance indicator for project-level RSL calculations, because: (1) it quantifies the functional performance of pavement systems—the aspect most road users care about—as well as giving some indirect idea of the structural performance of a pavement system, (2) it has been adopted as a standard for the Federal Highway Performance Monitoring System (Miller and Bellinger 2014), and (3) it is also one of the condition metrics identified for use by the FHWA (Visintine et al. 2018). The same threshold level recommended by the FHWA for poor pavement conditions (an IRI value of 170 in./mi) was selected in this study as the threshold value for project-level RSL calculations (Visintine et al. 2018).

The RSL for each pavement section was calculated using the following steps:

1. Statistically (or mathematically) defined pavement performance models were developed for each pavement section for each pavement type.
2. Using the developed pavement performance models, future IRI predictions were calculated for each pavement section.
3. Whether or not future IRI predictions had reached the threshold limit (170 in./mi) was checked.

- If yes, the RSL value for each pavement section was calculated by subtracting the present year from the year when IRI predictions first reached the threshold limit (170 in./mi).
- If no, the future IRI predictions had not reached 170 in./mi over a long period of analysis time (i.e., 50 years), based on available measured IRI data. In other words, these pavement sections performed very well in terms of smoothness criteria. Including more data points (i.e., future performance measurements) would change the model and increase its accuracy.

The process is demonstrated in Figure 10.

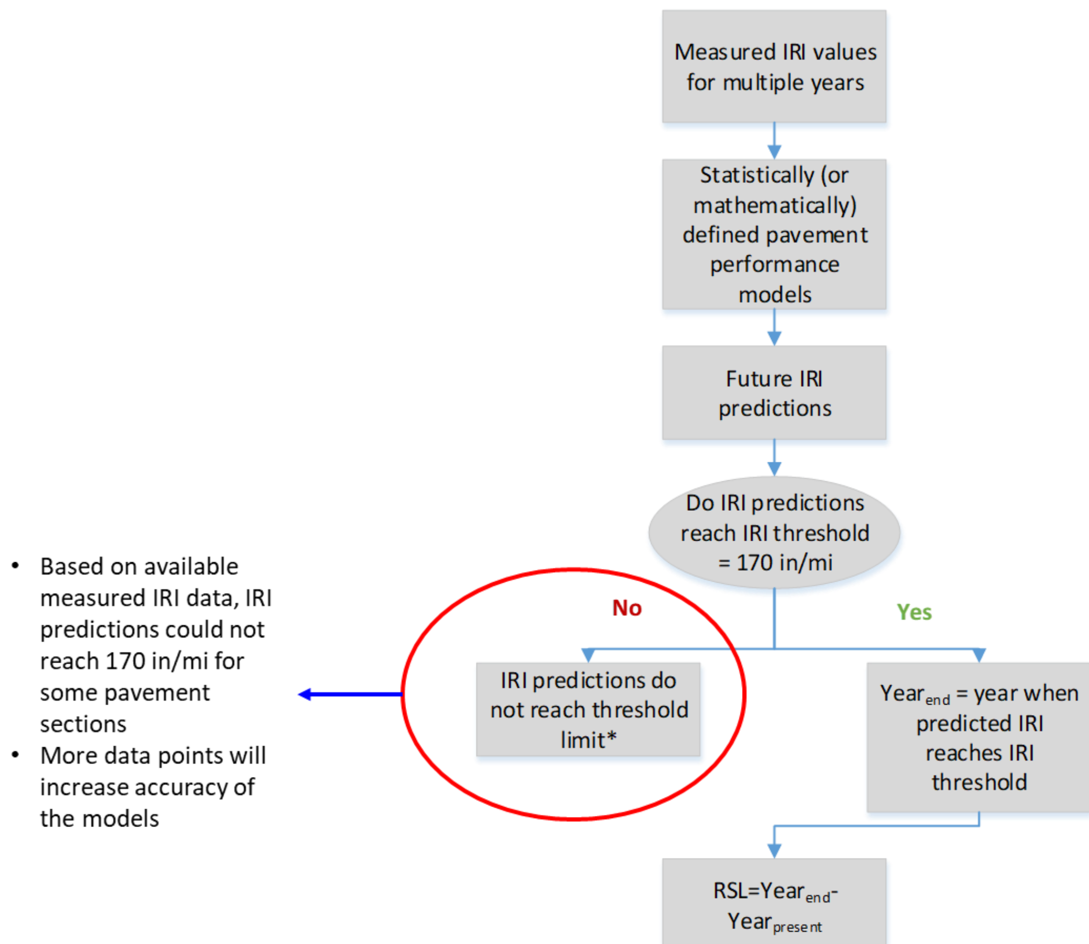
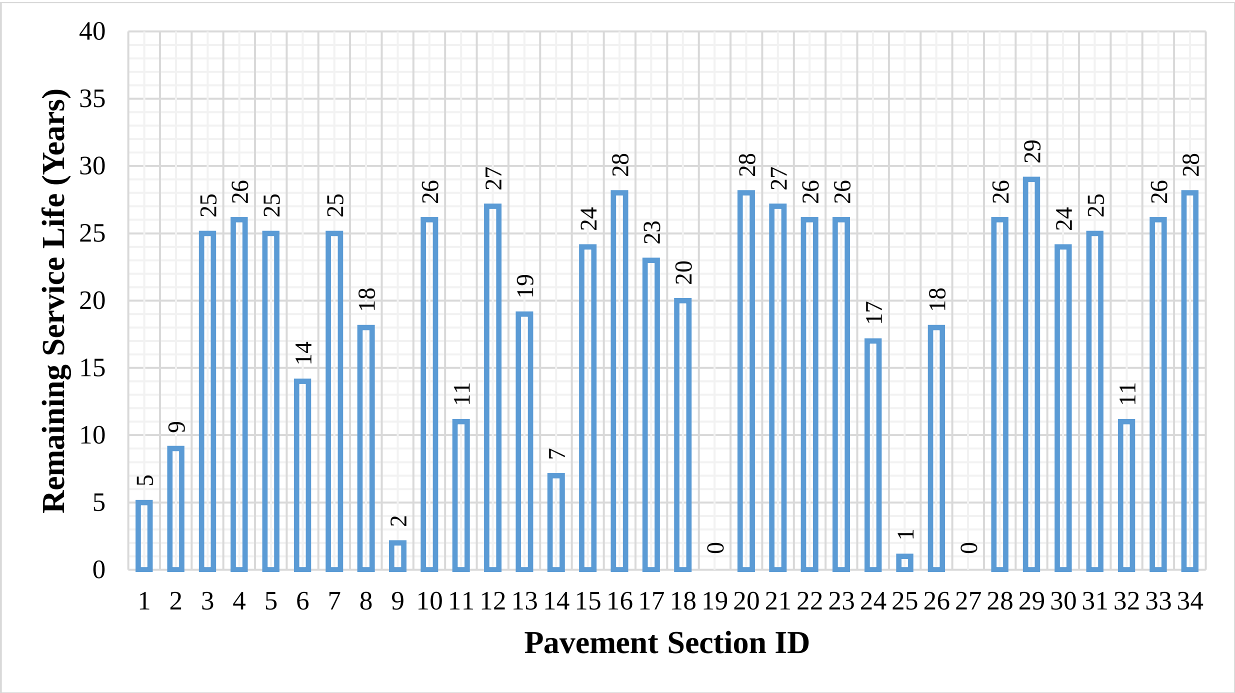
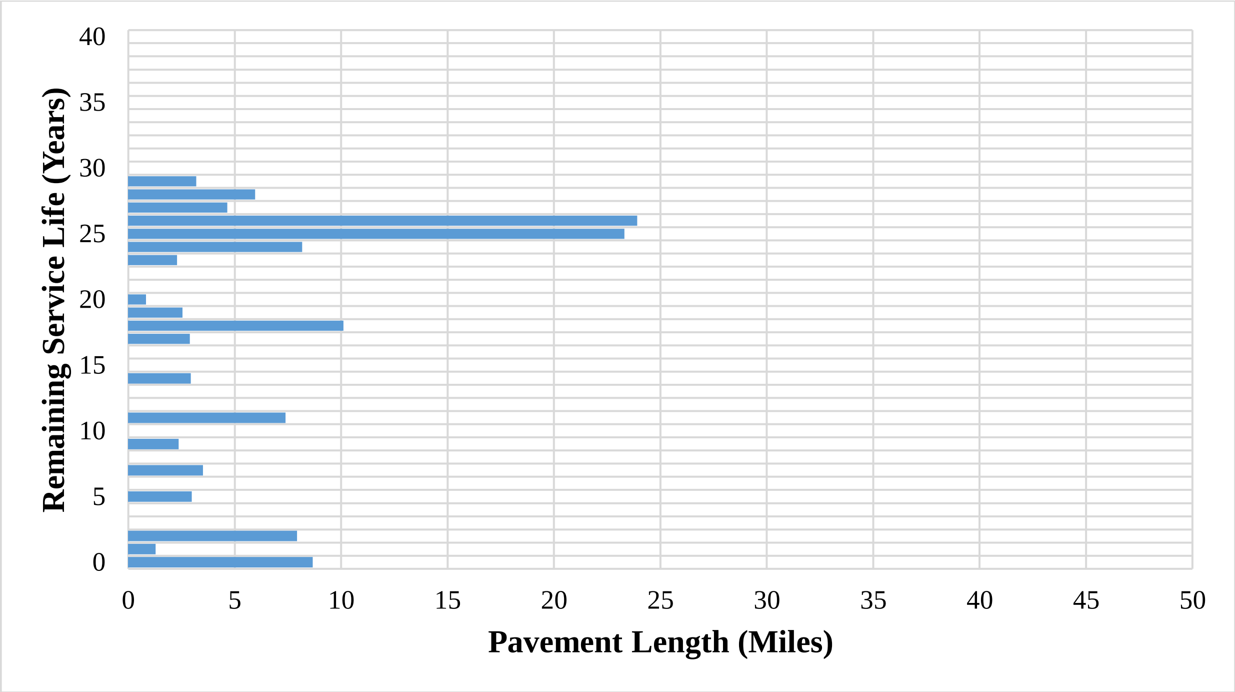


Figure 10. Statistics-based pavement RSL calculation steps

Figure 11, Figure 12, and Figure 13 show the distribution of RSL for JPCP, AC, and AC over JPCP sections evaluated in this study, respectively.

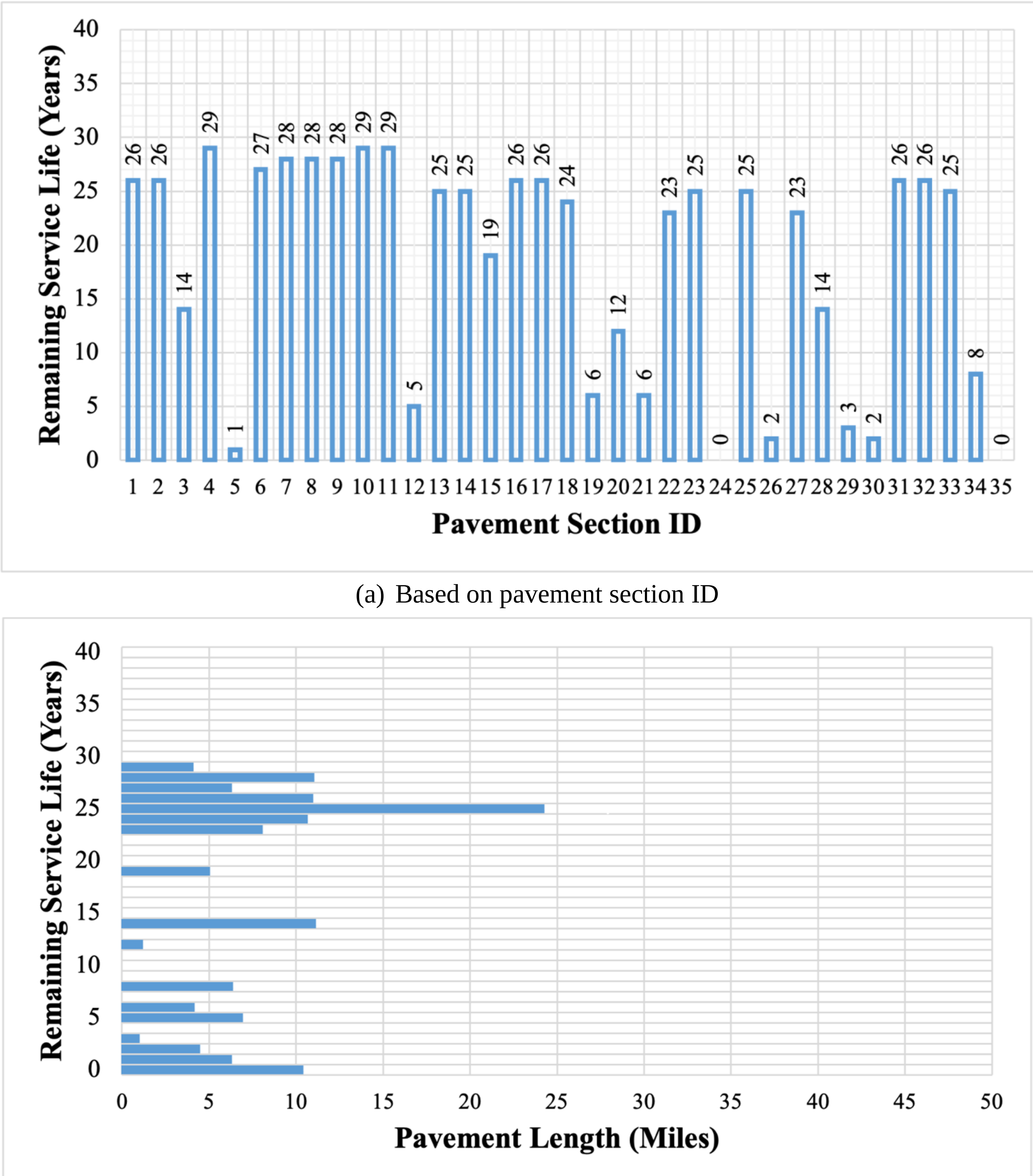


(a) Based on pavement section ID



(b) Based on pavement length

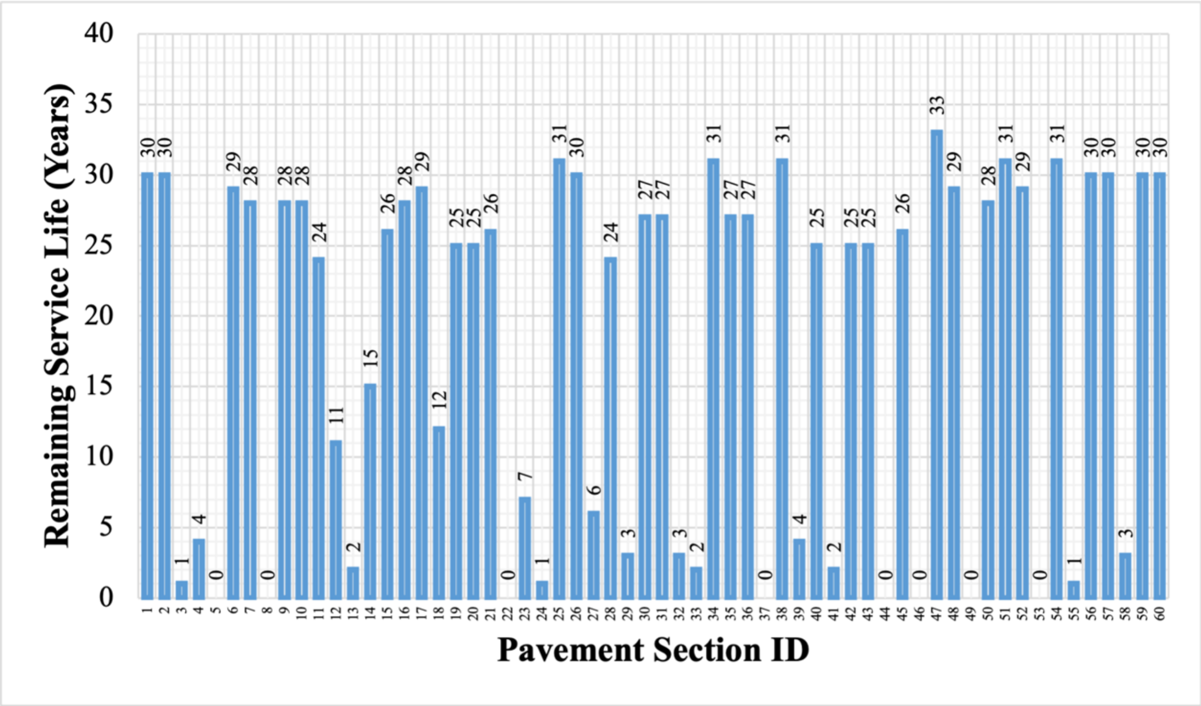
Figure 11. RSL distribution for JPCP pavement sections (rigid)



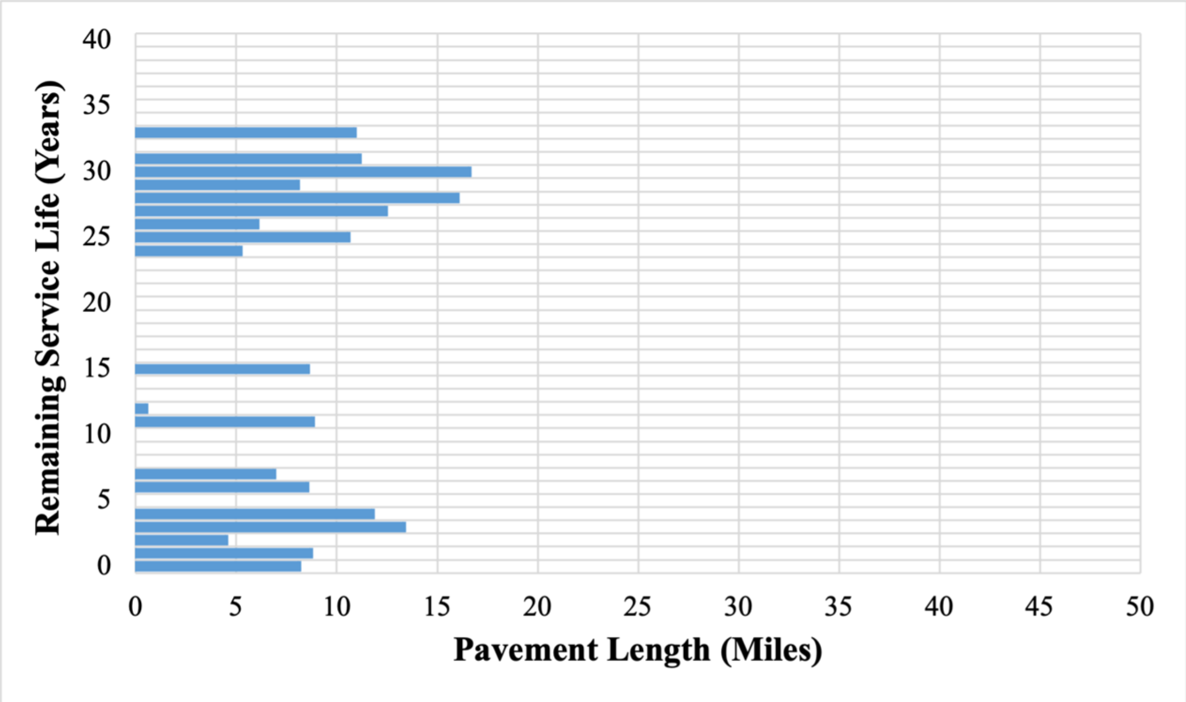
(a) Based on pavement section ID

(b) Based on pavement length

Figure 12. RSL distribution for AC pavement sections (flexible)



(a) Based on pavement section ID



(b) Based on pavement length

Figure 13. RSL distribution for composite pavement sections (AC over JPCP)

Average RSL for JPCP, AC, and composite AC over JPCP sections were found to be 7.2, 9.3, and 4.4 years, respectively.

ANN-Based Pavement Performance Model Development and Accuracy Evaluations

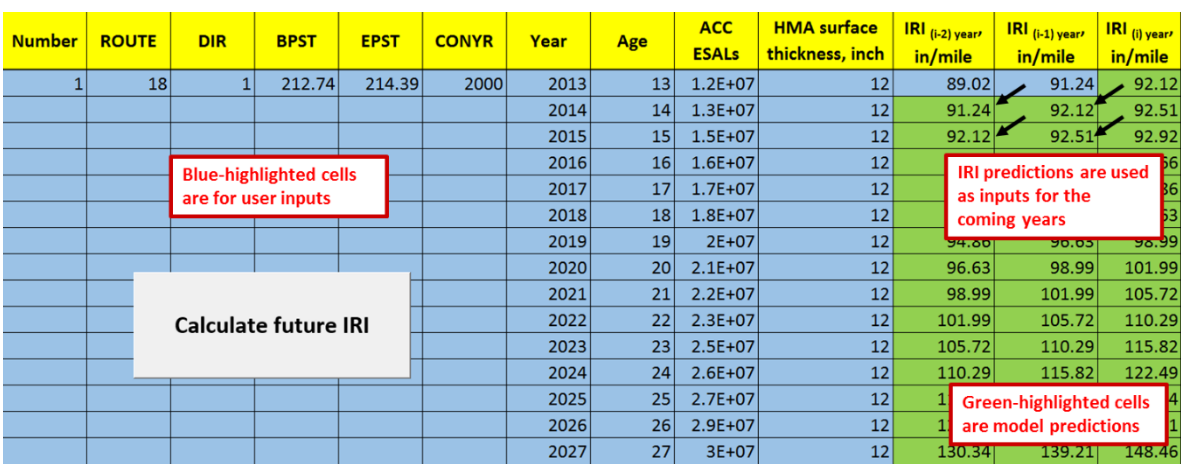
AI-based pavement performance models were used for network-level pavement performance model development in this study. AI techniques such as ANNs have been widely used to model complex pavement engineering problems (Ceylan et al. 2014, Kaya et al. 2017, Kaya et al. 2018a, Kaya et al. 2018b, Citir et al. 2020a). ANN-based models can be very useful tools for modeling pavement deterioration when considering many pavement sections with various traffic volumes, thicknesses (network-level), or deterioration trends, and they are also very fast tools, with thousands of pavement scenarios for which various traffic volumes, thicknesses, and conditions can be solved in seconds. Both these features of ANN models make them useful tools for use in the development of network-level pavement performance modeling.

In this study, an ANN-based pavement performance model was developed for each pavement performance indicator (i.e., distress, IRI) and each pavement type: rigid (JPCP), flexible (AC), and composite (AC over JPCP). The study used 80% of all data points in the model development for each pavement type, and from this set of data points, 48%, 8%, and 24%, respectively, were used as training, testing, and validation data sets. The remaining 20% of all data points were unused in model development but instead used as an independent testing data set.

ANN models must have the following capabilities:

- High accuracy: they must successfully produce results very similar to those from measured distresses
- Physically meaningful future distress predictions: distress predictions must increase in the future unless a maintenance or repair activity occurs

A Microsoft Excel macro-based network-level pavement performance prediction automation tool was developed that predicts future pavement performance using developed ANN models (Figure 14).



Number	ROUTE	DIR	BPST	EPST	CONYR	Year	Age	ACC ESALs	HMA surface thickness, inch	IRI $_{(i-2)\ year}$, in/mile	IRI $_{(i-1)\ year}$, in/mile	IRI $_{(i)\ year}$, in/mile
1	18	1	212.74	214.39	2000	2013	13	1.2E+07	12	89.02	91.24	92.12
						2014	14	1.3E+07	12	91.24	92.12	92.51
						2015	15	1.5E+07	12	92.12	92.51	92.92
						2016	16	1.6E+07	12	[illegible]	[illegible]	[illegible]
						2017	17	1.7E+07	12	[illegible]	[illegible]	[illegible]
						2018	18	1.8E+07	12	[illegible]	[illegible]	[illegible]
						2019	19	2E+07	12	94.86	96.63	98.99
						2020	20	2.1E+07	12	96.63	98.99	101.99
						2021	21	2.2E+07	12	98.99	101.99	105.72
						2022	22	2.3E+07	12	101.99	105.72	110.29
						2023	23	2.5E+07	12	105.72	110.29	115.82
						2024	24	2.6E+07	12	110.29	115.82	122.49
						2025	25	2.7E+07	12	[illegible]	[illegible]	[illegible]
						2026	26	2.9E+07	12	[illegible]	[illegible]	[illegible]
						2027	27	3E+07	12	130.34	139.21	148.46

Figure 14. ANN-based pavement performance prediction automation tool

This tool calculates future pavement performance predictions for any pavement performance indicator. The following steps were used in the development of this tool:

1. ANN models were developed in the MATLAB environment using 6 training algorithms and a variable number of hidden neurons (from 5 to 60).
2. The ANN model producing the highest accuracy was selected as the final model for the pavement performance indicator.
3. Weights and biases for the final ANN model were extracted into the automation tool.
4. Using these extracted weights and biases, and using matrix multiplication, future distress predictions were calculated for each given thickness, accumulated ESAL traffic, age, and previous two years' pavement performance records for any pavement performance indicator. The study assumed 1% compound truck traffic growth in calculating future traffic.

As part of this study, an ANN model for each pavement type was developed for the following pavement performance indicators:

- JPCP pavements: transverse cracking and IRI
- AC and AC over JPCP: rutting, longitudinal cracking, transverse cracking, and IRI

Input parameters used in the ANN model development and ANN model results for each pavement performance indicator in each pavement type are presented in the following paragraphs.

ANN-Based JPCP Performance Models

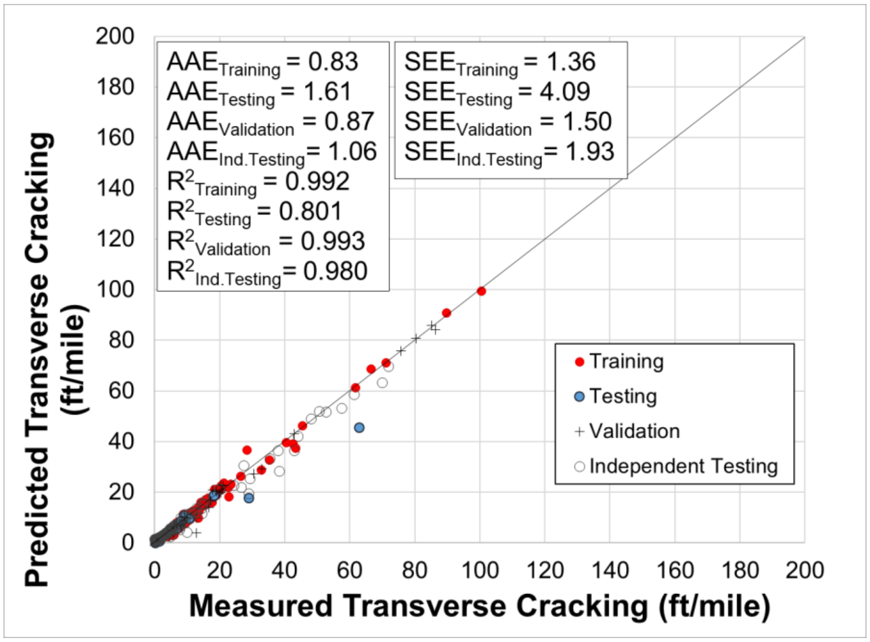
Three pavement performance ANN models were developed for JPCP pavements: transverse cracking, IRI approach 1, and IRI approach 2. The study used 34 JPCP pavement sections with 396 data points in model development and independent testing. It used 190, 32, 95, and 79 data points, respectively, for training, testing, validation, and independent testing data sets. Table 9 summarizes the input and output parameters used in the three ANN models developed for JPCP.

Table 9. Parameters for three ANN models' development for JPCP pavements

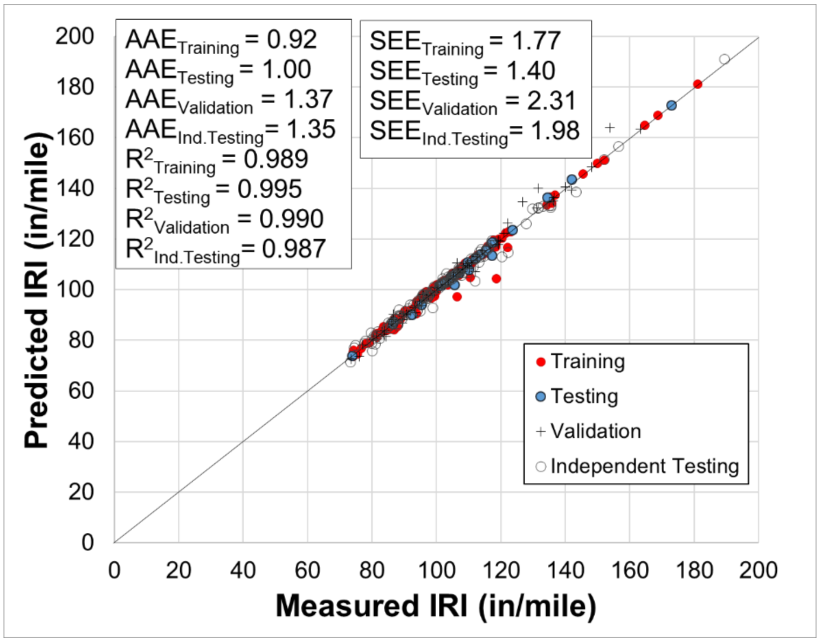
Model name	Input parameters	Output parameter
Transverse cracking	PCC thickness (in.), traffic (accumulated ESALs), age, transverse cracking $_{(i-2)\ year}$ (% slab cracked), transverse cracking $_{(i-1)\ year}$ (% slab cracked)	Transverse cracking $_{(i)\ year}$ (% slab cracked)
IRI approach 1	PCC thickness (in.), traffic (accumulated ESALs), age, IRI $_{(i-2)\ year}$ (in./mi), IRI $_{(i-1)\ year}$ (in./mi)	IRI $_{(i)\ year}$ (in./mi)
IRI approach 2	Age, transverse cracking $_{(i)\ year}$ (% slab cracked), IRI $_{(i-2)\ year}$ (in./mi), IRI $_{(i-1)\ year}$ (in./mi)	IRI $_{(i)\ year}$ (in./mi)

As can be seen in Table 9, PCC slab thickness, traffic (accumulated ESAL), age, and previous two-year pavement performance records were used in transverse cracking and IRI approach 1 model development. In approach 2, an IRI model was developed using age, measured distress values (transverse cracking in this case), and the previous two years of measured IRI data. In approach 2, ANN-model-predicted transverse cracking values along with other input parameters were used as inputs to predict future IRI values.

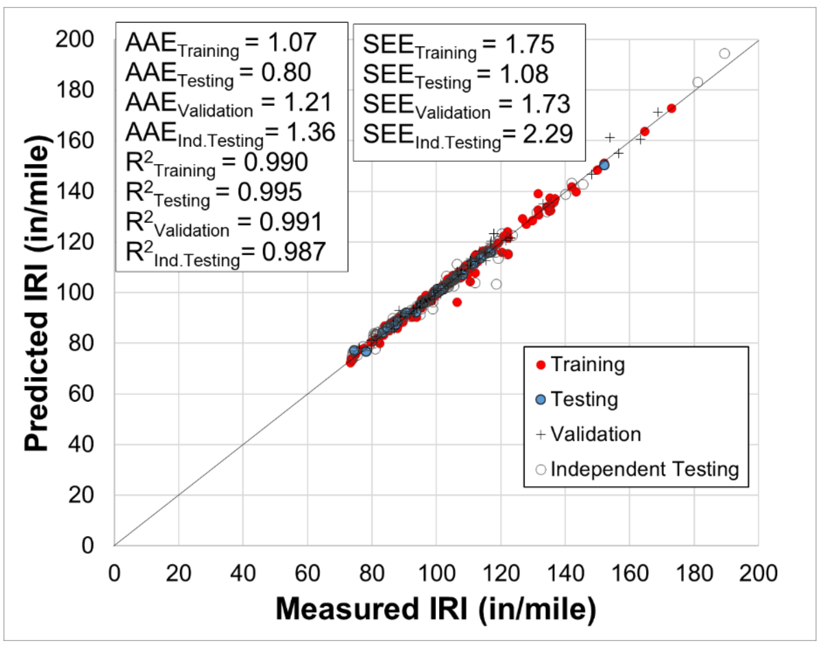
Figure 15 compares measured pavement condition records and ANN model predictions for JPCP using (a) transverse cracking, (b) IRI approach 1, and (c) IRI approach 2 ANN models, respectively.



(a) Transverse cracking



(b) IRI approach 1

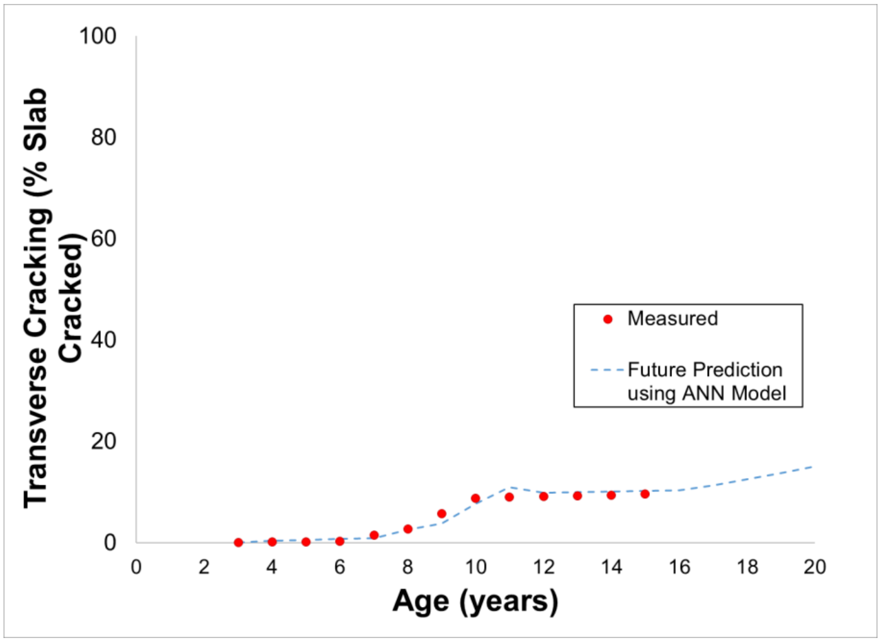


(c) IRI approach 2

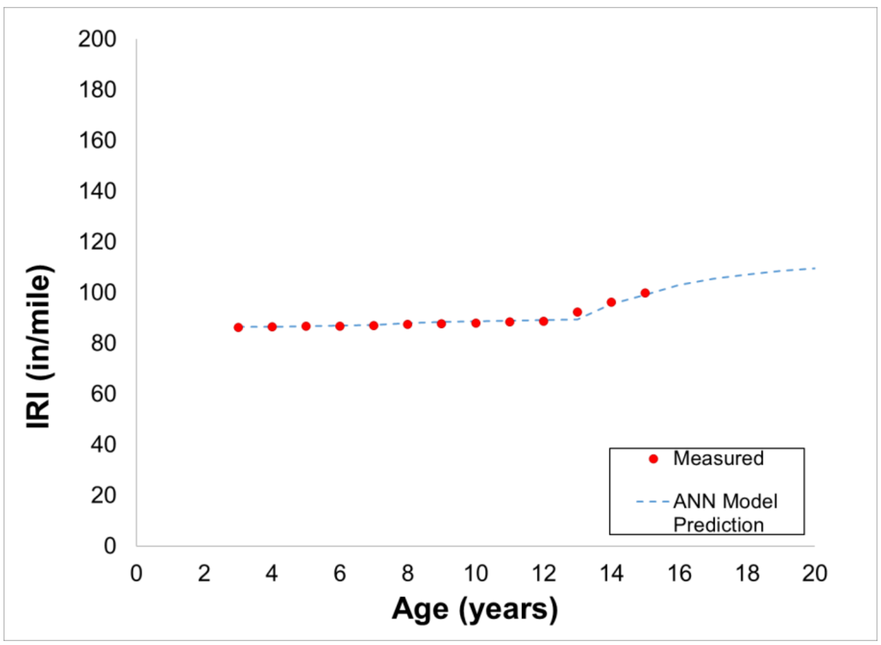
Figure 15. Measured pavement condition records vs. ANN model predictions for JPCP pavements

While the ANN models accurately predicted corresponding pavement performance indicators, IRI models produced more accurate predictions than the transverse cracking model because of their higher R^2 and lower AAE values, and IRI models developed using approach 1 and approach 2 produced similar accuracies. In all cases, high R^2 and low AAE values were obtained for all training, testing, validation, and independent testing data sets.

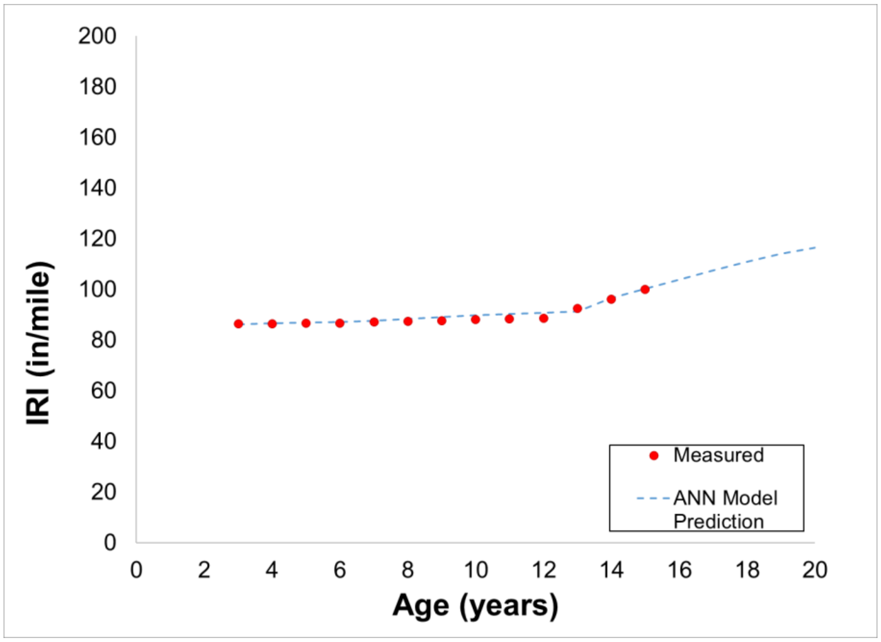
Figure 16 compares measured pavement condition records and ANN model predictions using (a) transverse cracking, (b) IRI approach 1, and (c) IRI approach 2 ANN models, respectively, using a JPCP section as an example.



(a) Transverse cracking



(b) IRI approach 1



(c) IRI approach 2

Figure 16. Measured pavement condition records vs. ANN model predictions for a particular JPCP pavement section as an example

The section used in Figure 16 is on Iowa 5, from milepost 85.24 to 88.06, northbound, with an AADTT of 799, and it was constructed in 1999.

As can be seen in Figure 16, the ANN models not only produced very similar results to measured pavement condition records but also produced physically meaningful future pavement condition predictions. Moreover, the IRI models developed using approach 1 and approach 2 produced very similar IRI predictions.

ANN-Based AC Pavement Performance Models

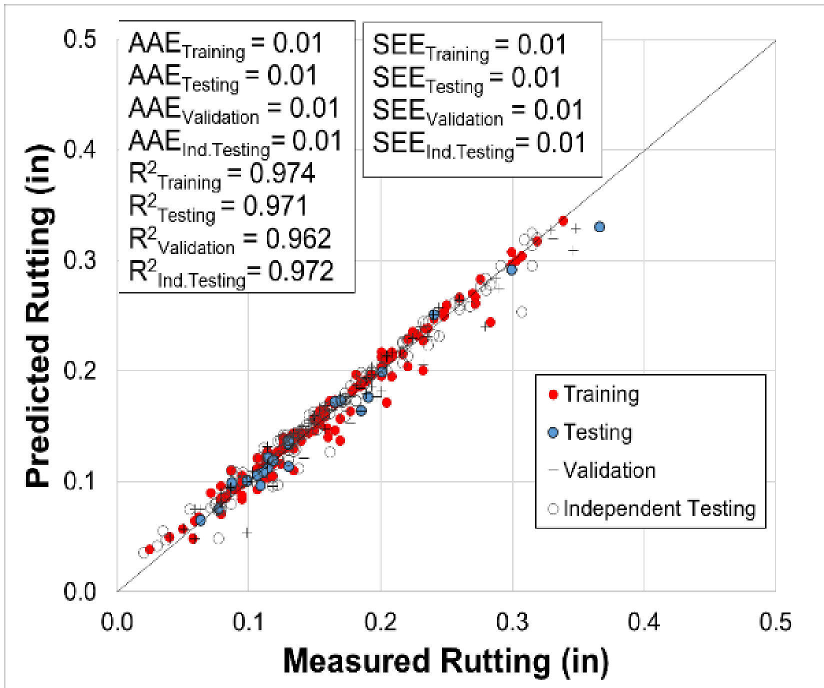
Five pavement performance ANN models were developed for AC pavements: rutting, longitudinal cracking, transverse cracking, IRI approach 1, and IRI approach 2. The study used 35 AC pavement sections with 360 data points in model development and for independent testing. It used 172, 30, 86, and 72 data points, respectively, for training, testing, validation, and independent testing data sets. Table 10 summarizes input and output parameters used in the five ANN models developed for AC pavements.

Table 10. Parameters for five ANN models' development for flexible pavements

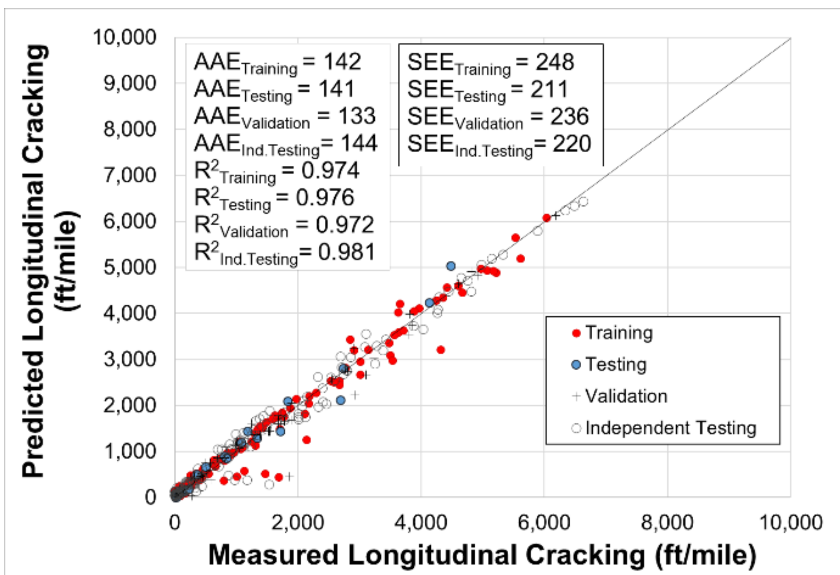
Model name	Input parameters	Output parameter
Rutting	AC thickness (in.), traffic (accumulated ESALs), age, rut $_{(i-2)\ year}$ (in.), rut $_{(i-1)\ year}$ (in.)	Rut $_{(i)\ year}$ (in.)
Longitudinal cracking	AC thickness (in.), traffic (accumulated ESALs), age, longitudinal cracking $_{(i-2)\ year}$ (ft/mi), longitudinal cracking $_{(i-1)\ year}$ (ft/mi)	Longitudinal cracking $_{(i)\ year}$ (ft/mi)
Transverse cracking	AC thickness (in.), traffic (accumulated ESALs), age, transverse cracking $_{(i-2)\ year}$ (ft/mi), transverse cracking $_{(i-1)\ year}$ (ft/mi)	Transverse cracking $_{(i)\ year}$ (ft/mi)
IRI approach 1	AC thickness (in.), traffic (accumulated ESALs), age, IRI $_{(i-2)\ year}$ (in./mi), IRI $_{(i-1)\ year}$ (in./mi)	IRI $_{(i)\ year}$ (in./mi)
IRI approach 2	Age, rut $_{(i)\ year}$ (in.), longitudinal cracking $_{(i)\ year}$ (ft/mi), transverse cracking $_{(i)\ year}$ (ft/mi), IRI $_{(i-2)\ year}$ (in./mi), IRI $_{(i-1)\ year}$ (in./mi)	IRI $_{(i)\ year}$ (in./mi)

As can be seen in Table 10, AC layer thickness, traffic (accumulated ESAL), age, and previous two-year pavement performance records were used in rutting, longitudinal cracking, transverse cracking, and IRI approach 1 model development. In approach 2, the IRI model was developed using age, measured distress values (rutting, longitudinal cracking, and transverse cracking in this case), and the previous two years of measured IRI data. In approach 2, ANN-model-predicted rutting and longitudinal and transverse cracking values, along with other input parameters, were used as inputs to predict future IRI.

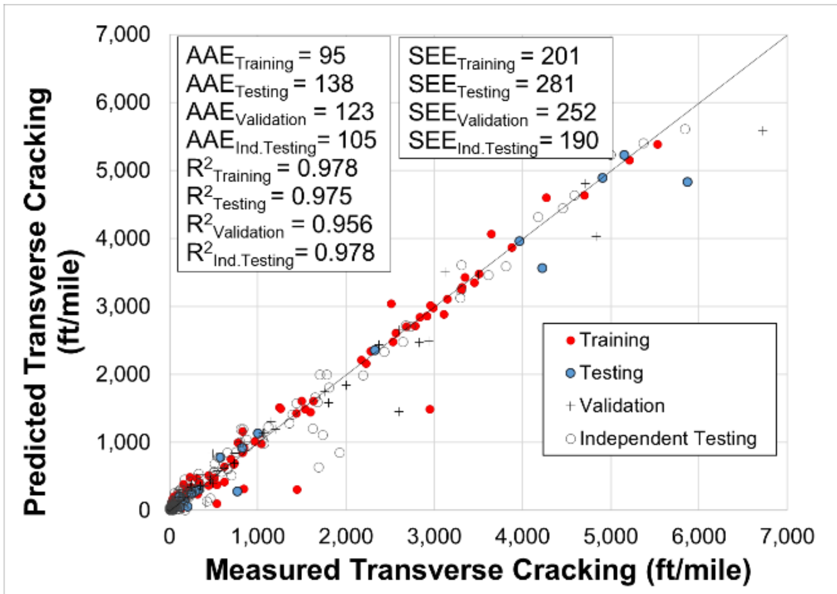
Figure 17 compares measured pavement condition records and ANN model predictions using (a) rutting, (b) longitudinal cracking, (c) transverse cracking, (d) IRI approach 1, and (e) IRI approach 2 ANN models, respectively.



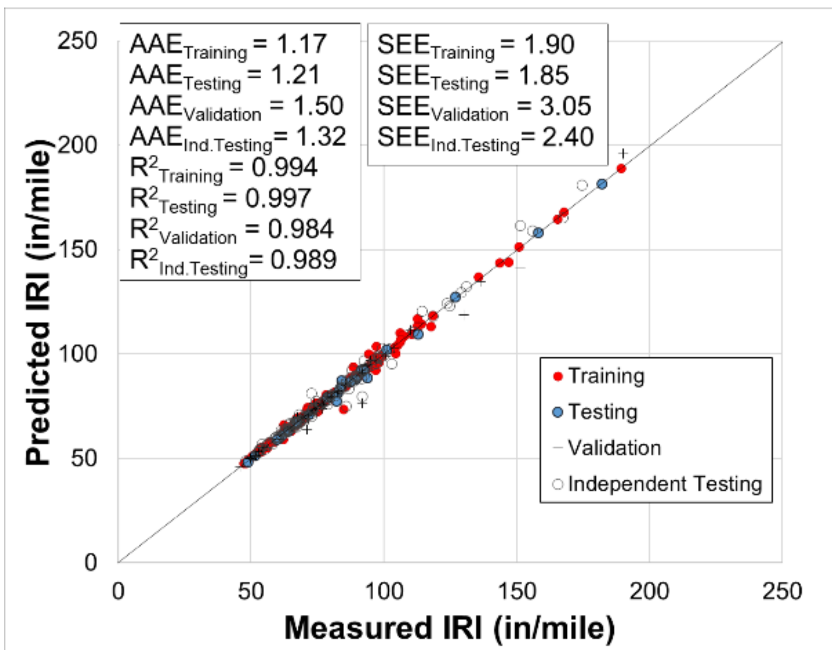
(a) Rutting



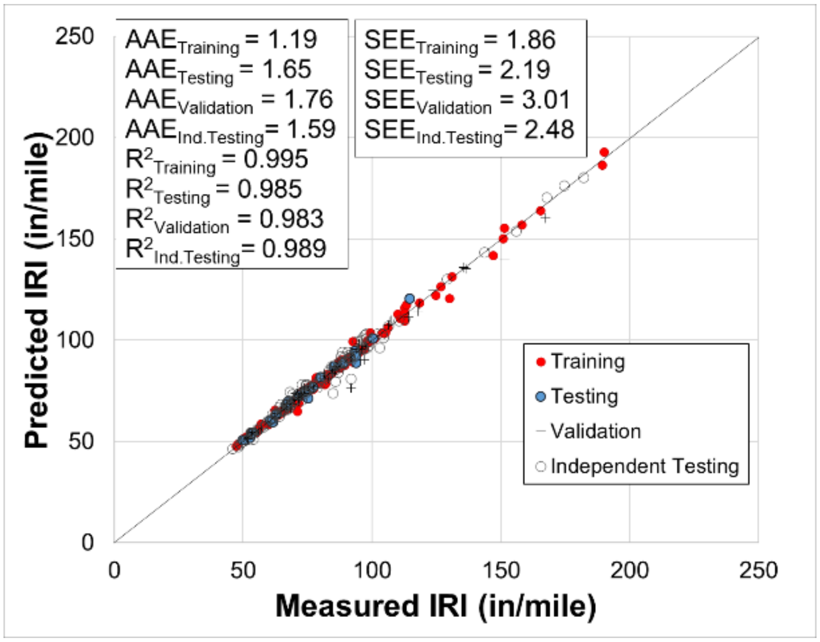
(b) Longitudinal cracking



(c) Transverse cracking



(d) IRI approach 1

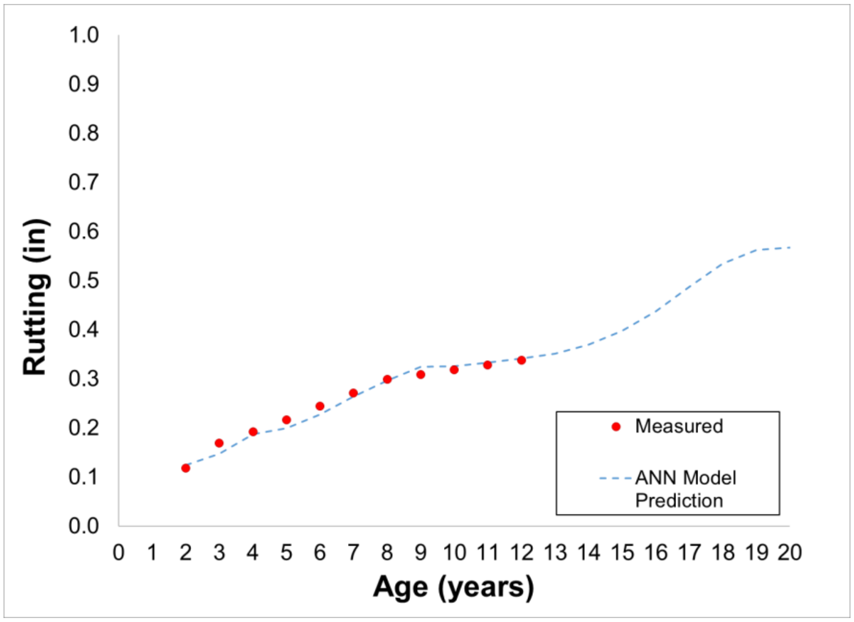


(e) IRI approach 2

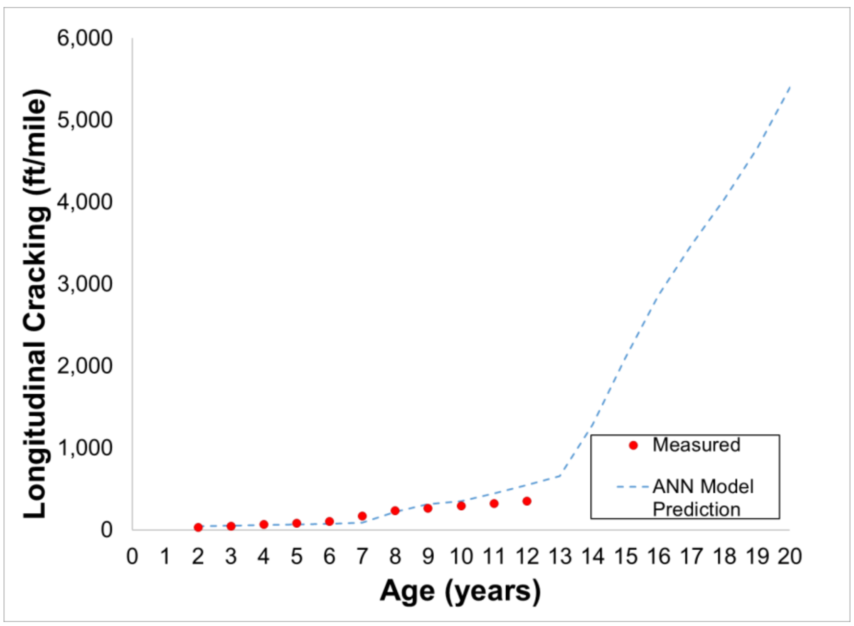
Figure 17. Measured pavement condition records vs. ANN model predictions for flexible pavements

While the ANN models accurately predicted corresponding pavement performance indicators, the IRI models produced more accurate predictions compared to the rutting, longitudinal cracking, and transverse cracking models as shown by their higher R^2 and lower AAE values. The IRI models developed using approach 1 and approach 2 produced similar accuracies. In all cases investigated, high R^2 and low AAE values were obtained for all training, testing, validation, and independent testing data sets.

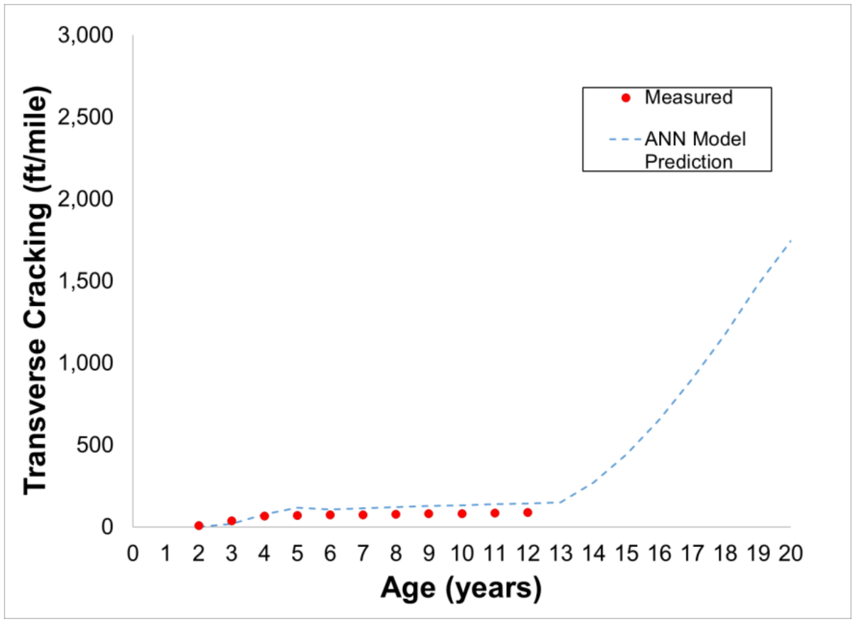
Figure 18 compares measured pavement condition records and ANN model predictions using (a) rutting, (b) longitudinal cracking, (c) transverse cracking, (d) IRI approach 1, and (e) IRI approach 2 ANN models, respectively, for a flexible pavement section as an example.



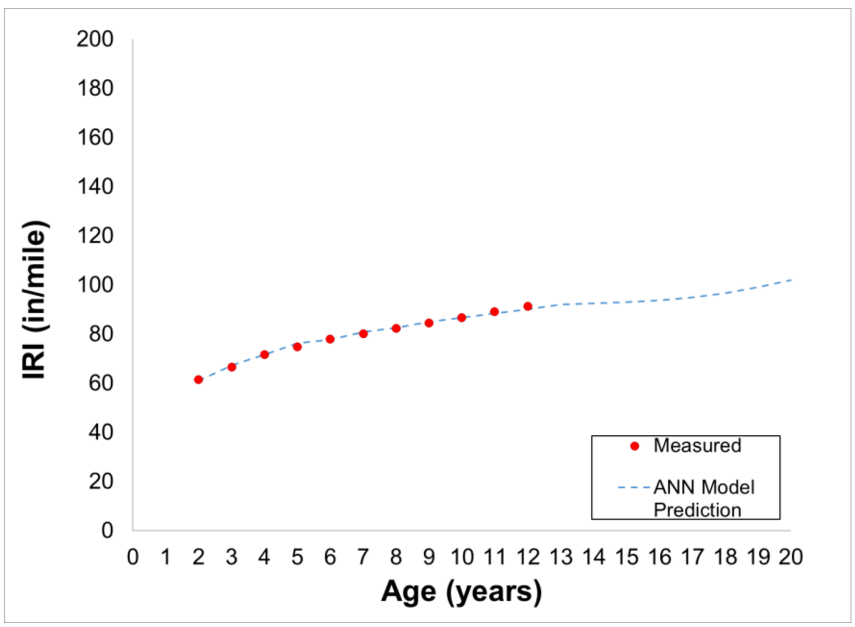
(a) Rutting



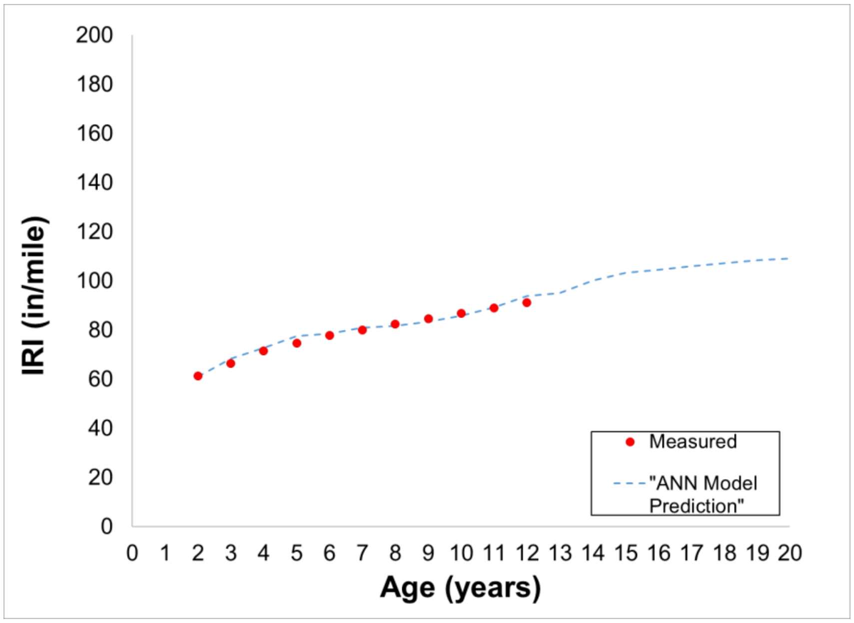
(b) Longitudinal cracking



(c) Transverse cracking



(d) IRI approach 1



(e) IRI approach 2

Figure 18. Measured pavement condition records vs. ANN model predictions for a particular flexible pavement section as an example

The section used in Figure 18 is on US 18, from milepost 212.74 to 214.39, eastbound, with an AADTT of 1,885, and it was constructed in 2000.

As can be seen in the Figure 18, the ANN models not only produced results very similar to those from measured pavement condition records but also made physically meaningful future pavement condition predictions. Moreover, the IRI models developed using approach 1 and approach 2 produced very similar IRI predictions.

ANN-Based AC over JPCP Pavement Performance Models

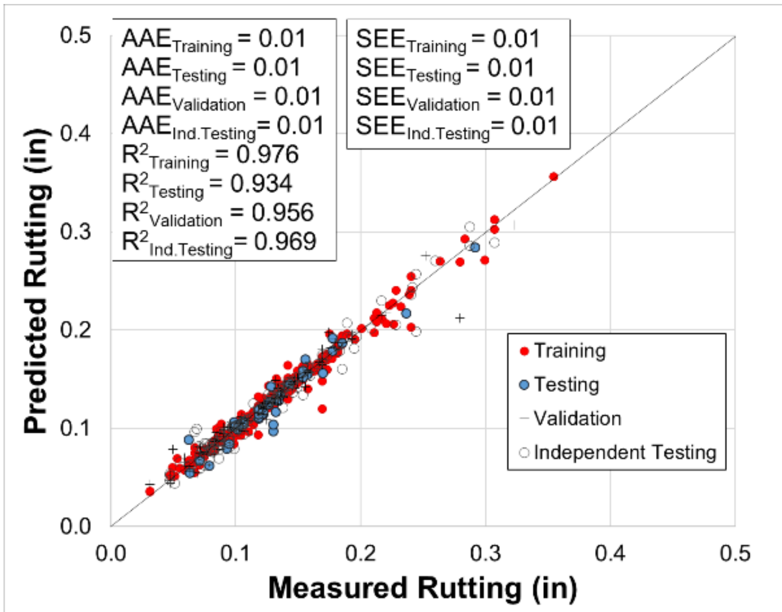
Five pavement performance ANN models—rutting, longitudinal cracking, transverse cracking, IRI approach 1, and IRI approach 2—were developed for composite pavements. The study used 60 composite pavement sections with 524 data points in model development and independent testing, and it used 251, 42, 126, and 105 data points, respectively, for training, testing, validation, and independent testing data sets. Table 11 summarizes input and output parameters used in the five ANN models developed for composite pavements.

Table 11. Parameters for five ANN models' development for composite pavements

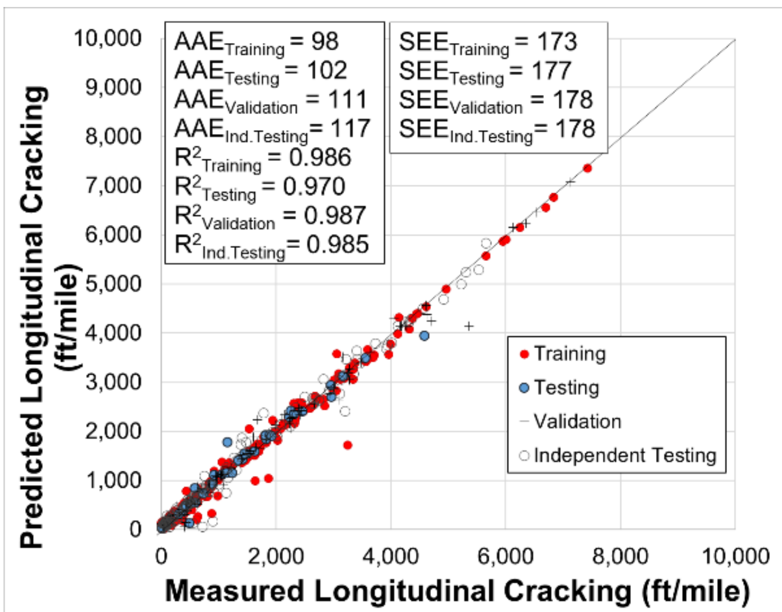
Model name	Input parameters	Output parameter
Rutting	AC thickness (in.), traffic (accumulated ESALs), age, rut $_{(i-2)\ year}$ (in.), rut $_{(i-1)\ year}$ (in.)	Rut $_{(i)\ year}$ (in.)
Longitudinal cracking	AC thickness (in.), traffic (accumulated ESALs), age, longitudinal cracking $_{(i-2)\ year}$ (ft/mi), longitudinal cracking $_{(i-1)\ year}$ (ft/mi)	Longitudinal cracking $_{(i)\ year}$ (ft/mi)
Transverse cracking	AC thickness (in.), traffic (accumulated ESALs), age, transverse cracking $_{(i-2)\ year}$ (ft/mi), transverse cracking $_{(i-1)\ year}$ (ft/mi)	Transverse cracking $_{(i)\ year}$ (ft/mi)
IRI approach 1	AC thickness (in.), traffic (accumulated ESALs), age, IRI $_{(i-2)\ year}$ (in./mi), IRI $_{(i-1)\ year}$ (in./mi)	IRI $_{(i)\ year}$ (in./mi)
IRI approach 2	Age, rut $_{(i)\ year}$ (in.), longitudinal cracking $_{(i)\ year}$ (in./mi), transverse cracking $_{(i)\ year}$ (in./mi), IRI $_{(i-2)\ year}$ (in./mi), IRI $_{(i-1)\ year}$ (in./mi)	IRI $_{(i)\ year}$ (in./mi)

As shown in Table 11, AC thickness, traffic (accumulated ESAL), age, and previous two-year pavement performance records were used in rutting, longitudinal cracking, transverse cracking, and IRI approach 1 model development. In approach 2, an IRI model was developed using age, measured distress values (rutting, longitudinal cracking, and transverse cracking in this case), and the previous two-year measured IRI data. In approach 2, rutting, longitudinal, and transverse cracking values, which other ANN models predicted along with other input parameters, were used as inputs for predicting future IRI.

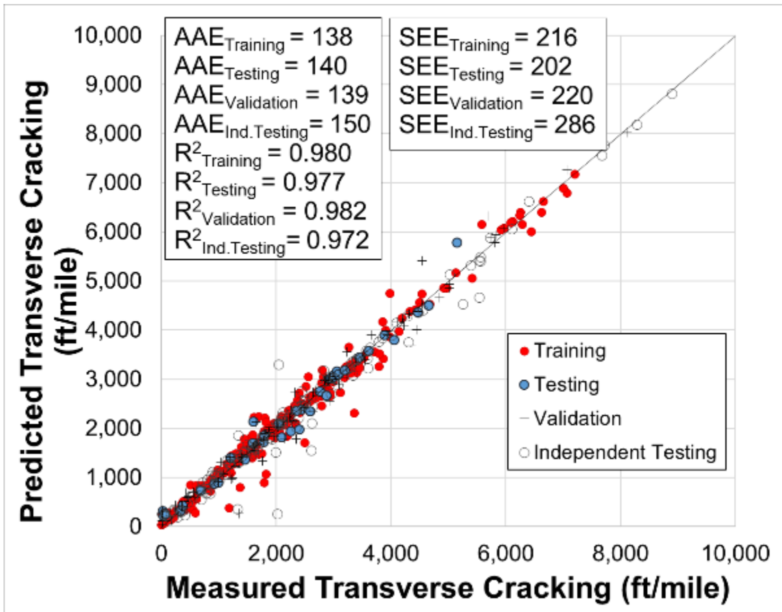
Figure 19 compares measured pavement condition records and ANN model predictions using (a) rutting, (b) longitudinal cracking, (c) transverse cracking, (d) IRI approach 1, and (e) IRI approach 2 ANN models, respectively.



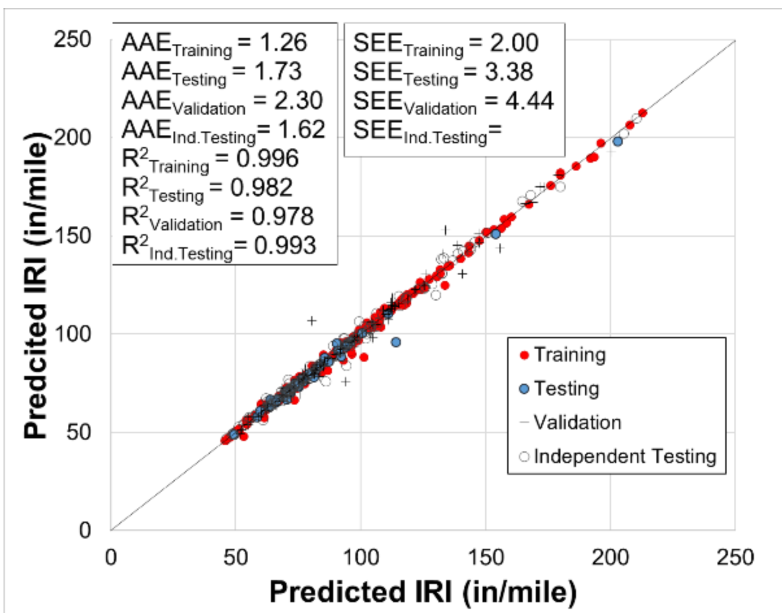
(a) Rutting



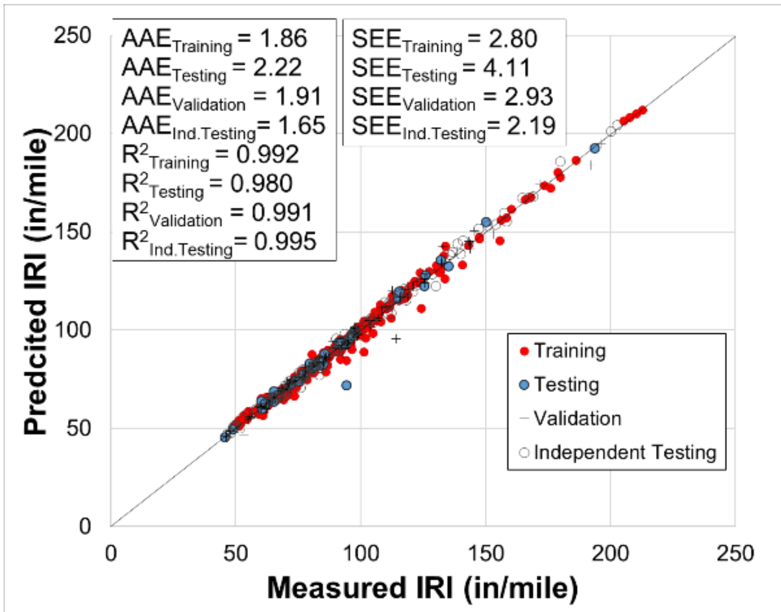
(b) Longitudinal cracking



(c) Transverse cracking



(d) IRI approach 1

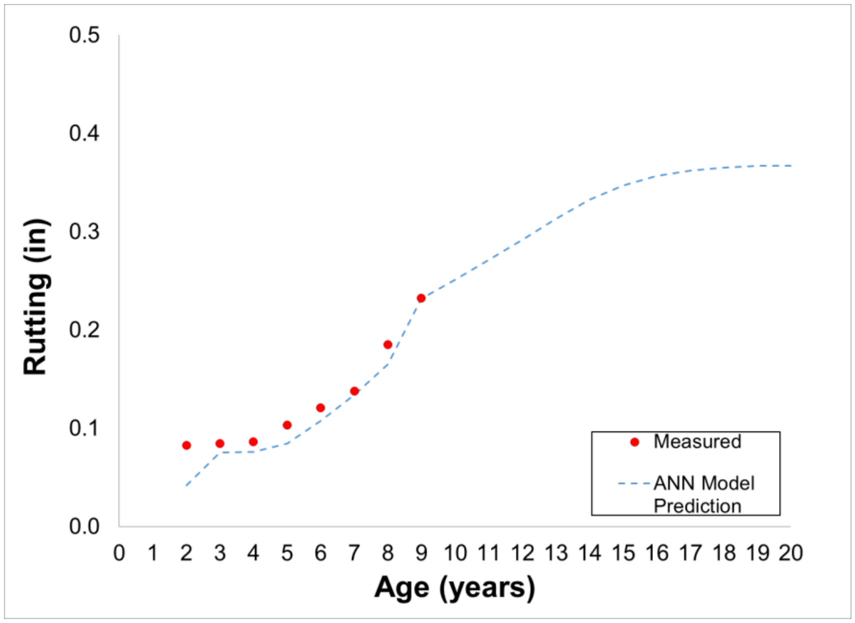


(e) IRI approach 2

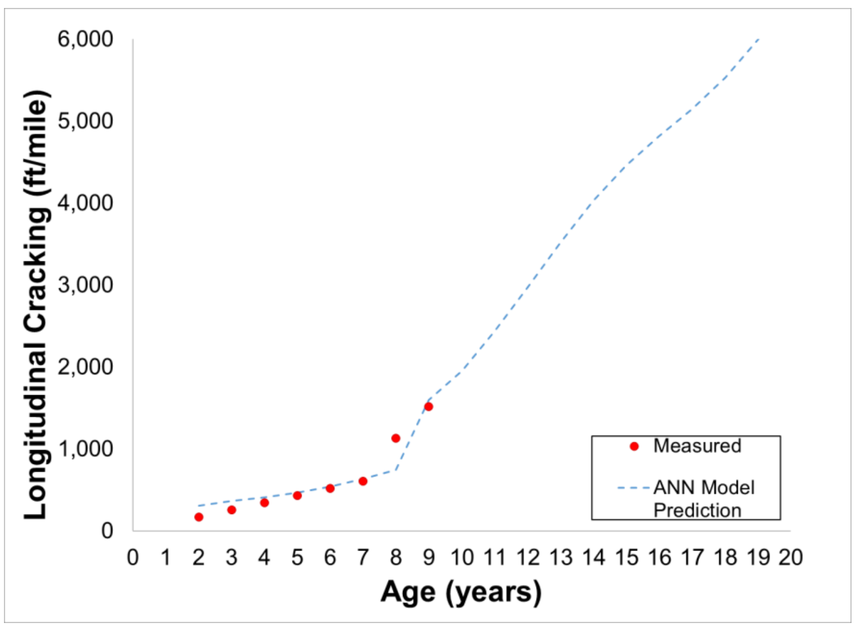
Figure 19. Measured pavement condition records vs. ANN model predictions for composite pavements

While the ANN models accurately predicted corresponding pavement performance indicators, the IRI models produced more accurate predictions compared to the rutting, longitudinal cracking, and transverse cracking models as shown by their higher R^2 and lower AAE values. The IRI models developed using approach 1 and approach 2 produced similar accuracies. In all cases investigated, high R^2 and low AAE values were obtained for all training, testing, validation, and independent testing data sets.

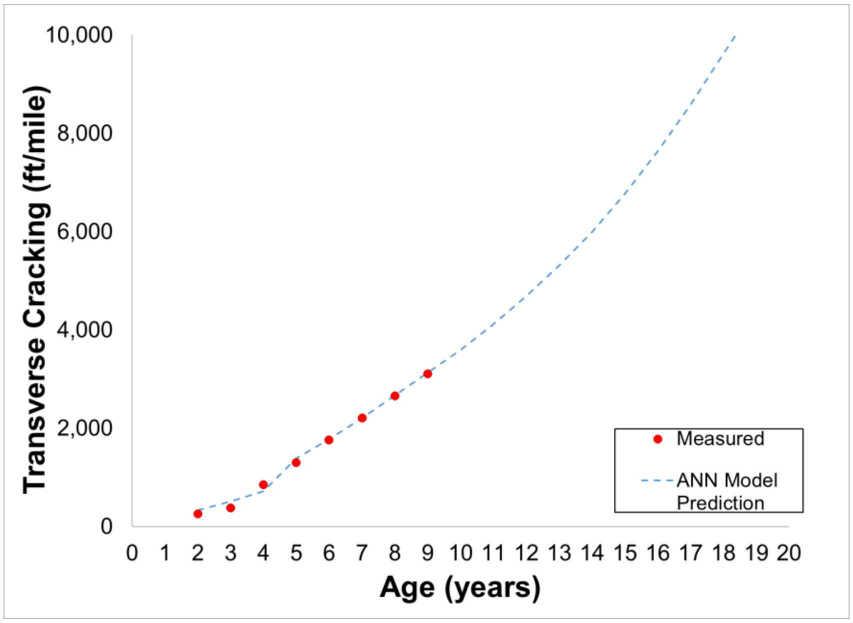
Figure 20 compares measured pavement condition records and ANN model predictions using (a) rutting, (b) longitudinal cracking, (c) transverse cracking, (d) IRI approach 1, and (e) IRI approach 2 ANN models, respectively, using a composite pavement section as an example.



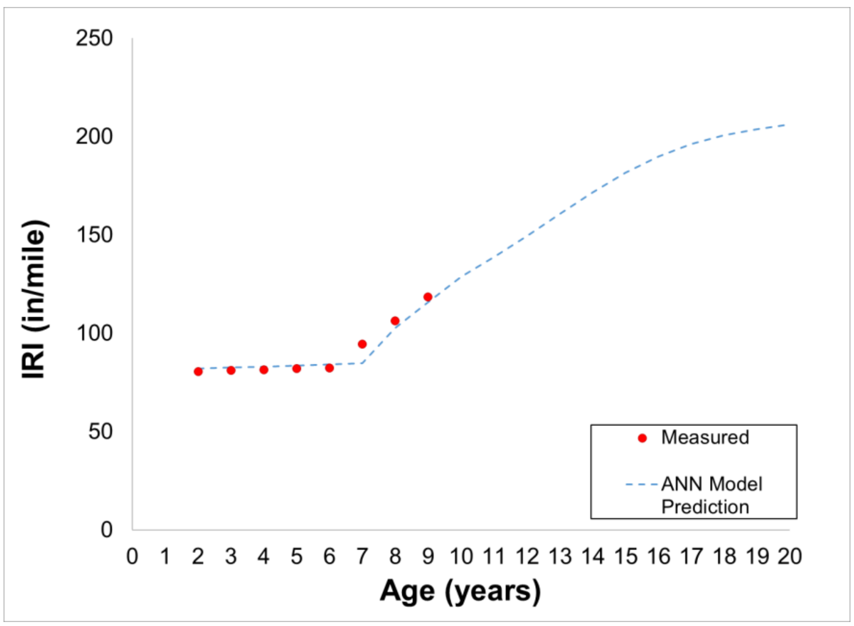
(a) Rutting



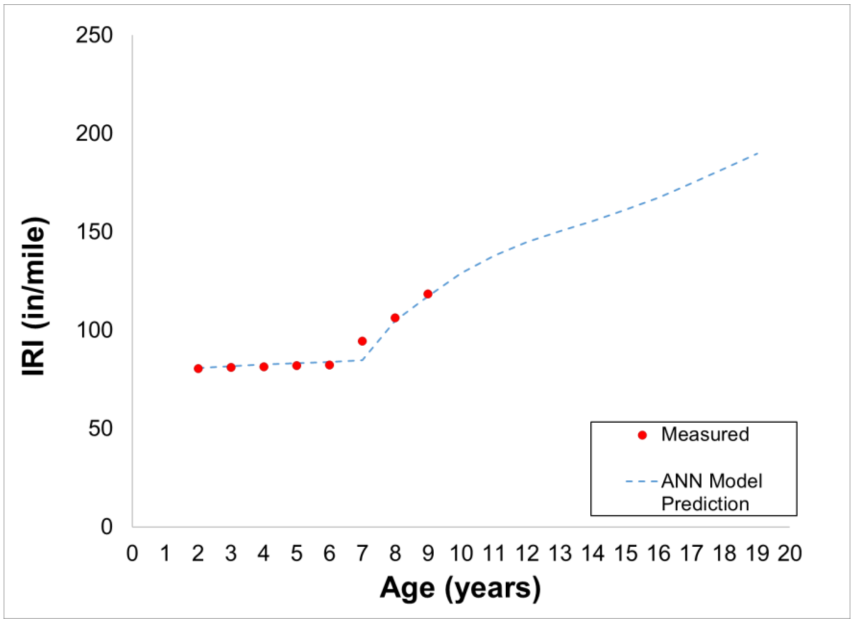
(b) Longitudinal cracking



(c) Transverse cracking



(d) IRI approach 1



(e) IRI approach 2

Figure 20. Measured pavement condition records vs. ANN model predictions for a particular composite pavement section as an example

The section used in Figure 20 is on US 20, from milepost 1.64 to 4.37, eastbound, with an AADTT of 2,848, and it was restored in 2004.

As can be seen in the figure, the ANN models not only produced results very similar to measured pavement condition records but also produced physically meaningful future pavement condition predictions. Moreover, the IRI models using approach 1 and approach 2 produced very similar IRI predictions.

ANN-Based Pavement RSL Model Development and Results

Once network-level pavement performance models were developed for each pavement performance indicator or condition metric, the RSL for each pavement section in a road network, as explained in the previous section, could be calculated using these performance models and corresponding threshold limits for the pavement performance indicators. In this study, rutting, percent cracking, and IRI were used as performance indicators for network-level RSL calculations, because, as stated earlier, these condition metrics were determined by the FHWA (HR 4348 2012, Visintine et al. 2018). RSL is determined based on the year when future performance predictions reach a poor condition threshold (these thresholds and corresponding condition metrics were highlighted previously in Table 4).

The RSL value for each pavement section in a road network was calculated based on the following steps:

1. Using developed ANN-based pavement performance models, future pavement condition predictions were calculated for each pavement section.
2. Whether or not future pavement condition predictions reached threshold limits were checked for each corresponding condition metric previously shown in Table 4.

- If yes, the RSL value for each pavement section was calculated by subtracting the present year from the year when pavement condition predictions first reached the threshold limit.
- If no, based on available pavement condition data, future pavement condition predictions do not reach 170 in./mi over a long period of analysis time (i.e., 50 years). In other words, this means that these pavement sections perform very well in terms of the corresponding condition metric. However, adding more data points (i.e., future performance measurements) would increase the accuracy of the predictions.

The process is demonstrated in Figure 21.

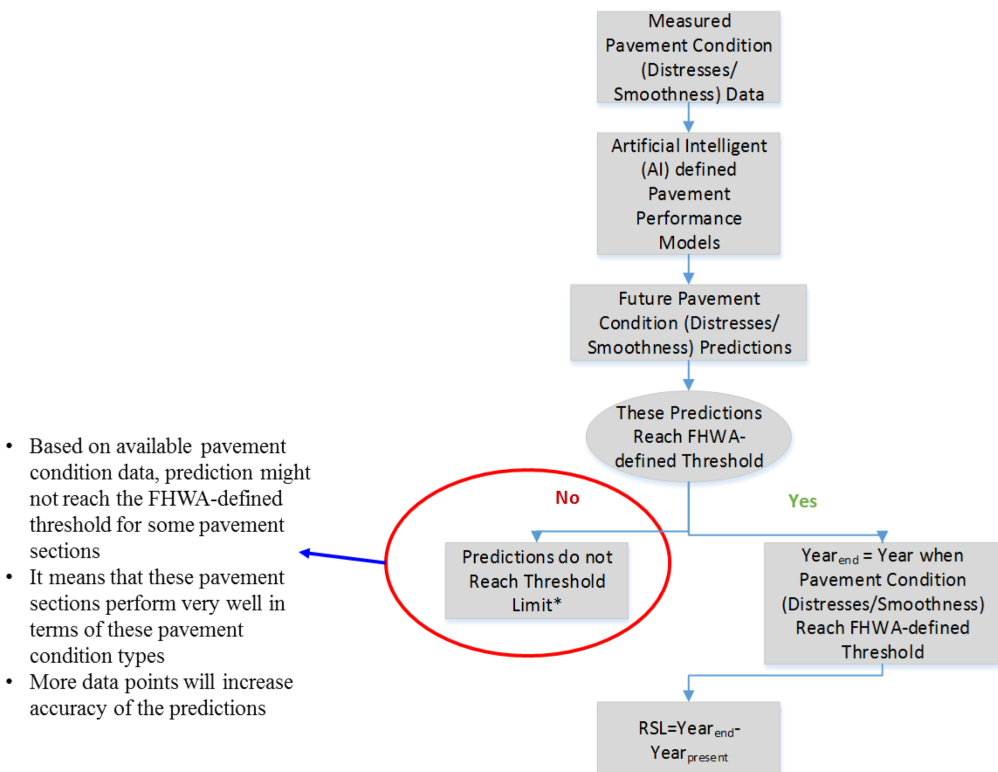
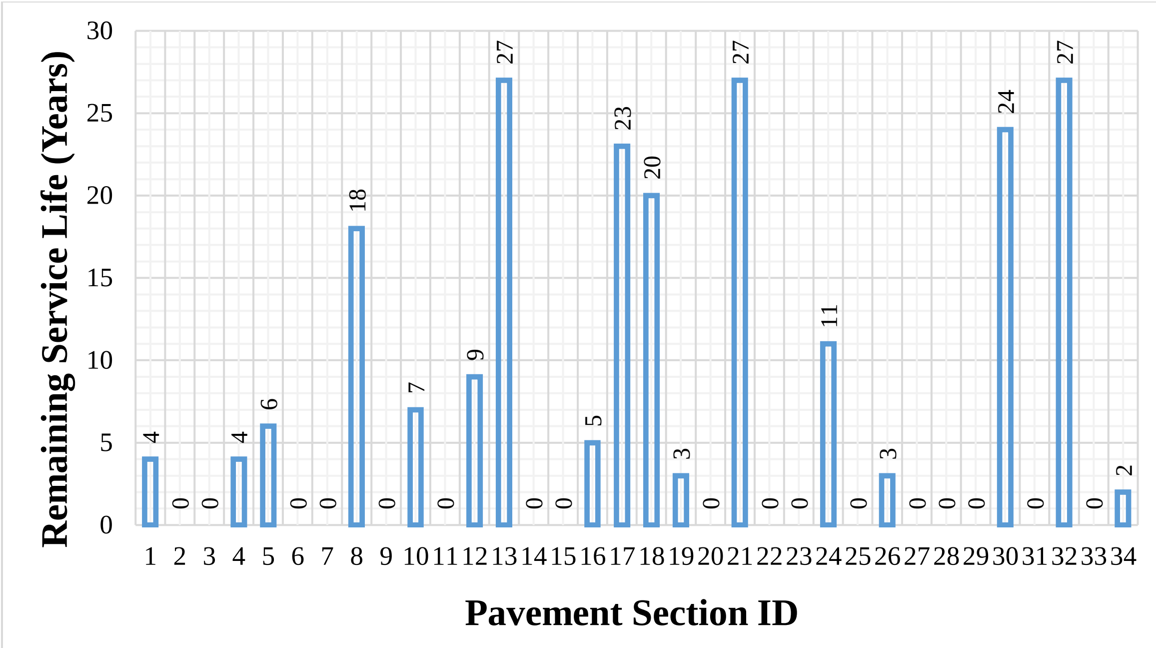


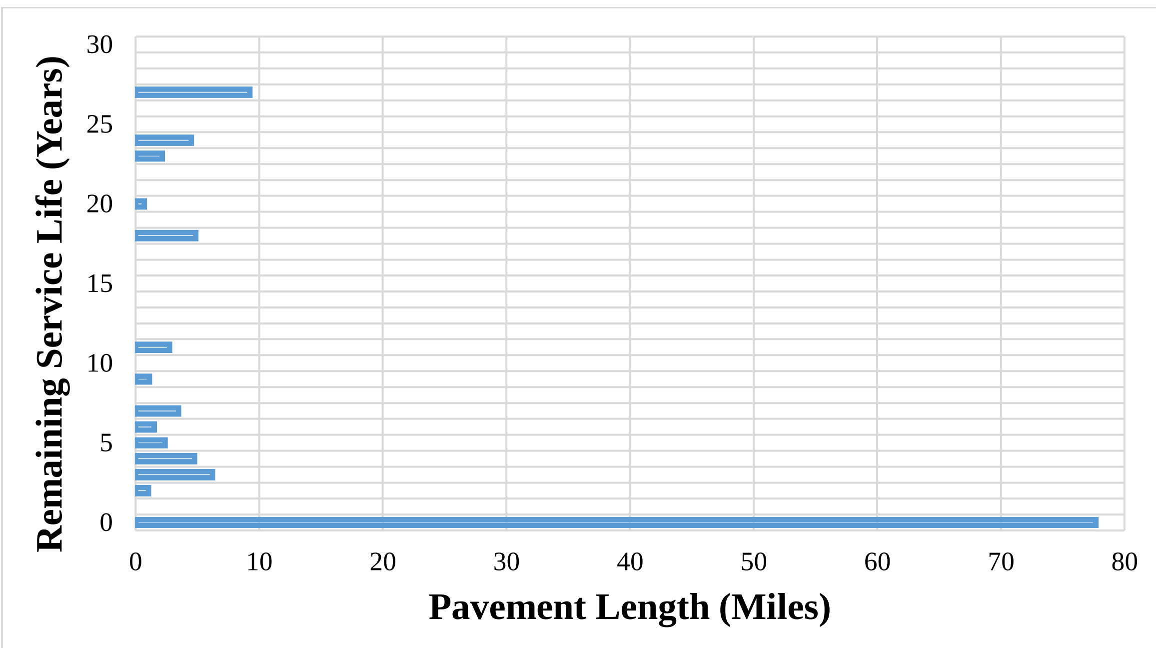
Figure 21. Network-level RSL calculation steps

ANN-Based JPCP RSL Models

Figure 22 shows the distribution of RSL for 34 JPCP pavement sections when a percent cracking threshold limit of 15% was used. An ANN-based network-level transverse cracking model was used as the pavement performance model to calculate RSL values, and the average RSL for the JPCP pavement sections was found to be 2.0 years.



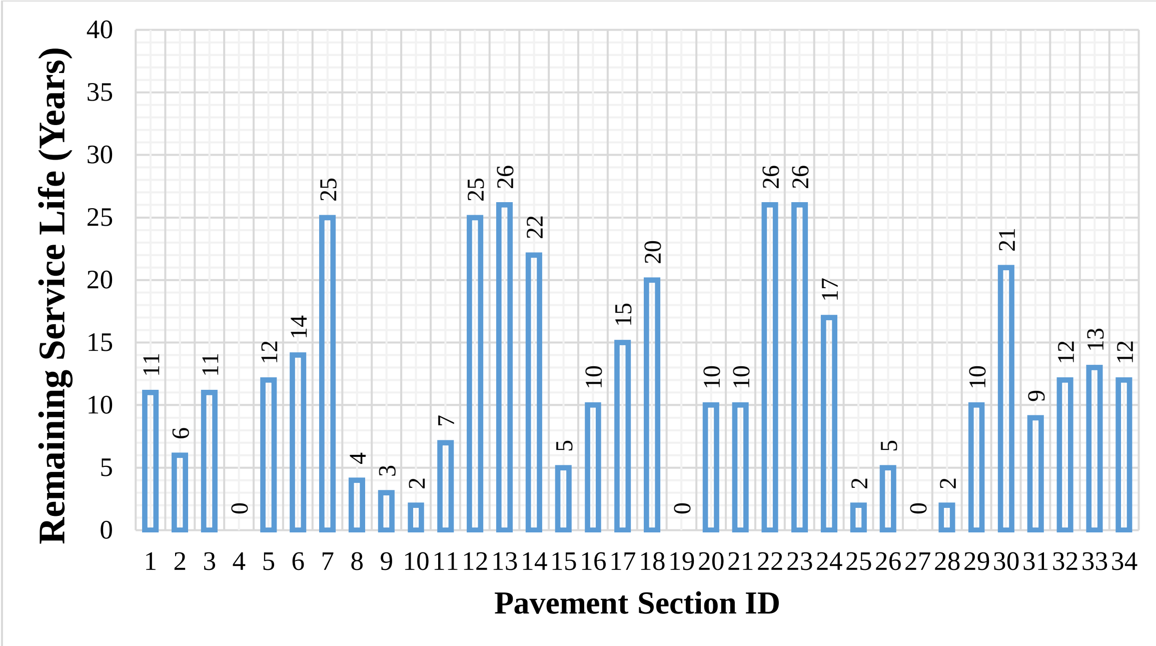
(a) Based on pavement section ID



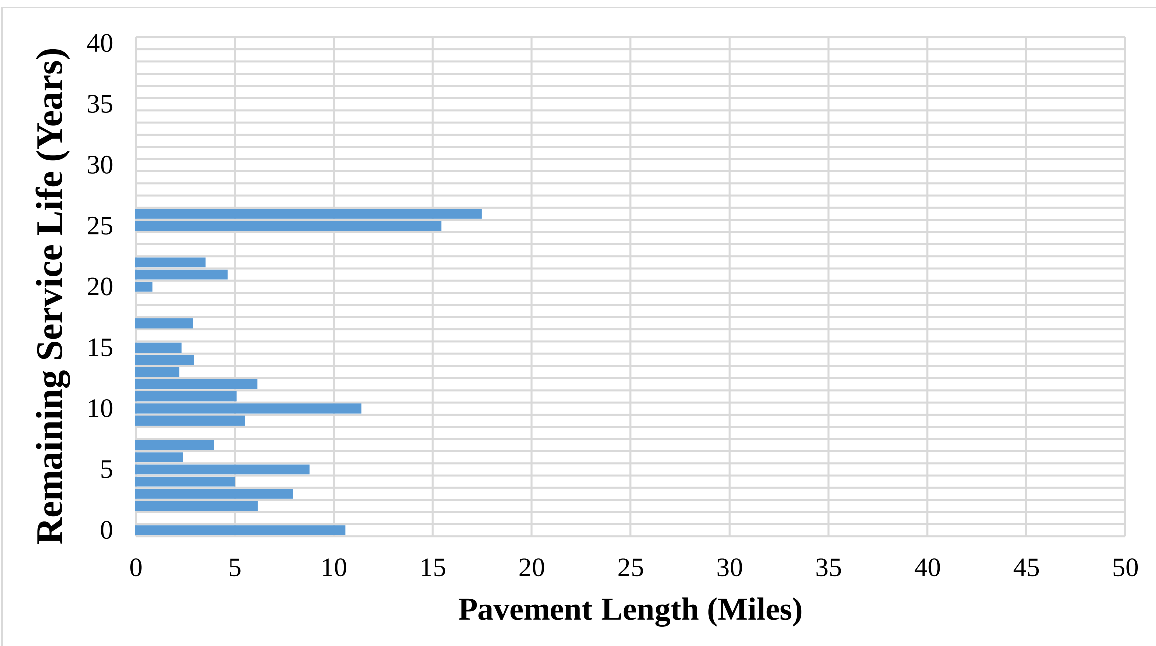
(b) Based on pavement length

Figure 22. RSL distribution for JPCP pavement sections using transverse cracking model and 15% cracking threshold limit

Figure 23 shows the distribution of RSL for 34 JPCP pavement sections when: (1) an IRI threshold limit of 170 in./mi was used as the threshold limit, and (2) the ANN-based network-level IRI model approach 1 was used as the pavement performance model in the calculation of RSL values. The average RSL for the JPCP pavement sections was found to be 9.6 years.



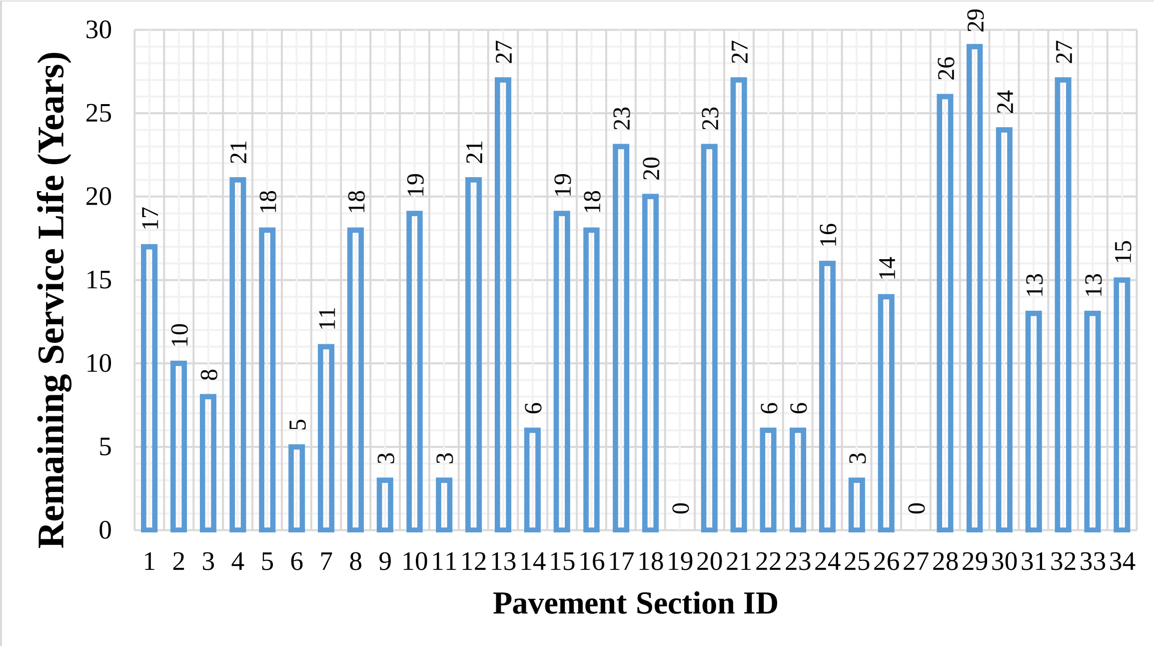
(a) Based on pavement section ID



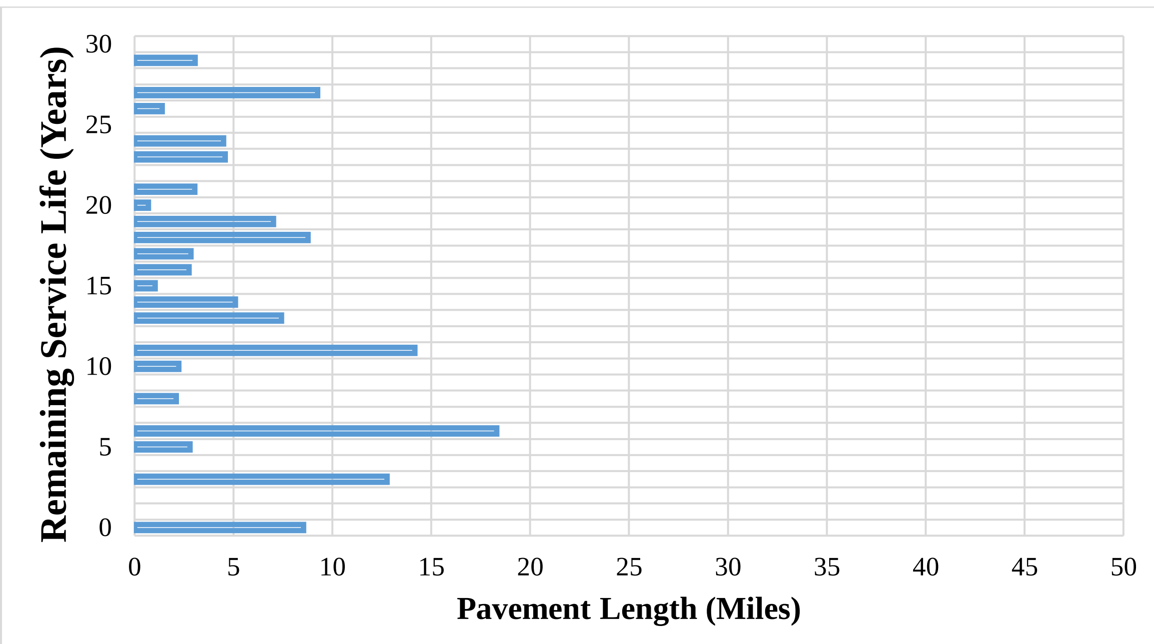
(b) Based on pavement length

Figure 23. RSL distribution for JPCP pavement sections using IRI approach 1 model and 170 in./mi threshold limit

Figure 24 shows the distribution of RSL for 34 JPCP pavement sections when: (1) an IRI threshold limit of 170 in./mi was used as the threshold limit, and (2) an ANN-based network-level IRI model approach 2 was used as the pavement performance model in the calculation of RSL values. The average RSL for the JPCP pavement sections was found to be 11.5 years.



(a) Based on pavement section ID



(b) Based on pavement length

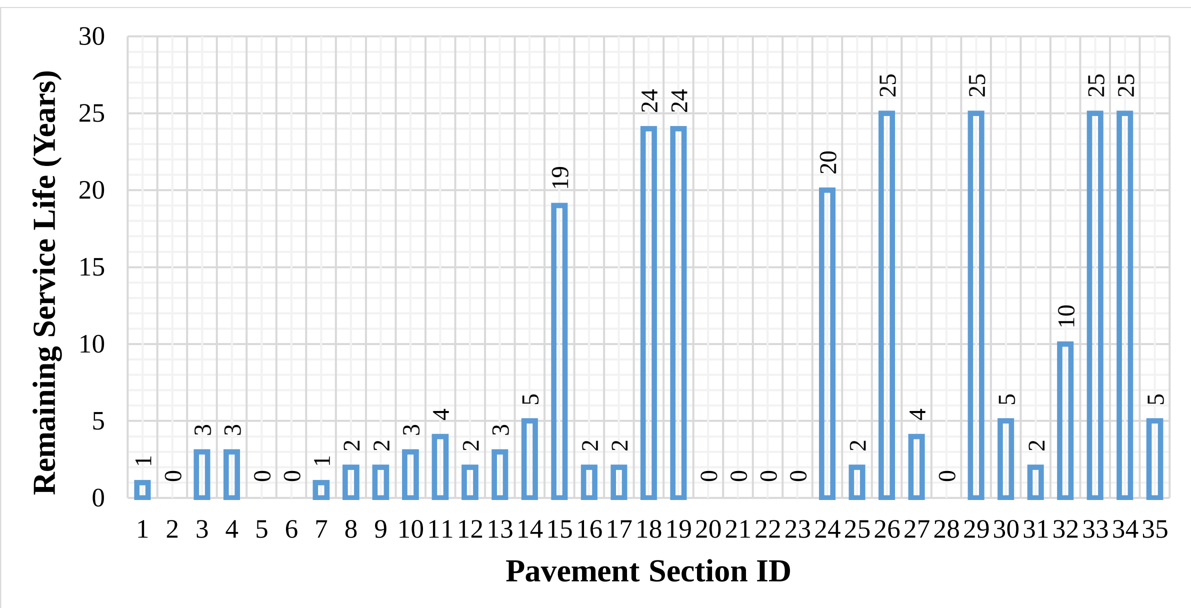
Figure 24. RSL distribution for JPCP pavement sections using IRI approach 2 model and 170 in./mi threshold limit

In summary, different average RSL results (7.2, 9.6, and 11.5 years of RSL) for the JPCP pavement sections were found when project-level and network-level approach 1 and approach 2 pavement performance models, respectively, were used in the calculation of RSL. This difference in average RSL results might be because different pavement performance models were used in the calculation of RSL. Network-level pavement performance models were developed for each pavement performance indicator, and a single model was used to make future pavement condition predictions for all pavement sections of a given pavement type. Even if development considered various input variables (thickness, traffic, previous years' condition records, etc.), it can't be sufficiently comprehensive to consider all variables determining deterioration of the pavement systems.

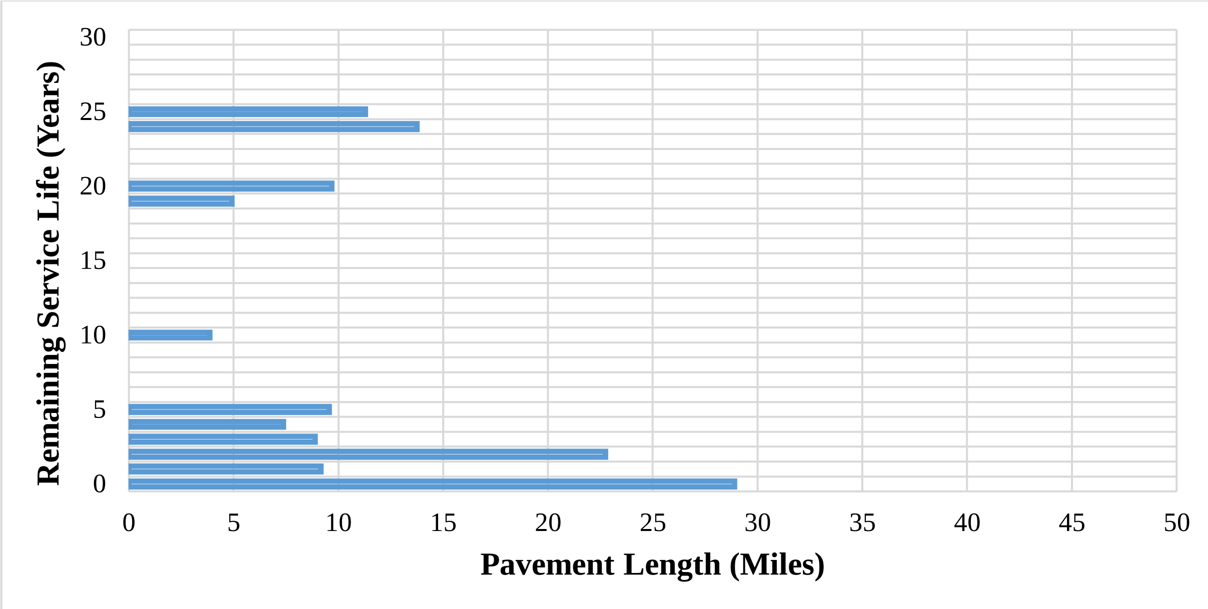
On the other hand, project-level pavement performance models—valid only for the sections for which they were developed—were developed for each pavement section, and for pavement sections with not many pavement conditions records, the accuracy might not be sufficiently high; adding more data points (i.e., future performance measurements) would most likely increase these models' accuracy. Engineers should consider various parameters in determining which pavement performance model (project- or network-level) should be used in the calculation of RSL. They might consider using network-level models if they have an insufficient number of pavement performance records for developing accurate project-level pavement performance models. Similarly, project-level models developed using many pavement performance records might better reflect the deterioration trend of a pavement section and enable more realistic pavement performance predictions compared to network-level models.

ANN-Based AC Pavement RSL Models

Figure 25 shows the RSL distribution for 35 flexible pavement sections when a rutting threshold limit of 0.4 in. was used. An ANN-based network-level rutting model was used as the pavement performance model in the calculation of RSL values, and the average RSL for the flexible pavement sections was found to be 2.3 years.



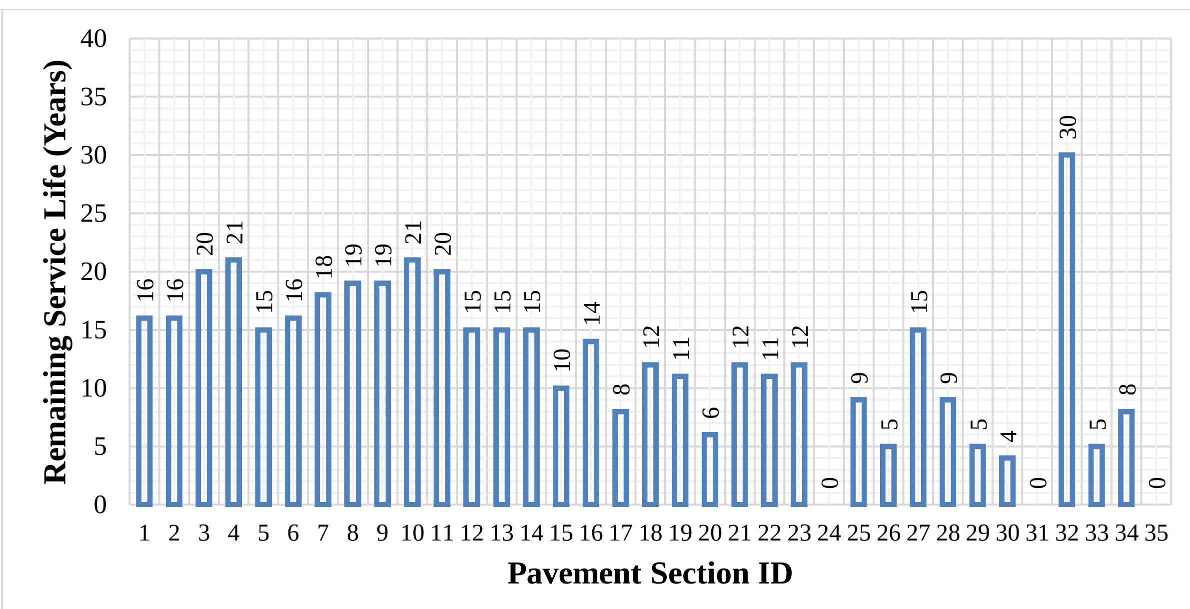
(a) Based on pavement section ID



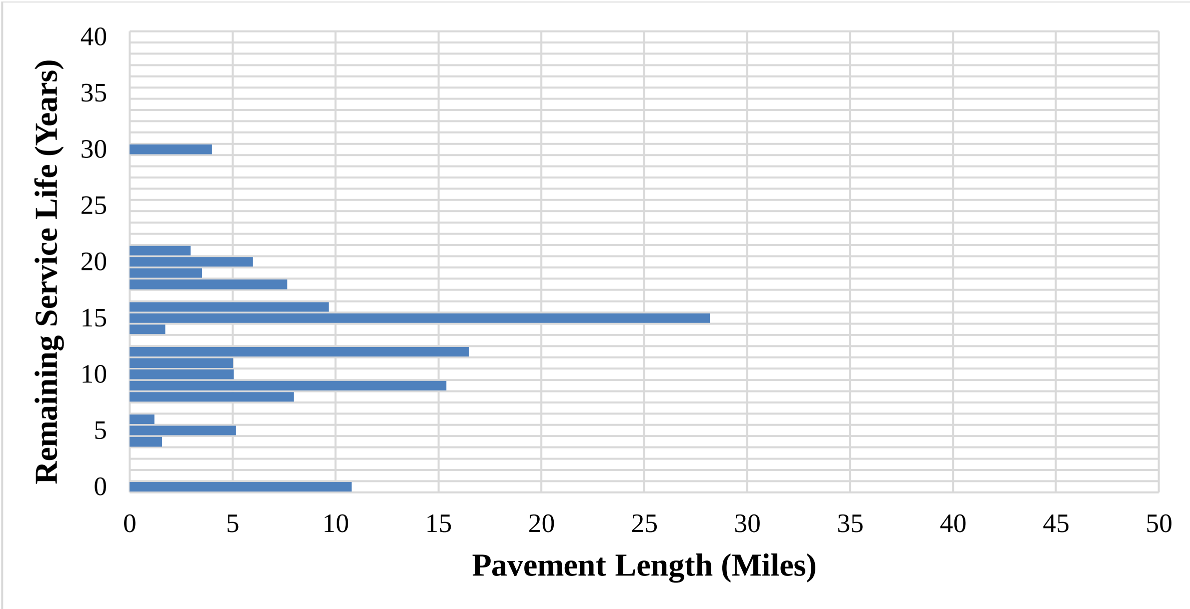
(b) Based on pavement length

Figure 25. RSL distribution for flexible pavement sections using rutting model and 0.4 in. threshold limit

Figure 26 shows the RSL distribution for 35 flexible pavement sections when: (1) an IRI threshold limit of 170 in./mi was used as the threshold limit, and (2) an ANN-based network-level IRI model approach 1 was used as the pavement performance model in the calculation of RSL values. The average RSL value for the flexible pavement sections was found to be 11.8 years.



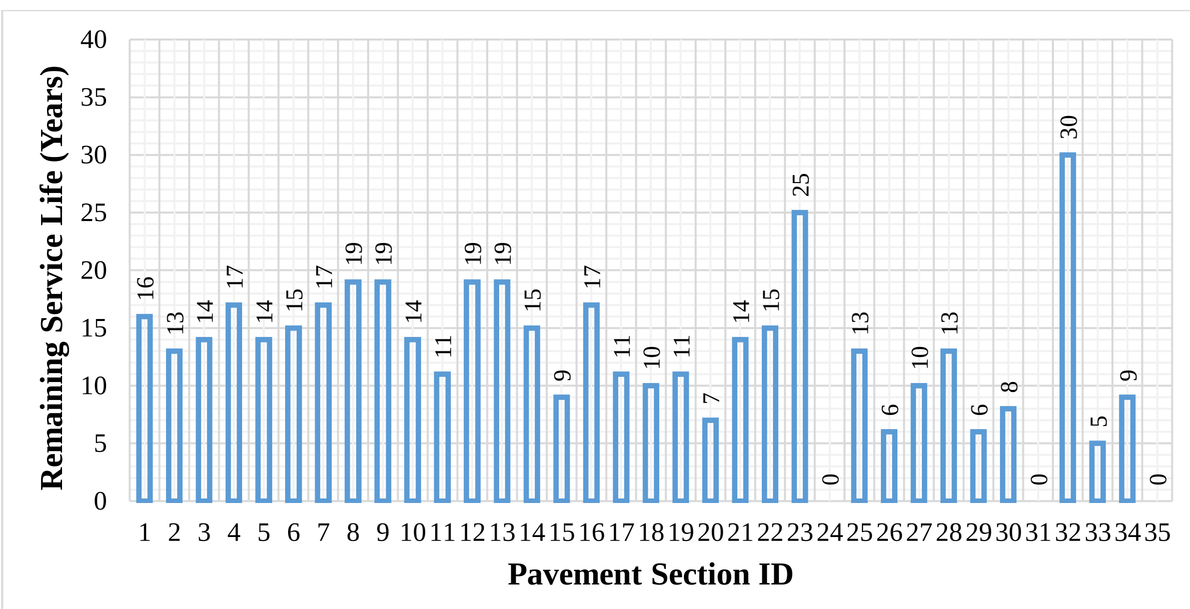
(a) Based on pavement section ID



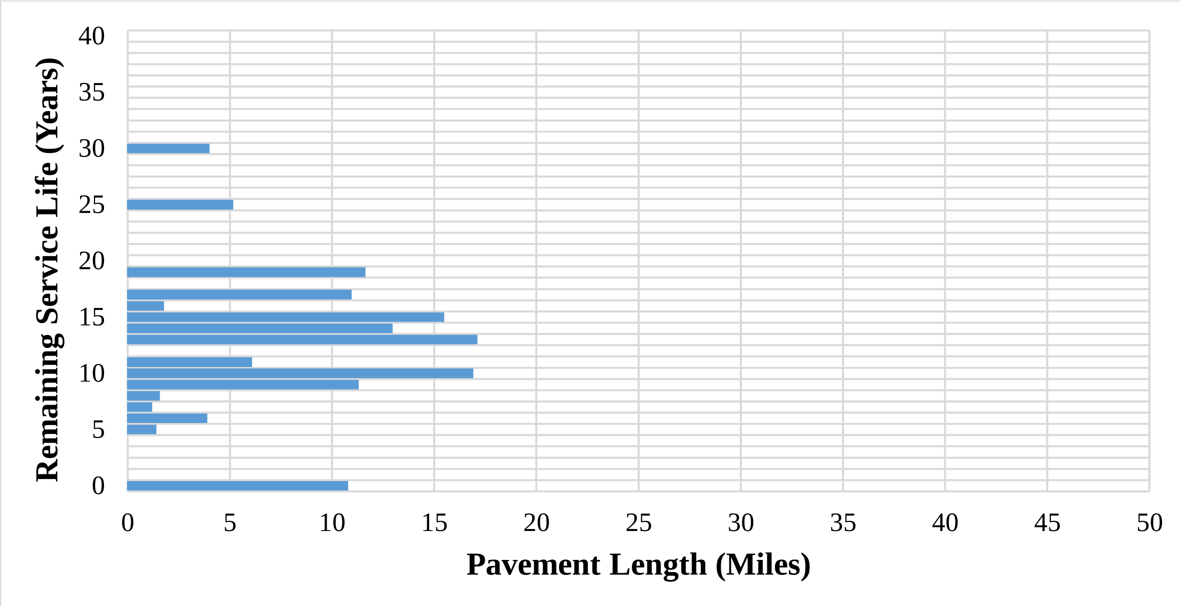
(b) Based on pavement length

Figure 26. RSL distribution for flexible pavement sections using IRI approach 1 model and 170 in./mi threshold limit

Figure 27 shows the RSL distribution for 35 flexible pavement sections when: (1) an IRI threshold limit of 170 in./mi was used as the threshold limit, and (2) an ANN-based network-level IRI model approach 2 was used as the pavement performance model in the calculation of RSL values. The average RSL value for the flexible pavement sections was found to be 11.7 years.



(a) Based on pavement section ID



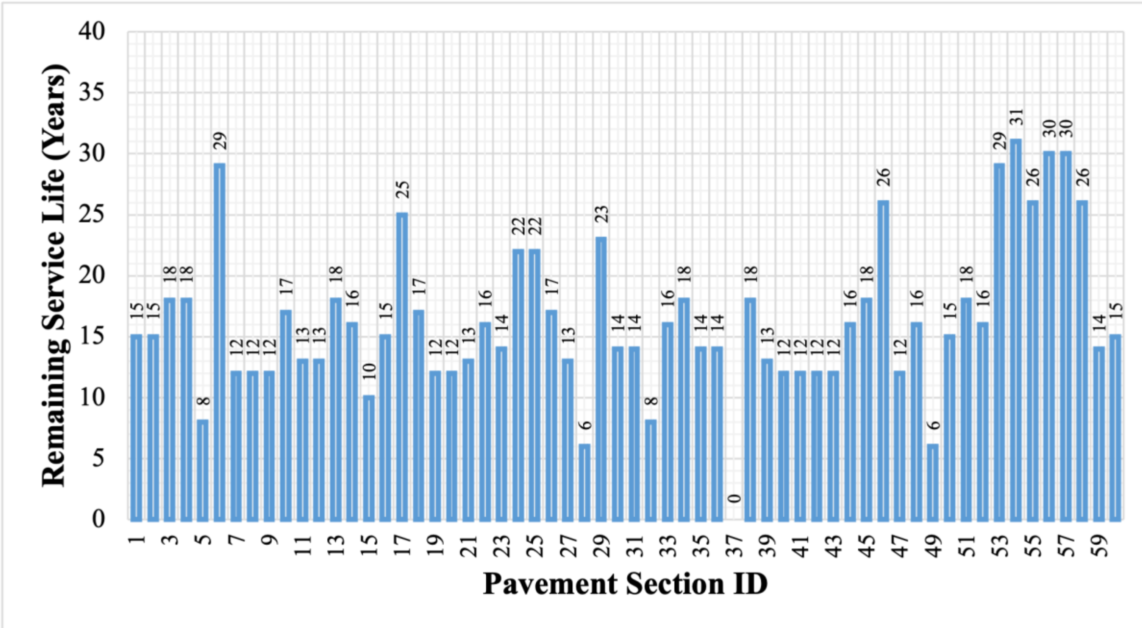
(b) Based on pavement length

Figure 27. RSL distribution for flexible pavement sections using IRI approach 2 model and 170 in./mi threshold limit

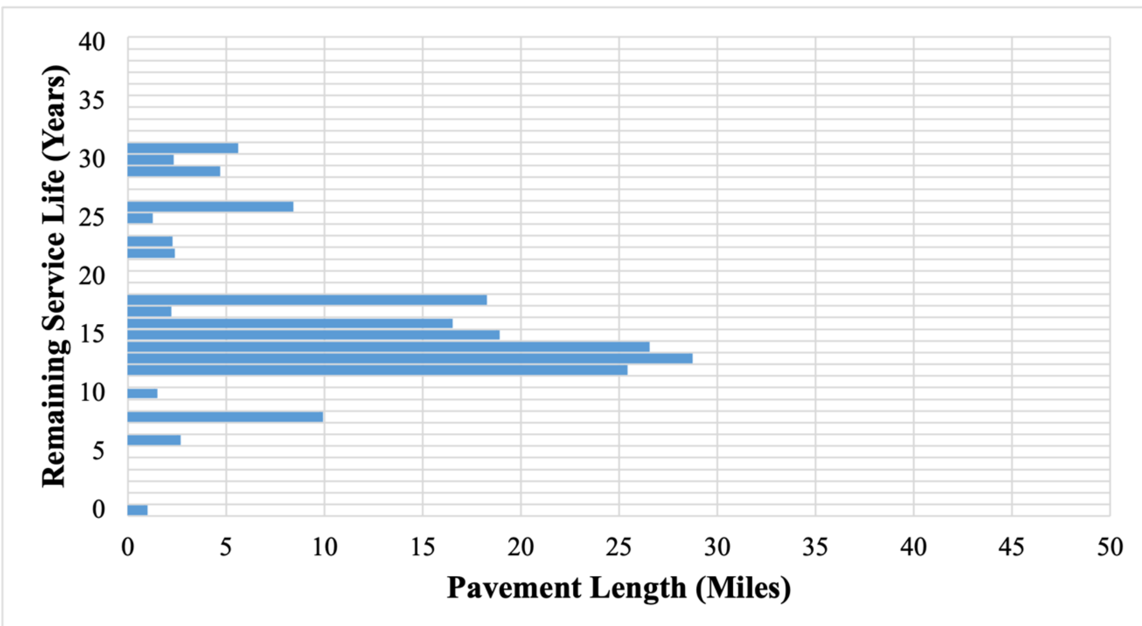
There was no significant difference in average RSL results between cases when ANN-based network-level IRI approach 1 and approach 2 models were used as pavement performance models in the calculation of RSL. The average RSL result for the flexible pavement sections was slightly lower (9.3 years) when a project-level IRI model was used as the pavement performance model in the calculation of RSL compared to when ANN-based network-level IRI models were used (11.8 and 11.7 years).

ANN-Based AC over JPCP RSL Models

Figure 28 shows the RSL distribution for 60 AC over JPCP sections when a rutting threshold limit of 0.4 in. was used. An ANN-based network-level rutting model was used as the pavement performance model in calculating RSL values, and the average RSL value for the flexible pavement sections was 14.4 years.



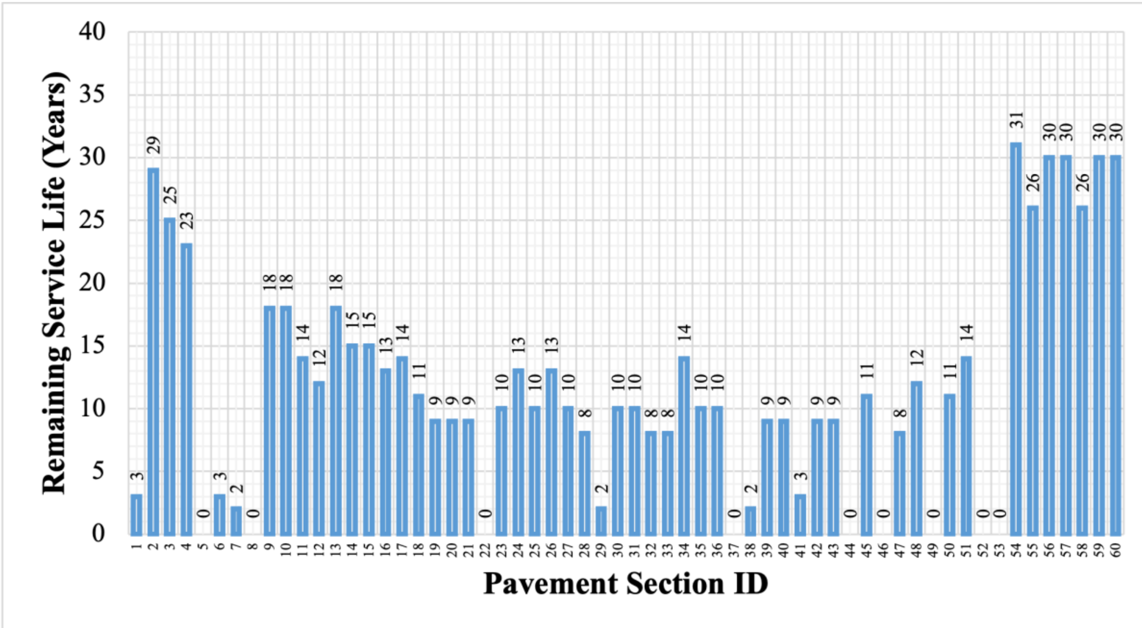
(a) Based on pavement section ID



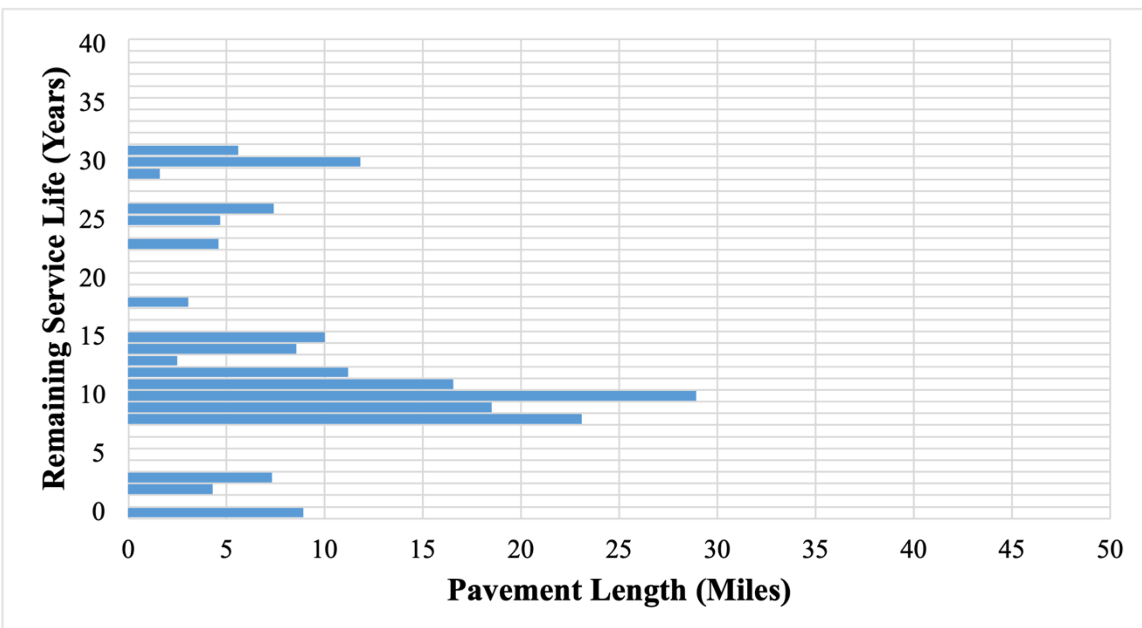
(b) Based on pavement length

Figure 28. RSL distribution for composite pavement sections using rutting model and 0.4 in. threshold limit

Figure 29 shows the RSL distribution for 60 AC over JPCP sections when: (1) an IRI threshold limit of 170 in./mi was used as the threshold limit, and (2) an ANN-based network-level IRI model approach 1 was used as the pavement performance model in the calculation of RSL values. The average RSL for the composite pavement sections was found to be 9.3 years.



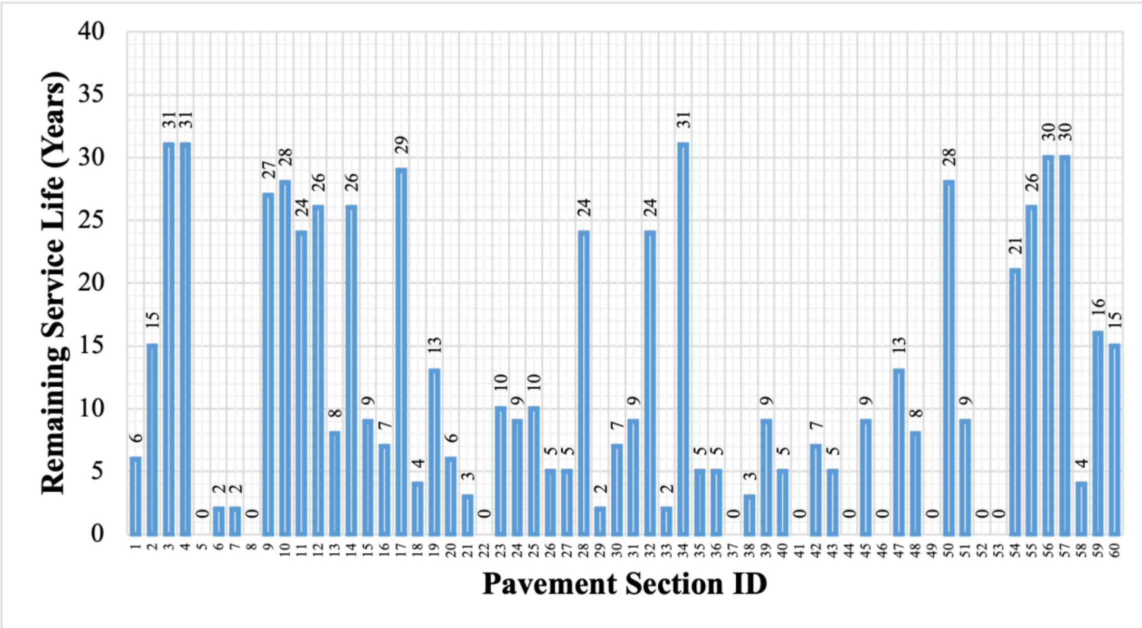
(a) Based on pavement section ID



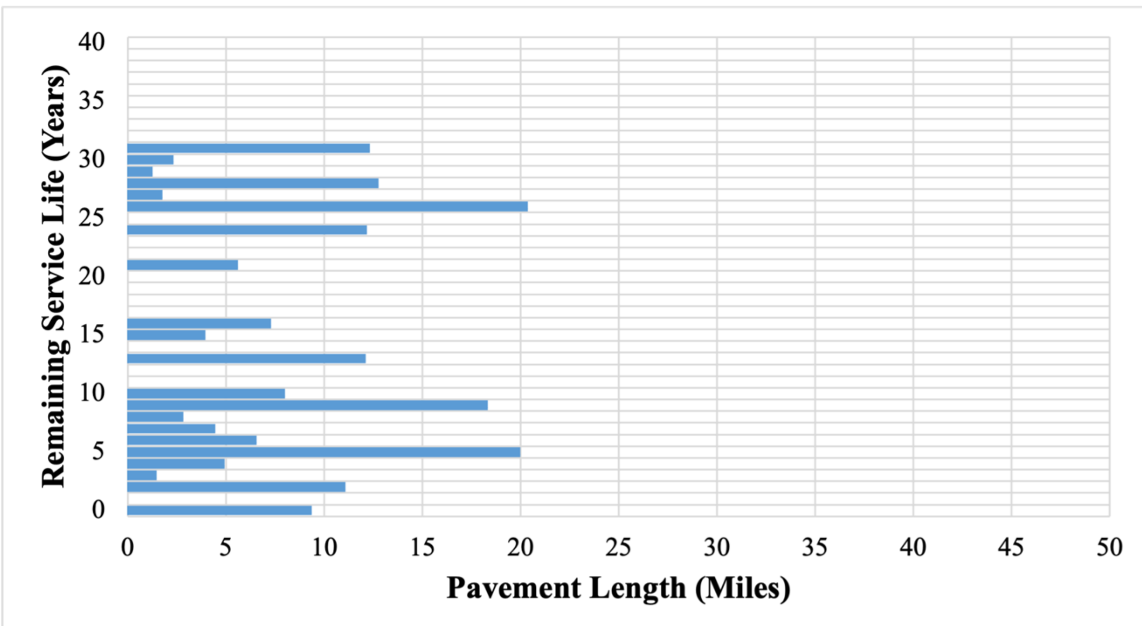
(b) Based on pavement length

Figure 29. RSL distribution for composite pavement sections using IRI model approach 1 and 170 in./mi threshold limit

Figure 30 shows the RSL distribution for 60 AC over JPCP sections when: (1) an IRI threshold limit of 170 in./mi was used as the threshold limit, and (2) an ANN-based network-level IRI model approach 2 was used as the pavement performance model in the calculation of RSL values. The average RSL value for the composite pavement sections was found to be 6.1 years.



(a) Based on pavement section ID



(b) Based on pavement length

Figure 30. RSL distribution for composite pavement sections using IRI model approach 2 and 170 in./mi threshold limit

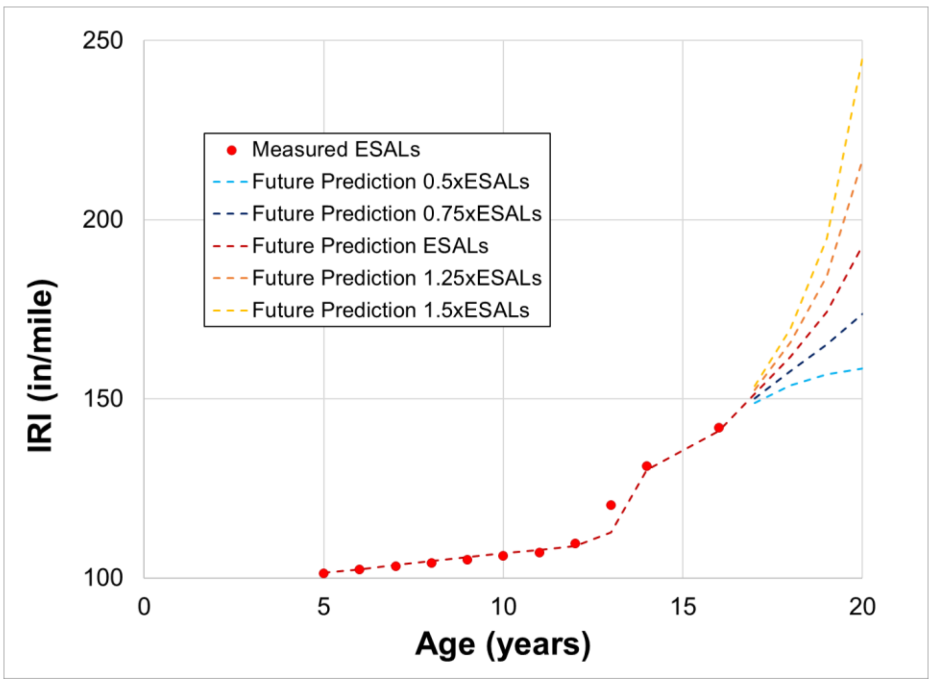
Average RSL values when project-level and ANN-based network-level performance models approach 1 and approach 2 were used to calculate RSL values for the composite pavement sections were found to be 4.4, 9.3, and 6.3 years.

Consequence Analysis of Traffic on Pavement Performance Predictions

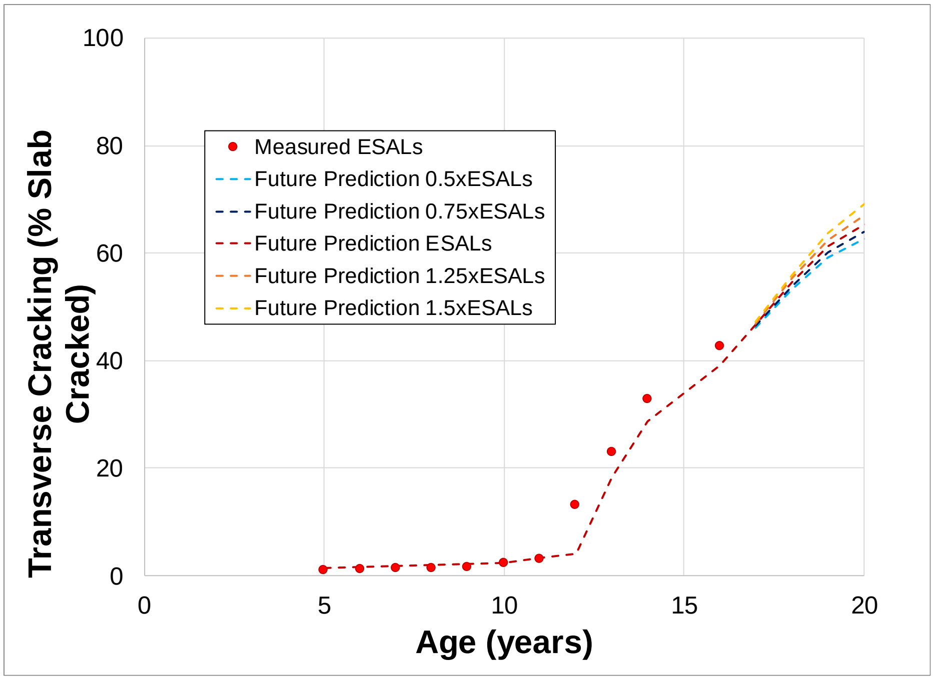
Impact of Traffic on JPCP Performance

As part of this study, a consequence analysis of the developed network-level pavement performance models (network-level IRI approach 1 and transverse cracking), presented earlier in this chapter, was carried out to evaluate the effect of traffic on the ANN-based model predictions.

For the sake of demonstration, a JPCP section was selected, and accumulated ESAL levels for this pavement section were obtained from the PMIS database. Figure 31 shows measured IRI and transverse cracking data for the pavement section, as well as network-level IRI approach 1 and transverse cracking model predictions for various traffic levels (50% reduced, 25% reduced, actual, 25% increased, and 50% increased).



(a) IRI



(b) Transverse cracking

Figure 31. ANN-based performance prediction model predictions for various traffic levels for a new JPCP section as an example

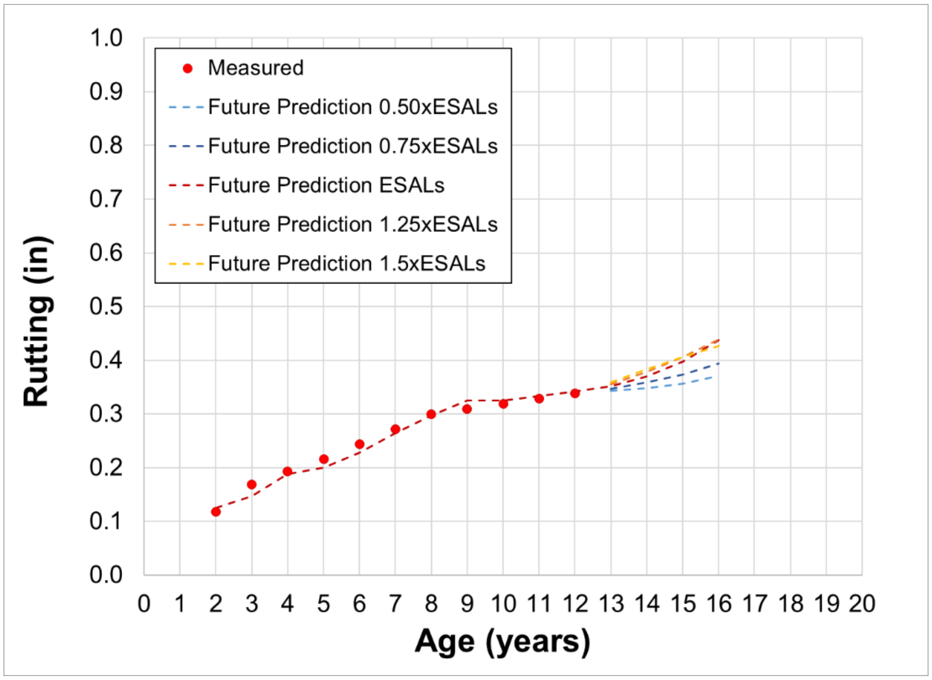
The section used in the Figure 31 example is on US 151, from milepost 36.68 to 37.83, northbound, with an AADTT of 1,398, and it was constructed in 1998.

As shown in Figure 31, network-level IRI and transverse cracking models produced very similar predictions to measured values when the actual traffic levels were used as inputs in the models. Moreover, the network-level models made higher IRI and transverse cracking predictions as the level of traffic in the model inputs increased, and vice versa.

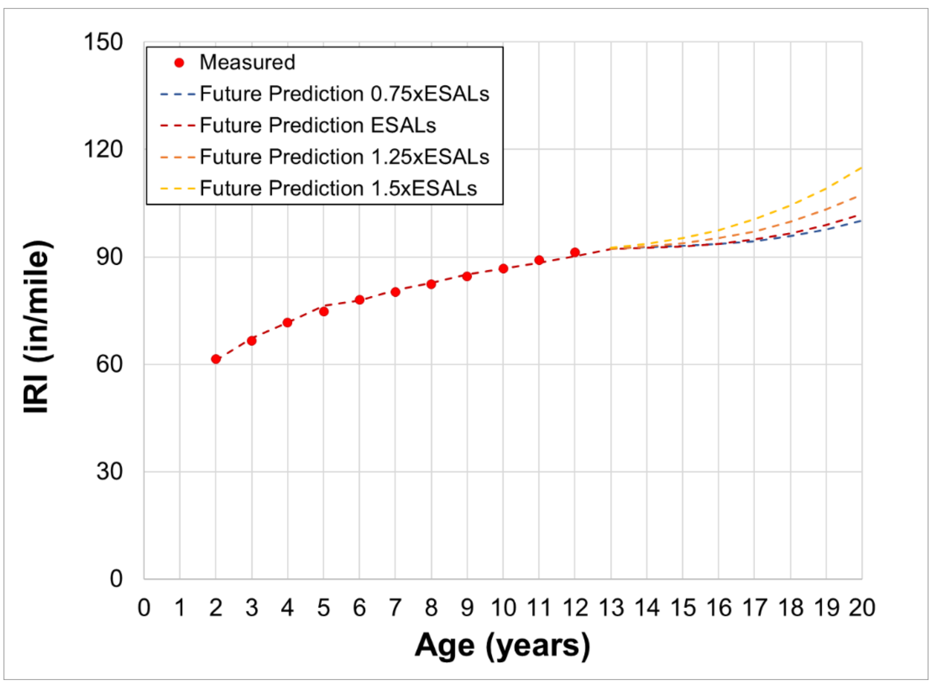
Impact of Traffic on AC Pavement Performance

As part of this study, a consequence analysis of the developed network-level pavement performance models, as presented earlier in the chapter, was carried out to evaluate the effect of traffic on the ANN-based model predictions.

For the sake of demonstration, an AC section was selected, and accumulated ESAL levels for this pavement section were obtained from the PMIS database. Figure 32 shows measured rutting and IRI data for the pavement section as well as network-level rutting and IRI approach 1 model predictions for various traffic levels (50% reduced, 25% reduced, actual, 25% increased and 50% increased).



(a) Rutting



(b) IRI

Figure 32. ANN-based performance prediction model predictions for various traffic levels for a particular AC section as an example

The section used as an example in Figure 32 is on US 18, from milepost 212.74 to 214.39, eastbound, with an AADTT of 1,885, and it was constructed in 2000.

As can be seen in Figure 32, network-level rutting and IRI approach 1 models produce predictions very similar to measured values when the actual traffic levels are used as inputs in the models. Moreover, the network-level models produced higher rutting and IRI predictions as the level of traffic in the model inputs increases, and vice versa.

CHAPTER 4. EVALUATION OF PAVEMENT PERFORMANCE AND RSL PREDICTION MODELS FOR IOWA COUNTY PAVEMENT SYSTEMS

Description of Overall Approaches and Data Preparation

The next step of this study involved evaluating both statistical and ANN-based models developed using Iowa DOT's PMIS database for two pavement types, JPCP and AC pavements, utilizing the Iowa county pavement database. First, a historical performance databank (i.e., HPD) that specifically included pavements in Lee County was developed for Iowa county pavements. Figure 33 indicates the stages of databank development, model validation, and development for pavement performance.

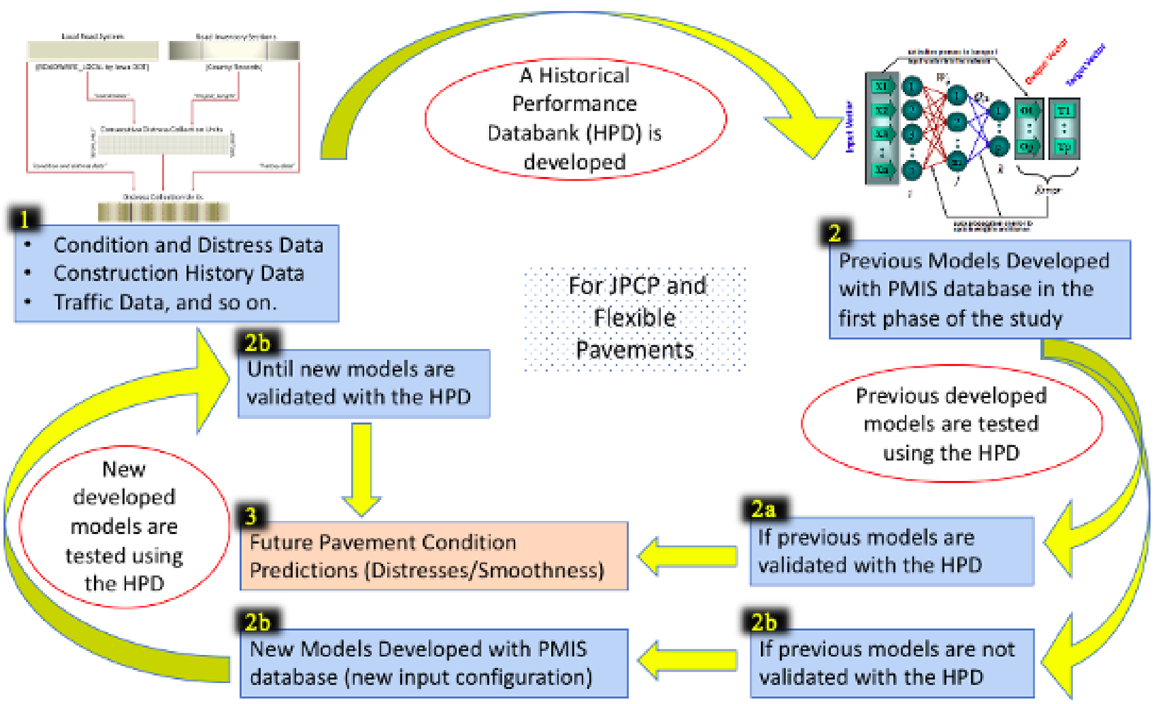


Figure 33. Stages of HPD development and model validation

An HPD consists of a processed distress and condition data for each road section, obtained from the Iowa DOT as raw data; construction, and maintenance history of pavements, generally provided by county engineer's offices; and traffic data, obtained from the Iowa DOT Roadway Asset Management System (RAMS)/open data online. Based on input parameters used in the previously developed statistical- and ANN-based models, additional data such as traffic data or PCI could be obtained from different sources if required. A detailed step-by-step methodology of creating this databank, including processing raw county data, along with the standard procedure to develop Iowa county pavement HPD presented in Appendix A, is described in this chapter.

All models presented in Chapter 3 were analyzed as to whether or not they were validated with the HPD. In cases with no validation with the HPD, new models were developed using the PMIS database. After the accuracies of these models had been ensured for model development purposes, they were independently tested with the HPD for model testing purposes.

As mentioned earlier, in the first stage shown in Figure 33, the HPD was developed for Iowa county pavements. To process the data mentioned above, two consecutive procedures were followed: segmentation followed by summarization. In the segmentation procedure, the beginning and ending points of each road section were determined, using a dynamic segmentation approach, a function of the geographic information system (GIS). Dynamic segmentation is a process that can calculate the locations of condition and distress data on pavement management sections at run time either in milepost or Global Positioning System (GPS) coordinates.

Figure 34 reflects the segmentation procedure described in this study that consists of two processes: matching and sectioning. Distress and condition data for each road section, obtained from the Iowa DOT, include raw data for each 52 ft, or 1/100 of a mile.

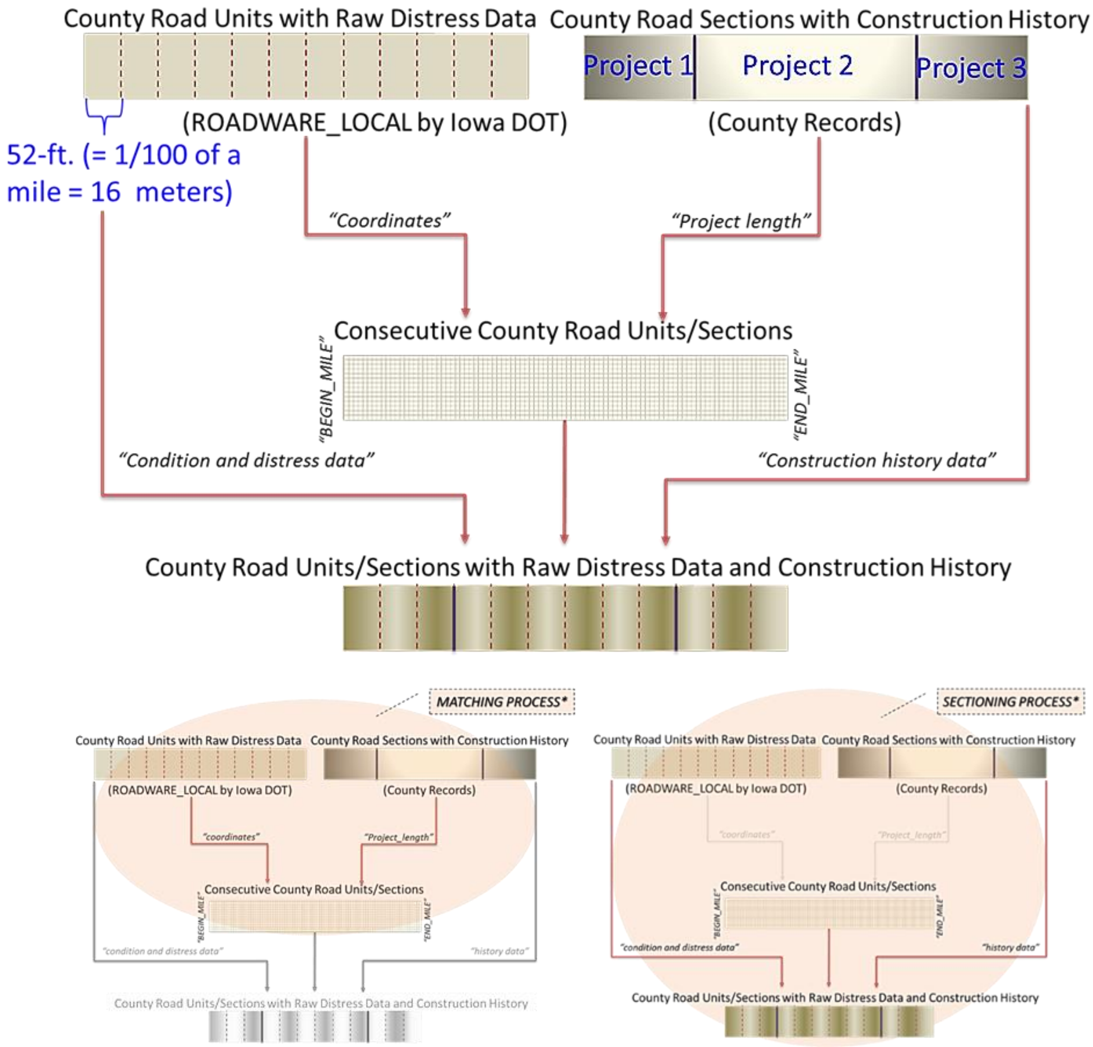


Figure 34. Display of a pavement system used in segmentation procedures

In Figure 34, the county road units with raw distress data are referred to as ROADWARE_LOCAL by the Iowa DOT. The GPS coordinates along with the distress and condition data were utilized from this database. The county road sections with construction history were obtained from the County Records database, and with these data, the project length of each road section could be determined. During the matching process of the segmentation procedure, the GPS coordinates from the Iowa DOT and project lengths from the County Records were matched in the county road system to determine the exact locations of county roads and road sections. In the sectioning process of the segmentation procedure, the distress and condition raw data from the Iowa DOT and construction history data from the County Records were joined to the determined county roads, and each county road was then divided into county road sections so that each had its own raw data. More step-by-step details are provided in Appendix A.

Figure 35 shows an example of a summarization (i.e., processing of data) procedure for IRI data, with each distress and condition data value having its own summarization method.

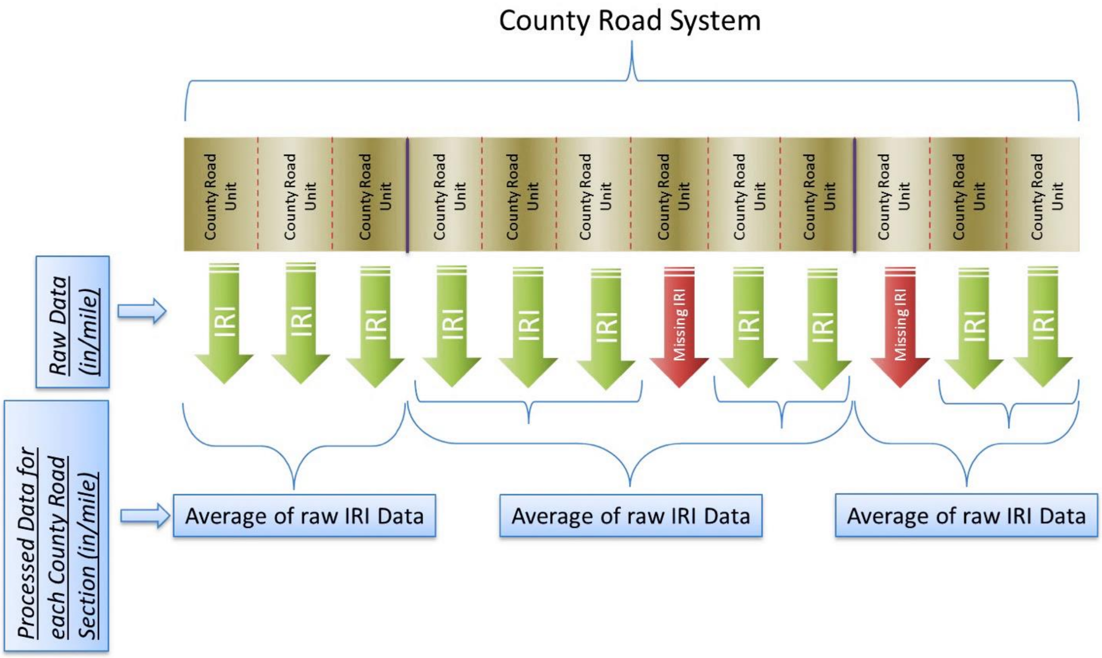
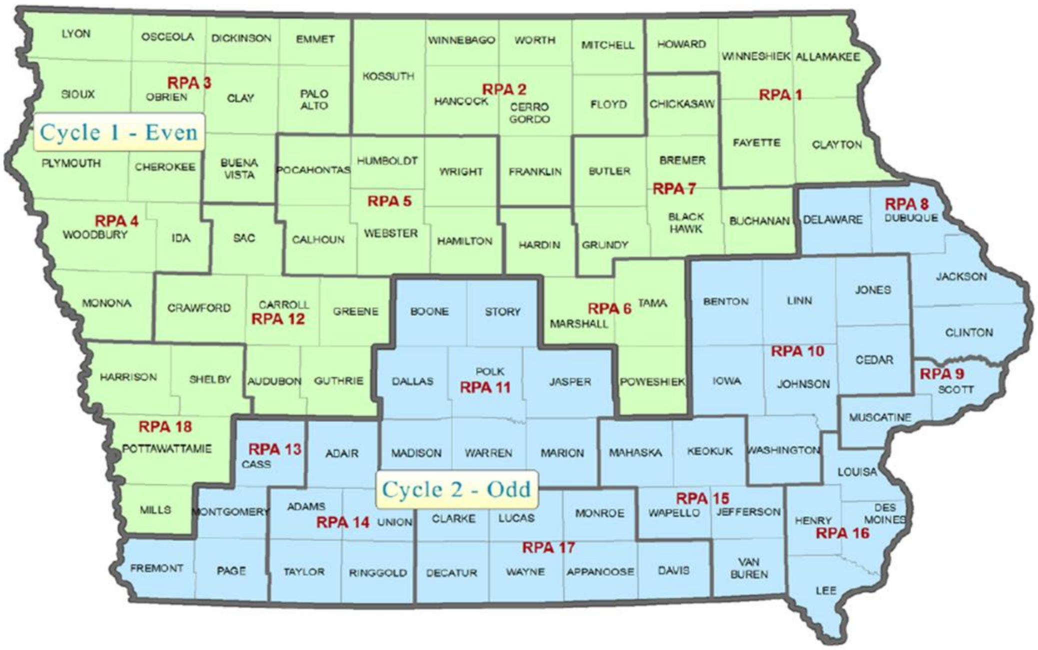


Figure 35. Pavement system summarization procedure for IRI data after segmentation

For each county road unit, referred to as 52 ft, IRI data were collected, and based on each road section, an average of these collected IRI data were taken to obtain one processed IRI data per county road section. Because of mistakes in data collection, there may sometimes be missing data in IRI for some county road units, and in the case of missing IRI data in a road section, the average of existing raw IRI data was taken and missing data ignored, as seen in Figure 35. While taking an average and ignoring missing data are the approaches used to process IRI raw data, they may be different for other distress data, such as transverse and longitudinal cracking, as explained in detail in Appendix A.

The Iowa DOT has archived the raw distress data collected by third-party vendors since 2013 when statewide collection of non-National Highway System (non-NHS) federal-aid-eligible roads data began. The collected and archived data from 2013, 2015, and 2017 includes 46 counties, while the collected and archived data from 2014, 2016, and 2018 consists of 53 counties, meaning that data are collected every year for half of the state, as seen in Figure 36.



Haubrich 2016

Figure 36. Statewide collection cycles of local road raw data in Iowa

The files are named in the Iowa DOT database as follows:

- ROADWARE_LOCAL_2013
- ROADWARE_LOCAL_2014
- ROADWARE_LOCAL_2015
- ROADWARE_LOCAL_2016
- ROADWARE_LOCAL_2017

These files are displayed in Figure 37, including all information related to collecting raw data, with Microsoft Access and/or Excel software utilized to import and export data from the Iowa DOT database. The developed pavement HPD is stored in an Excel format.

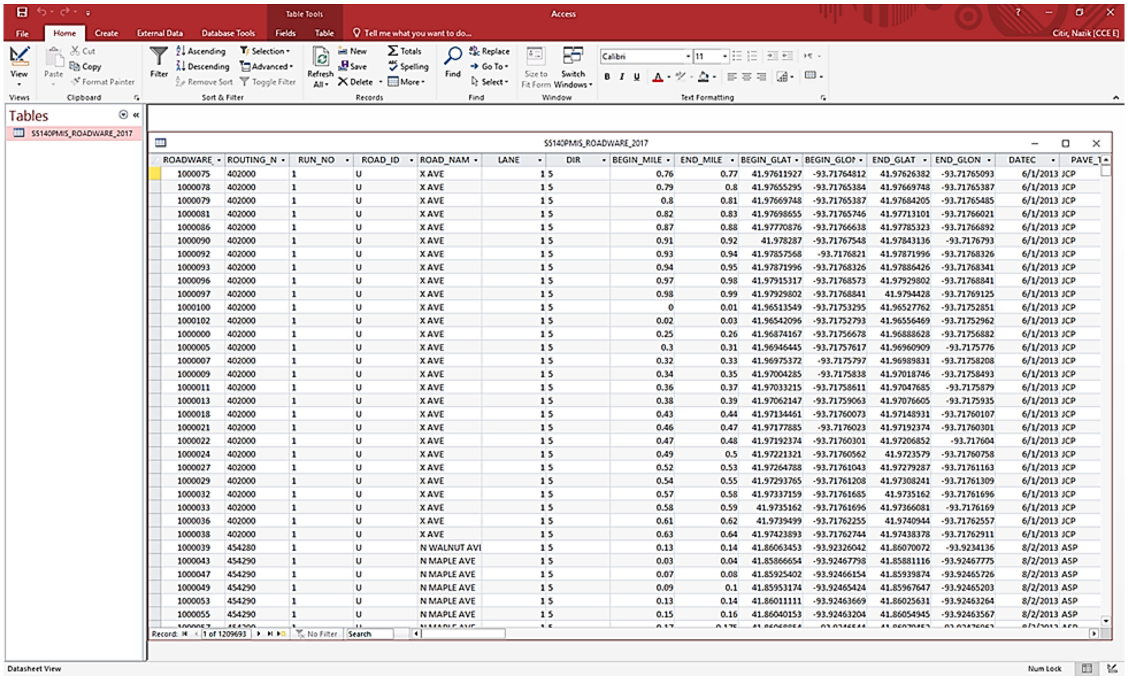


Figure 37. ROADWARE_LOCAL raw data file provided by Iowa DOT

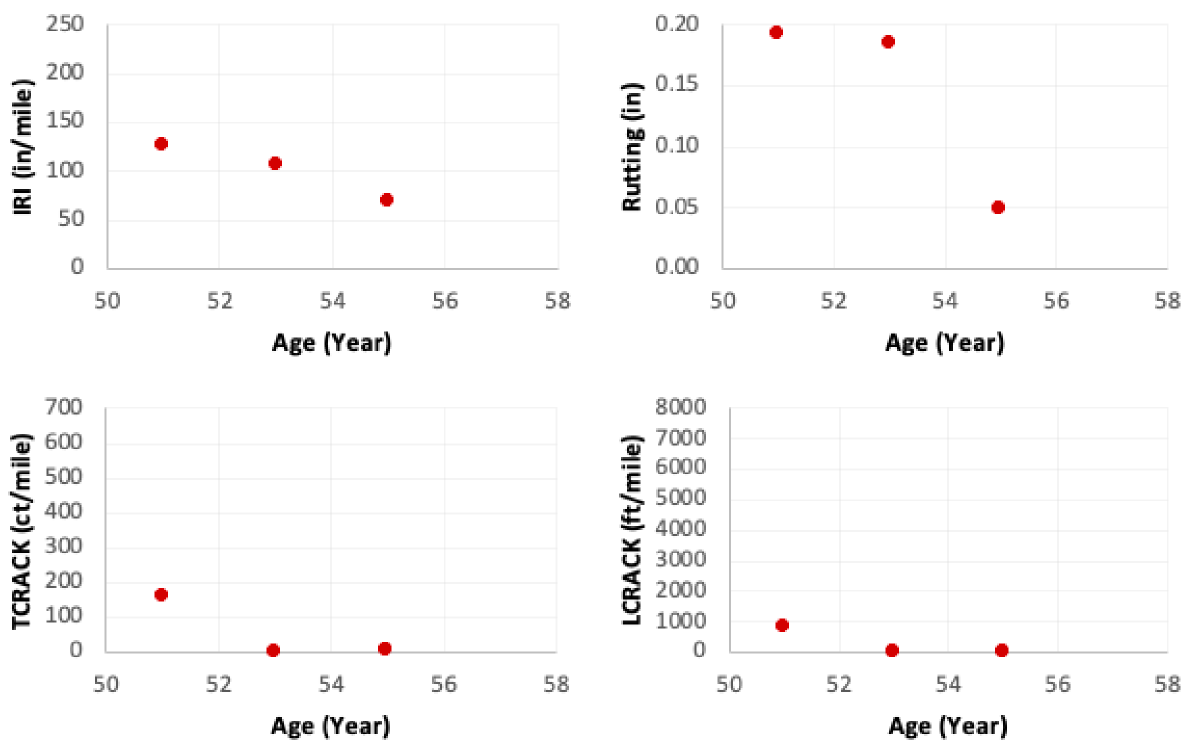
The independent testing data sets formed by the HPD for testing of ANN models were created for Lee County, Iowa, which was chosen among the 99 counties in Iowa because the Lee County Engineer's Office had provided its historical pavement database. The database had a total of 62 pavement sections and based on the availability of data and accuracy of existing data (e.g., road names, surface types) of County Records, 51 pavement sections were extracted including 20 flexible pavement sections and 31 concrete pavement sections. The next data extraction was done based on availability and accuracy of ROADWARE_LOCAL data (e.g., raw condition and distress data) and traffic data. The number of pavement sections used in the models varied based on the input parameters of the ANN models.

The number of pavement sections and the total number of data points for each pavement type and each ANN model used in this study are as follows:

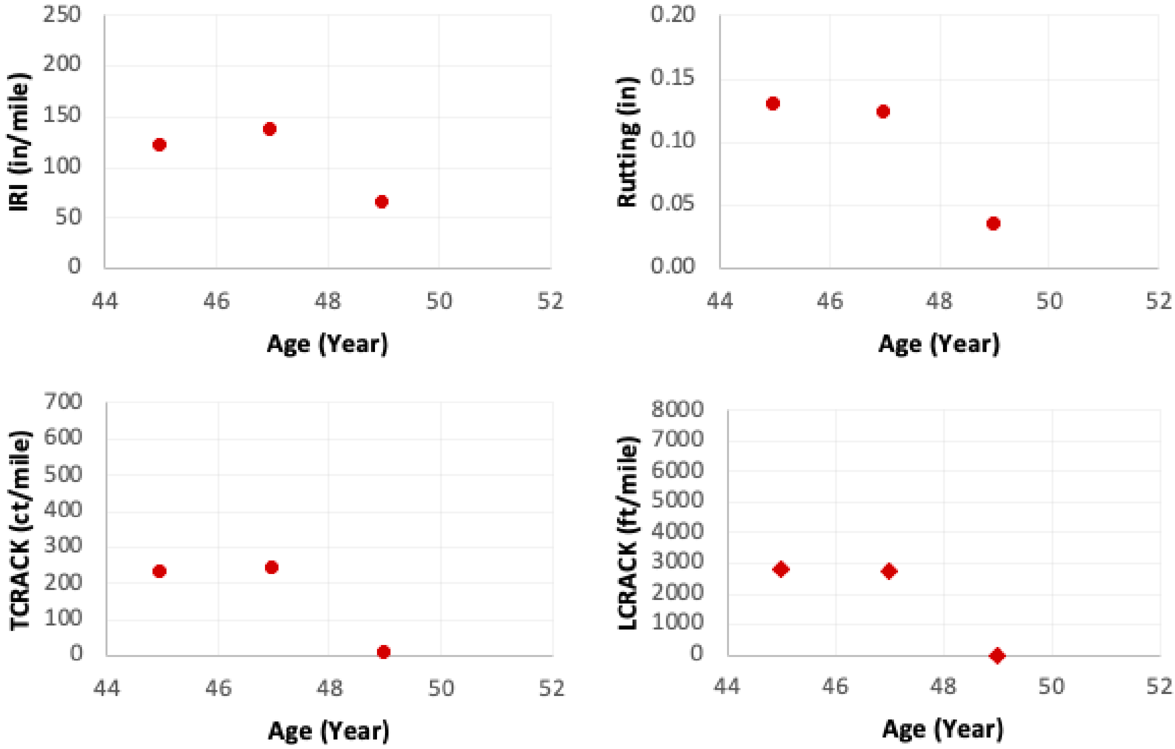
- ANN models for JPCPs:
  - 17 road sections for transverse cracking (102 data points)
  - 6 road sections for IRI approach 1 (36 data points)
  - 6 road sections for IRI approach 2 (36 data points)
- ANN models for AC pavements:
  - 16 road sections for transverse cracking (96 data points)
  - 16 road sections for longitudinal cracking (96 data points)
  - 10 road sections for rutting (60 data points)
  - 13 road sections for IRI approach 1 (78 data points)
  - 13 road sections for IRI approach 2 (78 data points)

The accuracy of condition and distress predictions for the road sections, corresponding to the proposed model performances, were assessed by plotting target condition and distress data against predictions through line-of-equality and statistical criteria such as AAE and R^2, and also SEE was utilized because these assessments were used during the first stage of the project. Overall, higher R^2 and lower AAE and SEE values indicate higher accuracy in the model performance.

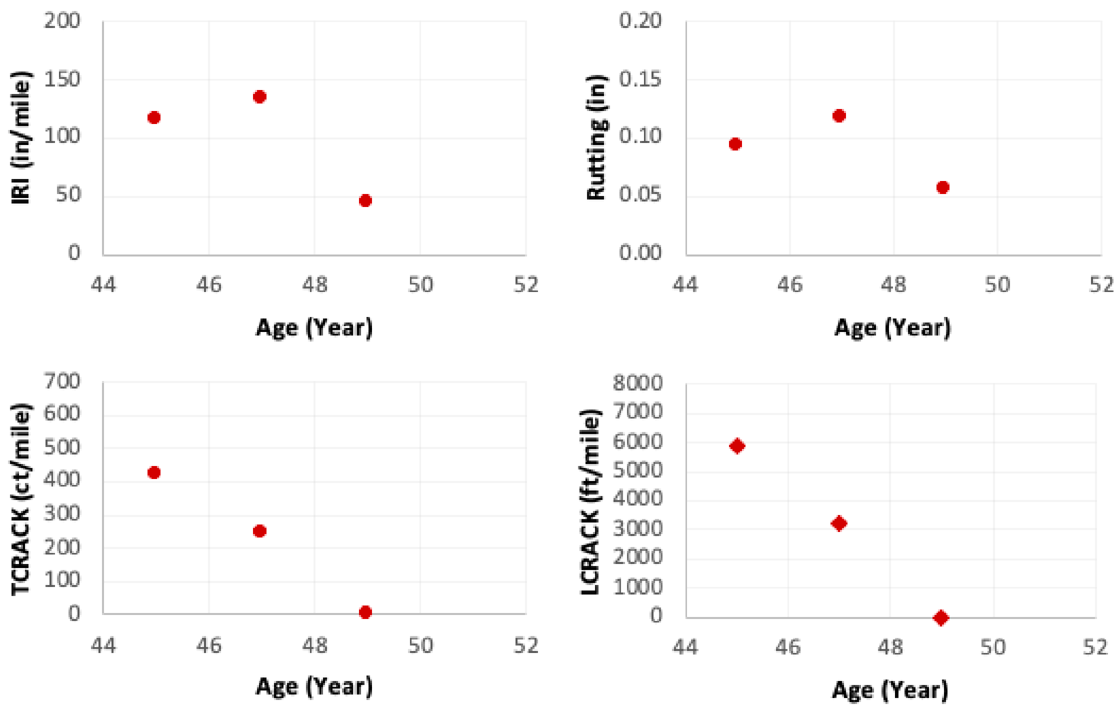
In the local road data set, it was found that some pavement sections had decreased or unchanged measured pavement conditions and distress values over the years without observing any pavement maintenance or rehabilitation. Also, data sets had missing data points since the data provided for 2013, 2015, and 2017 for Lee County had already been collected. In these cases, data were first analyzed with respect to whether or not any data preparation methodology could be applied. If no data preparation methodology was applied to a road section, its data were eliminated. Figure 38 presents examples of three road sections in Lee County.



(a) County Highway J72, Ambrosia Lane section



(b) County Highway W74, Pilot Grove Road (between Pilot Grove and J38)



(c) County Highway J38, St Paul Rd (between 130th Street and 205th Avenue)

Figure 38. Field IRI, rutting, and transverse and longitudinal cracking data records collected in 2013, 2015, and 2017 for Lee County

For each road section, four pavement performance indicators for three years were provided: IRI, rutting, transverse cracking, and longitudinal cracking. As can be seen in Figure 38, the overall trend lines representing condition and distress measurements were downward over the years, meaning that the road section experienced less distress with the passing years. If there was no record showing maintenance on these road sections that might have accounted for this over the years, road sections similar to those in Figure 38 were eliminated at the beginning.

However, in any case of applying a data preparation methodology, a linear increase was assumed between the first and last year when data were provided, similar to the first stage of this study. Between the first and last year, the data that started the same as the previous year and slightly less than the previous year were adapted to a linear increment.

Figure 39 provides an example of a road section in Lee County that presents four pavement performance indicators—IRI, rutting, transverse cracking, and longitudinal cracking—before and after applying this data preparation methodology to a flexible pavement section.

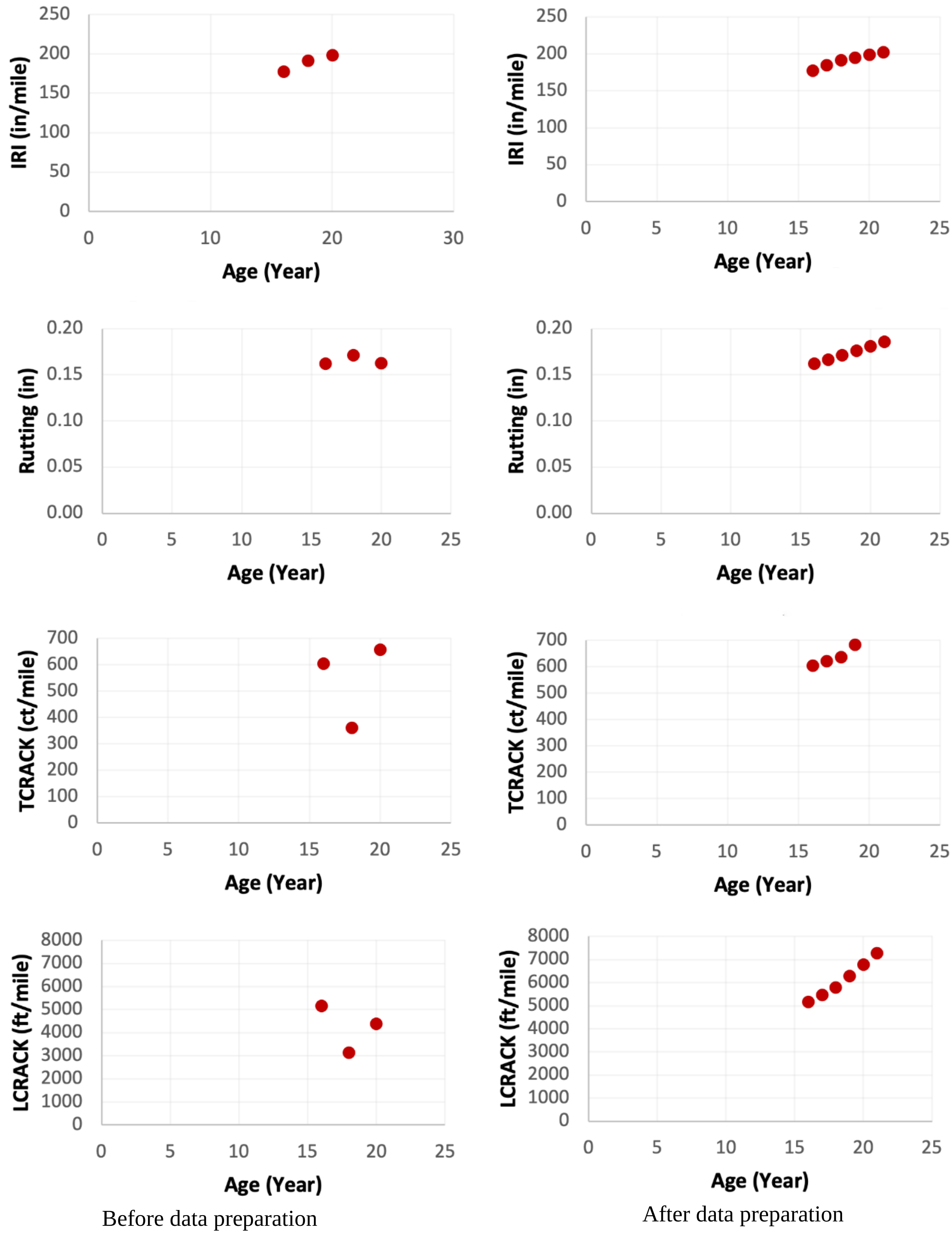


Figure 39. Before and after applying data preparation methodology to four pavement performance indicators using a sample flexible pavement section

The section used in Figure 39 is on Ortho Road in Lee County, with an annual average daily traffic (AADT) in 2014 of 500, was constructed in 1962, and with an overlay in 1997.

Using this data preparation methodology, pavement condition and distress data records can be made more realistic, resulting in more accurate pavement performance models and more robust RSL models.

Data processing for transverse and longitudinal cracking was different than that for IRI and rutting measurements. Processed IRI and rutting data were achieved by taking an average of the raw IRI and rutting data. Before and after processing the data, the units are the same: inch/mile for IRI and inches for rutting, but transverse and longitudinal cracking have more raw data types, e.g., low, medium, and high severity and sealed transverse cracking, and low, medium, and high severity and sealed longitudinal cracking.

The Iowa DOT staff recommended that it would be better to sum transverse cracking with different severity levels, because if transverse cracks are sealed, they are categorized as low-severity transverse cracks. Whether or not seals are no longer in place or used, such transverse cracks are called high-severity transverse cracks, meaning that the models considered whether or not transverse cracking is sealed in all severities. The raw transverse cracking data were thus converted into legacy values before processing data. Details on how to convert the raw data into processed data are provided in Appendix A. In this case, the data preparation methodology mentioned above was applied to each type of raw data then processed as shown in Figure 39.

Iowa County JPCP Case

Statistical-Based JPCP Performance Models and RSL Models

In this work, statistical- and AI-based methods were used to evaluate county pavement performance. Here, both types of models can be utilized for each county road section without considering project- or network-level status. A statistically defined sigmoid pavement deterioration curve-based approach was utilized for IRI and PCI calculations for county JPCPs in Iowa. The same procedure used for developing the project-level pavement performance model in the first stage of the project was followed for developing the sigmoidal equations. For IRI calculation, equation 4 (shown previously) was used to generalize the sigmoidal equation in which C1, C2, C3, and C4 indicate coefficients representing contributions of different input parameters. For PCI calculation, equation 5 (shown previously) was used to generalize the sigmoidal equation in which C and D are coefficients representing contributions of different input parameters. The sigmoidal curve fitting to measure IRI values was carried out by minimizing the error, the square of differences between the target, and predicted IRI values.

Figure 40 through Figure 45 indicate some examples of IRI prediction models for county JPCPs that can be used to predict future IRI values for these road sections.

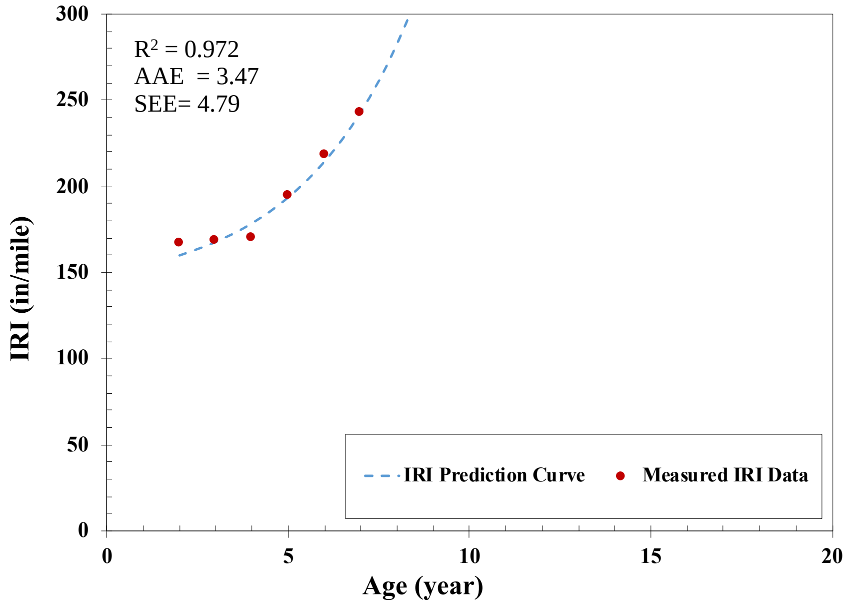


Figure 40. Statistical-based IRI prediction model results for JPCP section at 233rd Street

The IRI prediction equation used to generate the results shown in Figure 40 is as follows:

$$IRI = 140 + \frac{7327.19}{1 + e^{(6.56 - 0.33 \times age)}}$$

The AADT in 2014 for the 233rd Street section was 210, and the section was constructed in 2011.

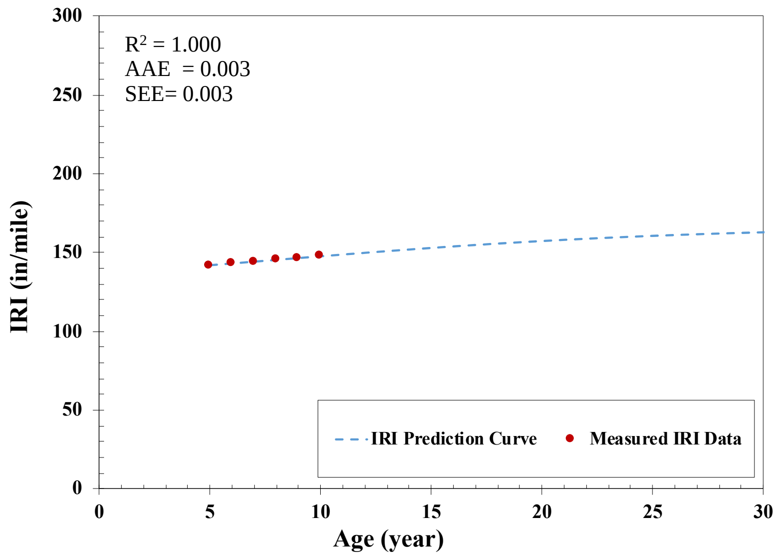


Figure 41. Statistical-based IRI prediction model results for JPCP section at Croton Road

The IRI prediction equation used to generate the results shown in Figure 41 is as follows:

$$IRI = 123.07 + \frac{43.15}{1 + e^{(0.78 - 0.10 \times age)}}$$

The AADT in 2014 for this section of Croton Road, or County Highway J62, was 170, and the section was constructed in 2008.

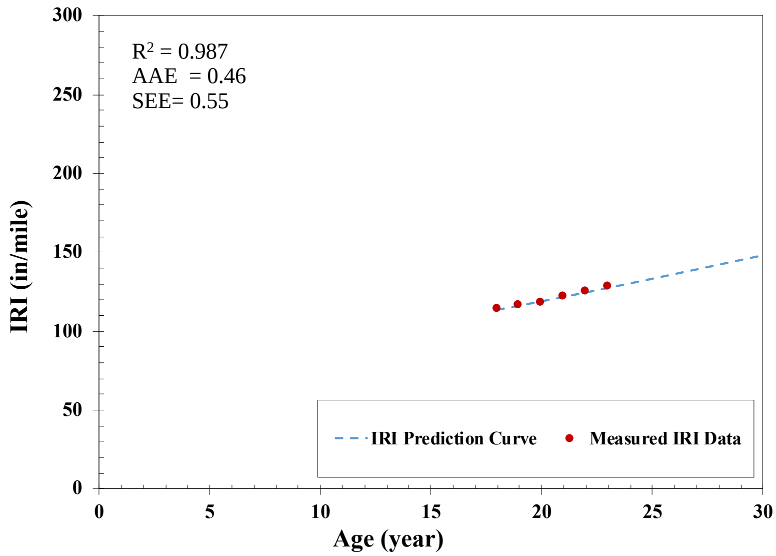


Figure 42. Statistical-based IRI prediction model results for JPCP section at Wirtz Lane

The IRI prediction equation used to generate the results shown in Figure 42 is as follows:

$$IRI = 54.78 + \frac{176.91}{1 + e^{(1.92 - 0.07 \times age)}}$$

The AADT in 2014 for the Wirtz Lane section was 170, and the section was constructed in 1995.

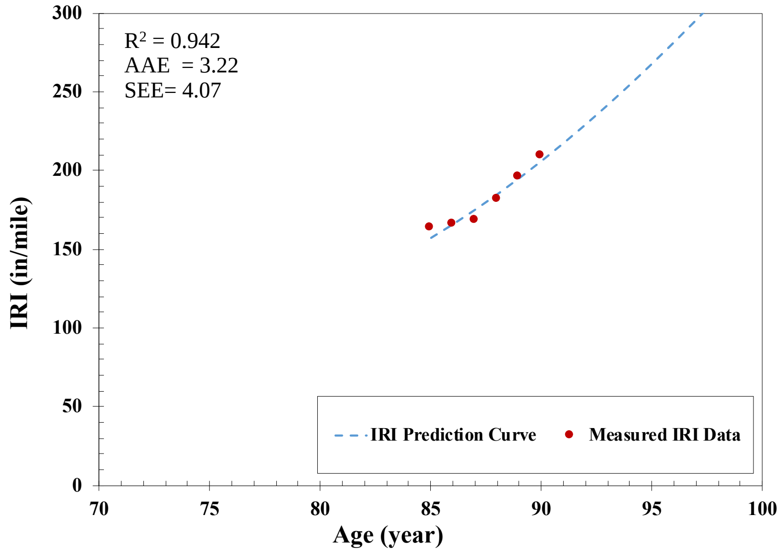


Figure 43. Statistical-based IRI prediction model results for JPCP section at 180th Avenue

The IRI prediction equation used to generate the results shown in Figure 43 is as follows:

$$IRI = 46.20 + \frac{669.36}{1 + e^{(9.35 - 0.09 \times age)}}$$

The AADT in 2014 for the 180th Avenue section, from old US 61 to 155th Street, was 7,300, and the section was constructed in 1928.

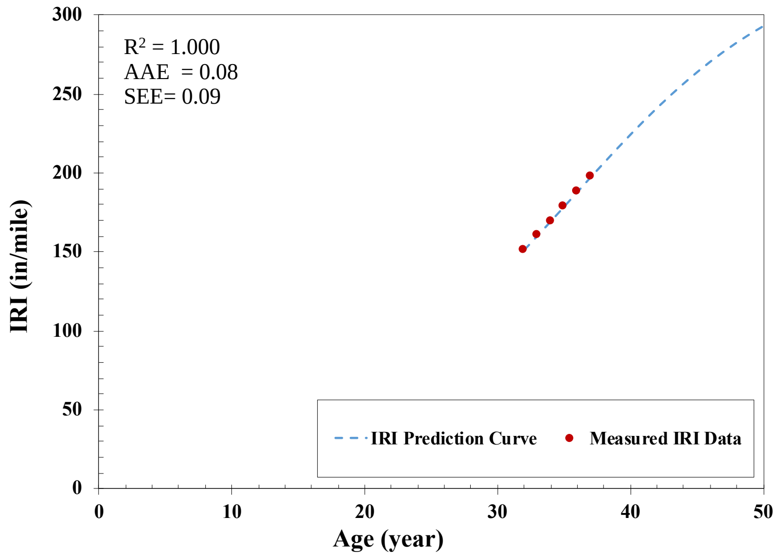


Figure 44. Statistical-based IRI prediction model results for JPCP section at Augusta Road from J48 to Iowa 16

The IRI prediction equation used to generate the results shown in Figure 44 is as follows:

$$IRI = 30.67 + \frac{308.83}{1 + e^{(4.31 - 0.12 \times age)}}$$

The AADT in 2014 for this section of Augusta Road, also called County Highway X38, from County Highway J48 to Iowa 16, was 390, and the section was constructed in 1981.

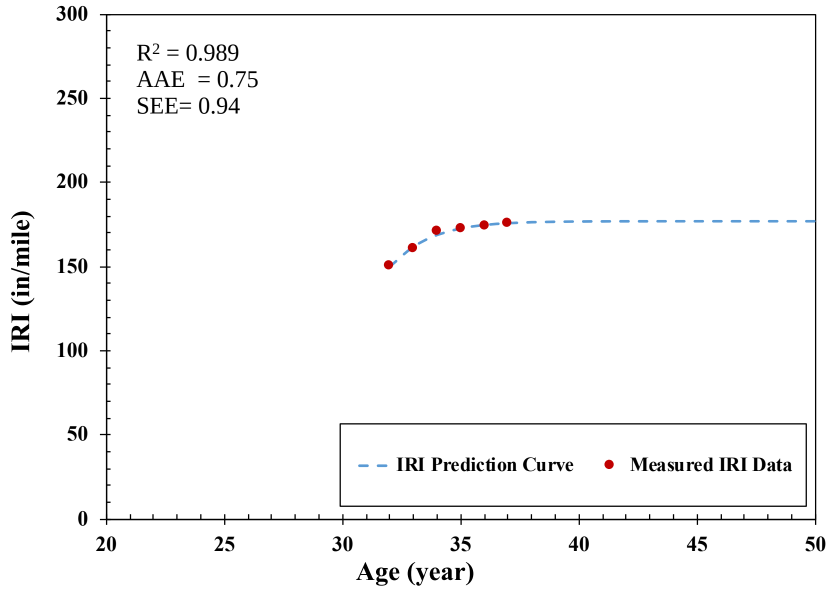


Figure 45. Statistical-based IRI prediction model results for JPCP section at Augusta Road from J48 South to Business US 61

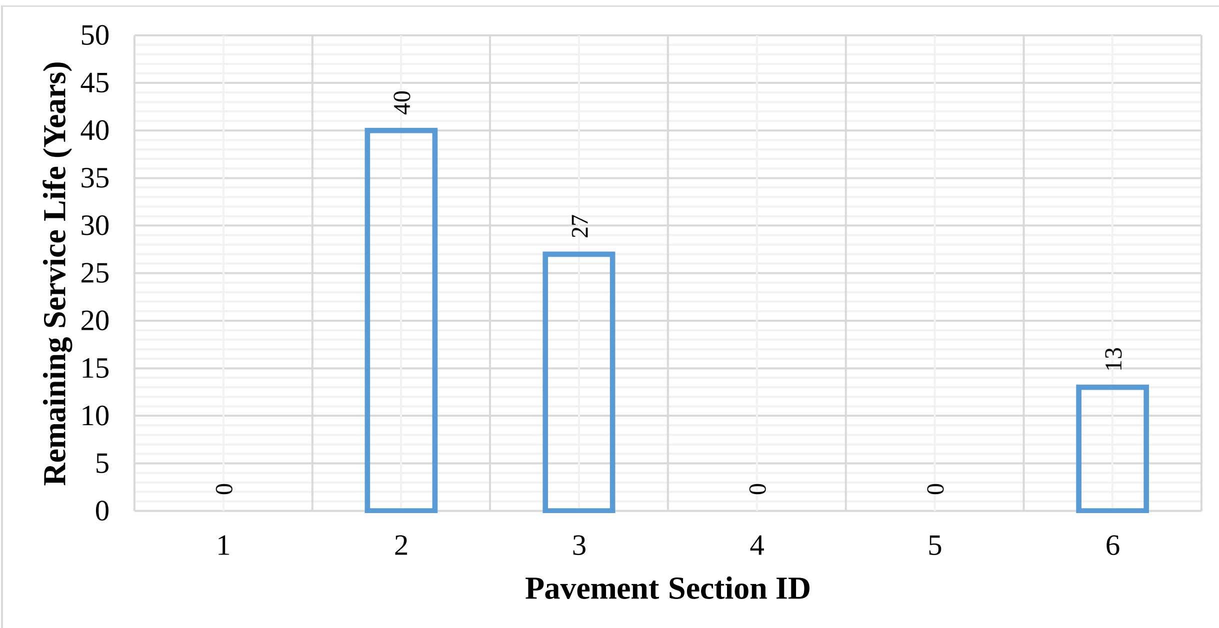
The IRI prediction equation used to generate the results shown in Figure 45 is as follows:

$$IRI = 30.00 + \frac{146.98}{1 + e^{(19.93 - 0.67 \times age)}}$$

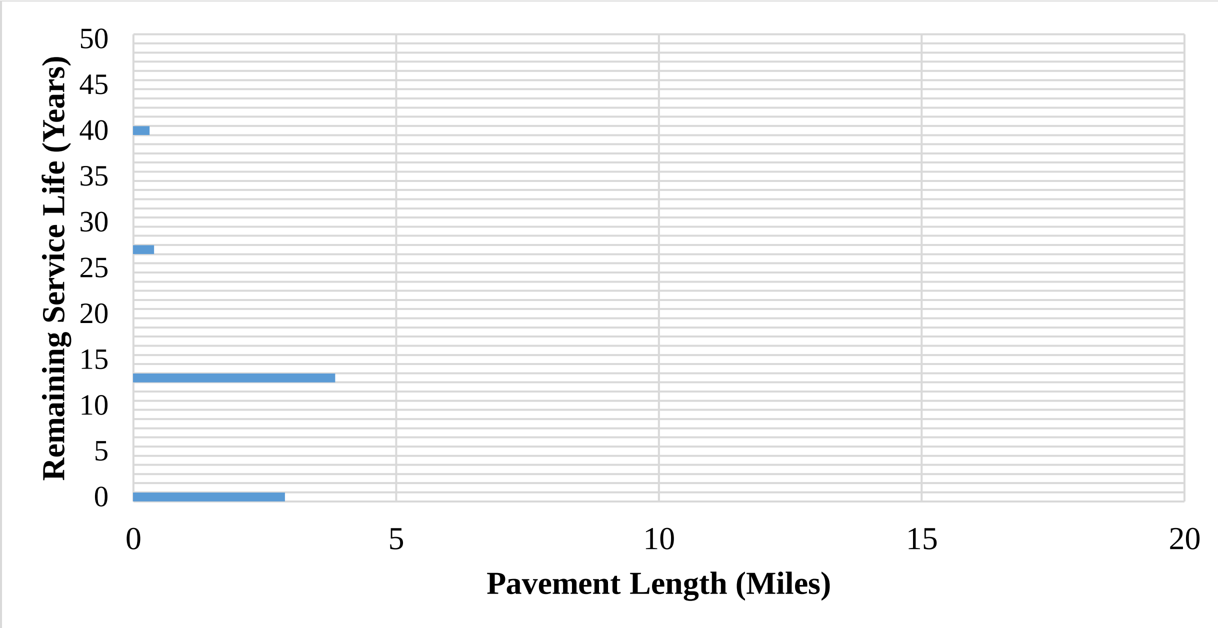
The AADT in 2014 for this section of Augusta Road, also called County Highway X38, from County Highway J48 southbound to Business US 61, was 420, and the section was constructed in 1981.

While the sigmoidal curve-fitting models developed for measuring PCI values can also be utilized for county pavement systems so long as previous PCI values are provided, the HPD developed for Iowa county pavements does not include PCI values for county roads. A developed Microsoft Excel macro-based automation tool was therefore used to predict IRI and PCI values for county pavement systems, and as more county road data were added into the model, the model accuracy increased.

After predicting county roads' future pavement performance, the RSLs of these roads can be calculated by considering the threshold limits of pavement performance indicators. As mentioned earlier in this report, IRI was chosen as a critical performance indicator of pavements for RSL calculations because the FHWA had used it and adopted it as a standard for the Highway Performance Monitoring System (HPMIS) as a primary indicator of functional performance of pavement systems (Visintine et al. 2018, Miller and Bellinger 2014). Using 170 in./mi as a threshold value recommended by the FHWA (Visintine et al. 2018), the RSL of a county pavement section can be calculated by following the steps previously presented in Figure 10 in Chapter 3. Based on the RSL calculation, Figure 46 shows the distribution of RSL for county JPCP sections. The average RSL for county JPCP sections in Lee County was found to be 13.3 years.



(a) Based on pavement section ID



(b) Based on pavement length

Figure 46. RSL distribution for JPCP pavement sections in Lee County

ANN-Based JPCP Performance Models and RSL Models

AI-based pavement performance models were used for evaluating county pavement performance in this study. As mentioned in earlier sections in this report, AI-based ANN models have previously been utilized for complex pavement engineering problems and found to be useful and fast tools for a variety of pavement cases. This section describes the ANN-based pavement performance models developed in this study for predicting each distress and condition for JPCPs. As previously shown in Figure 33, the second step was to validate the existing ANN models developed using the PMIS database in the first stage of this study, and if those previous models were not validated by using the HPD, new ANN models were developed utilizing the PMIS database but with a new input configuration chosen based on the available data in the HPD, as indicated previously in Figure 33 in the step 2b.

In this section, ANN-based pavement performance models for each performance indicator were validated or improved for county JPCP sections. The performance indicators were determined to be transverse cracking and IRI for concrete pavement. While the PMIS database was utilized for model development, PMIS and HPD databases were used to independently test the developed models. The study used 80% of the JPCP data points in the PMIS database in model development and used the remaining 20% for independent model testing. Model development included training, validation, and testing data sets created using 60%, 30%, and 10% of the model development data set, respectively.

The study used 34 rigid pavement sections composed of 396 data points for each pavement performance indicator to develop three different ANN models: transverse cracking, IRI approach

1, and IRI approach 2. It used 190, 95, 32, and 79 data points from the PMIS database in training, validation, testing, and independent testing, respectively. Additionally, 17 and 6 county JPCP sections with 102 and 36 data points were used for independently testing ANN-based transverse cracking model and IRI approaches 1 and 2 models, respectively.

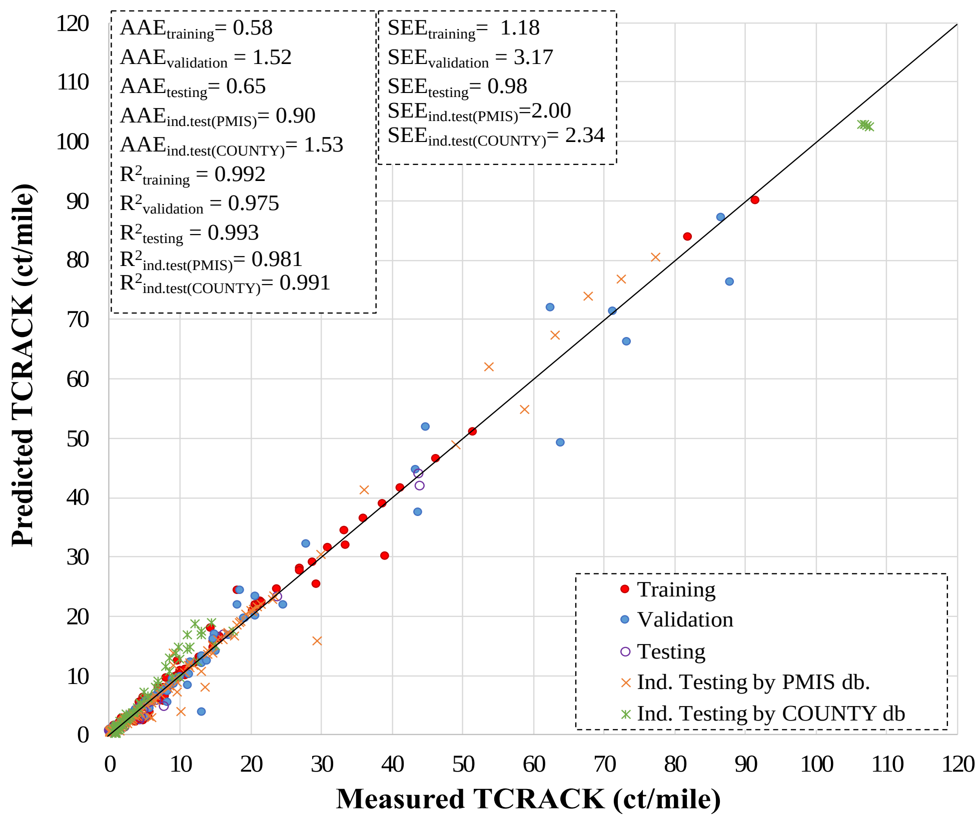
As seen in Table 12, PCC slab thickness, traffic (accumulated AADT), pavement age, and a pavement performance feature ratio along with the previous two years of measured IRI data were chosen as inputs in model development to obtain transverse cracking as an output.

Table 12. Parameters for three ANN models' development for JPCP sections

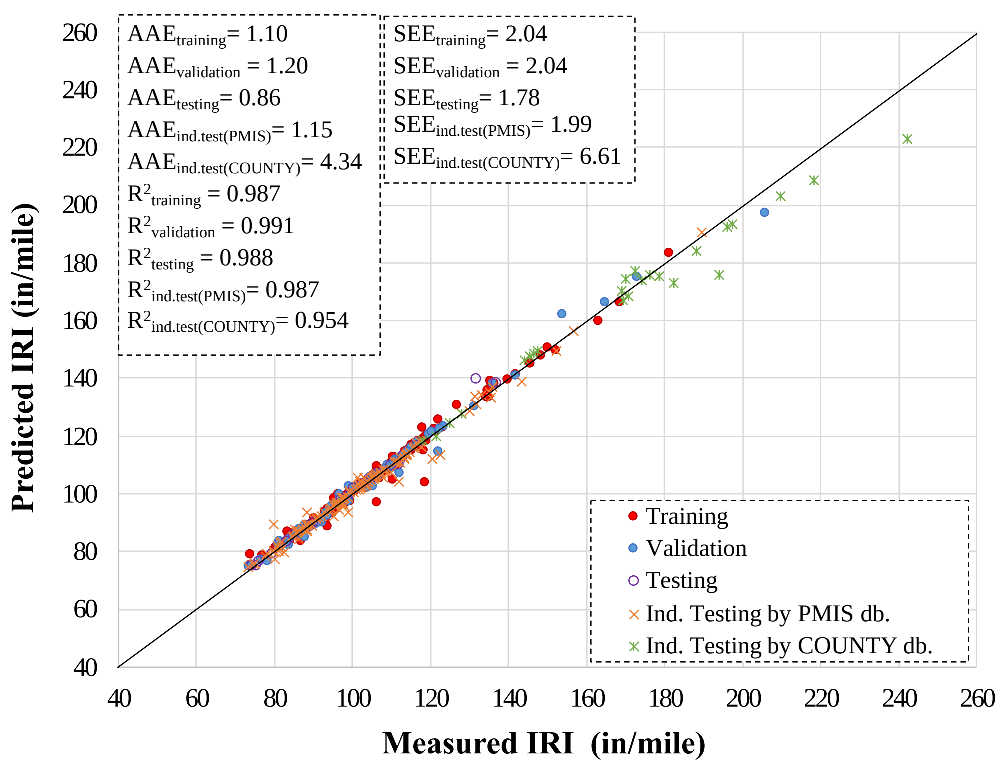
Model name	Input parameters	Output parameter
Transverse cracking	PCC thickness (in.), traffic (accumulated AADT), age, transverse cracking $_{(i-2)\ year}$ (ct./mi)/thickness (in.), transverse cracking $_{(i-1)\ year}$ (ct./mi)/thickness (in.)	Transverse cracking $_{(i)\ year}$ (ct./mi)
IRI approach 1	PCC thickness (in.), traffic (accumulated AADT), age, IRI $_{(i-2)\ year}$ (in./mi), IRI $_{(i-1)\ year}$ (in./mi)	IRI $_{(i)\ year}$ (in./mi)
IRI approach 2	Age, transverse cracking $_{(i)\ year}$ (ct./mi)/age, IRI $_{(i-2)\ year}$ (in./mi), IRI $_{(i-1)\ year}$ (in./mi)	IRI $_{(i)\ year}$ (in./mi)

Here, a pavement performance feature ratio was the proportion of transverse cracking in units of count per mile to slab thickness. The reason for using such a ratio in this part of the study was that county JPCP roads reflected sensitivity to the amount of transverse cracking associated with PCC slab thickness. Also, accumulated AADT instead of ESAL was used as the traffic input because of the availability of AADT data for county roads. Pavement age was updated based on the existence of an overlay through the service life. The input parameters of the IRI approach 1 model were similar to the transverse cracking model except for the pavement performance feature ratio, where the previous two years of IRI values were used instead. Unlike the IRI approach 1 model, in IRI approach 2, another pavement performance feature ratio of traffic and thickness records was used to predict IRI values. This ratio is the proportion of transverse cracking in a unit of count/mile, and it can be obtained from another ANN model reflecting pavement age. It was found here that the association of transverse cracking with pavement age affected future IRI predictions.

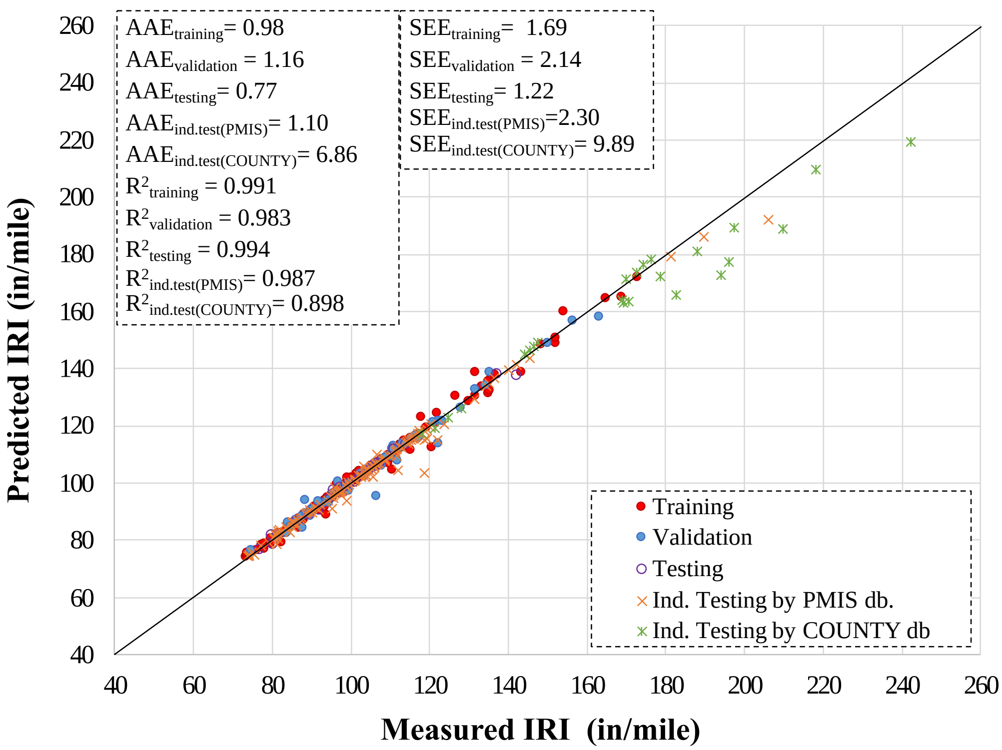
Figure 47a–c compares transverse cracking and IRI measured in the field to that predicted by the ANN models of (a) transverse cracking, (b) IRI approach 1, and (c) IRI approach 2.



(a) Transverse cracking



(b) IRI approach 1



(c) IRI approach 2

Figure 47. Measured pavement condition records vs. ANN model predictions

While the ANN models accurately predicted corresponding pavement performance indicators, the transverse cracking model produced slightly more accurate predictions than the IRI models as reflected in their higher average R^2 and lower AAE values. While IRI models developed using approach 1 and approach 2 produced similar accuracy in model development, IRI approach 1 resulted in better results for independently testing PMIS and county databases than IRI approach 2. In all cases, high R^2 and low AAE values were obtained for all training, testing, validation, and independent testing data sets.

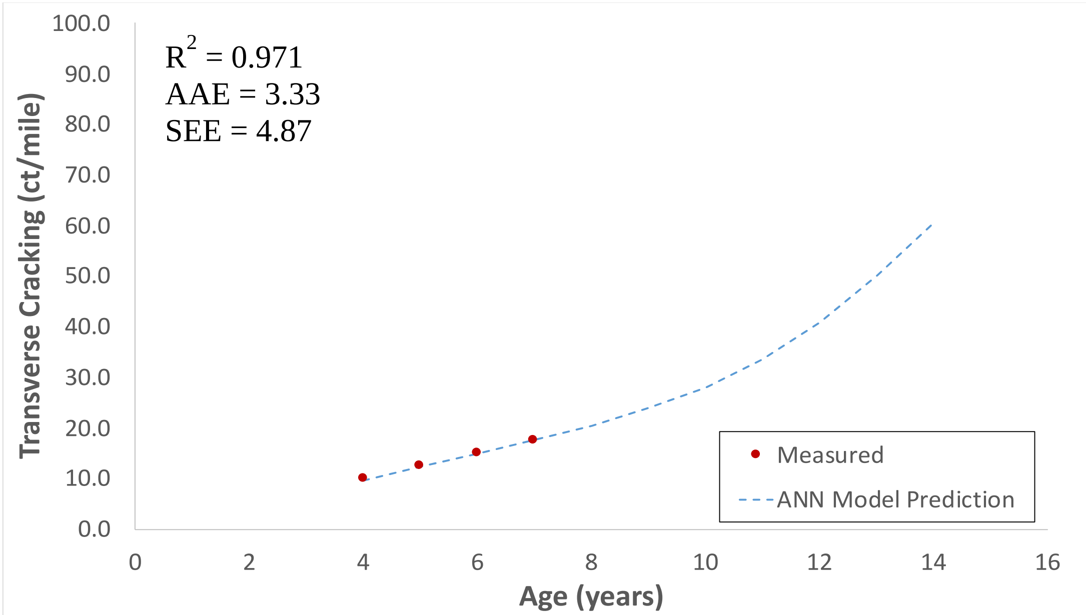
Table 13 presents all limitations of ANN models developed using the PMIS database and measured data of county roads used in independent testing of ANN models.

Table 13. Limitations of PMIS database used in ANN model development and county road database used in testing ANN models for JPCP sections

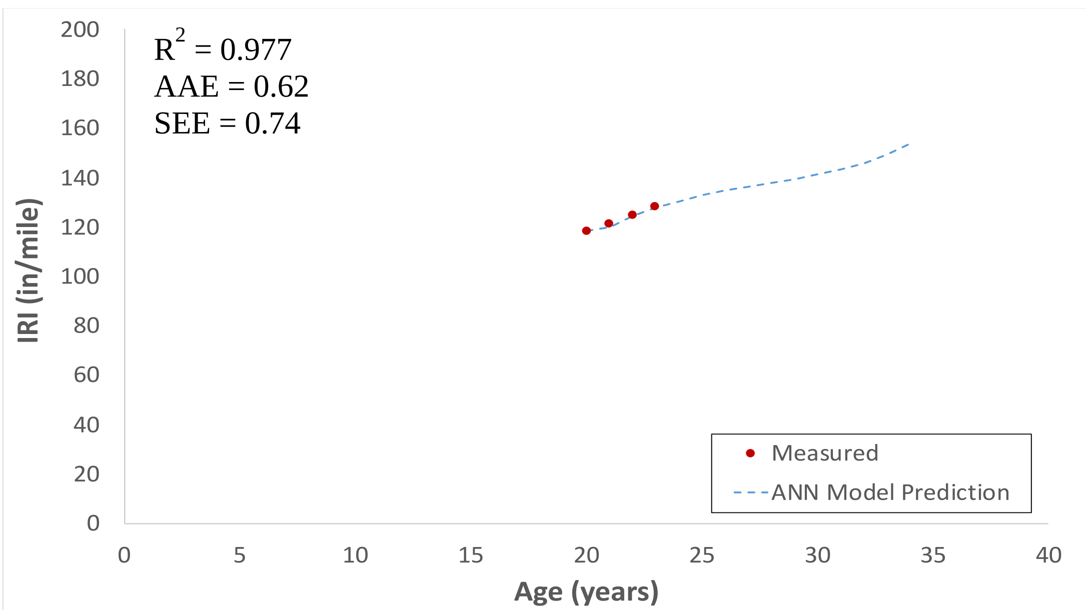
Transverse cracking	ANN model limitations (from PMIS database)		Measured data limitations (from COUNTY database)	
	Min	**Max**	**Min**	**Max**
PCC thickness (in.)	9	13	7	10
Traffic (accumulated AADT)	8,720	973,800	523	44,300
Pavement age (yr)	2	23	4	90
Transverse cracking $_{(i\text{-}2)\ year}$ (ct./mi)/thickness (in.)	0.0	8.7	0.0	49.6
Transverse cracking $_{(i\text{-}1)\ year}$ (ct./mi)/thickness (in.)	0.0	9.2	0.0	58.7
IRI approach 1				
PCC thickness (in.)	9	13	7	10
Traffic (accumulated AADT)	8,720	973,800	505	44,300
Pavement age (yr)	2	23	4	90
IRI $_{(i\text{-}2)\ year}$ (in./mi)	67.8	181.2	114.2	193.9
IRI $_{(i\text{-}1)\ year}$ (in./mi)	73.3	189.5	116.1	218.1
IRI approach 2				
Pavement age (yr)	2	23	4	90
Transverse cracking $_{(i)\ year}$ (ct./mi)/age	0.0	14.5	0.0	5.3
IRI $_{(i\text{-}2)\ year}$ (in./mi)	64.0	156.5	114.2	194.0
IRI $_{(i\text{-}1)\ year}$ (in./mi)	73.1	164.7	116.1	218.1

Since the range of collected data for county roads is entirely different than those for the PMIS database, the tested data limitations might fall outside of model limitations that affect the accuracy shown in Figure 47 of the independent testing for county roads. Table 13 also points to the reasons for using pavement performance feature ratios as inputs. The ratio of transverse cracking to thickness used in the transverse cracking ANN model ranged from 0 to 8.7 in model development and from 0 to 49.6 in the County Records database. If the pavement section with the highest amount of transverse cracking had not been considered, the maximum ratio in the County Records database would be 12.6. It is clear that county pavement conditions differ even from one another based on transverse cracking. Also, since pavement sections with the same thickness of 7 in. could have the highest and lowest transverse cracking, using the relationship between transverse cracking and thickness produced high accuracies in model development and independent testing, with high R^2 and low AAE and SEE.

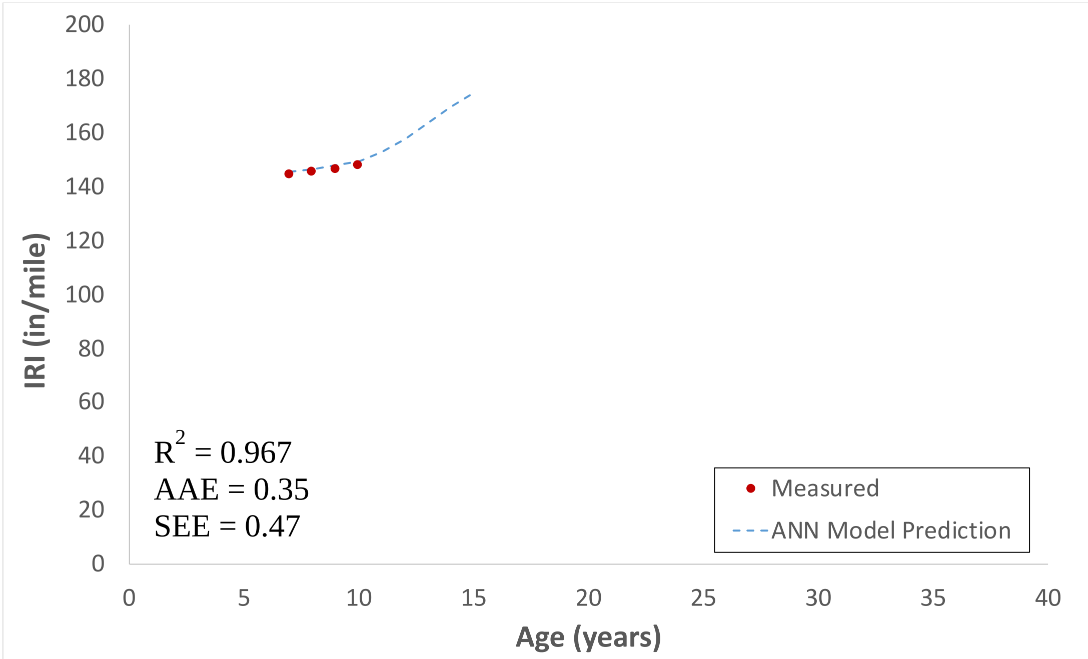
Figure 48 shows comparisons of the measured pavement condition records both with the ones predicted by ANN models and future pavement condition predictions for RSL purposes.



(a) Transverse cracking



(b) IRI approach 1

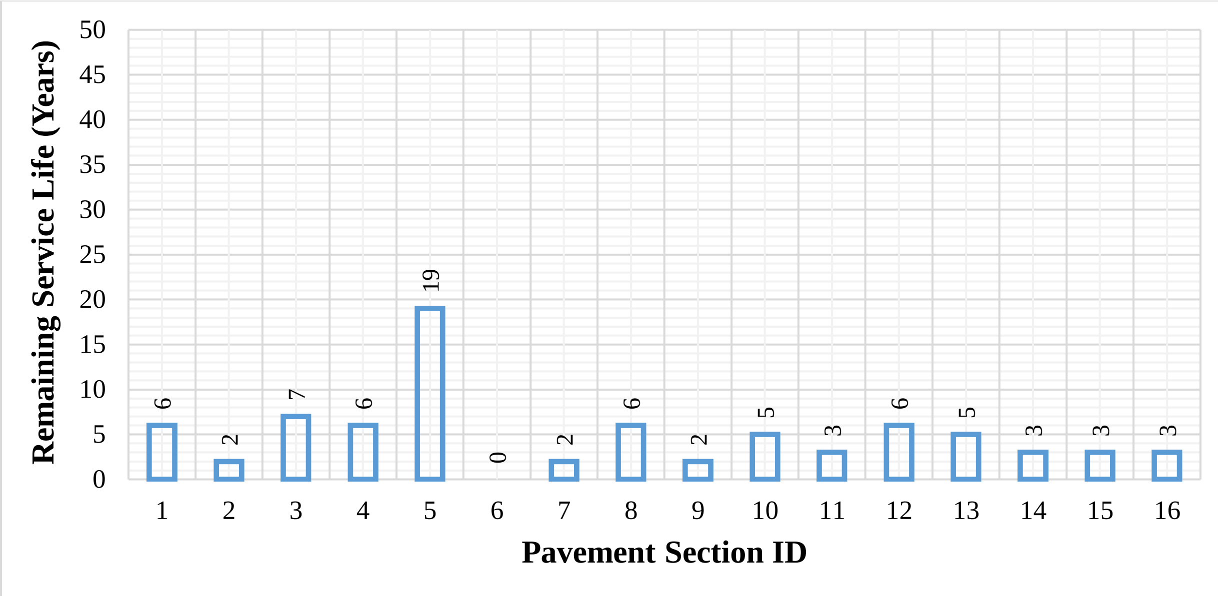


(c) IRI approach 2

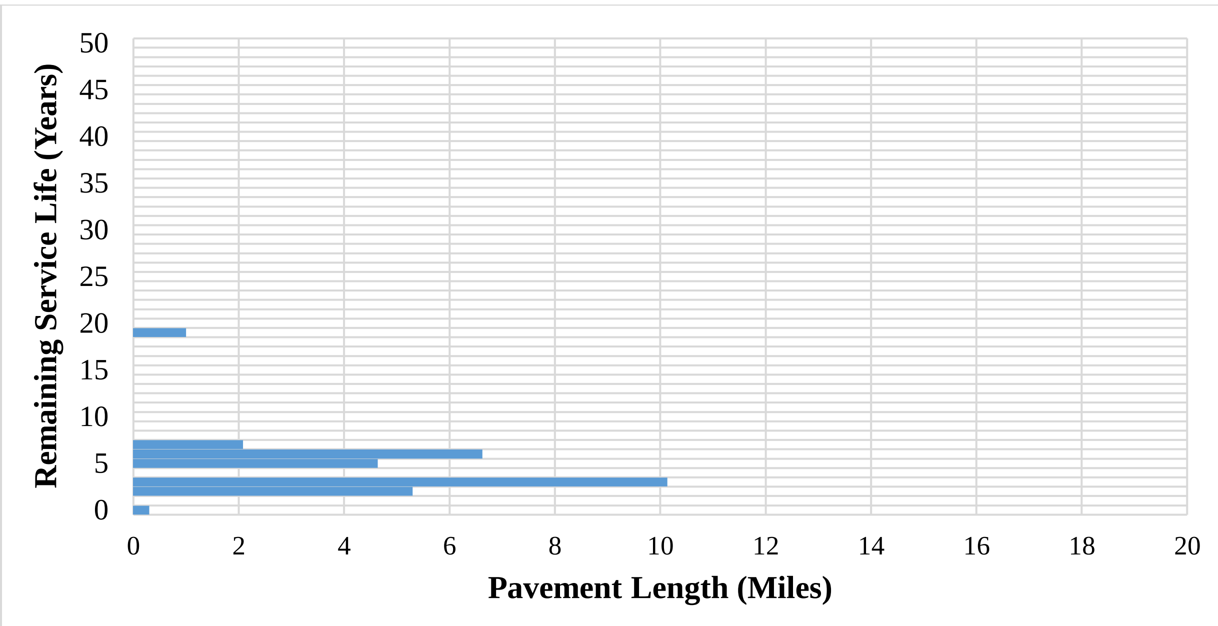
Figure 48. Measured pavement condition records vs. ANN model predictions for sample JPCP sections

Figure 48a shows the transverse cracking model results for the section of 233rd Street, with an AADT in 2014 of 210 and a construction year of 2011. Figure 48b shows the IRI approach 1 results for the section of Wirtz Lane, with an AADT in 2014 of 170 and a construction year of 1995. Figure 48c shows the IRI approach 2 results for the section of Croton Road, also called County Highway J62, with an AADT in 2014 of 170 and a construction year of 2008.

Once ANN models for predicting the performance of county JPCP sections had been developed, their RSLs could be calculated using these ANN models and corresponding threshold limits for pavement performance indicators such as the transverse cracking and IRI used here. Figure 49 through Figure 51 show RSL distributions using ANN-based transverse cracking model, IRI approach 1, and IRI approach 2 models, respectively, based on pavement ID and pavement length for county JPCP sections, with the threshold value for transverse cracking in Figure 49a taken as 15% slab cracking.

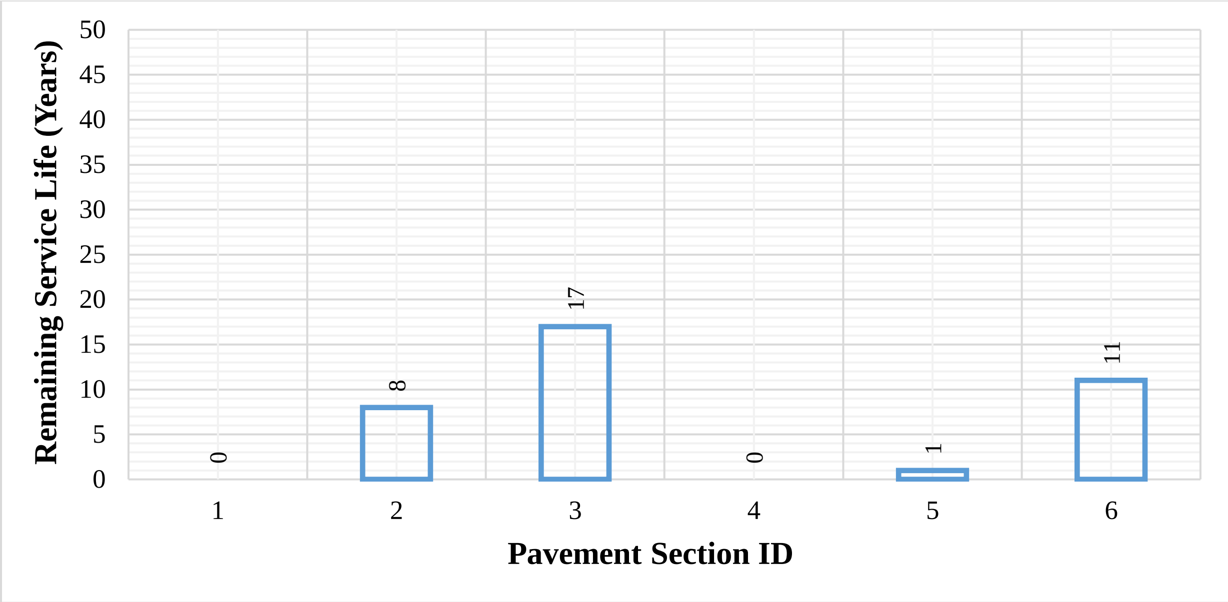


(a) Based on pavement section ID

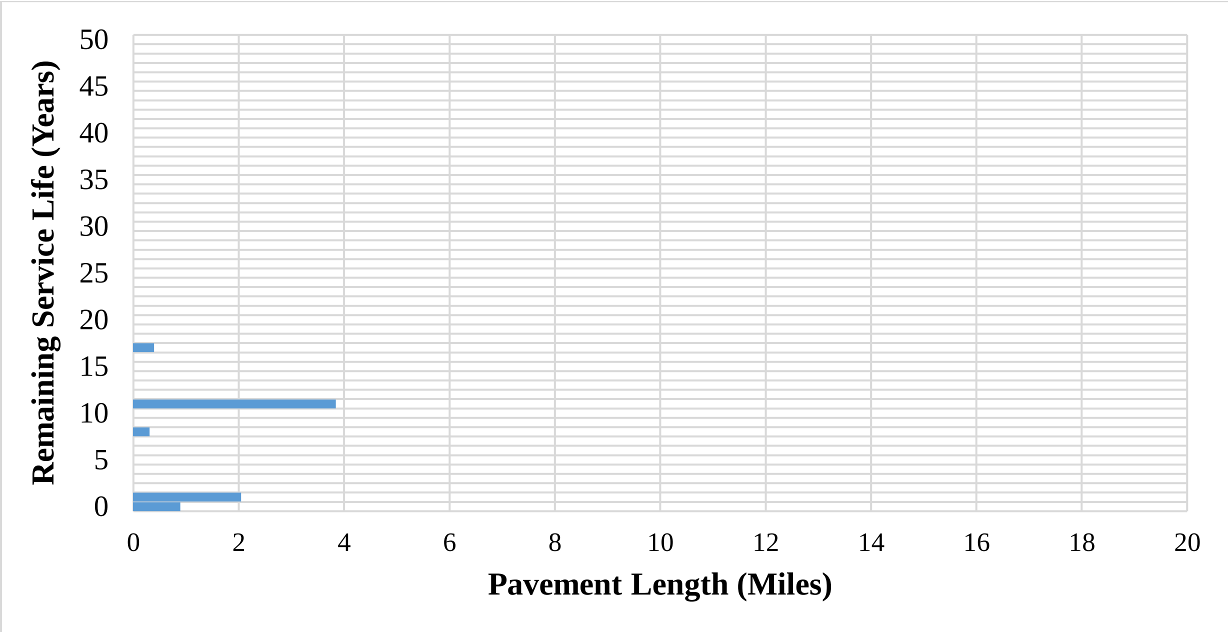


(b) Based on pavement length

Figure 49. RSL distributions using transverse cracking ANN models for rigid pavement

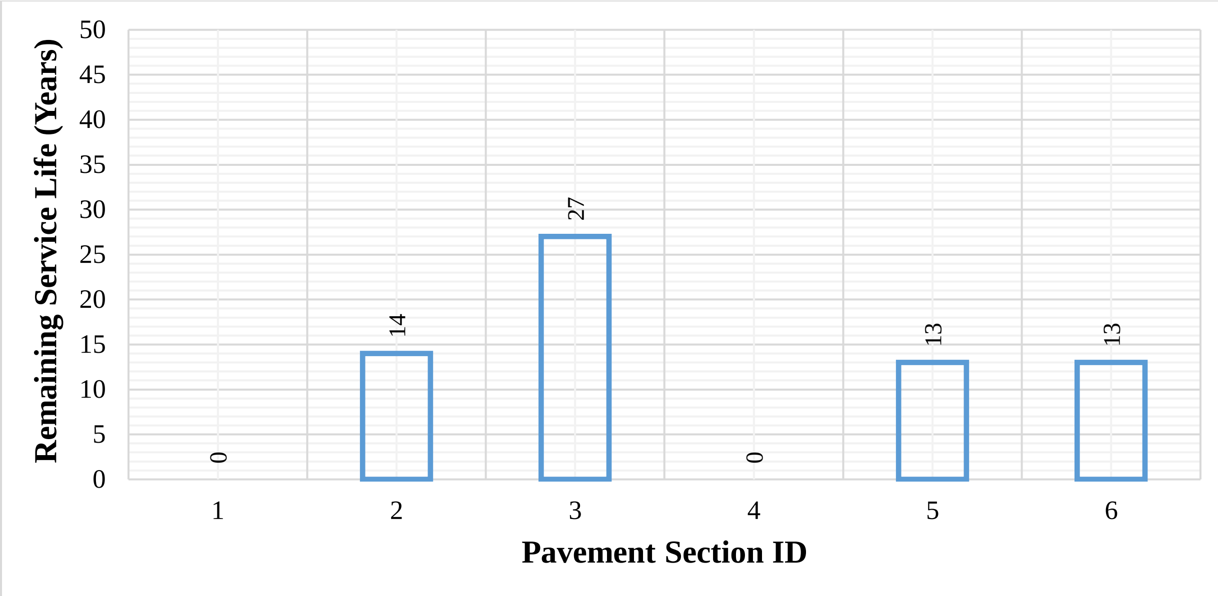


(a) Based on pavement section ID

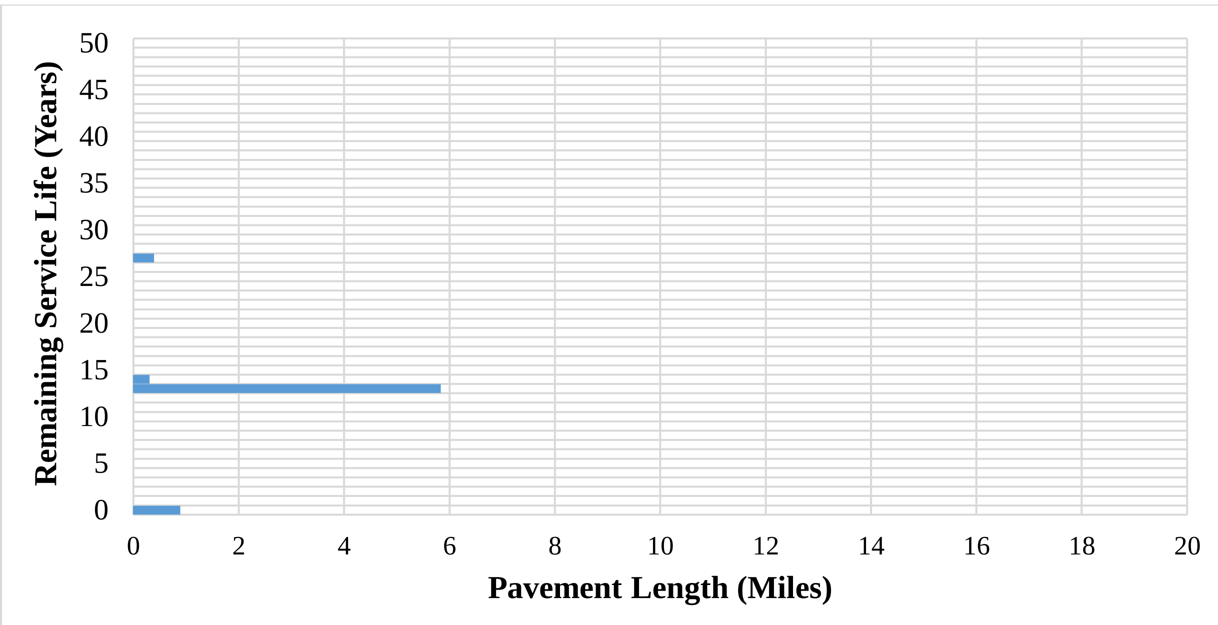


(b) Based on pavement length

Figure 50. RSL distributions using IRI approach 1 ANN models for rigid pavement



(a) Based on pavement section ID



(b) Based on pavement length

Figure 51. RSL distributions using IRI approach 2 ANN models for rigid pavement

The unit of count/mile in ANN predictions could be converted to percent cracking in RSL calculations. Since county JPCP sections have exhibited high IRI values, a threshold value for the JPCP section was considered to be 200 in./mi, although the 170 in./mi value recommended by the FHWA (Visintine et al. 2018) had been considered a threshold value for IRI for the rest of the study. The average RSL values for county JPCP sections in Lee County were found to be about 4.9, 6.2, and 11.2 years using the ANN-based transverse cracking, IRI approach 1, and IRI approach 2 models, respectively.

In summary, different approximate RSL values (13.3, 6.2, and 11.2 years) for county JPCP sections were found when a statistical-based model and ANN-based IRI approach 1 and 2 models, respectively, were used in calculation of RSL, and this difference might be due to using different performance models. Although different pavement performance models for each type of pavement performance indicator were developed using the ANN approach, a single model for RSL was used to predict future pavement condition and distress values for all pavement sections of a given pavement type. While the ANN-based models also consider the various input parameters presented previously in Table 12, there might be other factors affecting the deterioration of the pavement systems that were not considered in the models. Since the county database suffers from being created with less collected field data and a lack of historical records for some pavement sections, the missing data points had to be statistically populated, and this might decrease the model accuracies when comparing to real field data in the models.

The statistical-based models were developed for each pavement section, and considering the situation of insufficient pavement condition records, the model using them might have less accurate results, adding more field data into the models would in all likelihood increase model accuracies for future performance measurements. Overall, engineers should consider every parameter that could be used as an input into models to determine the best pavement performance model (i.e., statistical-based or ANN-based) for use in predicting the RSL of pavements. If there is less consecutive condition/distress data but a greater number of various input parameters (e.g., thickness, traffic), one might think of using ANN-based models. In the case of having a sufficient number of pavement performance records (i.e., IRI), the statistical-based models might be used to predict future pavement performance because of their better reflectivity when using a greater amount of real field data.

Iowa County AC Pavement Case

Statistical-Based AC Pavement Performance Models and RSL Models

A statistically defined sigmoid pavement deterioration curve-based approach was utilized for IRI and PCI calculations for county ACs in Iowa. The same procedure for project-level pavement performance model development used in the first stage of the project was followed for developing the sigmoidal equations. For IRI calculation, the previously given equation 4 can be used to generalize the sigmoidal equation, where C1, C2, C3, and C4 indicate coefficients representing different input parameters' contributions. For PCI calculation, the previously given equation 5 can be used to generalize the sigmoidal equation, where C and D indicate coefficients representing contributions of different input parameters. The sigmoidal curve-fitting to measure IRI values was carried out by minimizing the error, i.e., the square of differences between the target and predicted IRI values.

Figure 52 and Figure 53 show some examples of IRI prediction models for county ACs that can predict future IRI values for these road sections.

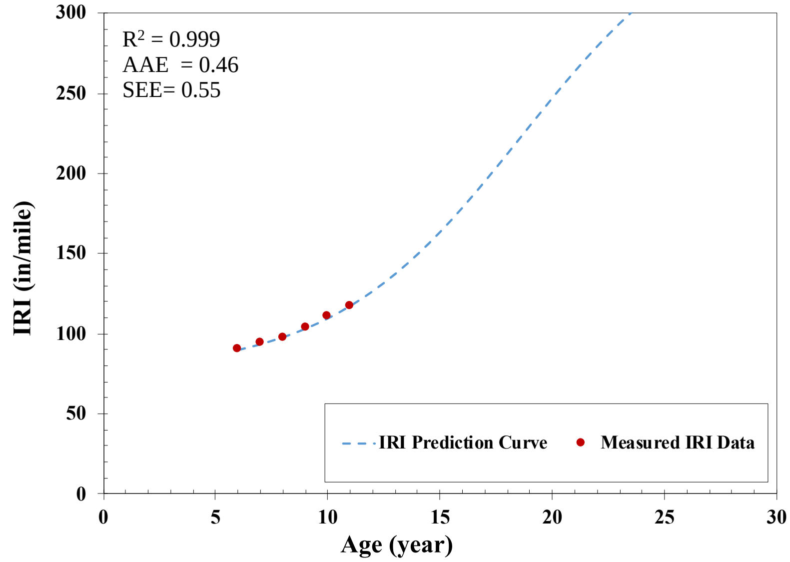
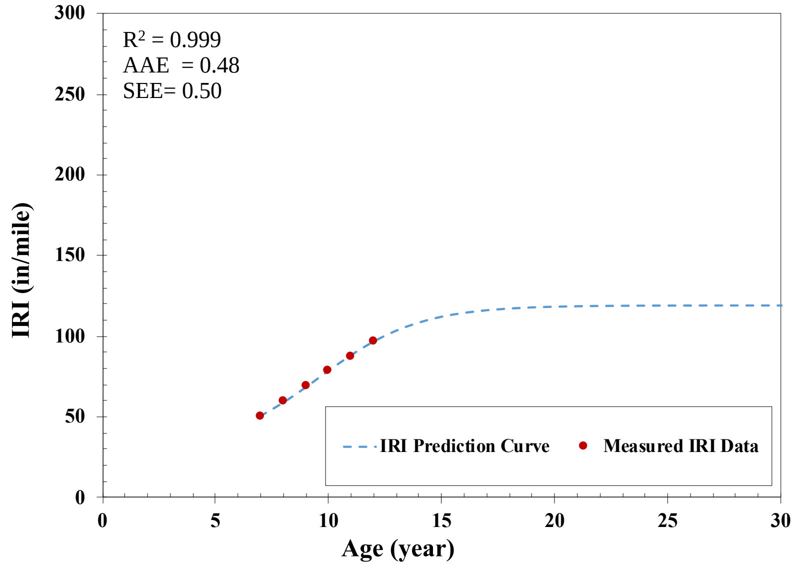


Figure 52. Statistical-based IRI prediction model results for Charleston Road AC section

The equation used to generate the results in Figure 52 is as follows:

$$IRI = 76.09 + \frac{295.60}{1 + e^{(4.41 - 0.24 \times age)}}$$

The AADT in 2014 for the section of Charleston Road, also called County Highway J62 and 255th Street, was 1,310, and the section was constructed 1976, with an overlay in 2007.



(b)

Figure 53. Statistical-based IRI prediction model results for J40 AC section

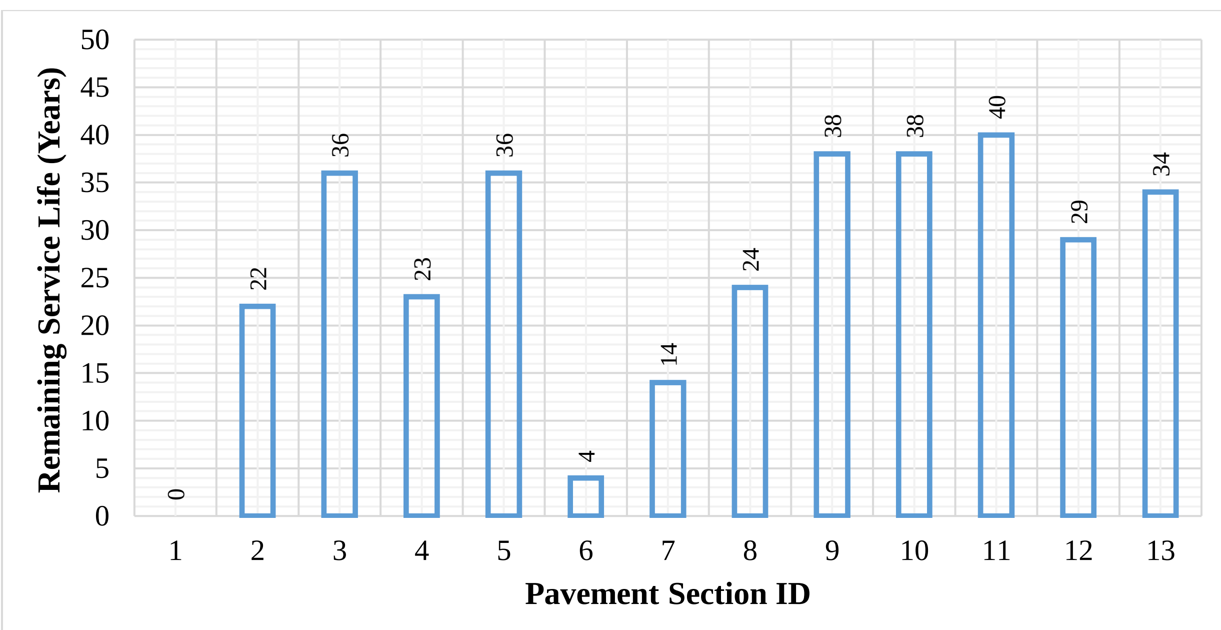
The equation used to generate the results in Figure 53 is as follows:

$$IRI = 30.00 + \frac{88.82}{1 + e^{(4.37 - 0.46 \times age)}}$$

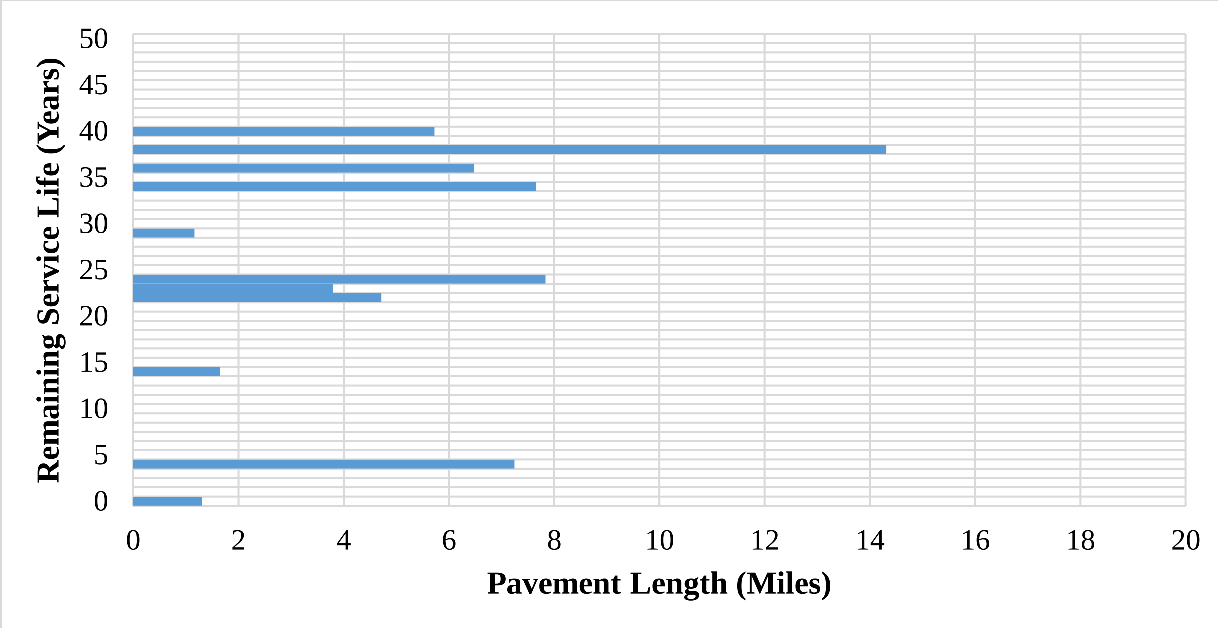
The AADT in 2014 for the section of County Highway J40, from US 218 to Fort Madison, was 2,200, and the section was constructed in 1985, with an overlay in 2006.

The sigmoidal curve-fitting models developed for measuring PCI values can also be utilized for county pavement systems as long as previous PCI values are available, but the HPD developed for Iowa county pavements does not include PCI values for county roads. Therefore, a Microsoft Excel macro-based automation tool was developed to predict IRI and PCI values for county pavement systems. As more county road data were added into the models, their accuracy increased.

After predicting future pavement performance of county roads, their RSLs could be calculated by considering threshold limits of pavement performance indicators, as presented in the previous sections. IRI was chosen as a critical performance indicator of pavement for RSL calculations since it is used by the FHWA and has been adopted as a standard for HPMIS as a primary indicator of functional performance of pavement systems (Visintine et al. 2018, Miller and Bellinger 2014), as mentioned earlier in this report. Using 170 in./mi, the threshold value recommended by the FHWA (Visintine et al. 2018), the RSL of a county pavement section can be calculated by following the steps previously presented in Figure 10 in Chapter 3. Based on RSL calculation, Figure 54 indicates the distribution of RSL for county AC sections. The average RSL for county AC sections in Lee County was found to be 26 years.



(a) Based on pavement section ID



(b) Based on pavement length

Figure 54. RSL distribution for AC pavement sections in Lee County

ANN-Based AC Pavement Performance Models and RSL Models

AI-based pavement performance models were also used for evaluating county pavement performance in this study, and this section presents the developed ANN-based pavement performance models for predicting each distress and condition for ACs. As indicated previously in Figure 33, the second step is to validate the existing ANN models developed using the PMIS database from the first stage of this study. If we suppose previous ANN models have not been validated using the HPD, new ANN models can be developed by utilizing the PMIS database but with a new input configuration based on the available data in the HPD, as indicated in Figure 33 in step 2b.

This section discusses the ANN-based pavement performance model for each performance indicator that was validated or improved for county AC sections. These performance indicators for flexible pavement were determined for rutting, longitudinal cracking, transverse cracking, and IRI. While the PMIS database was utilized for model development, both the PMIS and HPD databases were utilized for independent testing of developed models. The study used 80% of AC data points in the PMIS database in model development, and the remaining 20% were used to test the model independently. Model development included training, validation, and testing data sets created using 60%, 30%, and 10% of the model development data set, respectively.

The study used 35 flexible pavement sections composed of 360 data points for each pavement performance indicator to develop five different ANN models for rutting, longitudinal cracking, transverse cracking, IRI approach 1, and IRI approach 2. The study used 172, 30, 86, and 72 data points from the PMIS database in training, validation, testing, and independent testing, respectively. It used 16, 10, and 6 county AC sections with 96, 60, and 78 data points for independently testing ANN-based models for longitudinal cracking and transverse cracking, rutting, IRI approach 1, and IRI approach 2 models, respectively.

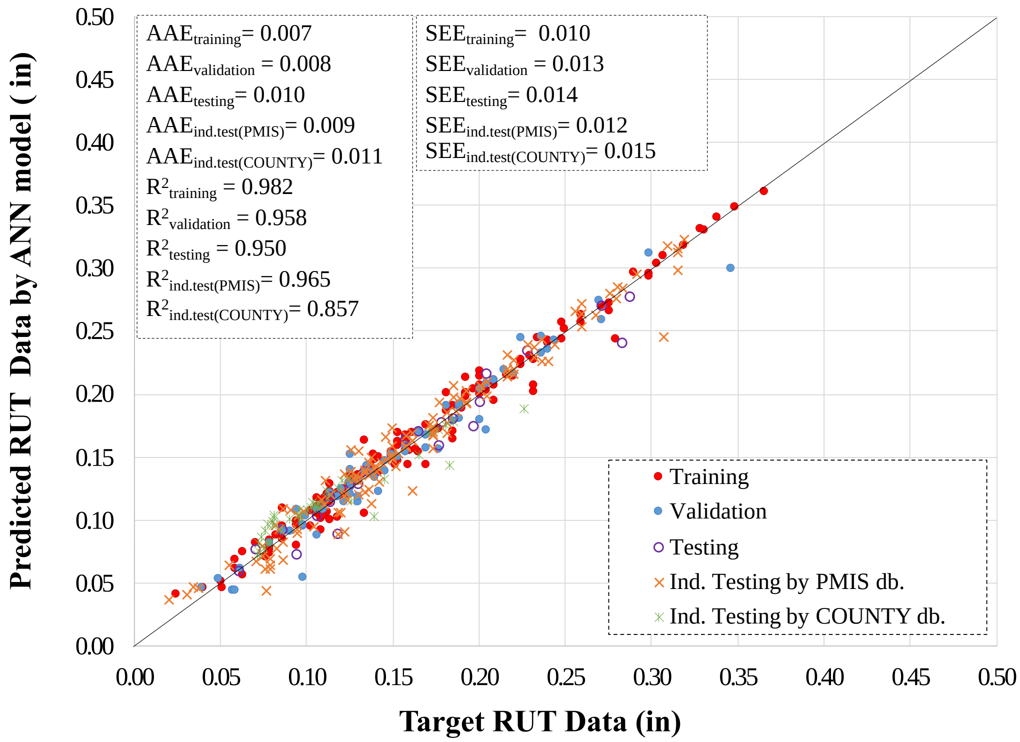
As seen in Table 14, AC slab thickness, traffic (accumulated AADT), pavement age, and pavement performance values over the previous consecutive two years were chosen as inputs in model development to obtain rutting, longitudinal cracking, transverse cracking, and IRI approach 1 as output.

Table 14. Parameters for five ANN models' development for flexible pavements

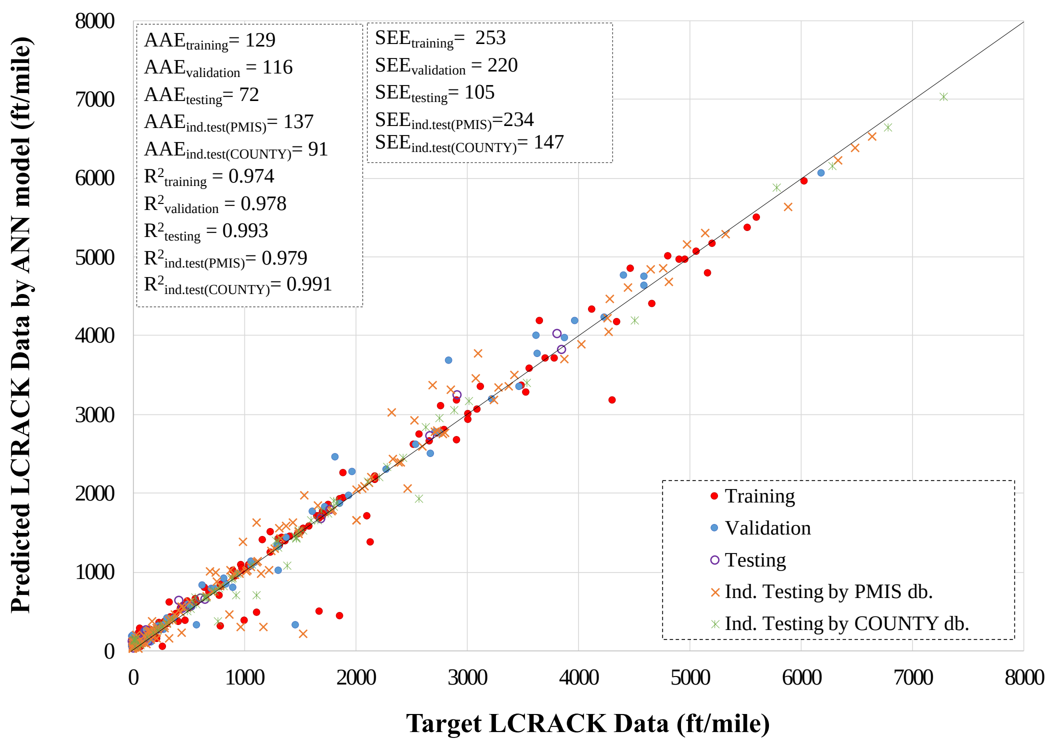
Model name	Input parameters	Output parameter
Rutting	AC thickness (in.), traffic (accumulated AADT), age, rut $_{(i-2)\ year}$ (in.), rut $_{(i-1)\ year}$ (in.)	Rut $_{(i)\ year}$ (in.)
Longitudinal cracking	AC thickness (in.), traffic (accumulated AADT), age, longitudinal cracking $_{(i-2)\ year}$ (ft/mi), longitudinal cracking $_{(i-1)\ year}$ (ft/mi)	Longitudinal cracking $_{(i)\ year}$ (ft/mi)
Transverse cracking	AC thickness (in.), traffic (accumulated AADT), age, transverse cracking $_{(i-2)\ year}$ (ft/mi), transverse cracking $_{(i-1)\ year}$ (ft/mi)	Transverse cracking $_{(i)\ year}$ (ft/mi)
IRI approach 1	AC thickness (in.), traffic (accumulated AADT), age, IRI $_{(i-2)\ year}$ (in./mi),, IRI $_{(i-1)\ year}$ (in./mi)	IRI $_{(i)\ year}$ (in./mi)
IRI approach 2	Age, rut $_{(i)\ year}$ (in.), longitudinal cracking $_{(i)\ year}$ (ft/mi), transverse cracking $_{(i)\ year}$ (ft/mi), IRI $_{(i-2)\ year}$ (in./mi), IRI $_{(i-1)\ year}$ (in./mi)	IRI $_{(i)\ year}$ (in./mi)

Here, accumulated AADT instead of ESAL was used as the traffic input because of the availability of AADT data for county roads. Pavement age was updated based on the existence of overlay through the service life. Compared to the IRI approach 1 model, in IRI approach 2, rutting, longitudinal cracking, and transverse cracking were used instead of traffic and thickness records to predict IRI values.

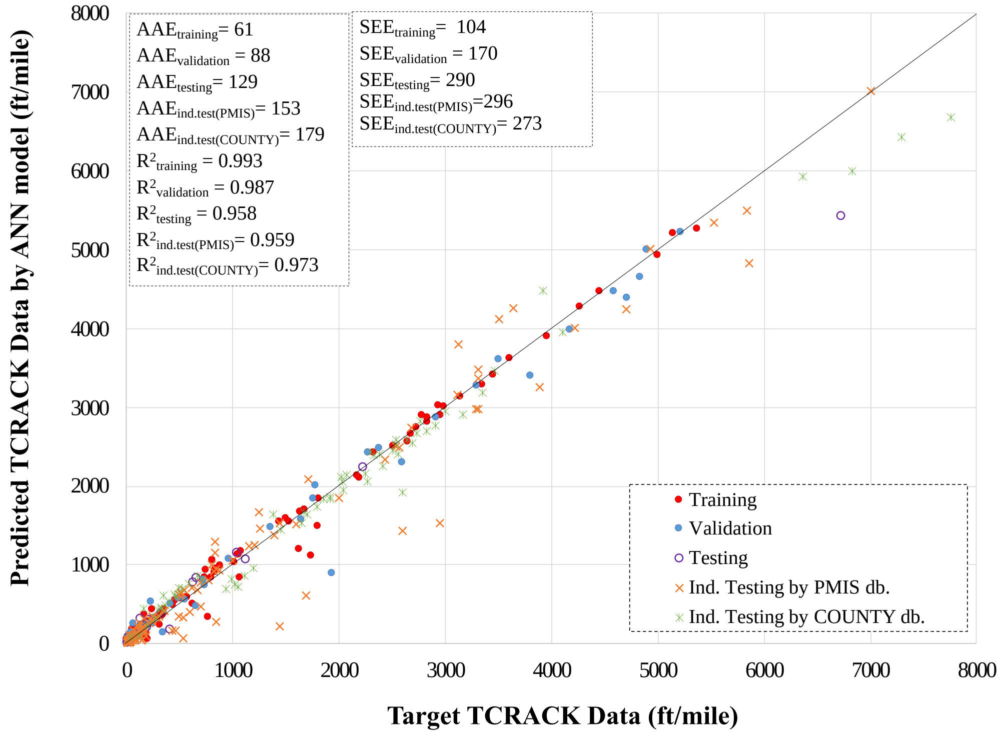
Figure 55a–e compares rutting, longitudinal cracking, transverse cracking, and IRI measured in the field to that predicted by ANN models of (a) rutting (b) longitudinal cracking, (c) transverse cracking, (d) IRI approach 1, and (e) IRI approach 2.



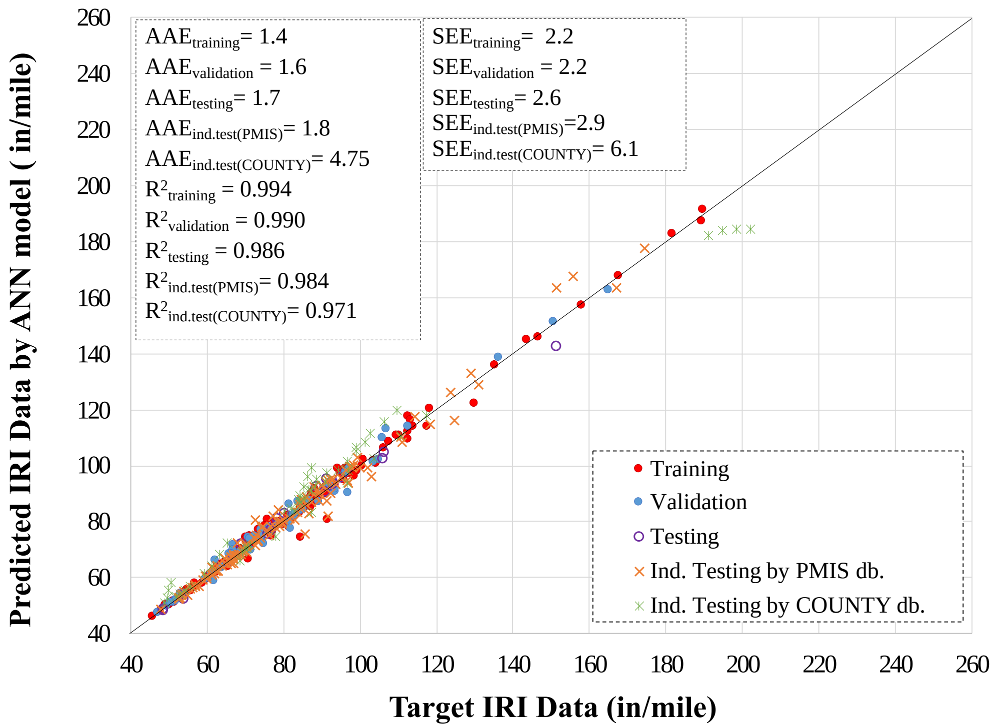
(a) Rutting



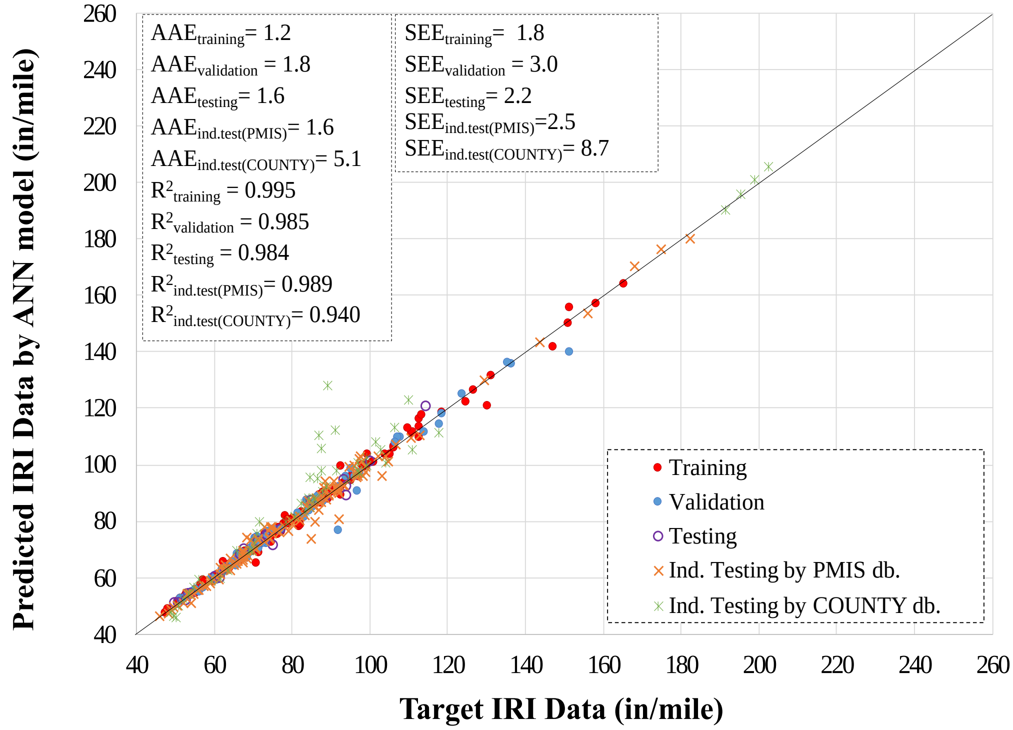
(b) Longitudinal cracking



(c) Transverse cracking



(d) IRI approach 1



(e) IRI approach 2

Figure 55. Measured pavement condition records vs. ANN model predictions

While the ANN models developed accurately predicted corresponding pavement performance indicators, the rutting model produced less accurate predictions based on their lower R^2 values for independent testing of county database than other types of distress models. IRI models developed using approach 1 produced slightly better accuracies than IRI approach 2. In all cases, high R^2 and low AAE values were obtained for all training, testing, validation, and independent testing data sets.

Table 15 lists all limitations of ANN models developed using the PMIS database and measured data of county roads used in independent testing of ANN models.

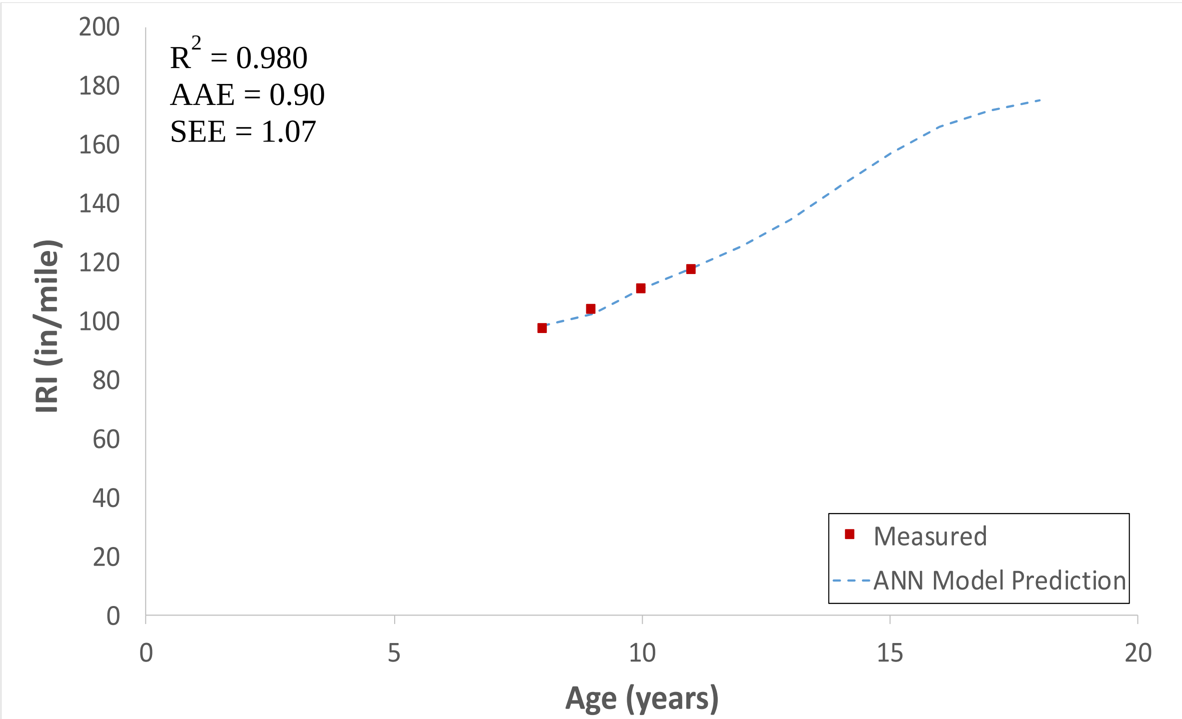
Table 15. Limitations of PMIS database used in ANN model development and county road database used in testing ANN models for AC sections

Rutting	ANN model limitations (from PMIS database)		Measured data limitations (from COUNTY database)	
	Min	**Max**	**Min**	**Max**
AC thickness (in.)	7.5	16.5	10	18
Traffic (accumulated AADT)	1,240	110,280	417.5	9,460
Pavement age (yr)	2	17	7	21
Rut $_{(i-2)\ year}$ (in.)	0	0.3307	0.0673	0.1760
Rut $_{(i-1)\ year}$ (in.)	0.0124	0.3484	0.0695	0.1829
Longitudinal cracking				
AC thickness (in.)	7.5	16.5	6.5	22.5
Traffic (accumulated AADT)	1,230	110,280	417.5	13,700
Pavement age (yr)	2	18	3	27
Longitudinal cracking $_{(i-2)\ year}$ (ft/mi)	0	5,889.8	0	6,286.3
Longitudinal cracking $_{(i-1)\ year}$ (ft/mi)	0.8	6,039.8	10.5	6,785.5
Transverse cracking				
AC thickness (in.)	7.5	16.5	6.5	22.5
Traffic (accumulated AADT)	1,010	110,280	417.5	13,700
Pavement age (yr)	2	18	3	27
Transverse cracking $_{(i-2)\ year}$ (ft/mi)	0	4,926.2	0	6,825
Transverse cracking $_{(i-1)\ year}$ (ft/mi)	1.6	5,149.5	20	7,290
IRI approach 1				
AC thickness (in.)	7.5	16.5	6.5	22.5
Traffic (accumulated AADT)	1,010	110,280	417.5	13,700
Pavement age (yr)	2	18	4	21
IRI $_{(i-2)\ year}$ (in./mi)	37.4	182.1	48.4	195.0
IRI $_{(i-1)\ year}$ (in./mi)	44.4	189.5	48.6	198.7
IRI approach 2				
Pavement age (yr)	2	17	4	21
Rut $_{(i)\ year}$ (in.)	0.0248	0.3661	0.0714	0.2264
Longitudinal cracking $_{(i)\ year}$ (ft/mi)	2.6	6,639.6	18.5	7,284.8
Transverse cracking $_{(i)\ year}$ (ft/mi)	3.9	7,001.3	160.0	7,755.0
IRI $_{(i-2)\ year}$ (in./mi)	44.5	182.1	48.4	195.0
IRI $_{(i-1)\ year}$ (in./mi)	45.9	189.5	48.6	198.7

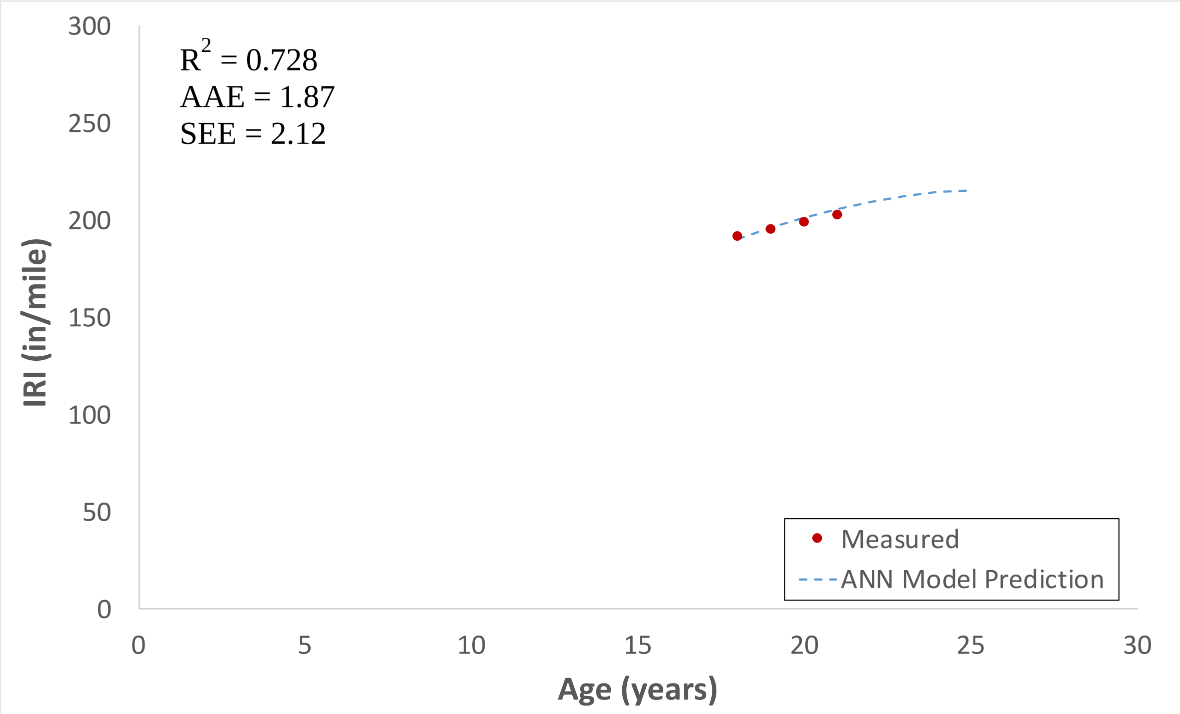
Since the range of collected data for county roads is completely different than that for the PMIS database, the tested data limitations might fall outside of model limitations and affect the accuracy of independent testing for the County Records database seen in Figure 55.

For example, for the ANN-based rutting model, comparing the range of accumulated AADT and pavement age between PMIS and county database, it can be seen that secondary roads have much less traffic and greater ages than primary roads, causing them to fall outside model limitations and resulting in less accuracy in independent testing. Likewise, the maximum values of parameters in the county database for the ANN-based IRI approach 2 model exceeded the model limitations for the PMIS database and that might cause loss of accuracy in model performance.

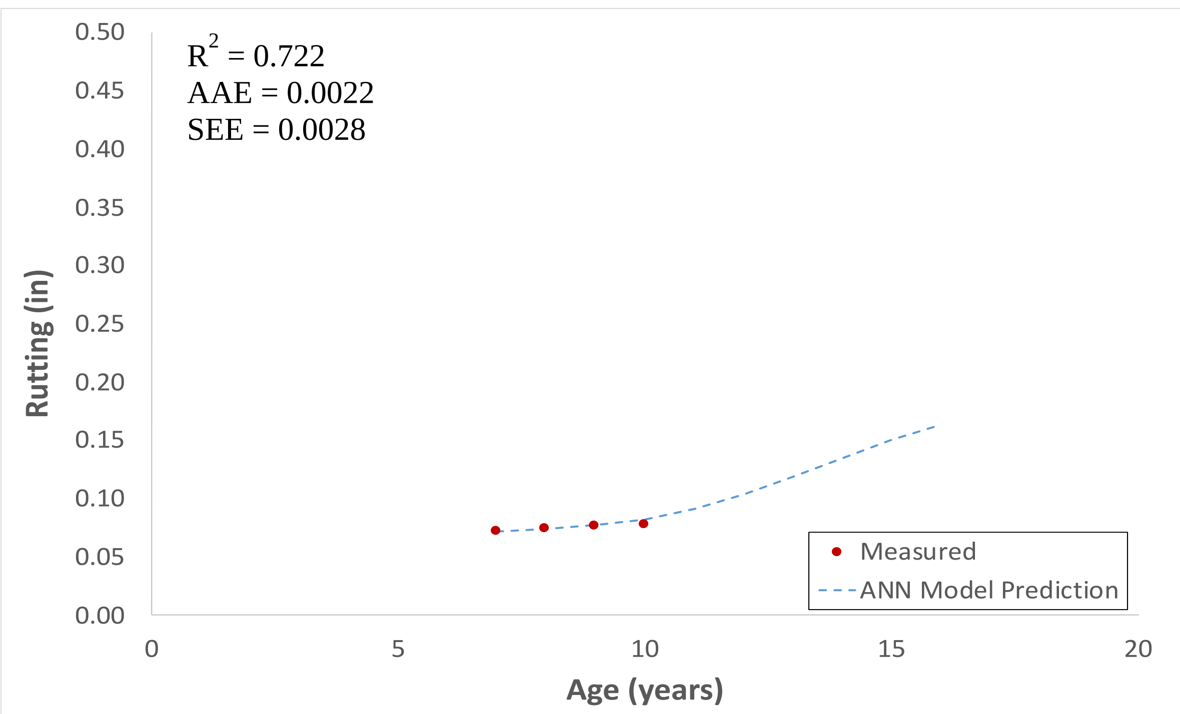
Figure 56 compares measured pavement condition records with ones predicted by ANN models and future pavement condition predictions for RSL purposes. Pavement performance predictions for flexible county pavements are made by ANN-based IRI approach 1, IRI approach 2, rutting, longitudinal cracking, and transverse cracking models.



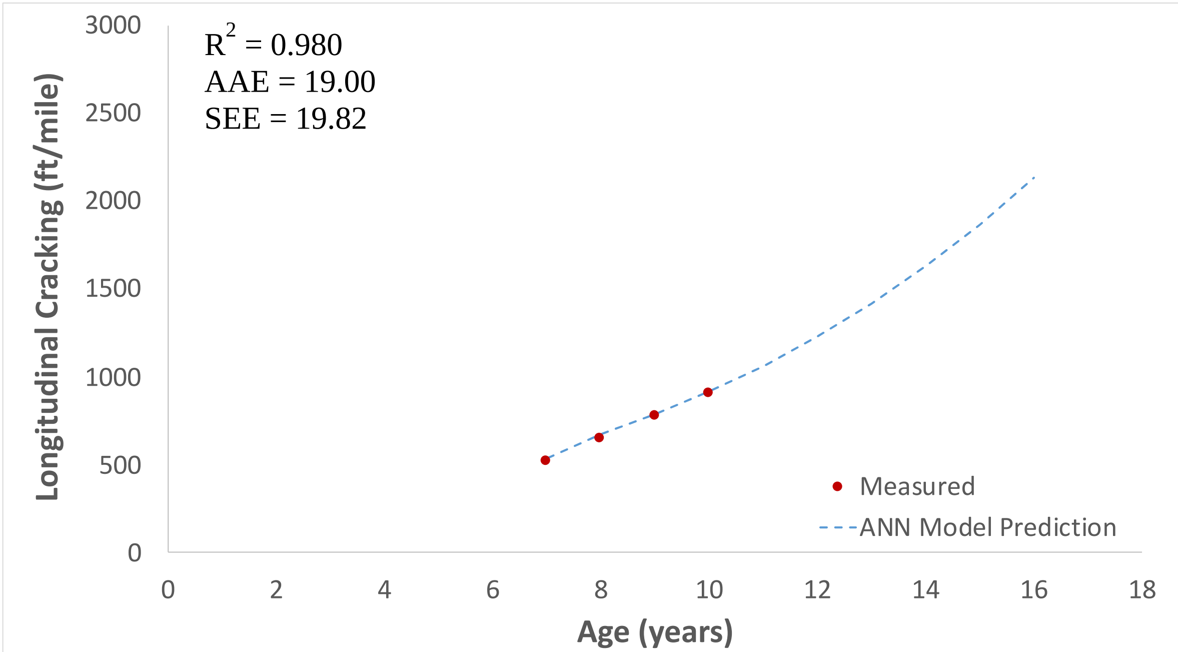
(a) IRI approach 1



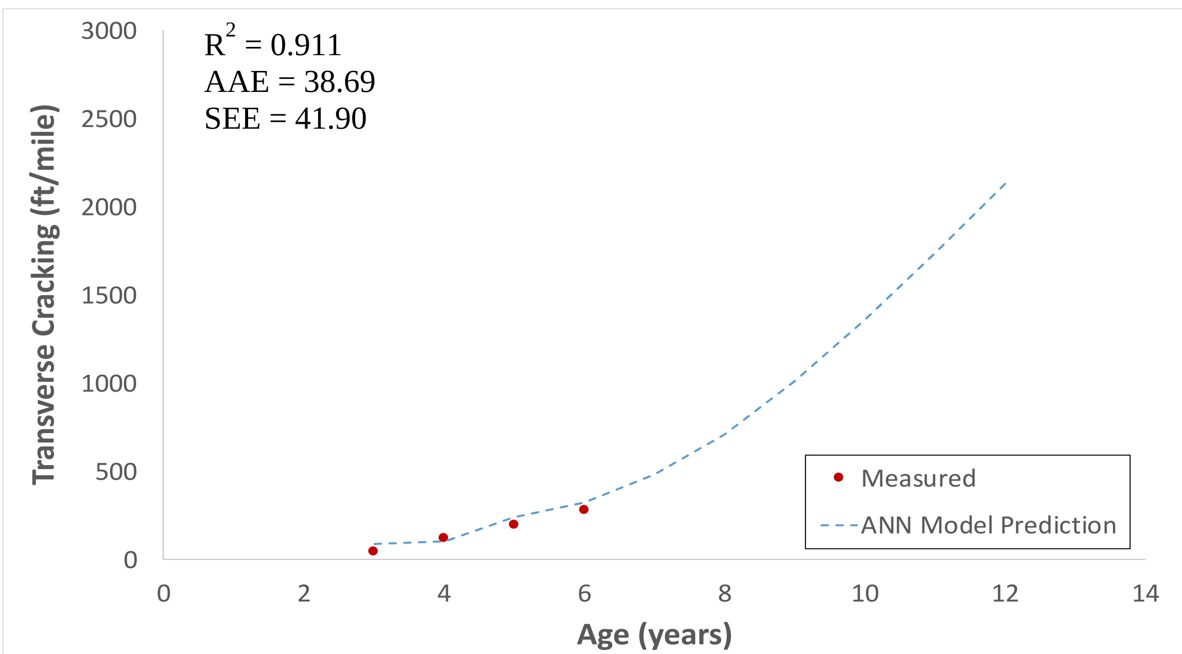
(b) IRI approach 2



(c) Rutting



(d) Longitudinal cracking



(e) Transverse cracking

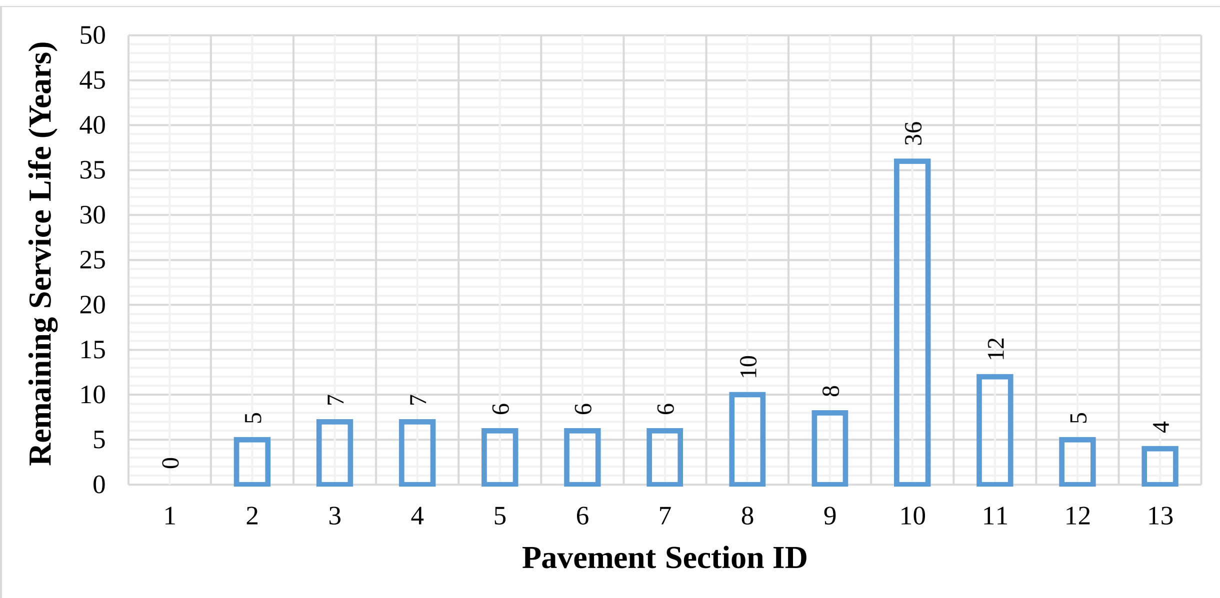
Figure 56. Comparisons between measured pavement condition records and ANN model predictions using various models

The sections used in Figure 56a–e, respectively are as follows:

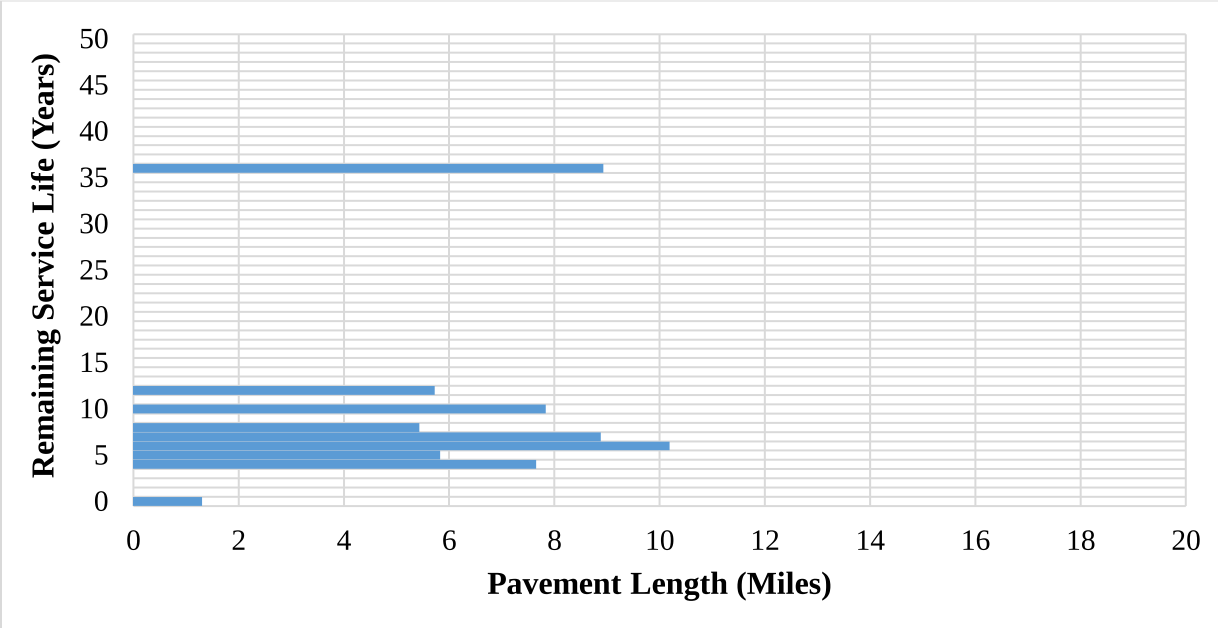
- IRI approach 1: Charleston Road, also called County Highway J62 and 255th Street, had an AADT in 2014 of 1,310, and it was constructed in 1976, with an overlay in 2007

- IRI approach 2: Ortho Road had an AADT in 2014 of 500, and it was constructed in 1962, with an overlay in 1997
- Rutting: County Highway X23, from Iowa 2 to West Point, had an AADT in 2014 of 1,560, and it was constructed in 1976, with an overlay in 2008
- Longitudinal cracking: Same section as rutting
- Transverse cracking: Primrose Road, also called County Highway J56, at 200th Street, had an AADT in 2014 of 360, and it was constructed in 1968, with an overlay in 2012

Once ANN models for predicting the performance of county AC sections were developed, their RSLs could be calculated using these ANN models and corresponding threshold limits for pavement performance indicators such as rutting, longitudinal cracking, transverse cracking, and IRI. Based on RSL calculation, Figure 57 and Figure 58 show the RSL distributions using ANN-based IRI approach 1 and IRI approach 2 models, respectively, based on pavement ID and pavement length for county flexible pavement sections.

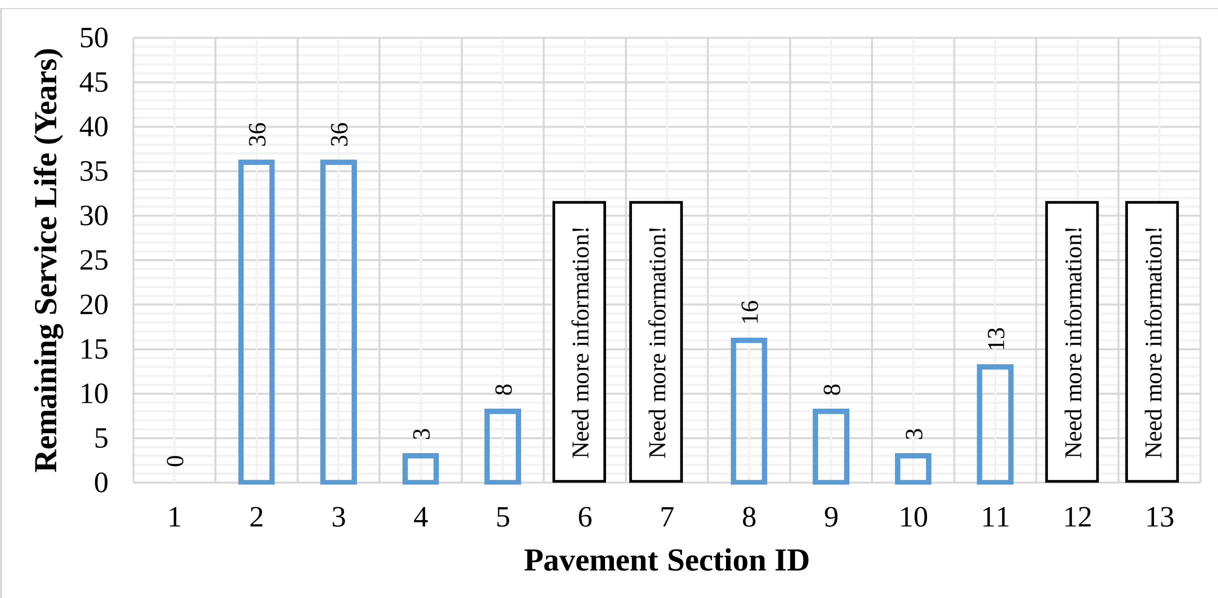


(a) Based on pavement section ID

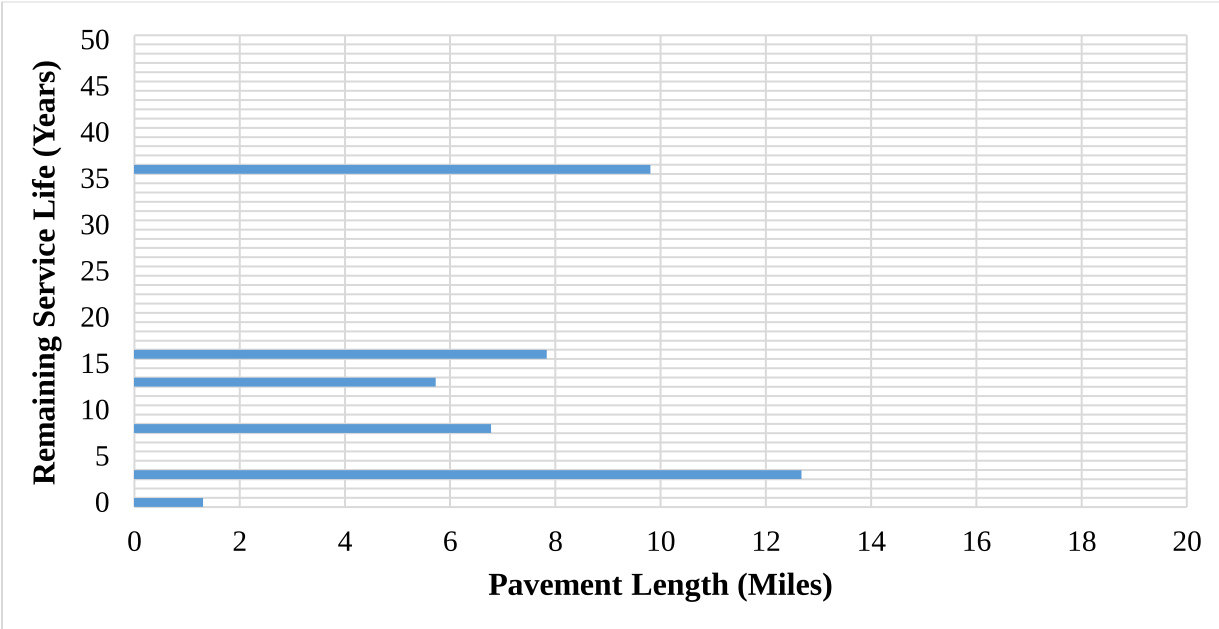


(b) Based on pavement length

Figure 57. RSL distributions by using IRI approach 1 ANN models for flexible pavement



(a) Based on pavement section ID



(b) Based on pavement length

Figure 58. RSL distributions by using IRI approach 2 ANN models for flexible pavement

The threshold value for IRI in Figure 57 and Figure 58 is 170 in./mi, as recommended by the FHWA (Visintine et al. 2018). More information is needed for some pavement sections with respect to their performance and traffic values to predict their future performance based on the IRI approach 2 model. Under these conditions, the average RSL for county AC sections in Lee County was found to be about 8.6 and 13.7 years by using ANN-based IRI approach 1 and IRI approach 2 models, respectively.

In summary, different approximate RSL values (26, 8.6, and 13.7 years) for county AC sections were found for the statistical-based model and the ANN-based IRI approach 1 and 2 models, respectively, used in the calculation of RSL. This difference might be due to using different performance models. Although different pavement performance models for each type of pavement performance indicator were developed using the ANN approach, a single model for RSL was used to predict future pavement condition and distress values for all pavement sections of a given pavement type. The ANN-based models consider various input parameters also previously presented in Table 14, but there might be other factors not considered in the models that could affect pavement system deterioration. The county database also suffers from being created from a smaller amount of collected field data and a lack of historical records for some pavement sections, as mentioned earlier. The missing data points therefore had to be statistically populated, possibly decreasing model accuracy when compared to real field data in models. Based on RSL calculations, when the statistical-based IRI model was used, the average RSL (26 years) was higher than that produced by ANN-based models (8.6 and 13.7 years).

CHAPTER 5. DEVELOPMENT AND EVALUATION OF PAVEMENT PERFORMANCE AND RSL PREDICTION MODELS FOR IOWA COUNTY PCC OVERLAYS

Description of Overall Approaches and Data Preparation

The rationality of the statistical and ANN-based modeling approaches described in the previous chapters could be further demonstrated using the Iowa county PCC overlay database developed as part of IHRB Project TR-698 (Gross et al. 2017) and then incorporated into the IPAT tool development. A historical database was provided by the Iowa Concrete Paving Association (ICPA) and a condition database was provided by the IPMP. Both databases were linked together by assigning longitude and latitude coordinates for the beginning and end of each project location as well as assigning a unique project identifier (Road ID) to each set of data attributed to a single project.

A pavement performance model for use at both project and network levels was developed using an ANN-based approach. Microsoft Excel-based automation tools have also been developed for project-level pavement performance modeling and analysis, to make future pavement performance predictions, and to estimate RSL developments for any given road section. These tools can be incorporated into pavement management processes and help engineers make better infrastructure planning decisions using real pavement performance data to create realistic future condition predictions.

RSL values for the pavement sections were calculated using threshold limits for the performance indicator once the pavement performance model had been developed. IRI was used as a rehabilitation trigger for deciding each management level RSL calculation, with RSL determined as the time between the current pavement age and the age at which future performance prediction reaches its threshold limit.

The success of the pavement performance prediction models in mimicking measured pavement performance indicators was quantified using R^2 (given previously in equation 1), AAE (given previously in equation 2), and SEE (given previously in equation 3). Higher R^2 and lower AAE and SEE values are indications of accurate model prediction.

Iowa County PCC Overlay Case

Statistical-Based PCC Overlay Performance Models and RSL Models

A statistically defined sigmoid pavement deterioration curve-based approach was utilized for IRI and PCI calculations for county PCC overlaid pavement sections in Iowa. The same procedure used in project-level pavement performance model development in the first stage of the project described in Chapter 3 was followed for developing sigmoidal equations. For IRI calculation, equation 4 (shown previously) was used to generalize the sigmoidal equation where C1, C2, C3, and C4 indicate coefficients representing contributions of different input parameters. For PCI calculation, equation 5 (shown previously) was used to generalize the sigmoidal equation, where C and D indicate coefficients representing contributions of different input parameters. Sigmoidal curve-fitting to measured IRI/PCI values was carried out by minimizing the error, the square of differences between the target and predicted IRI/PCI values.

Figure 59 through Figure 61 show some examples of IRI prediction models for county PCC overlays that can be used to predict future IRI values for these road sections.

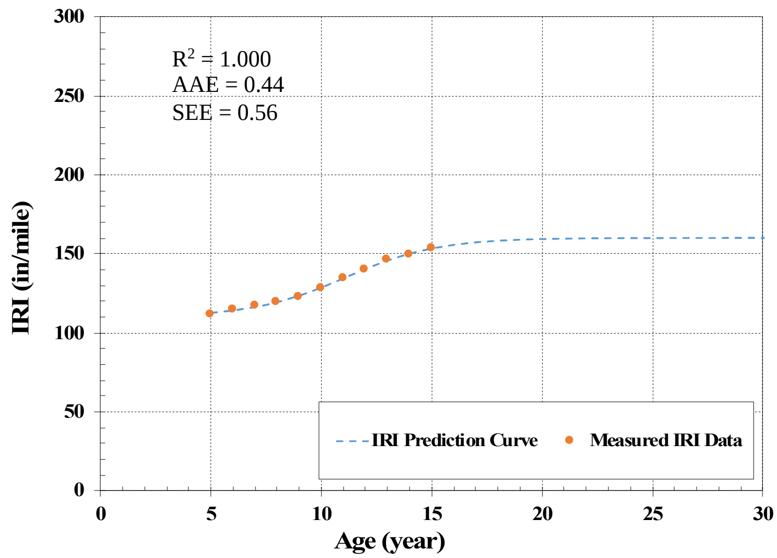


Figure 59. Statistical-based IRI prediction model results for Road ID section 1194

The equation used to generate the results in Figure 59 is as follows:

$$IRI = 110.07 + \frac{49.64}{1 + e^{(5.31 - 0.48 \times age)}}$$

The section used in Road ID1194 had an AADT in 2014 of 360, and it had an overlay in 1999.

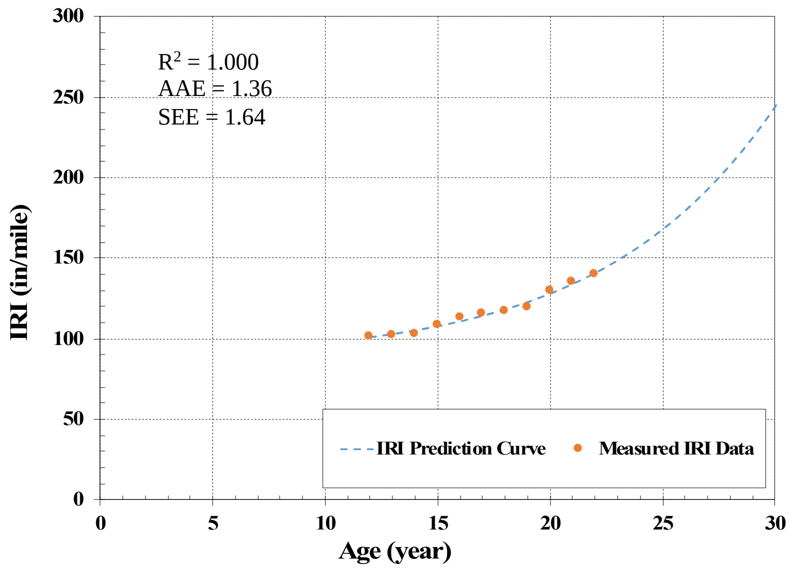


Figure 60. Statistical-based IRI prediction model results for Road ID section 1134

The equation used to generate the results in Figure 60 is as follows:

$$IRI = 87.98 + \frac{1734.59}{1 + e^{(6.62 - 0.14 \times age)}}$$

The section used in Road ID 1134 had an AADT in 2014 of 560, and it had an overlay in 1992.

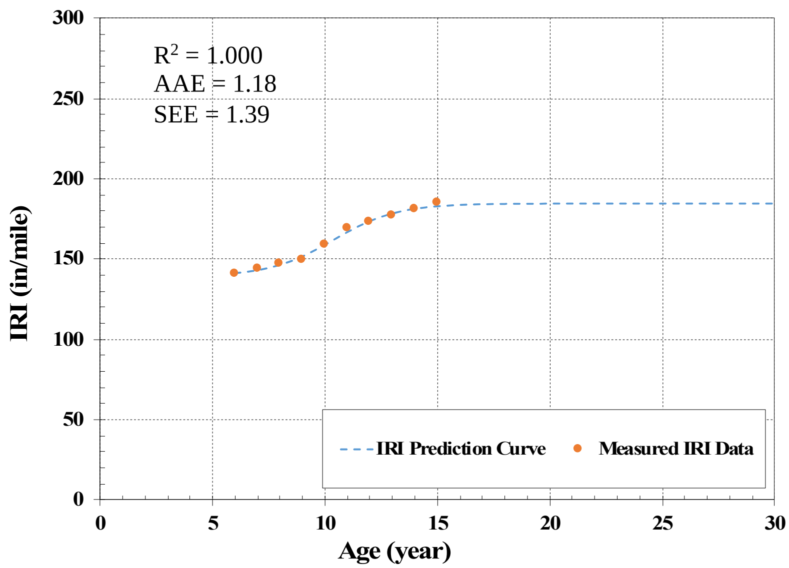


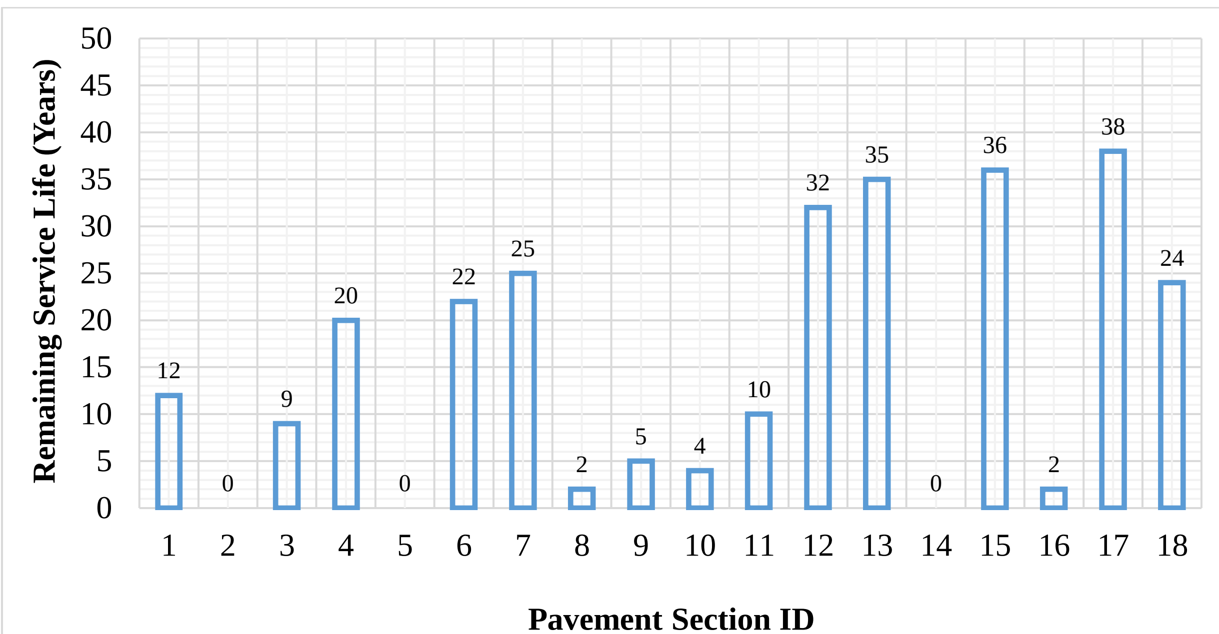
Figure 61. Statistical-based IRI prediction model results for Road ID section 1120

The equation used to generate the results in Figure 61 is as follows:

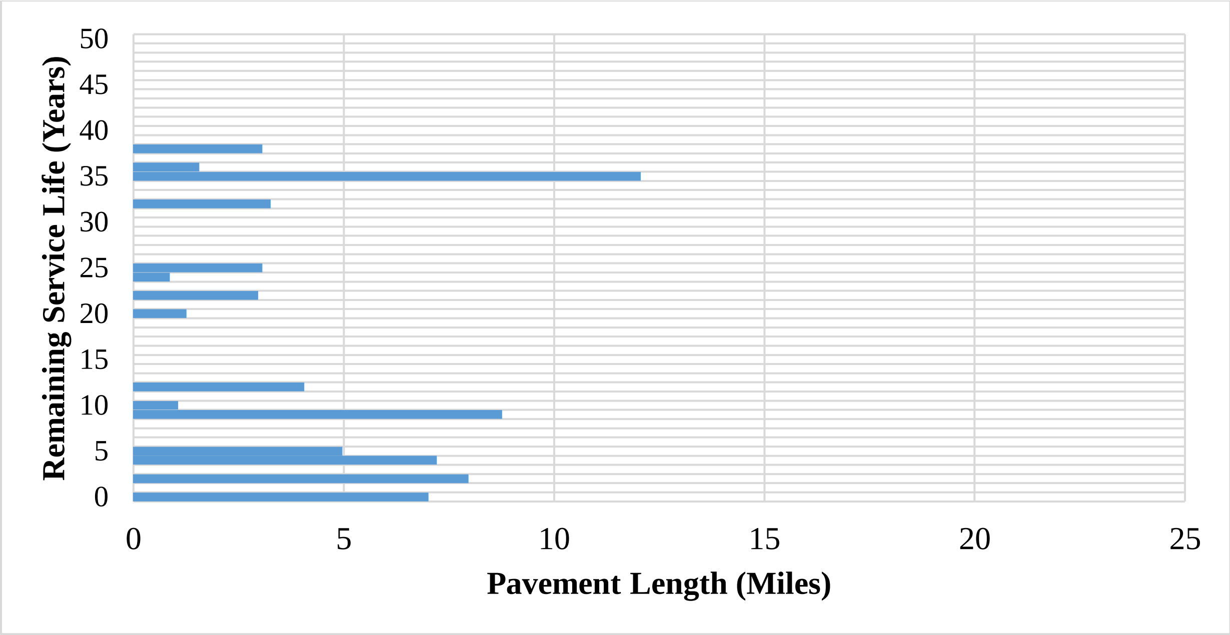
$$IRI = 139.26 + \frac{45.45}{1 + e^{(7.36 - 0.71 \times age)}}$$

The section used in Road ID 1200 had an AADT in 2015 of 1,120, and it had an overlay in 2000.

After future pavement performance of county roads was predicted, the RSLs of these roads could be calculated considering threshold limits of pavement performance indicators, as presented in the previous sections. IRI was chosen as a critical performance indicator of pavement for RSL calculations since it is used by the FHWA and adopted as a standard for HPMIS as a primary indicator of functional performance of pavement systems (Visintine et al. 2018, Miller and Bellinger 2014), as mentioned earlier in this report. Using 170 in./mi as the threshold value recommended by the FHWA (Visintine et al. 2018), the RSL of a county pavement section was calculated by following the steps previously presented in Figure 10 in Chapter 3. Based on RSL calculation, Figure 62 indicates the distribution of RSL for county PCC overlay sections.



(a) Based on pavement section ID



(b) Based on pavement length

Figure 62. RSL distribution for PCC overlay pavement sections

A total of 18 pavement sections are shown for illustration purposes only since the results for the 148 pavement sections used might not be readable on the RSL graph. The average RSL for county PCC overlay sections was found to be 15.3 years.

ANN-Based PCC Overlay Performance Prediction and RSL Models

In this part of the study, based on data available in the Iowa county database, the AI-based pavement performance model was improved and used for evaluating county composite (PCC overlay) pavement performance. The model predicts IRI for county PCC overlays. The database obtained from the Iowa DOT was utilized for model development and independent testing of developed models. About 85% of composite pavement data points in the county database were used in model development, and 15% of them, corresponding to 20 road sections, were used for independent testing of the developed model. In detail, the study used 148 PCC overlay pavement sections with 1,284 data points in model development and independent testing. It used 900, 128, 256, and 194 data points, respectively, as training, testing, validation, and independent testing data sets.

Table 16 lists the input parameters used to develop the ANN model, i.e., overlay thickness, traffic (accumulated AADT), pavement age, joint spacing, and previous consecutive two years of IRI measurements (IRI $_{(i-2)\ year}$ and IRI $_{(i-1)\ year}$) and the output parameter was the current year IRI (IRI $_{(i)\ year}$).

Table 16. ANN model development parameters for concrete overlay sections

Model name	Input parameters	Output parameter
IRI	Overlay thickness (in.), traffic (accumulated AADT), age joint spacing (ft), IRI $_{(i-2)\ year}$ (in./mi), IRI $_{(i-1)\ year}$ (in./mi)	IRI $_{(i)\ year}$ (in./mi)

Figure 63 compares IRI values measured in the field to those predicted by the ANN-based IRI model. The IRI model produced high accuracy in model development, with high R^2 and low AAE values obtained for all training, validation, testing, and independent testing data sets.

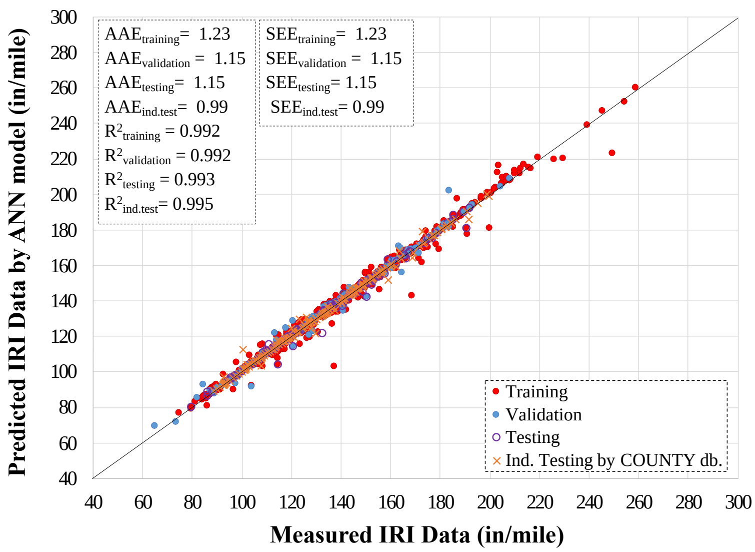


Figure 63. Measured pavement condition record vs. ANN model predictions by IRI

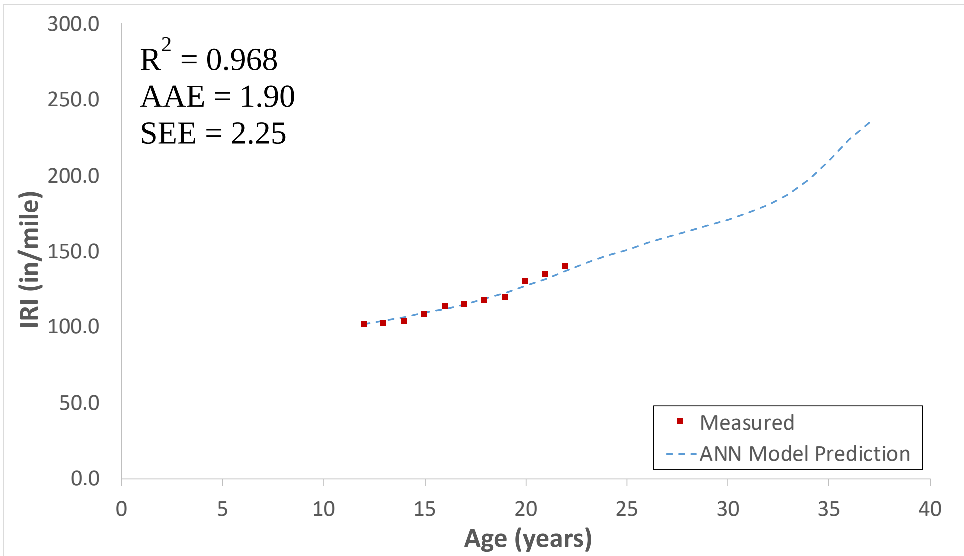
Table 17 presents limitations of the ANN-based IRI model developed by using the county database and of the data set formed by the county database and used for independent testing.

Table 17. Limitations of county database used in ANN model development and testing ANN models for concrete overlay sections

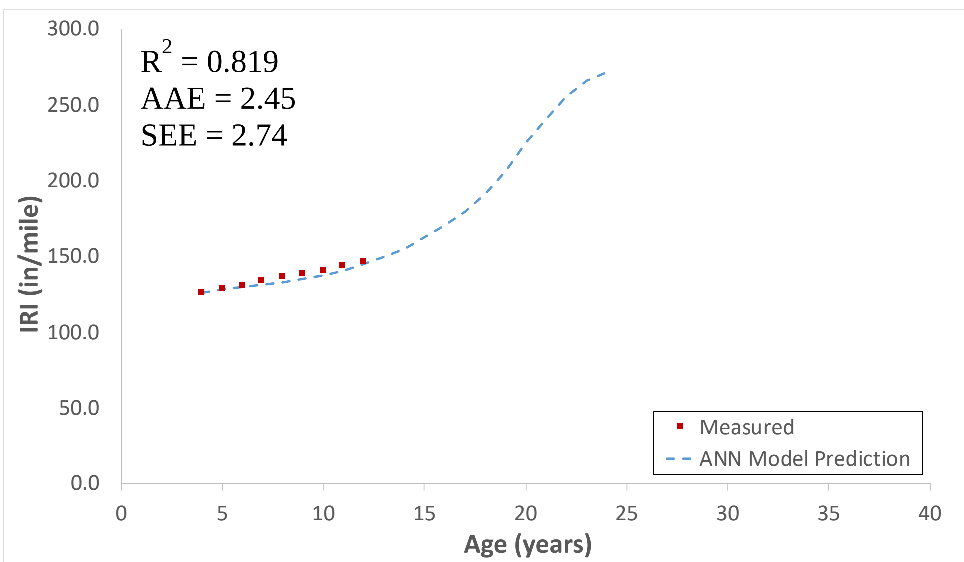
IRI	ANN model Limitations (from COUNTY database)		Measured data limitations (from COUNTY database)	
	Min	**Max**	**Min**	**Max**
Overlay thickness (in.)	2	10	5	8
Traffic (accumulated AADT)	120	90,600	240	38,750
Pavement age (yr)	4	52	4	38
Joint spacing (ft)	0	40	6	20
IRI $_{(i-2)\ year}$ (in./mi)	60.5	249.7	82.4	190.9
IRI $_{(i-1)\ year}$ (in./mi)	62.8	254.5	87.5	195.3

Since the range of the independent testing data set lies within the range of ANN model limitations, independent testing accuracy as seen in Figure 63 was high, meaning that the predicted IRI values were almost overlapped with the measured IRI values.

Figure 64 shows comparisons of both the measured pavement condition records with the predicted ones by ANN models and future pavement condition predictions for RSL purposes.



(a) Road ID 1134

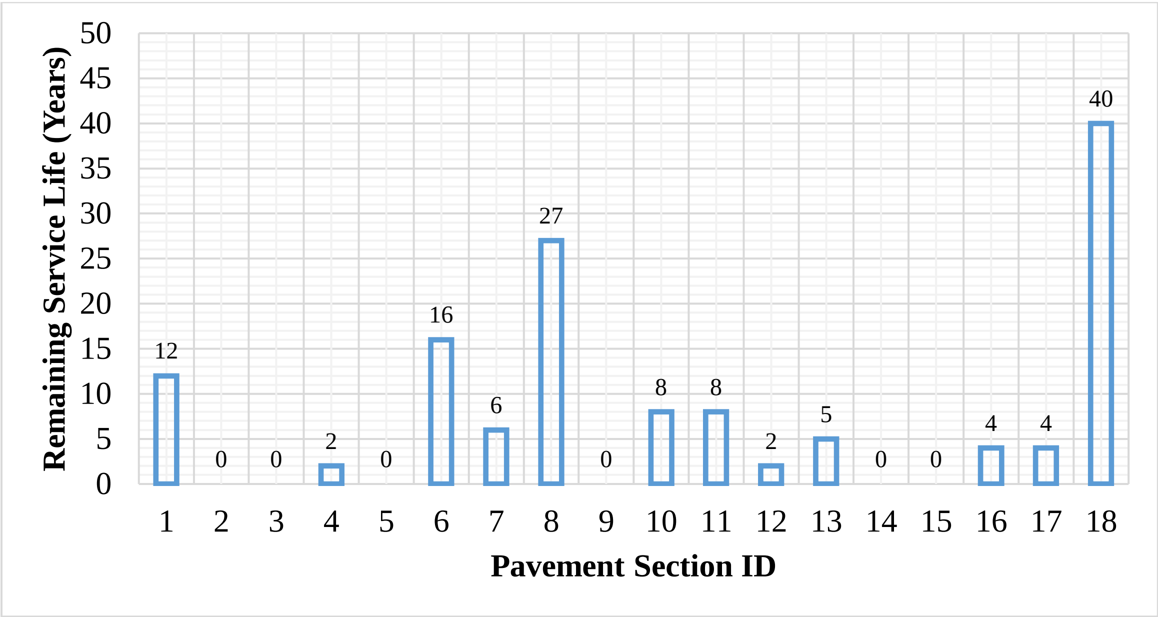


(b) Road ID 1247

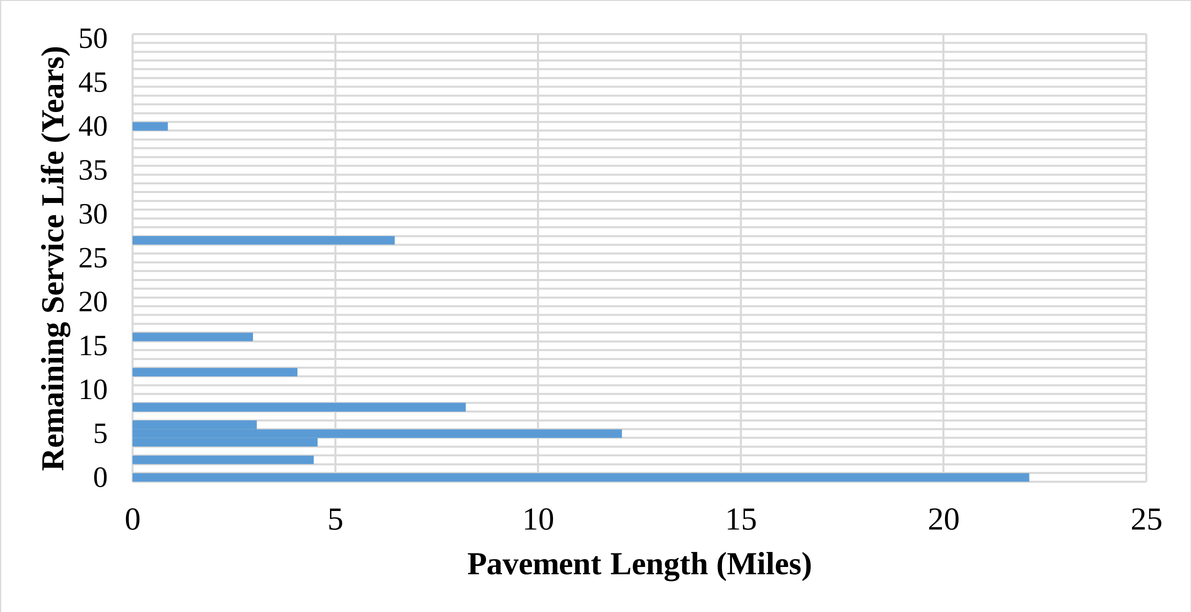
Figure 64. Measured pavement condition records vs. ANN model predictions using ANN-based IRI model

The AADT in 2002 for Road ID 1134 was 560, and it had an overlay in 1992; the AADT in 2004 for Road ID 1247 was 890 to 1,770, and it had an overlay in 2003.

The RSLs of county pavements could be calculated using the ANN-based IRI model and the corresponding threshold limit as the pavement performance indicator. Figure 65 shows RSL distributions based on RSL calculation using the IRI ANN model based on pavement ID and pavement length for county concrete overlay sections.



(a) Based on pavement section ID



(b) Based on pavement length

Figure 65. RSL distributions by using IRI ANN model for concrete overlay pavement sections

The threshold value for IRI was taken to be 170 in./mi. For illustration purposes, only 18 county concrete overlay sections among a total of 148 road sections from the independent testing database are presented. Using the ANN-based IRI model, the average RSL for county composite sections in Iowa was found to be about 7.4 years.

In summary, an IRI threshold limit of 170 in./mi was used in the calculation of RSL, and different approximate RSL values for network-level county PCC overlay sections were found when statistical-based and ANN-based IRI models were used to calculate RSL. When the statistical-based IRI model was used, the average RSL value (15.3 years) was higher than for the ANN-based IRI model (7.4 years). The biggest challenge here is that concrete overlays do not reach their IRI threshold limit within their design life. Specifically, a statistics-based model that uses sigmoidal equations with low initial slope in time increments could not reach the threshold limit within the service life because of the low IRI increments for concrete overlay sections. In this case, RSL was calculated based on design life, taken to be 40 years. Since taking an average of only 18 pavement sections among 148 sections for the sake of demonstration could also affect the average RSL results when considering the network-level system, when comparing individual pavement cases, and evaluating the network-level system, the statistics-based model estimated higher RSL values than the ANN model.

CHAPTER 6. FEASIBILITY OF INTEGRATING PAVEMENT TREATMENT TECHNIQUES INTO PAVEMENT RSL MODELS

Distresses formed for each type of pavement due to material faults, traffic loading, climate or environment effects, and misapplications during construction, provide an estimation of pavement service lives and required treatment (Durham et al. 2018, Citir et al. 2020b, and Citir et al. 2021). Transportation agencies decide on appropriate pavement maintenance strategies for deteriorated pavement sections as a function of their benefits and costs. Benefits can be determined by considering recovery in pavement performance that results in pavement service life extension. Such improvement in pavement performance, including crack seal, seal coat, slurry and chip seal, thin asphalt overlay, micro surfacing, etc., for flexible pavements and diamond grinding for rigid pavements, can be achieved by pavement preservation techniques applied earlier than the pavement service limit. Pavement rehabilitation such as HMA overlay can also enhance the pavement structure by increasing its service life and load-carrying capacity (Tighe 2013).

Pavement management differs for each SHA preservation strategy and may reflect different climate and variable traffic volume conditions. For example, the New Jersey DOT (Bertucci 2009), the California DOT (Caltrans 2013), and the Nebraska DOT (which also adopts distress severities and serviceability index values) (Rilett 2016) consider using a level of distress, such as roughness, cracking, and rutting rates, in evaluating pavement conditions, while the Rhode Island DOT selects appropriate strategies based on trigger values for pavement performance in prioritizing their maintenance activities (Coffey et al. 2015).

As part of this study, the feasibility of integrating preservation and rehabilitation techniques for RSL predictions was investigated to identify the challenges and the research need and provide recommendations for incorporating such feasibility results into future IPAT tool updates.

Impact of Preservation Technique on JPCP Service Life

Data Collection and ANN Model Development

The data used in this part of the study were collected from the Iowa DOT’s PMIS. Pavement response models predicting IRI and resulting in the estimation of RSL in rigid pavements have been developed by the Iowa State University research team as a part of a previous research project (Kaya 2019).

Pavement response models predicting IRI and resulting in the prediction of RSL in rigid pavements were presented in Chapter 3 as IRI approach 1. Accuracy results for comparing IRI predictions by ANN and IRI measurements by the PMIS were shown previously in Figure 15b. The prediction model was trained using Levenberg-Marquardt ANN algorithms with a hyperbolic tangent activation function. The study used 34 pavement sections for rigid pavements from a total of 396 data points. It used 80% of the data points for model development and used the remaining 20% for independent testing of the model. Training, validation, and testing data sets were constructed using 60%, 30%, and 10% of the model development data set, respectively.

The final ANN model architecture was determined as 5-15-1 after many trials using various architectures. In the IRI ANN prediction model, a total of 15 hidden neurons in one hidden layer and five input parameters were used: PCC slab thickness, traffic (accumulated ESAL), pavement age, and consecutive previous two-year IRI records, IRI $_{(i-2)\ year}$ and IRI $_{(i-1)\ year}$. The output was the current year IRI value, IRI $_{(i)\ year}$. Table 18 presents the input parameters with their data ranges used in the development of the ANN model and the decision-making tool for preservation technique.

Table 18. Parameters and data range for ANN-based IRI model development for rigid pavements

Input parameters	PMIS data range	
	Min	Max
PCC slab thickness (in.)	2	23
Traffic (accumulated ESAL)	8,720	973,800
Pavement age (yr)	9	13
IRI $_{(i-2)\ year}$ (in./mi)	67.8	181.2
IRI $_{(i-1)\ year}$ (in./mi)	73.3	189.5

Identification of JPCP Treatments

In this study, impacts and contributions of a preservation treatment such as diamond grinding on JPCPs' performance and RSLs were investigated. Since it is a well-known effective and low-cost preservation treatment, the diamond grinding technique was selected as a preservation treatment and applied to JPCP sections. The overall expected life extension of this preservation treatment on JPCP varies between 8 and 17 years. Restoring smoothness and rideability, reducing noise, improving surface friction, and removing faulting are counted among the benefits of diamond grinding (Smith et al. 2014, Jung et al. 2008, Stubstad et al. 2005).

The FHWA Pavement Preservation Expert Task Group Rigid Subcommittee conducted a survey among SHAs regarding how concrete pavement preservation has been integrated into their pavement management system (PMS). A total of 60% of the responding agencies stated that they use some trigger values to decide among concrete pavement preservation options. Among these agencies, smoothness was reported to be the most commonly used indicator for triggering of pavement preservation options, although faulting, slab-cracking, and overall pavement condition were used as alternative indicators by some agencies (Scofield et al. 2011). Some SHAs have also recommended diamond grinding trigger values such as an IRI value of 107 in./mi in Michigan (Michigan DOT 2010) and IRI values of 100 in./mi for interstates and 125 in./mi for non-interstates in Iowa (Vitillo et al. 2015). A decision on whether diamond grinding is needed for a JPCP can be made depending on evaluating smoothness levels of the pavement. In this study, IRI was selected as the trigger criterion for the preservation treatment.

A methodology developed for the Indiana DOT characterizes the impact of treatments based on short-term and long-term treatment effectiveness (Ong et al. 2010), considering initial change in condition and rate of deterioration, respectively (Rada et al. 2018). The initial change in condition corresponds to the recovery in IRI after application of a treatment, i.e., it is the ratio as a percentage between the difference of two IRI values measured just before the treatment ($IRI_{pretreatment}$) and right after the treatment ($IRI_{post\text{-}treatment}$) and $IRI_{pretreatment}$. A study conducted to identify the effects of pavement preservation, restoration, and rehabilitation techniques indicated that an approximately 20% recovery in IRI after minimal repair on the pavement, including diamond grinding (Hall et al. 2002), could be achieved. Another study by Stubstad et al. (2005) found that IRI decreased by about 43% after diamond grinding.

In this study, for determining the recovery in IRI, 20 road sections throughout Iowa treated with diamond grinding were considered, analyzing data for these road sections obtained from the FHWA’s Long-Term Pavement Performance (LTPP’s) program’s General Pavement Studies (GPS)-3 database. Figure 66, left, shows the change in IRI (ΔIRI, in./mi) as a function of $IRI_{pretreatment}$ (in./mi) for all pavement sections analyzed. This relationship was utilized to calculate recovery in IRI (%) that in turn was used in the calculation of post-treatment IRI.

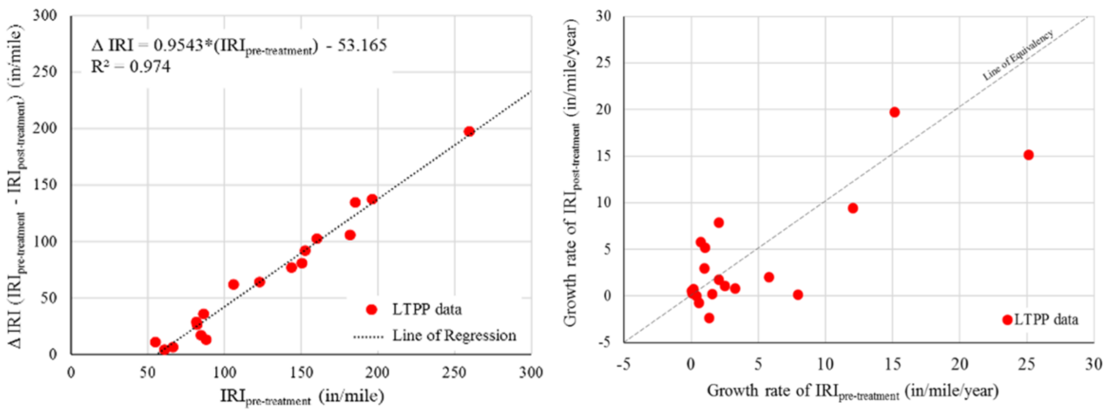


Figure 66. Regression results of LTPP JPCP sections for analyzing the immediate change in IRI, left, and growth rate of IRI with diamond grinding application, right

The rate of deterioration corresponds to the growth rate of IRI, reflecting changes in performance of a treated pavement section over time. It quantifies the pavement deterioration retarding effect by the application of treatment. The growth rate is the mean of all differences of two consecutive IRI values among the collected field data. For example, when a road section had three years of IRI data (i.e., 100, 102, 104 in./mi), differences of the consecutive IRIs were taken (2 in./mi and 2 in./mi) and mean of these differences then calculated ((2+2)/2 = 2 in./mi) as the growth rate of IRI for this pavement section. For long-term treatment effectiveness, the growth rate of IRI of treated pavement sections should be compared to the growth rate of IRI of untreated pavement sections (Rada et al. 2018).

Figure 66, right, compares the mean growth rates of $IRI_{pretreatment}$ (in./mi/year) and $IRI_{post\text{-}treatment}$ (in./mi/year) for the 20 Iowa LTPP sections mentioned previously. As can be seen in the figure, most data points fell under the line of equivalency, indicating that in most cases the pavement performance after application of the treatment is better than before the application of the treatment. Averages of mean growth rates of $IRI_{pretreatment}$ and of mean growth rates of $IRI_{post-treatment}$ for all road sections were separately calculated and then proportioned. The ratio of average growth rates between pre- and post- treatment was calculated as 0.86, and it can be interpreted that the growth rate of $IRI_{post-treatment}$ is 14% less than the growth rate of $IRI_{pretreatment}$ on average. This reduction in growth rate is expected to positively affect the deterioration curves and RSLs of the pavement sections. This ratio was applied to the ANN model to predict post-treatment IRI, as explained in the next section.

Analysis Results

Consequence analysis of treatment types on rigid pavement was done using a prototype analysis tool as a decision-making tool for future post-treatment IRI using the developed ANN model. The tool is a Microsoft Excel macro-based automation tool whose interface is shown in Appendix B for illustration purposes. Note that this tool is a prototype tool developed separately from the IPAT tool as part of this study.

To validate analysis accuracies of the ANN-based tool, a JPCP section (South Dakota 46-3012) from the LTPP database, with a history of diamond grinding preventive maintenance, was selected. This section was constructed in 1981 with a concrete slab thickness of 10.2 in., the LTPP began collecting data on this section in 1987, and diamond grinding was first applied to its surface in 1997. Considering the immediate change in IRI and growth rate after treatment, pretreatment and post-treatment IRI values for this JPCP section were predicted using the ANN-based analysis tool, and comparisons of measured and predicted IRI values for the section are presented in Figure 67.

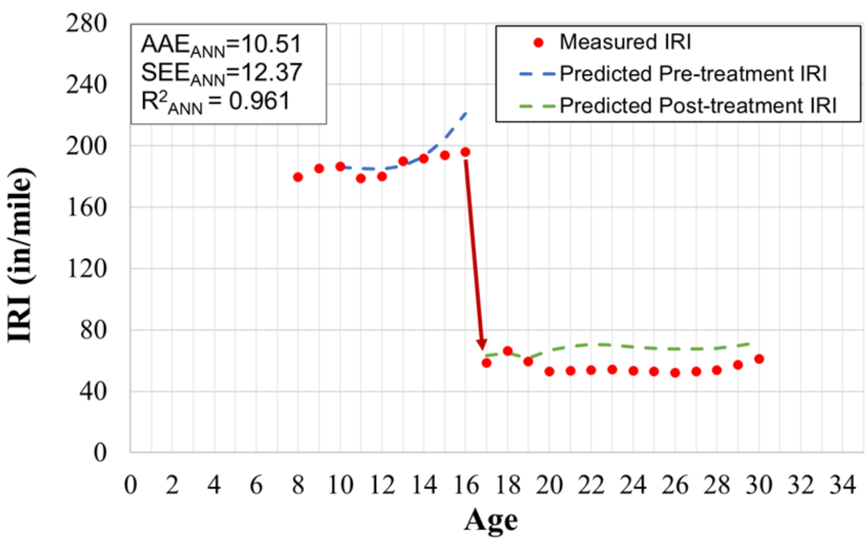
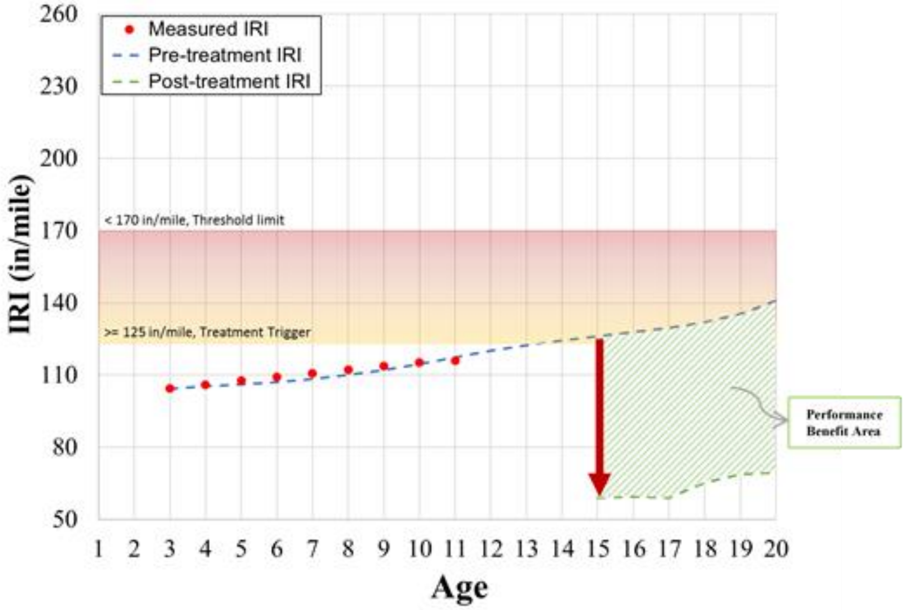


Figure 67. Comparisons of pre- and post-treatment measured IRI and IRI predicted by ANN model for a particular LTPP JPCP section

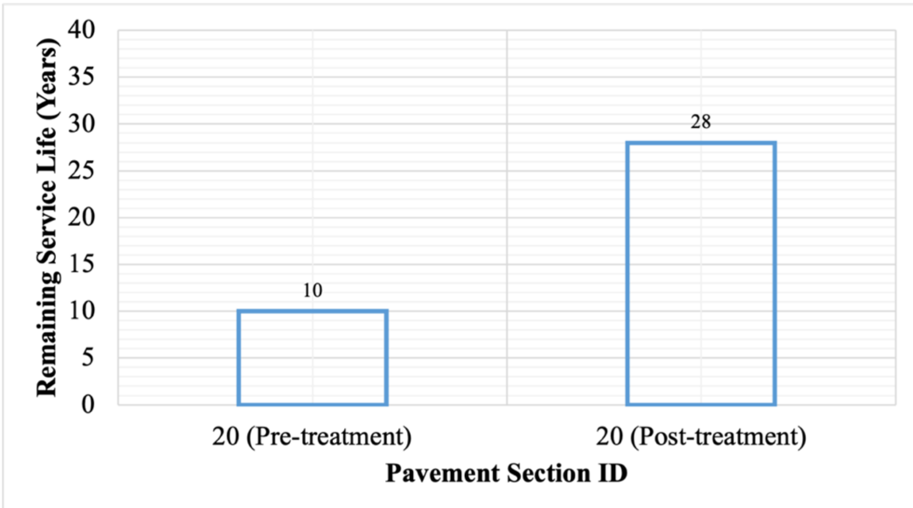
The section used in Figure 67 is in South Dakota, with a Road ID of 46-3012, with an ESAL in 2009 of 146,000, and was constructed in 1981.

As can be seen in the figure, the developed ANN model successfully predicted both pretreatment and post-treatment IRI values by producing predictions very similar to the measured IRI values.

In evaluating the impact of a preservation technique on rigid pavement life, IRI was predicted for a non-interstate highway both before and after treatment application by using the prototype tool to discover the effects of the diamond grinding preservation technique on the RSL of the JPCP. Figure 68a and b show future IRI predictions for a pavement section on US 65 and its RSL before and after treatment, respectively.



(a) IRI pretreatment and post-treatment performance prediction model results



(b) RSL distribution for a JPCP section before and after treatment

Figure 68. IRI and RSL estimations for a sample JPCP section

The treatment trigger value was selected as an IRI of 125 in./mi based on Iowa DOT applications. The threshold value of IRI was taken as 170 in./mi, determined by the FHWA (Visintine et al. 2018). Based on regression analysis results of the 20 Iowa LTPP sections presented in Figure 66, the recovery in IRI and change in growth rate after treatment were considered for ANN predictions. At the age of 15, the pavement exceeded the treatment trigger value, 125 in./mi, and diamond grinding was applied. Post-treatment IRI values were predicted using ANN-based developed model (IRI approach 1). The area between pretreatment and post-treatment IRI prediction curves represents the benefit area of improved performance of the pavement, and the larger the area, the more benefit obtained by the treatment, resulting in more pavement life extension. As can be seen in Figure 68b, the diamond grinding preservation technique resulted in a life extension by nearly 18 years. Note that users can adjust treatment trigger and recovery percentage values based on their own applications.

Key Findings and Recommendations

A network-level pavement performance prediction automation tool using a machine-learning technique was explored for a proof-of-concept demonstration of the integration of JPCP preservation techniques with RSL predictions. Using the developed ANN model, this tool can be used as a decision-making tool for predicting both future pretreatment IRI and future post-treatment IRI, depending on the selection of a particular treatment such as the currently used diamond grinding. The key findings and recommendations of this work can be summarized as follows:

- ANN models developed for rigid pavement systems, requiring only five input parameters of pavement thickness, age, traffic, and previous years' IRI values, can predict IRI with high accuracy when compared to actual IRI measurements from the PMIS database.
- Since it has been trained with an adequately large number of field data points, the same model developed for predicting pretreatment IRI can be used for predicting post-treatment IRI.
- There are several significant parameters to be defined before predicting post-treatment IRI: preservation treatment triggers and performance recovery percentages. The automated decision-making tool can provide flexibility for entering these parameters for predicting post-treatment IRI.
- Improving the network-level automation tool permitted the user to predict post-treatment IRI values. The tool is capable of providing realistic pavement performance and RSL estimations and could be successfully used as part of performance-based pavement management strategies and helping decision-makers to make better informed pavement management decisions by prioritizing preservation and rehabilitation needs for local agencies' pavement assets.

Impact of Preservation and Rehabilitation Techniques on AC Pavement Service Life

Data Collection and ANN Model Development

The data used in this part of study were collected from the Iowa DOT's PMIS. IRI prediction models resulting in the estimation of RSL in AC pavements were developed (Kaya et al. 2020) and are presented in Chapter 3 as IRI approach 1. For comparison of IRI predictions by ANN and IRI measurements by PMIS, the accuracy results were previously shown in Figure 17d. The prediction model was trained using Levenberg-Marquardt ANN algorithms with a hyperbolic tangent activation function. The study used 35 pavement sections for AC pavements, corresponding to a total of 430 data points. It used 80% of the data points in model development, and it used the remaining 20% for independent testing of the model. Training, validation, and testing data sets were constructed using 60%, 30%, and 10% of the model development data set, respectively.

After many trials on different architectures, the final ANN model architecture was chosen to be 5-15-1. In the IRI ANN prediction model, a total of 15 hidden neurons in one hidden layer and five input parameters were used: asphalt thickness, traffic (accumulated ESAL), pavement age, and consecutive previous two-year IRI records, IRI $_{(i-2)\ year}$ and IRI $_{(i-1)\ year}$. The output was the current year IRI value, IRI $_{(i)}$. Table 19 lists the input parameters with their data range used in the development of the ANN model and the decision-making tool for use in preservation and rehabilitation techniques.

Table 19. Parameters and data range used in ANN-based IRI model development for AC pavements

Input parameters	PMIS data range	
	Min	**Max**
AC thickness (in.)	7.5	16.5
Traffic (accumulated ESAL)	1,010	110,280
Pavement age (yr)	2	18
IRI $_{(i-2)\ year}$ (in./mi)	37.4	182.1
IRI $_{(i-1)\ year}$ (in./mi)	44.4	189.5

Identification of AC Pavement Treatments

Each SHA can focus on different pavement treatments, i.e., maintenance, preservation, and rehabilitation techniques, to improve the functional and/or structural performance of pavements. Based on the literature and field data provided by the LTPP program, the Iowa DOT includes mostly chip seal, crack seal, slurry seal, and thin overlays as preservation and AC overlay rehabilitation techniques.

Many studies have analyzed the effectiveness of different pavement treatments for AC pavements and evaluated performance of such treatments on pavement life using performance indicators such as IRI, pavement condition rating (PCR), PCI, fatigue cracking, and rut depth (Hall et al. 2002, Lu and Tolliver 2012) to assess treatment performance.

In this study, because IRI has been found to sufficiently characterize the overall road quality, it was considered as the sole performance indicator for evaluation of treatments that include thin

AC overlay (i.e., non-structural or functional overlay) and structural AC overlay. Multiple factors, such as pavement age, ESAL, and pretreatment IRI value, impact IRI after overlay, significantly affect the initial effects of treatment on post-treatment IRI. Case studies indicate that higher initial post-treatment IRI would be expected on asphalt pavements overlaid when they are rougher compared to when they are smoother (Hall et al. 2002). Before developing a decision-making tool using ANN, the parameters related to pavement treatments must be identified as follows:

- Expected treatment life
- Expected life extension of a pavement system
- Recovery percentage in IRI or initial IRI measurement after treatment
- The trigger value at which a pavement condition is considered to require treatment

While a non-structural or functional thin AC overlay improves minor rutting, surface deficiencies, friction, ride quality, and serviceability, and reduces pavement deterioration and aging, it does not structurally increase pavement strength. Depending on the pavement project, typical service life varies between 2 and 14 years on average (DeSousa 2011 and 2012, Wilde et al. 2014, Irfan et al. 2009). Structural AC overlay increases pavement strength, restores serviceability, and reduces aging to extend pavement service life perhaps by between 3 and 18 years on average depending on the project. Treatment effectiveness in this study was assessed based on two criteria: treatment service life and pavement service life.

Initial effects of preservation and rehabilitation techniques on IRI can be evaluated by comparing the last IRI measurement before treatment with the first IRI measurement after treatment. A study assessing the effects of pavement preservation and rehabilitation techniques using more than 50 pavement sections from the LTPP database indicated an approximately 15% IRI recovery after applying a thin overlay treatment. Mean post-treatment IRI measurements of more than 130 pavement sections were also found to be approximately 60 in./mi with application of a structural AC overlay of thicknesses of 2 in. and 5 in. (Hall et al. 2002).

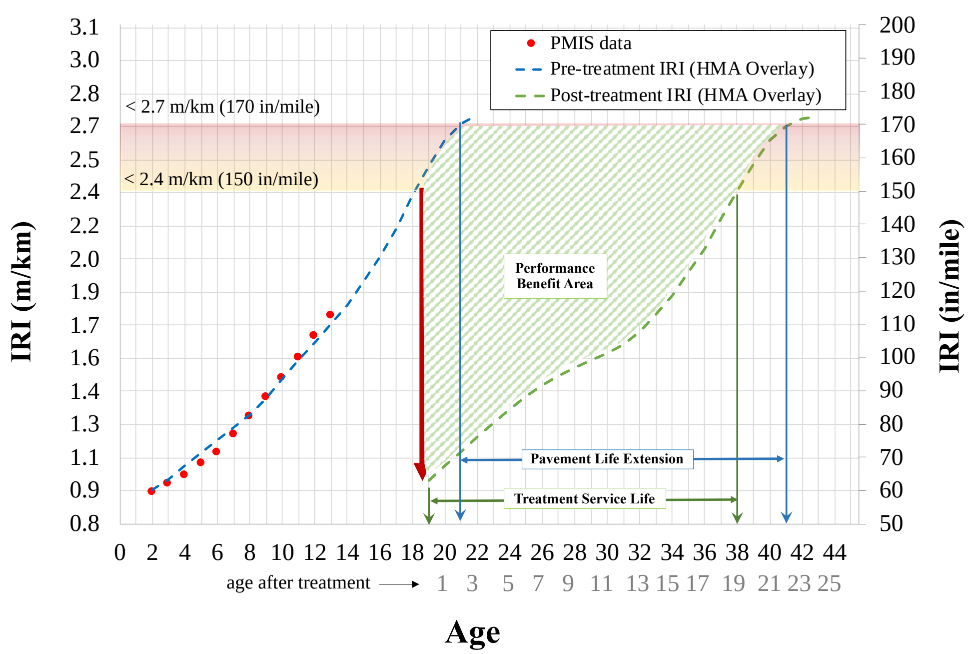
SHAs and other similar transportation agencies use different pavement preservation programs, including a decision-tree matrix, to determine whether a treatment needs to be applied for a deteriorated pavement system. Since this matrix may be different for each agency depending on its unique needs, there are no clear rules for timing the application of treatments. A decision tree included in pavement management software (i.e., Highway Pavement Management Application) was used by MnDOT to identify an appropriate treatment based on a PSR trigger value of 2.5 (Wood et al. 2009). Average trigger IRI values for applying structural AC overlay and thin AC overlay on the pavement sections were found to be 138 in./mi and 124 in./mi, respectively (Irfan et al. 2009). Based on evaluation of the LTPP database with respect to structural AC overlay and thin AC overlay (nominally 1.5 in.), trigger values, means of pretreatment IRI measurements for specific pavement studies SPS-3 (preventive maintenance of flexible pavement) and SPS-5 (rehabilitation of flexible pavement), were determined as 110 in./mi and 87 in./mi on average, respectively (Hall et al. 2002). A study using Indiana DOT data determined triggers for pavement treatments and recommended thin overlay treatment for pavements with IRI values less than 150 in./mi. It also described other research studies mentioning that thin AC overlays are generally applied to well-conditioned pavement with IRI values less than 80 in./mi (Ong et al. 2010). Based on the LTPP database examined from this study, 10 pavement sections throughout the Midwest with thin AC overlays of thicknesses between 0.5 in. and 1.5 in. had IRI trigger values of 94 in./mi on average before treatment.

It is worthwhile to note that, while seal coat is commonly used in Iowa pavement sections, based on an evaluation of the LTPP data performed both by the project team and found in the literature, seal coat has no significant beneficial impact on IRI. Slurry seal application might slightly increase the post-treatment IRI value if the pretreatment value is less than 80 in./mi or may decrease the post-treatment IRI if pretreatment IRI is more than 95 in./mi (Hall et al. 2002).

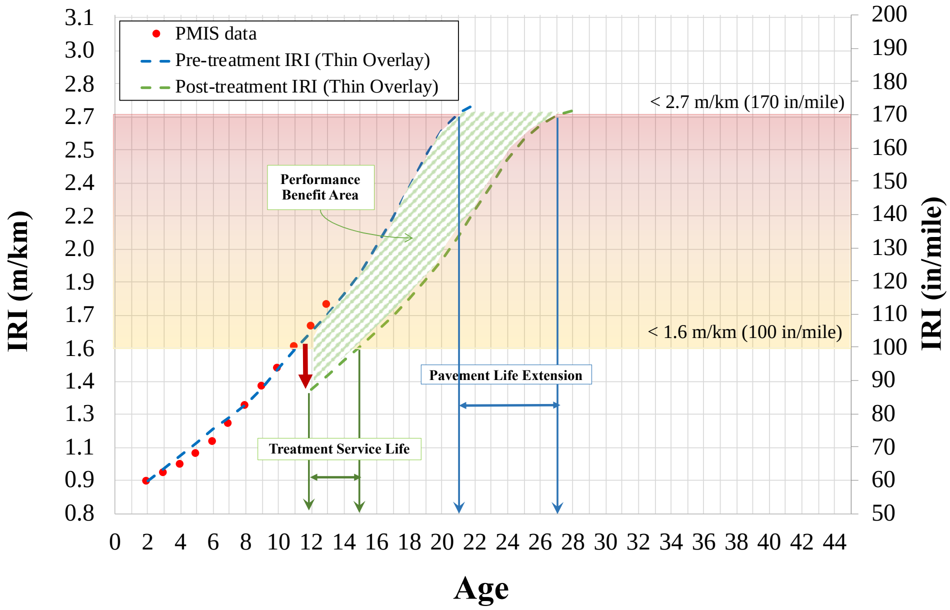
Analysis Results

Consequence analysis of treatment types on flexible pavement was done using a prototype analysis tool as a decision-making tool for future post-treatment IRI using the developed ANN model. The tool is a Microsoft Excel macro-based automation tool whose interface is shown in Appendix B. Note that this tool is the prototype tool developed separately as part of this study in addition to the IPAT tool.

In evaluating the impact of preservation and rehabilitation techniques on AC pavement life, IRI was predicted both before and after treatment application on a non-interstate highway using the prototype tool. Figure 69a and b provide a comparison of field PMIS data with future pretreatment and post-treatment IRI predictions based on IRI trigger value and threshold value for a pavement section on Iowa 149.



(a) Structural HMA overlay



(b) Functional thin overlay

Figure 69. Comparisons of field PMIS data with future pretreatment and post-treatment IRI predictions

Based on field data evaluations and DOT applications, respective treatment triggers for structural AC overlay and thin AC overlay were selected to be an IRI value of about 150 in./mi and about 100 in./mi for this study. The automation tool of pavement performance prediction provided the flexibility for changing these triggers based on an agency's decision.

The threshold value of IRI was 170 in./mi, as determined by the FHWA (Visintine et al. 2018), meaning that the pavement would be in poor condition if IRI reached this level. Based on previous case studies, the initial IRI value after HMA overlay rehabilitation was considered to be 63 in./mi. In Figure 69a, the pavement was overlaid with 2 in. asphalt at the age of 19, so its age was reset to 0, and a previous age of 20 since construction became an age of 1 after overlaying. The area between pretreatment and post-treatment IRI predictions denotes the performance benefit area of the improved pavement performance; the area becoming larger means that more benefit is achieved by the treatment, reflecting greater life extension. The time between initial IRI and trigger IRI after post-treatment is called the treatment service life, and the time between the threshold IRIs before and after treatment represents pavement life extension. Therefore, for the case of applying AC overlay rehabilitation to this pavement, pavement service life can be extended by approximately 20 years, and treatment service life was found to be about 19 years.

It was assumed that an approximate 15% IRI enhancement occurs after a thin overlay treatment, and Figure 69b indicates that the pavement exceeded the treatment trigger value, about 100 in./mi, at the age of 12. After the application of a thin overlay treatment, post-treatment IRI predictions passed the next trigger value at the age of 15. The duration between initial post-treatment IRI and trigger IRI after treatment is approximately three years, the approximate treatment service life. Using a thin overlay, the pavement service life extension was found to be six years, a value supported by both the literature and case studies. Note that for a particular application a user can adjust initial IRI, recovery percentage, and treatment trigger.

Figure 70 shows the failure ages of the 34 AC pavement sections from the PMIS database that reached the treatment trigger for thin overlay, about 100 in./mi, before and after treatment applications.

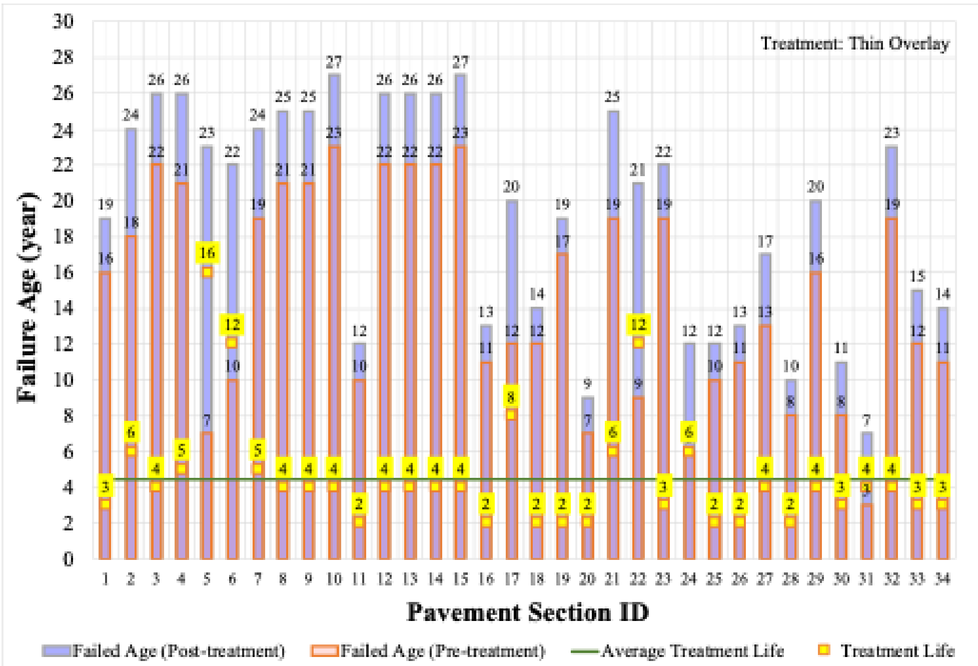


Figure 70. Illustration of effect of thin overlay on service life based on failure age

For example, pavement section ID 33 represents the pavement shown in Figure 69. At the age of 12 years, it failed by passing the treatment trigger, a thin overlay treatment was applied, and at the age of 15 years, the pavement again exceeded the treatment trigger level. The treatment service life for this pavement was three years, and the mean of all pavement sections' treatment service life was found to be four years for thin overlay, as denoted by the green line in Figure 70. The RSLs of pavements can be calculated for defining pavement design life.

Key Findings and Recommendations

A network-level pavement performance prediction automation tool using a machine-learning technique was explored for a proof-of-concept demonstration of the integration of AC pavement preservation and rehabilitation techniques on RSL predictions. Using the developed ANN model, this tool can be used as a decision-making tool for predicting both future pretreatment IRI and future post-treatment IRI, depending on the selection of treatments such as functional thin AC overlay and structural AC overlay. The findings and recommendations of this work can be summarized as follows:

- ANN models developed for AC pavement systems, requiring only five input parameters of pavement thickness, age, traffic, and previous years' IRI values, can predict IRI with high accuracy when compared to actual IRI measurements from the PMIS database.
- Since it has been trained with an adequately large number of field data points, the same model developed for predicting pretreatment IRI can be used for predicting post-treatment IRI.
- There are several significant parameters to be defined before predicting post-treatment IRI: initial IRI after treatment or recovery percentage in performance, treatment trigger, expected treatment service life, and remaining pavement service life extension. The automated decision-making tool can provide flexibility for entering these parameters for predicting post-treatment IRI.

CHAPTER 7. DEVELOPMENT AND FEATURES OF IPAT TOOL

The IPAT tool is a Microsoft Excel macro- and VBA-based automation tool that is comprised of a navigation panel (main tool) and sub-tools. As can be seen in Figure 71, the IPAT tool has been developed to navigate and utilize all sub-tools for both the statistics-based and AI-based models described in previous chapters (Chapter 3, Chapter 4, and Chapter 5).

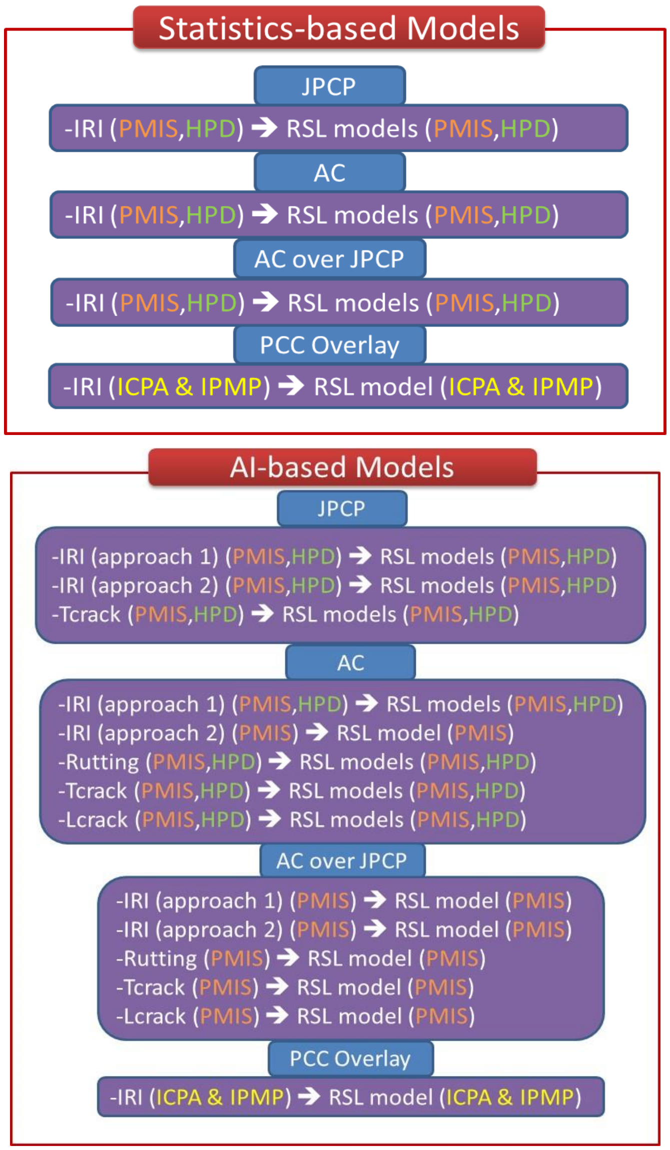


Figure 71. Overview of sub-tools for IPAT tool

A total of 14 sub-tools for statistics-based models and 42 sub-tools for AI-based models were developed to predict pavement performance and RSL.

The interface of the main tool is shown in Figure 72.

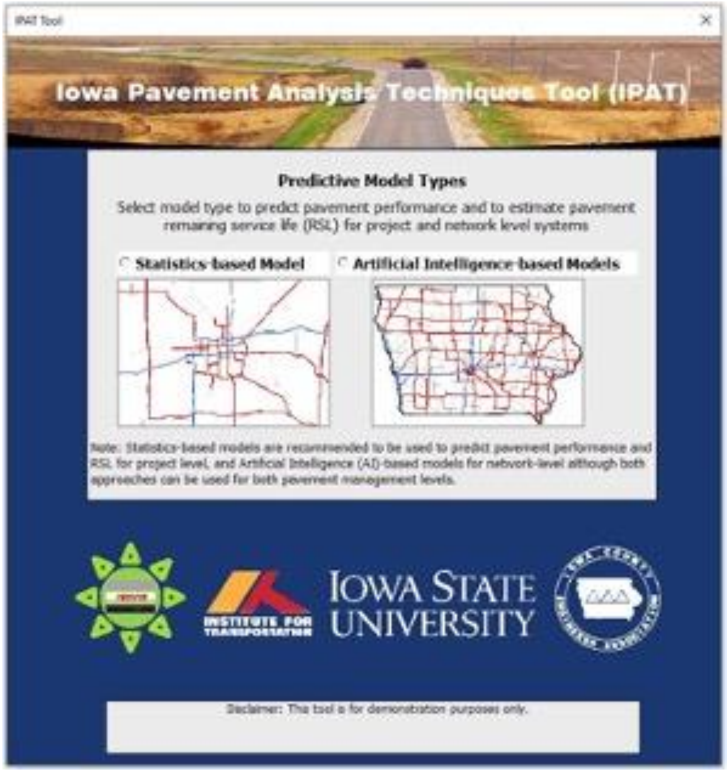


Figure 72. Interface of main IPAT tool

The process for AC over JPCP analysis is the same as for the process of AC analysis.

The IPAT source code is provided in Appendix C. In addition, details on how to use the IPAT tool are provided in a standalone user guide that was also developed as part of this project.

The flowcharts for each of the pavement performance and RSL prediction tools are shown in Figure 73 through Figure 81.

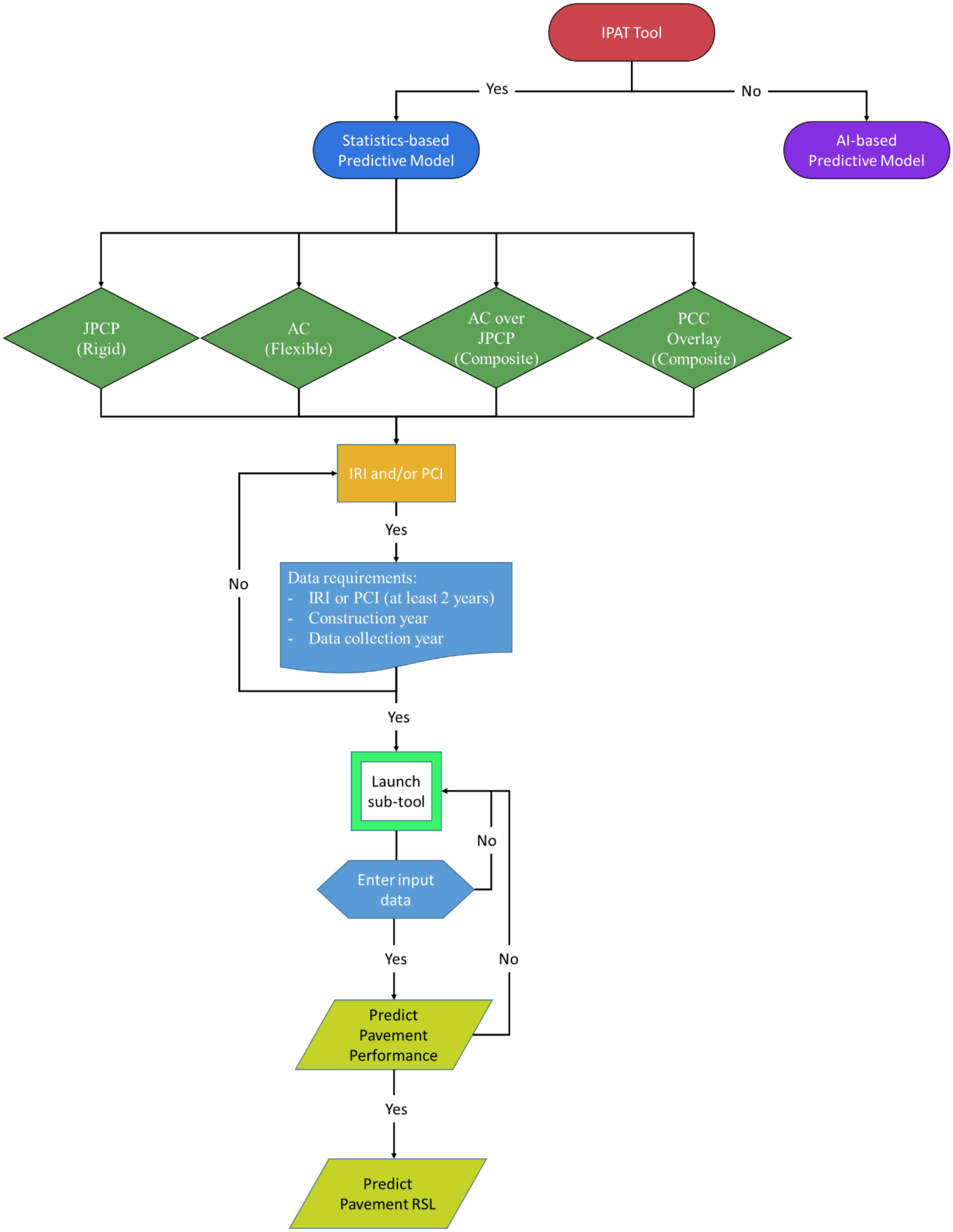


Figure 73. Flowchart of IPAT tool using statistics-based models for all pavement types

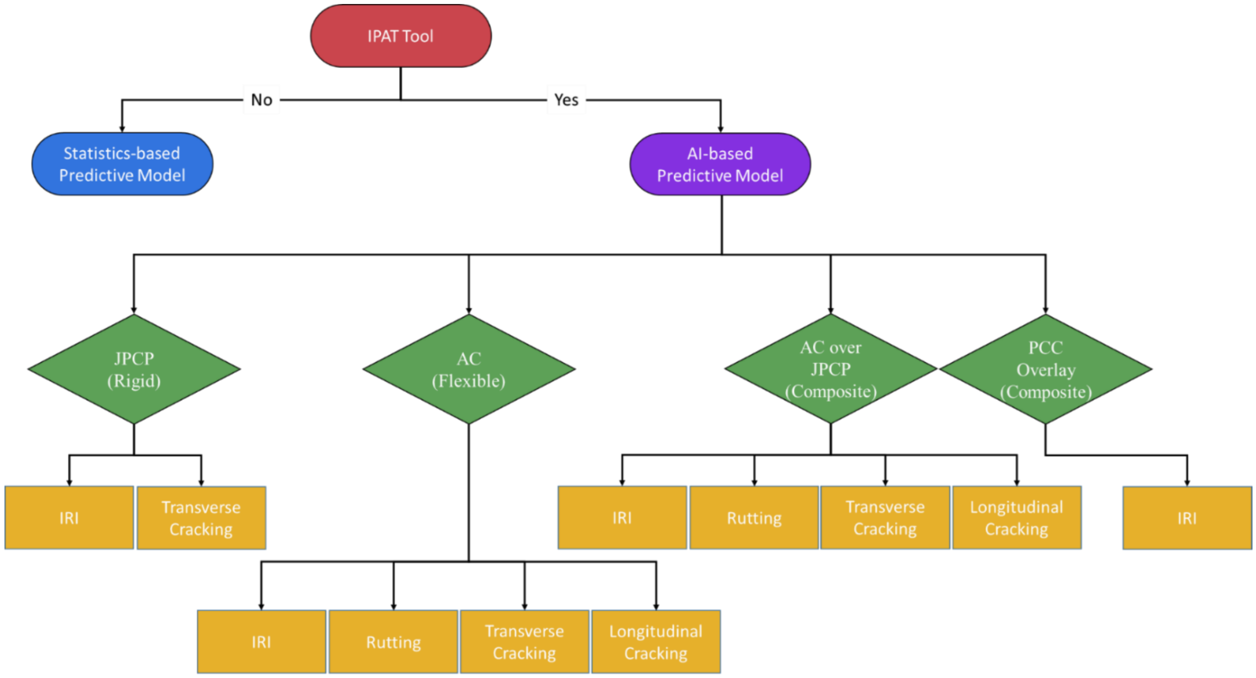


Figure 74. Flowchart of IPAT tool using AI-based models for all pavement types

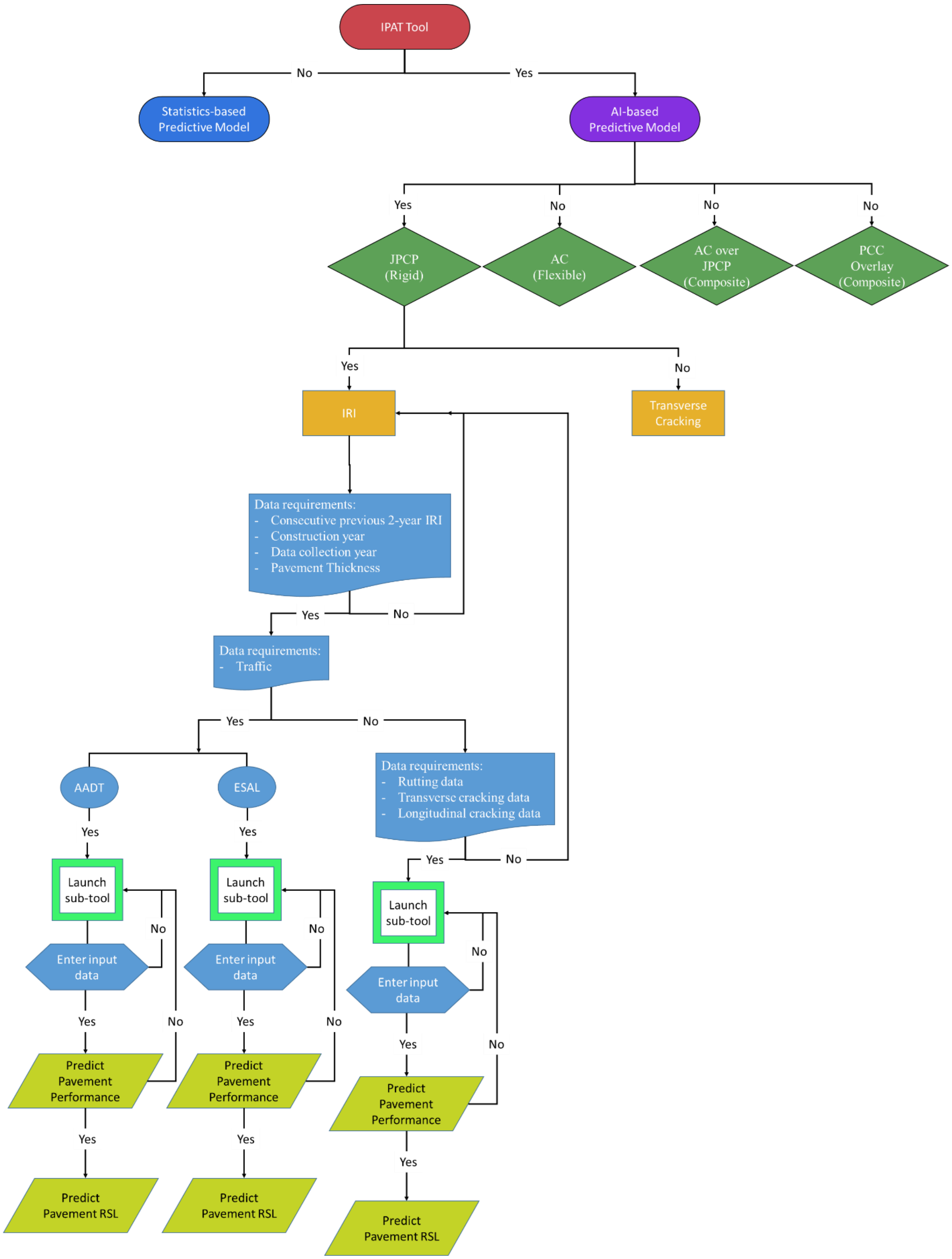


Figure 75. Flowchart of IPAT tool using AI-based IRI model for JPCP

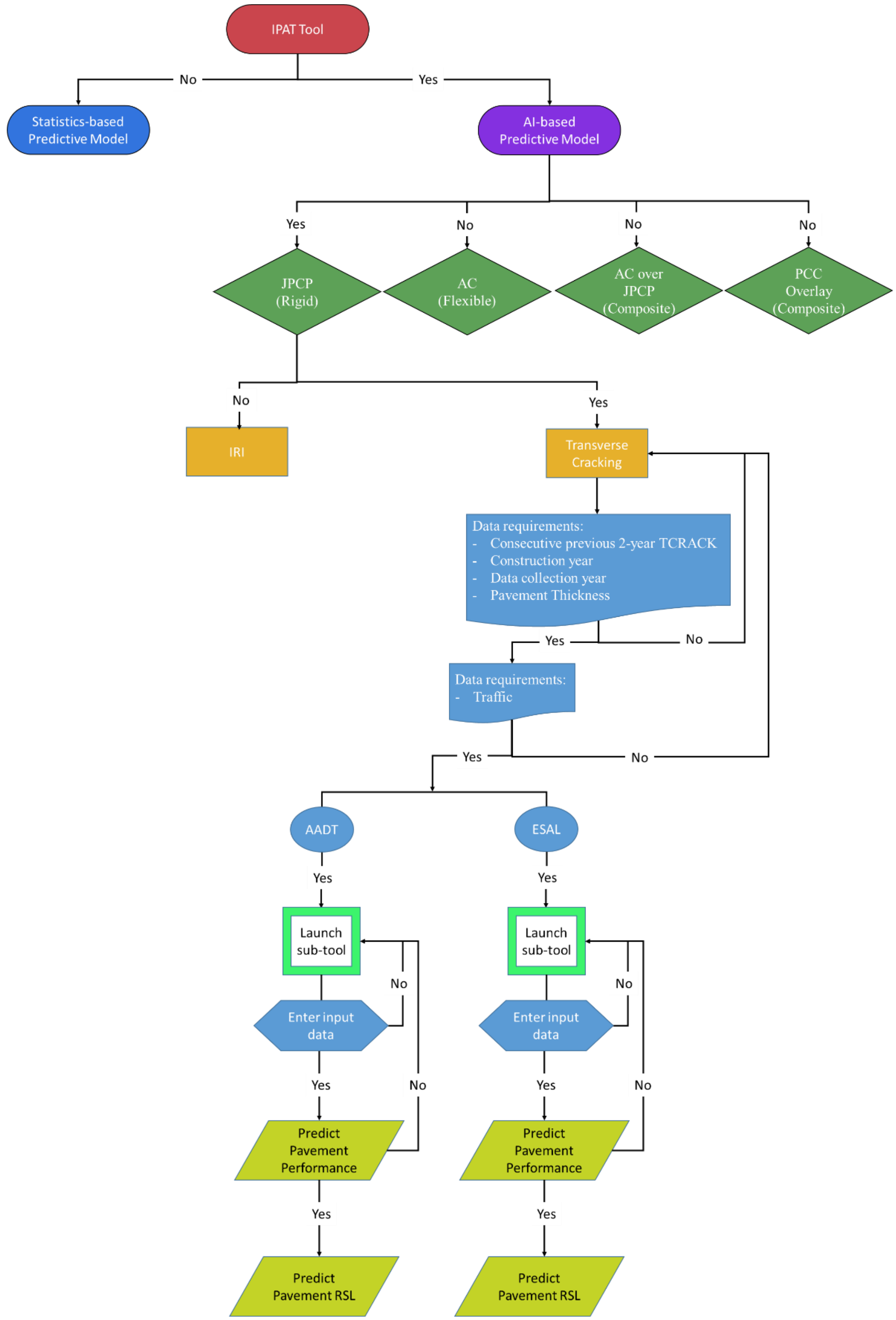


Figure 76. Flowchart of IPAT tool using AI-based TCRACK model for JPCP

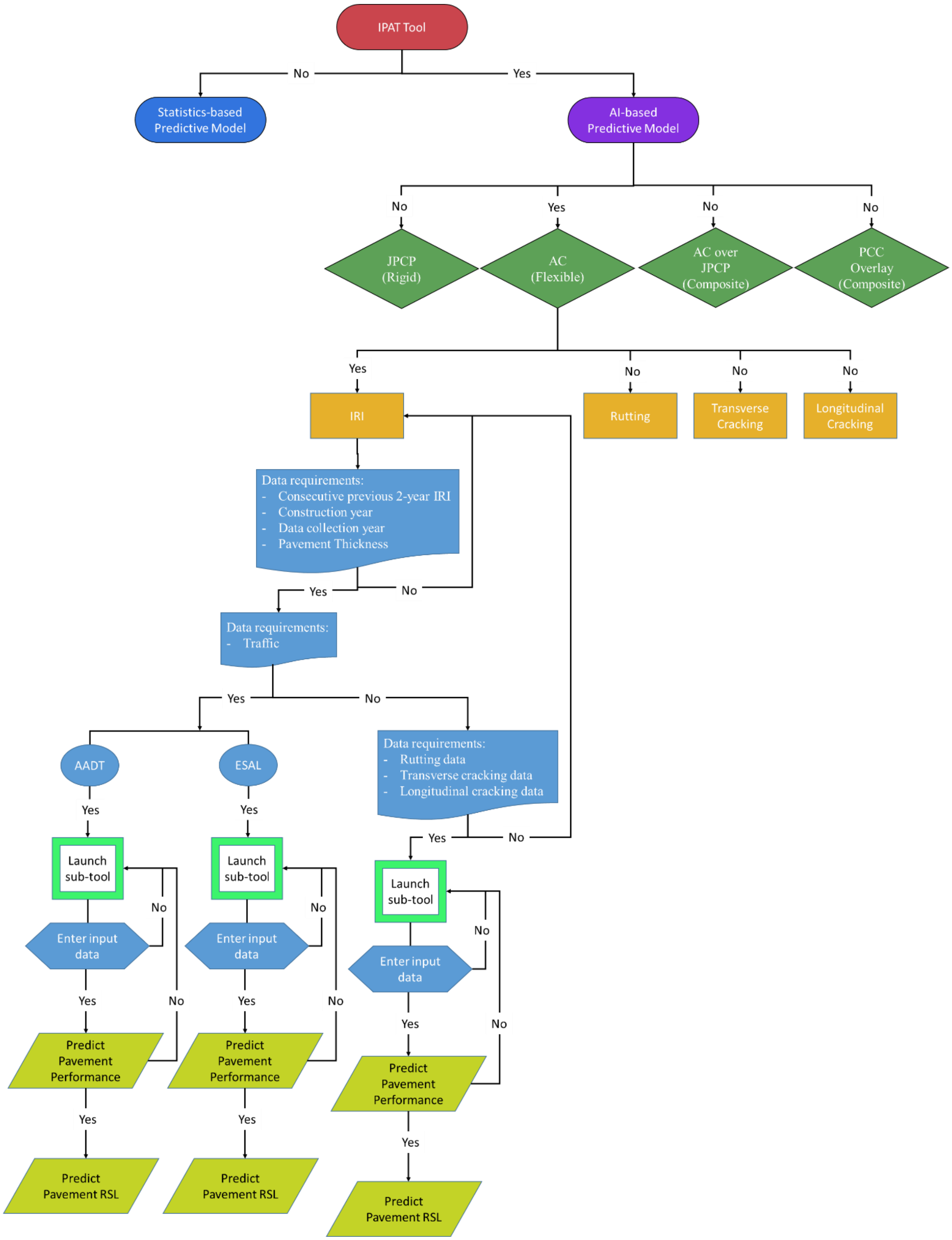


Figure 77. Flowchart of IPAT tool using AI-based IRI model for AC

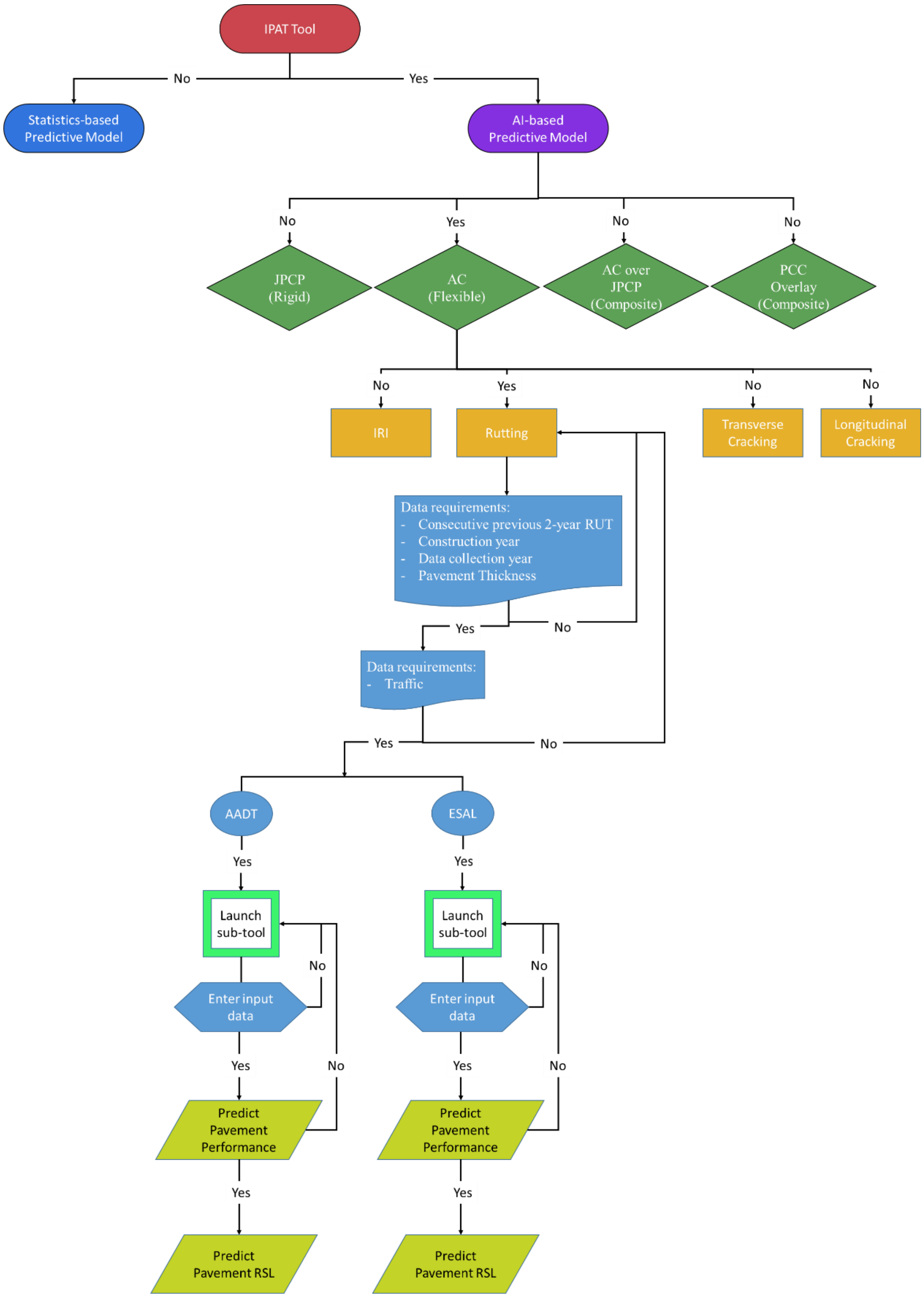


Figure 78. Flowchart of IPAT tool using AI-based RUT model for AC

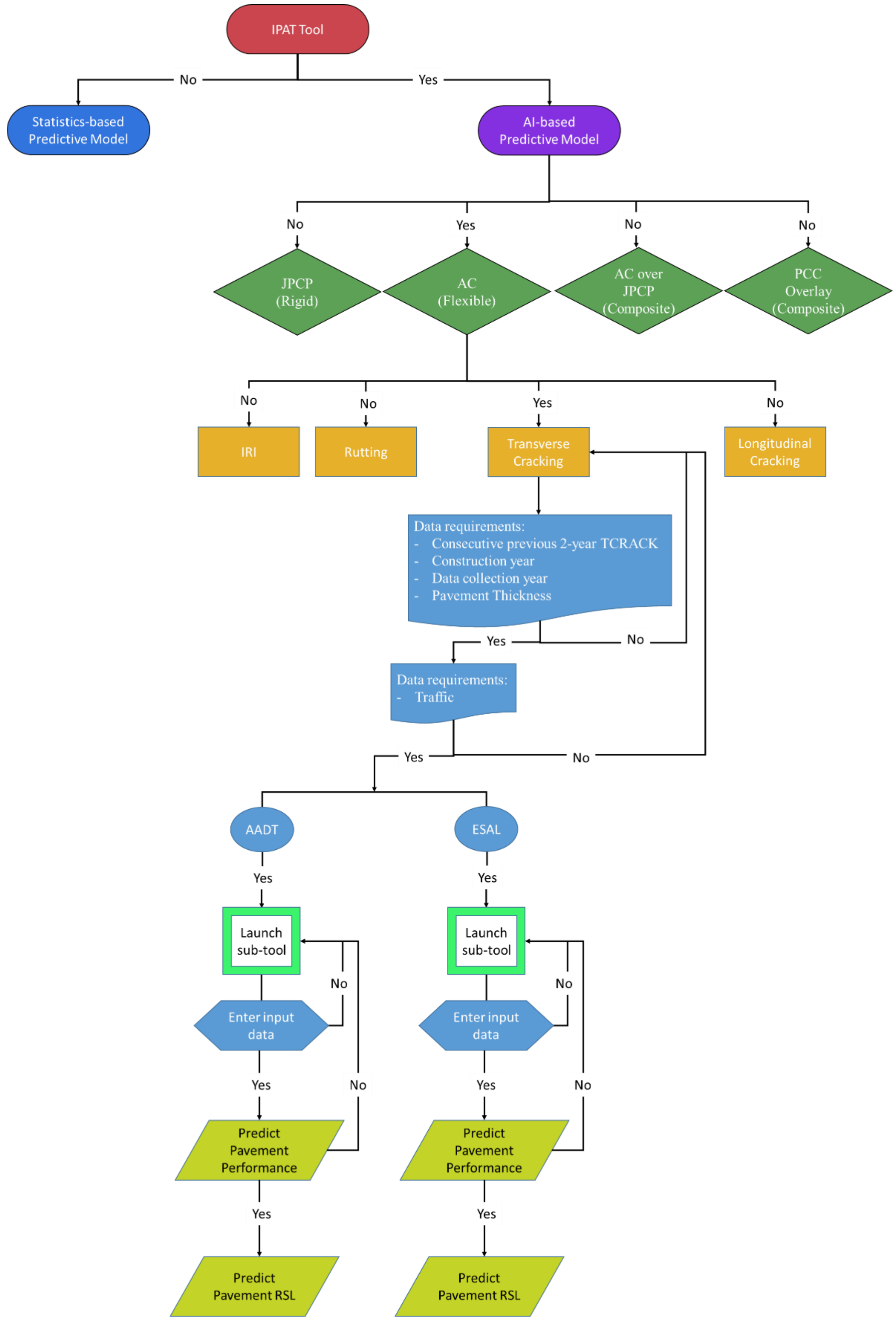


Figure 79. Flowchart of IPAT tool using AI-based TCRACK model for AC

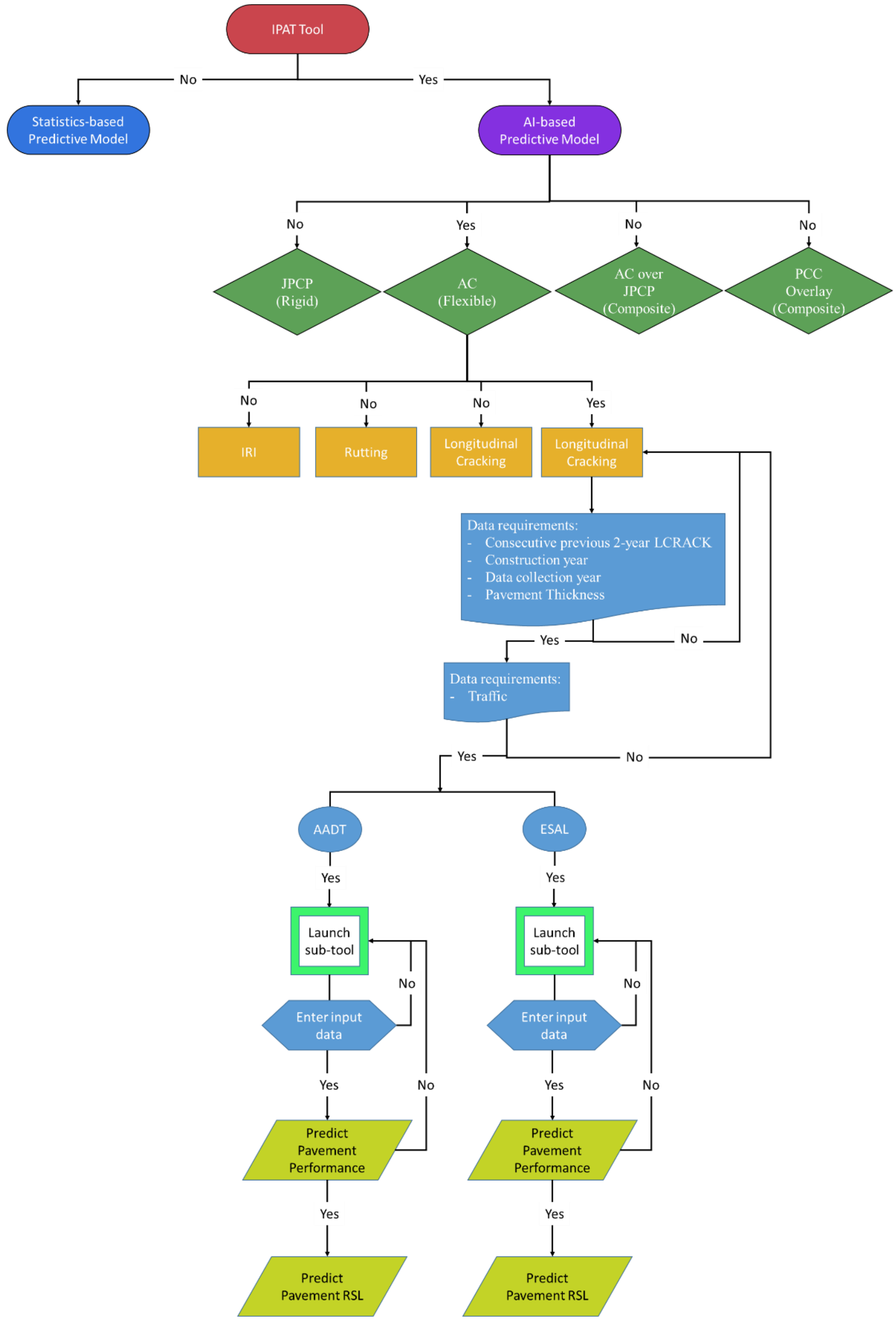


Figure 80. Flowchart of IPAT tool using AI-based LCRACK model for AC

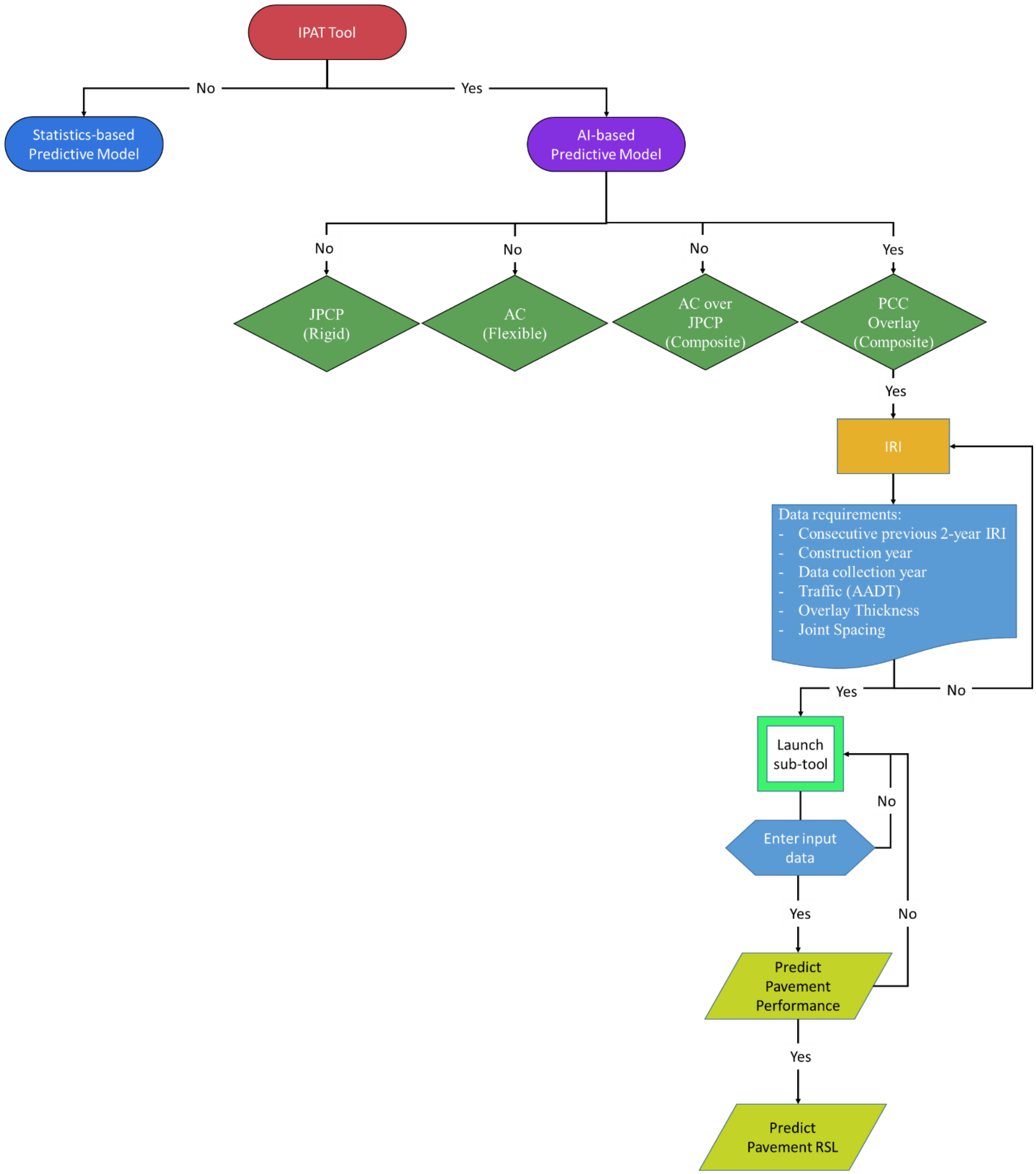


Figure 81. Flowchart of IPAT tool using AI-based IRI model for PCC overlay

CHAPTER 8. CONCLUSIONS

Overall Conclusions

A detailed step-by-step methodology for the development of pavement performance and RSL prediction models using real pavement performance data obtained from the Iowa DOT PMIS database have been described and discussed. To develop RSL models, project- and network-level pavement performance models were initially developed using two approaches: a statistically (or mathematically) defined approach primarily used for project-level modeling and analysis and an AI-based approach using an ANN to primarily be used for network-level modeling and analysis. Then, using various pavement performance indicators, including IRI for project-level models as well as rutting, percent cracking, and IRI for network-level models, and the FHWA-specified threshold limits for pavement performance indicators, RSL models were developed for four pavement types in Iowa: JPCPs representing rigid pavement systems, AC pavements representing rigid pavement systems, AC over JPCP representing composite pavement systems, and PCC overlay (concrete overlay). Network-level pavement deterioration prediction and RSL models were also further improved for JPCP, AC, and PCC overlays using available data related to Iowa county pavements.

A statistically (or mathematically) defined sigmoid pavement deterioration curve-based approach was used for project-level modeling and analysis. Sigmoidal equations were particularly used in the statistical model development because: (1) they have a low initial slope that increases with time, and (2) they follow a trend in which pavement condition always gets worse and the damage is irreversible; both these features make these models mimic pavement deterioration behavior observed in field studies. Sigmoidal equations were found to successfully model pavement deterioration when there was a single pavement deterioration trend (project-level). One of the benefits of project-level pavement performance models is that they can be developed using very sparse data, so they can be extensively used when only limited conditional or structural data and traffic data are available for given pavement sections.

AI-based pavement performance models were primarily used for network-level modeling and analysis. AI techniques such as ANN-based models have been found to be great tools for modeling pavement deterioration when there are many pavement sections with various traffic, thickness, and other various deterioration trends (network-level). They are also very fast tools that can solve thousands of pavement scenarios with various traffic, thickness, and conditions in seconds. Both these features of ANN models make them excellent tools for use in the development of network-level pavement performance modeling.

Network-level pavement performance models were also developed using statistical- and ANN-based approaches, with identical input parameters used in both approaches to evaluate their relative success for network-level pavement performance modeling. It was found that network-level ANN-based pavement performance models produced greater accuracy with higher R^2 and lower AAE values compared to project-level statistical models.

It is worth noting that while both statistics- and AI-based models can be utilized for project- and network-level pavement performance and RSL estimations, the research team recommends the utilization of statistics-based models if one is interested in analyzing project-level pavement systems, while AI-based models are recommended if network-level pavement systems are analyzed. The reason for this recommendation is that AI-based models were developed using network-level databases and are more capable of capturing a variety of scenarios in pavement systems. Statistics-based models were developed for individual road sections, and each time the models are used for these particular road sections, they can be updated using more data, so they rely more on project-level investigation.

As part of this study, Microsoft Excel-based automation tools collected in an IPAT tool were developed for both project- and network-level pavement performance modeling and analysis. The conclusions from the tool development are as follows:

- The project-level pavement performance modeling and RSL calculation tool is capable of developing project-based statistical models for predicting future pavement performance as well as calculating RSL values based on user-defined threshold limits. It is also capable of automatically updating and improving pavement performance prediction models because it allows more data to be added to the model development data set. The benefit of this tool is that, as engineers add more data into the model development data set, they will be able to automatically refine performance prediction models and make decisions using more recent and more accurate pavement performance models.

- The network-level pavement performance modeling tool is capable of making pavement performance predictions based on pre-developed ANN-based pavement performance models. While having only thickness, traffic, age, and the previous two years of pavement performance records for any pavement performance indicator, it can make future pavement performance calculations in less than a second for any pavement section. It is also capable of producing pavement performance predictions in seconds for thousands of pavement scenarios under various traffic, thickness, and other conditions. The network-level pavement performance modeling tool is also capable of: (1) making future pavement performance predictions for some distresses (transverse cracking, rutting, and longitudinal cracking), and then (2) using these predicted distress values as inputs in making future IRI predictions.

Conclusions for the JPCP Case

The JPCP case is described in Chapters 3 and 4, and specific related findings are summarized as follows:

- Thirty-four JPCP pavement sections were used in pavement performance model development in this study.

- Accurate project-level statistical-based IRI performance models and network-level AI-based transverse cracking, IRI approach 1, and IRI approach 2 models were developed for JPCP pavements. AI-based models using the PMIS database were further improved for county databases by incorporating different input parameters (e.g., AADT instead of ESAL, pavement performance thickness ratio instead of only pavement performance).

- Using the PMIS database:

  - *Statistics-based network-level RSL estimation*: An average RSL value of 7.2 years was found for 34 JPCP pavement sections when statistics-based pavement performance models were used to make future IRI predictions. An IRI threshold limit of 170 in./mi was used as a pavement performance indicator in project-level RSL models.

  - *AI-based network-level RSL estimation*: Average RSL values of 2.0, 9.6, and 11.5 years were found for 34 JPCP pavement sections when AI-based transverse cracking, IRI approach 1, and IRI approach 2 pavement performance models were used to make future pavement condition predictions. A percent cracking threshold limit of 15% and an IRI threshold limit of 170 in./mi were used in the calculation of RSL.

- Using the Iowa county database:

  - *Statistics-based network-level RSL estimation*: An average RSL value of 13.3 years was found for 34 JPCP pavement sections when statistics-based pavement performance models were used to make future IRI predictions. An IRI threshold limit of 200 in./mi was used as a pavement performance indicator in project-level RSL models.

  - *AI-based network-level RSL estimation*: Average RSL values of 4.9, 6.2, and 11.2 years were found for 34 JPCP pavement sections when AI-based transverse cracking, IRI approach 1, and IRI approach 2 pavement performance models were used to make future pavement condition predictions. The percent cracking threshold limit was taken as 15%. Since county JPCP sections have exhibited high IRI values at present, an IRI threshold limit of 200 in./mi was used in the calculation of RSL for illustration purposes.

- Different average IRI-based RSL results (7.2, 9.6, and 11.5 years of RSL for PMIS database and 13.3, 6.2, and 11.2 years of RSL for county database) for the JPCP pavement sections were found when statistics- and AI-based IRI approach 1 and approach 2 pavement performance models, respectively, were used in the calculation of RSL. This difference in average RSL results might be because different pavement performance models were used in the calculation of RSL. AI-based pavement performance models were developed for each pavement performance indicator, and Excel-based sub-tools were developed and utilized to predict future pavement condition for all pavement sections of a given pavement type. Even if they are developed considering various input variables (thickness, traffic, previous years' condition records, etc.), they cannot be sufficiently comprehensive to consider all variables determining deterioration of the pavement systems. On the other hand, statistics-based pavement performance models, valid only for the sections for which they were developed, were developed for given pavement sections. For pavement sections with few pavement condition records, accuracies might not be high enough, and adding more data points (i.e., future performance measurements) would most likely increase model accuracy.

Conclusions for the AC Pavement Case

The AC pavement case is described in Chapters 3 and 4, and specific related findings are summarized as follows:

- Thirty-five AC pavement sections were used in pavement performance model development in this study.

- Accurate project-level statistical-based IRI performance models and network-level AI-based rutting, longitudinal cracking, transverse cracking, IRI approach 1, and IRI approach 2 models were developed for AC pavements. AI-based models using the PMIS database were improved to be used for the county database by incorporating different input parameters (e.g., AADT instead of ESAL)

- Using PMIS database:

    - *Statistics-based network-level RSL estimation*: An average RSL value of 9.3 years was found for 35 AC pavement sections when statistics-based pavement performance models were used to make future IRI predictions. An IRI threshold limit of 170 in./mi was used as a pavement performance indicator in project-level RSL models.

    - *AI-based network-level RSL estimation*: Average RSL values of 2.3, 11.8, and 11.7 years were found for 35 AC pavement sections when AI-based rutting, IRI approach 1, and IRI approach 2 pavement performance models were used to make future pavement condition predictions, and a rutting threshold limit of 0.4 in. and an IRI threshold limit of 170 in./mi were used in the calculation of RSL.

- Using the Iowa county database:

    - *Statistics-based network-level RSL estimation*: An average RSL value of 26 years was found for 35 AC pavement sections when statistics-based pavement performance models were used to make future IRI predictions. An IRI threshold limit of 200 in./mi was used as a pavement performance indicator in project-level RSL models.

    - *AI-based network-level RSL estimation*: Average RSL values of 8.6 and 13.7 years were found for 35 AC pavement sections when AI-based IRI approach 1 and IRI approach 2 pavement performance models were used to make future pavement condition predictions. An IRI threshold limit of 170 in./mi was used in the calculation of RSL.

- In summary, when statistics-based and AI-based IRI approach 1 and approach 2 pavement performance models, respectively, were used in the calculation of RSL, there was an insignificant difference in average IRI-based RSL results (9.3, 11.8, and 11.7 years of RSL) for the PMIS database. In contrast, average IRI-based RSL results were obtained (26, 8.6, and 13.7 years of RSL) for the county database for the AC pavement sections. The reason for the wider range of years is that the county database suffers from less collected field data and a lack of historical records for some pavement sections. Thus, IRI may not reach the threshold limit in a pavement's design life based on the given limited inputs to the model. In this case, RSL is calculated based on the design life duration that might result in higher values in network-level RSL. Adding more data points (i.e., future performance measurements) would change the pavement performance models as well as the calculated RSL results.

Conclusions for the AC over JPCP Case

The AC over JPCP case is described in Chapters 3, and the specific related findings are summarized as follows:

- Sixty AC over JPCP sections were used in pavement performance model development in this study.

- Accurate project-level statistical-based IRI performance models and network-level AI-based rutting, longitudinal cracking, transverse cracking, IRI approach 1, and IRI approach 2 ANN models were developed for composite pavements.

- Using the PMIS database:

    - *Statistics-based network-level RSL estimation*: An average RSL value of 4.4 years was found for 60 composite pavement sections when statistics-based pavement performance models were used to make future IRI predictions, with an IRI threshold limit of 170 in./mi used in the calculation of RSL.

    - *AI-based network-level RSL estimation*: Average RSL values of 14.4, 9.3, and 6.1 years were found for 60 composite pavement sections when AI-based rutting, IRI approach 1, and IRI approach 2 pavement performance models were used to make future pavement condition predictions, with a rutting threshold limit of 0.4 in. and an IRI threshold limit of 170 in./mi used in the calculation of RSL.

- Because of lack of available data for AC over JPCP sections in the county database, AI-based models could not be improved.

- In summary, average RSL results for 60 composite pavement sections when statistics-based and ANN-based IRI performance models approach 1 and approach 2 were used to calculate

RSL values were 4.4, 9.3, and 6.3 years. Note that calculated RSL results are based on a limited number of data sets, developed pavement performance models, and the FHWA-specified threshold limits, so adding more data points (i.e., future performance measurements) would most likely change the pavement performance models as well as the calculated RSL results.

Conclusions for the PCC Overlay Case

The PCC overlay (county overlay) case is described in Chapters 5, and the specific related findings are summarized as follows:

- A total of 148 PCC overlaid pavement sections were used in pavement performance model development in this study.

- Accurate project-level statistical-based IRI performance models and a network-level AI-based IRI model were developed for PCC overlays. AI-based models using the Iowa county database were developed to reflect the importance of data availability and data limitations used in models.

- Using Iowa county overlay databases:

  - *Statistics-based network-level RSL estimation*: An average RSL value of 15.3 years was found for 18 PCC overlaid pavement sections when statistics-based pavement performance models were used to make future IRI predictions. An IRI threshold limit of 170 in./mi was used as a pavement performance indicator in project-level RSL models.

  - *AI-based network-level RSL estimation*: An average RSL value of 7.4 years was found for 18 PCC overlaid pavement sections when AI-based IRI pavement performance models were used to make future pavement condition predictions, with an IRI threshold limit of 170 in./mi used in the calculation of RSL.

- In summary, average RSL results for 18 PCC overlays when statistics-based and ANN-based performance models were used in the calculation of RSL values were 15.3 and 7.4 years. Note that calculated average RSL results are based on only a limited number of pavement sections, and since analyzed pavement sections also had low IRI values throughout the years of data collection, IRI could not reach the threshold limit within the pavement's design life, and RSL was calculated based on the design life, resulting in higher RSL values when using a statistics-based approach. However, it should be noted that the availability of more measured data for models could provide better patterns for predicting future data, as shown in the deterioration curves.

Conclusions for Feasibility of Integrating Pavement Treatment Techniques into RSL Models

The feasibility of integrating pavement treatment techniques into RSL models is described in Chapter 6, and the specific related findings are summarized as follows:

- Based on lessons learned from the feasibility study of integrating preservation and rehabilitation techniques to AI-based RSL models, the additional parameters to be identified and defined for improving model robustness include the following:
    - *JPCP:* preservation treatment trigger and recovery percentage
    - *AC pavements:* initial IRI after treatment or recovery percentage in performance, treatment trigger, expected treatment service life, and remaining pavement service life extension

CHAPTER 9. RECOMMENDATIONS FOR IMPLEMENTATION AND FUTURE RESEARCH

This study developed the IPAT tool that Iowa county engineers can use to estimate project- and network-level pavement performance and RSL. The tool provides a series of options for estimating RSL through different approaches based on various conditions and distress data availability of individual counties. Such RSL estimations will allow county engineers to distinguish between two pavement sections having the same current condition (i.e., the same current IRI). This can be an ideal approach to addressing transportation planning and performance management criteria requirements of the MAP-21 legislation.

Figure 82 illustrates how the Microsoft Excel-based IPAT tool described in this study could be integrated into Iowa county pavement asset management procedures.

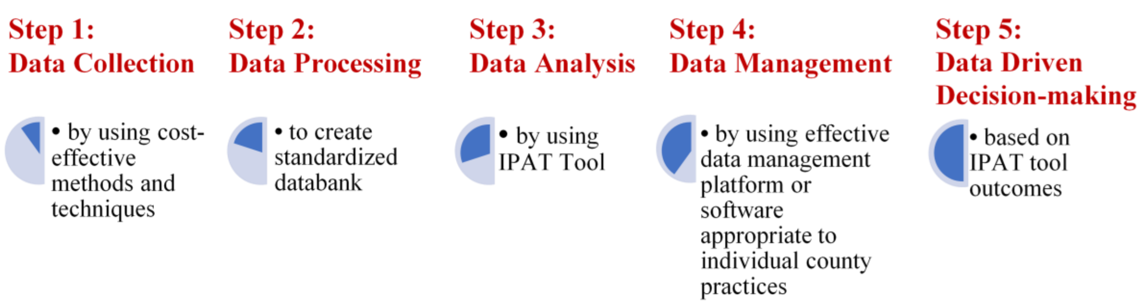


Figure 82. Pavement asset management procedures recommended by using IPAT tool

The procedure is outlined in the following recommended steps:

- **Step 1: Data collection.** Collect county pavement inventory data (e.g., construction history, maintenance activities) and performance history data using cost-effective methods and techniques.

- **Step 2: Data processing.** Segment and summarize the collected data by computing locations of events (e.g., condition/ distress data) on linear features (e.g., pavement management sections) at run time (dynamically) in linear measure (e.g., milepost, latitude, and longitude) for individual pavement sections, and then combine them to create a standardized databank that merges data from different sources while preventing overlapped data. Note that Appendix A offers a step-by-step detailed standardized procedure to illustrate how such a standardized databank (i.e., an Iowa county pavement HPD) concept could be developed.

- **Step 3: Data analysis.** Analyze the processed data by using the developed Microsoft Excel-based IPAT tool to estimate the performance and RSL of county pavements at both project and network levels.

- **Step 4: Data management.** Integrate and store the processed and analyzed data into an effective data management platform or software appropriate to individual county practices.

- **Step 5: Data-driven decision-making.** Prioritize and allocate resources for future pavement preservation and rehabilitation needs by using pavement performance and RSL predictions from the IPAT tool.

Future directions for the next phase(s) of this work have been developed and recommended to fulfill county engineer needs for fully implementing the recommended steps in Iowa county pavement asset management practices. These directions can be categorized into the following five topics related to each step:

- **Step 1: Improve data collection practices**
  Implement low-cost data collection tools for local road agencies to support more frequent collection of pavement performance data and establish a more synthesized and reliable database than what currently exists. By using such tools, local road agencies could more easily and accurately record the beginning and ending coordinates (latitude and longitude) for each road section using the standardized metadata at each agency level to prevent faults during data transfer and update the database when road alignments change. It is recommended that local agencies implement the recommendations of the IHRB project titled Development of a Smartphone-Based Road Performance Data Collection Tool (Ceylan et al. 2021), for which the research team has been developing standardized nonproprietary collection tools (i.e., a smartphone-based road performance data collection tool and a smart vehicle black box) with automatic vehicle location (AVL) technology.

- **Step 2: Automate or semi-automate data processing**
  Develop an automated or semi-automated data processing tool that could prevent errors in manual data handling and facilitate creating a databank that merges data from different sources and updating that database when road alignments change.

- **Step 3: Integrate maintenance/preservation/rehabilitation activities into the IPAT tool**
  Improve the robustness of the AI-based RSL models developed from the feasibility study by addressing identified challenges and incorporating solutions to them as additional sub-tools in subsequent IPAT tool updates.

- **Step 4: Integrate the IPAT tool into the geographic information system (GIS) platform and/or software and develop a smartphone application version of the IPAT tool as an official app under the Iowa County Engineers Association Service Bureau (ICEASB) AppSuite to provide better data management practices**
  Integrate IPAT predictions into a web-based platform and/or software (e.g., ArcGIS) appropriate to individual county practices. Such integration could provide a user-friendly interface, store all information in a dynamic map visualization, and track and predict pavement performance, access pavement data, and reevaluate pavements while observing them in the field to improve data management practices. The smartphone application version

of the IPAT tool could be developed as an official app under the ICEASB AppSuite or other existing database platforms used by Iowa county engineers.

- **Step 5: Develop multi-objective optimized RSL models to assist in better decision-making**
  Develop multi-objective optimized RSL models considering various pavement performance indicators with different priorities and budget and resource constraints. Such multi-objective optimized RSL models will assist in better decision-making by using strategies to prioritize projects for maintenance and rehabilitation plans and select cost-effective maintenance and rehabilitation techniques for given projects.

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APPENDIX A. PROCEDURE TO DEVELOP IOWA COUNTY PAVEMENT HISTORICAL PERFORMANCE DATABANK

Scope

This manual describes the procedures for developing a historical performance databank (HPD) for Iowa county pavements. This document, together with the application of methods used by the Iowa Department of Transportation (DOT) for primary roads (i.e., Pavement Management Information Systems [PMIS]), delineates the procedures for creating and processing raw data for pavements and the guidelines for developing an accurate database of the secondary roads in Iowa.

Data Sources

The necessary data are divided into three groups: (1) condition and distress data, (2) construction history, and (3) traffic data. The condition and distress data were obtained from the Iowa DOT as raw data, called ROADWARE_LOCAL in this document. The construction history was provided by some county engineer's offices, called County Records in this document. The traffic data were obtained from the Iowa DOT, the Roadway Asset Management System (RAMS)/open data online.

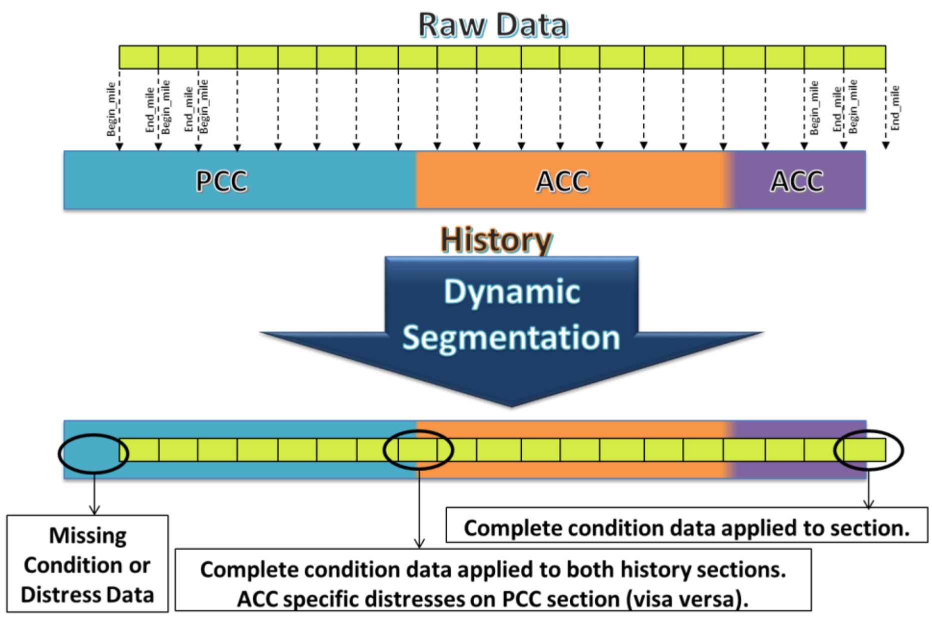
In this manual, the following terms are used for the descriptions of pavement systems:

- *County road unit* is defined as 1/100 of a mile (approximately 52 ft). The condition and distress data were collected for each county road unit. Also, each county road unit has its own beginning and ending milepost value.
- *County road section* is defined as each pavement section that has the same or different pavement type (e.g., flexible or rigid) in a county road system. The combination of all county road units is called consecutive county road units, which may form a county road section.
- *County road units with raw distress data* is defined as a county road system, which had raw data provided by the Iowa DOT. The combination of all consecutive county road units/sections is called a county road system.
- *County road sections with construction history* is defined as a county road system, which had pavement historical data obtained from County Records.

Description of Overall Procedures

An HPD for Iowa county pavements is developed by processing data including segmentation and summarization procedures. The segmentation procedure defines beginning and end points for a road section. Subsequent to determining these points, the road sections are created. Then, distress and condition data corresponding to these road sections are summarized to finalize the data processing. Thus, the summarization procedure calculates the condition and distress data for a specific road section by using different summarization techniques specified according to type of data.

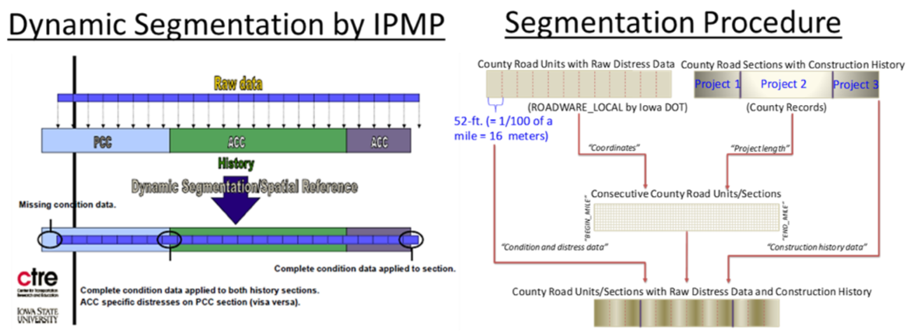
In the segmentation procedure, a dynamic segmentation method, which is a function of a geographic information system (GIS), is utilized. Dynamic segmentation is a process that has the ability to compute locations of events (e.g., condition/ distress data) on linear features (e.g., pavement management sections) at run time (dynamically) in linear measure (e.g., milepost, latitude, and longitude). Figure 83 indicates the overall process on how dynamic segmentation is applied on a database.



Reproduced from Nlenanya 2017, Institute for Transportation

Figure 83. Demonstration of application of dynamic segmentation on database

This process is the one used in Iowa DOT segmentation, which is shown on the Iowa Pavement Management Program (IPMP) website. Figure 84 shows a comparison of dynamic segmentation by IPMP and the segmentation procedure given in this manual. Raw data (ROADWARE_LOCAL) are provided by Iowa DOT and construction history data (County Records) are provided by Iowa county engineers.



Dynamic Segmentation	Segmentation Procedure
Raw Data	ROADWARE_LOCAL (provided by IA DOT)
History (PCC, ACC, ACC..)	County Records (provided by Iowa County)

Figure 84. Dynamic segmentation by IPMP vs. this manual's segmentation procedure

The segmentation procedure shown previously in Figure 34 in Chapter 4 is composed of two consecutive steps: the matching process and the sectioning process.

These steps help to create a databank that combines different data from different sources while preventing overlapped data. In the matching process, the project lengths are matched to specify the county road sections. County Records provided the project lengths. ROADWARE_LOCAL provided coordinates. Therefore, the project lengths need to be calculated by using these coordinates. In the sectioning process, after matching project lengths and/or coordinates of county road sections in the county road system, the consecutive county road units/sections are separated into portions. If the portion is the length of 52 ft, it is called a county road unit. If the portion is composed of consecutive county road units, it is called a county road section. Each portion has its own beginning and end mile and coordinates together with raw condition and distress data.

The summarization procedure shown previously in Figure 35 in Chapter 4 is implemented by processing each data corresponding to each county road unit.

An example using IRI distress data was indicated in Figure 35. To summarize IRI data for a road section, the average of raw IRI data of each county road unit is taken. In the event of missing IRI data in a road section, the average of existing raw IRI data was taken by ignoring missing data. More detail on this will be given in the following sections in this manual. Figure 83 and Figure 84 as well as the figures from Chapter 4 referenced above have indicated the overall process for the development of a databank, which is composed of the combination of segmentation and summarization procedures.

Description of the Segmentation Procedure

Step 1. Choice of County

Depending on the availability of construction history data (e.g., pavement thickness) found in County Records, a specific county is chosen.

Step 2. Preparation of Raw Data

The file of raw data obtained from the Iowa DOT, which includes the pavement condition, and distress data collected from the County Records database is selected based on its year and county ID and opened.

The Iowa DOT has archived the raw distress data collected by a third-party vendor since 2013 when statewide collection of non-National Highway System (non-NHS) federal-aid-eligible roads began. The collected and archived data in 2013, 2015, and 2017 includes 46 counties, and the collected and archived data in 2014, 2016, and 2018 includes 53 counties, meaning that data are collected every year for about half of the state as shown previously in Figure 36 in Chapter 4.

The files are named in the Iowa DOT database as follows:

- ROADWARE_LOCAL_2013
- ROADWARE_LOCAL_2014
- ROADWARE_LOCAL_2015
- ROADWARE_LOCAL_2016
- ROADWARE_LOCAL_2017

Each file is displayed as shown previously in Figure 37 in Chapter 4, including all information related to collected raw data. Microsoft Access and/or Excel software is utilized to import and export data from the Iowa DOT database. The developed pavement HPD is stored in an Excel format.

Step 3. Filtration of Selected Raw Data File Based on County ID

The selected ROADWARE_LOCAL raw data file is filtered based on the chosen county ID, as shown in Figure 85.

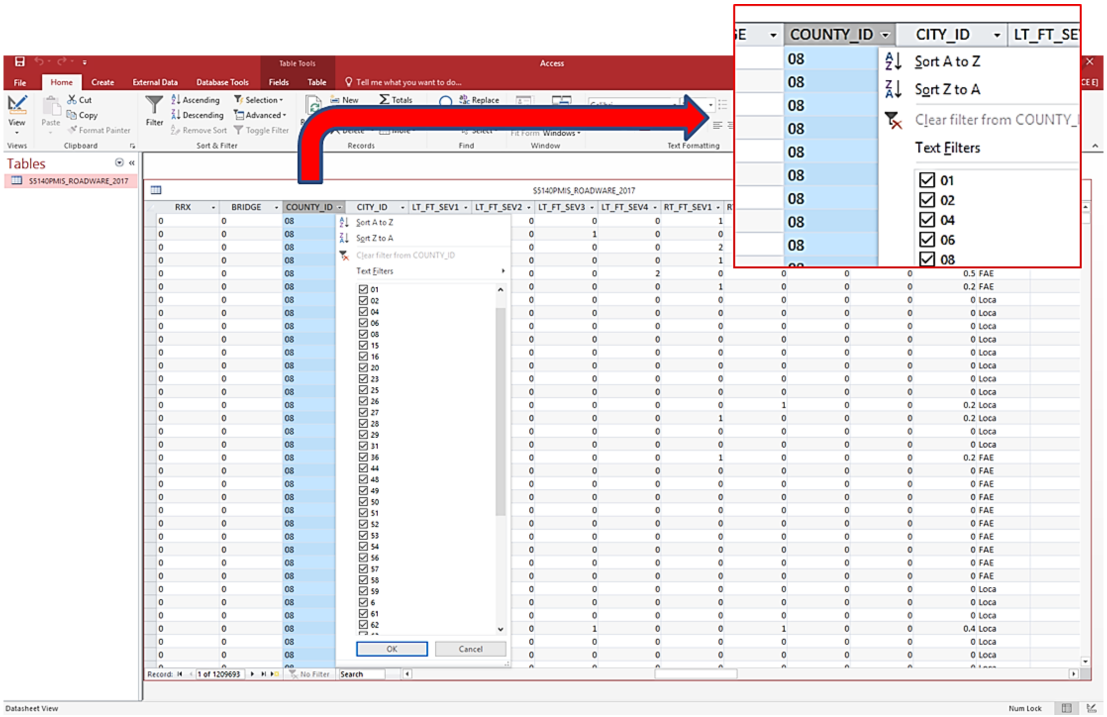


Figure 85. Filtration of ROADWARE_LOCAL based on county ID

Step 4. Filtration of Selected Raw Data File Based on Road Name

The County Records file is utilized to select a road name. After selection of road name, the ROADWARE_LOCAL raw data file is filtered based on road name, as shown in Figure 86.

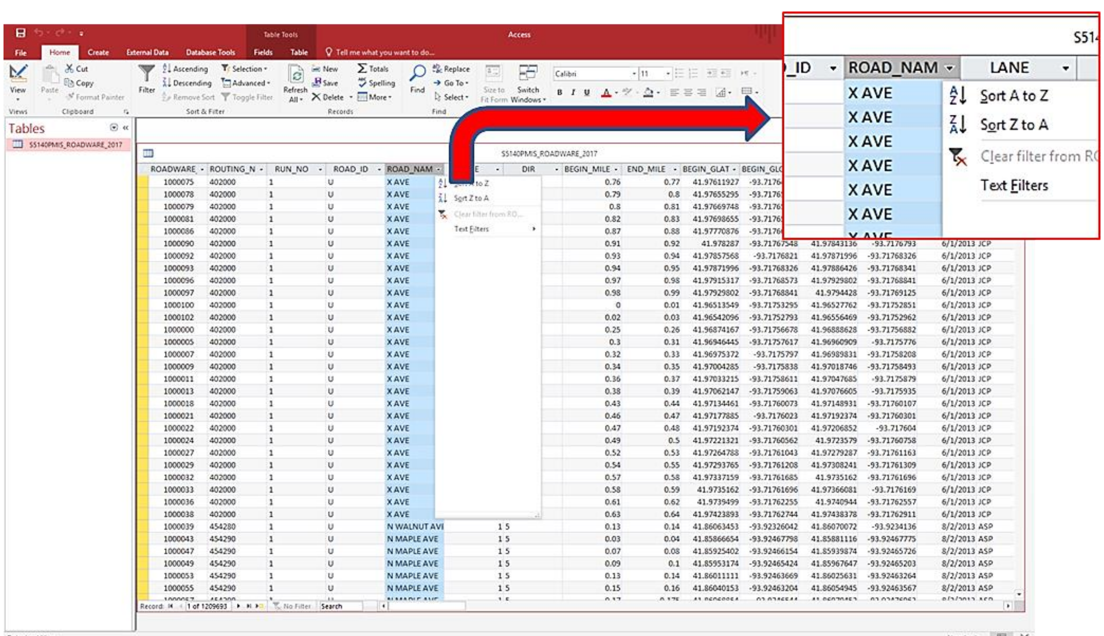


Figure 86. Filtration of ROADWARE_LOCAL based on road name

Here, the challenge is that a road name can be represented with a different name in every year. Thus, County Records and ROADWARE_LOCAL do not necessarily match. In such cases, there are some auxiliary sources to determine the changed road name. One of these sources is the Highway and Transportation Map corresponding to the related county to view each road name in different ways. Also, the coordinates of the chosen road section need to be compared between years to make sure that the same road section is surveyed in every year. Another source is Google Maps, which can be used to find the location and coordinates of the road sections.

Step 5. Sorting of County Road Units

The recorded mileages of the selected county road units are sorted in ascending order. The sorted column in ROADWARE_LOCAL file is named BEGIN_MILE before 2016 and FROM_MEASURE since 2016, as shown in Figure 87.

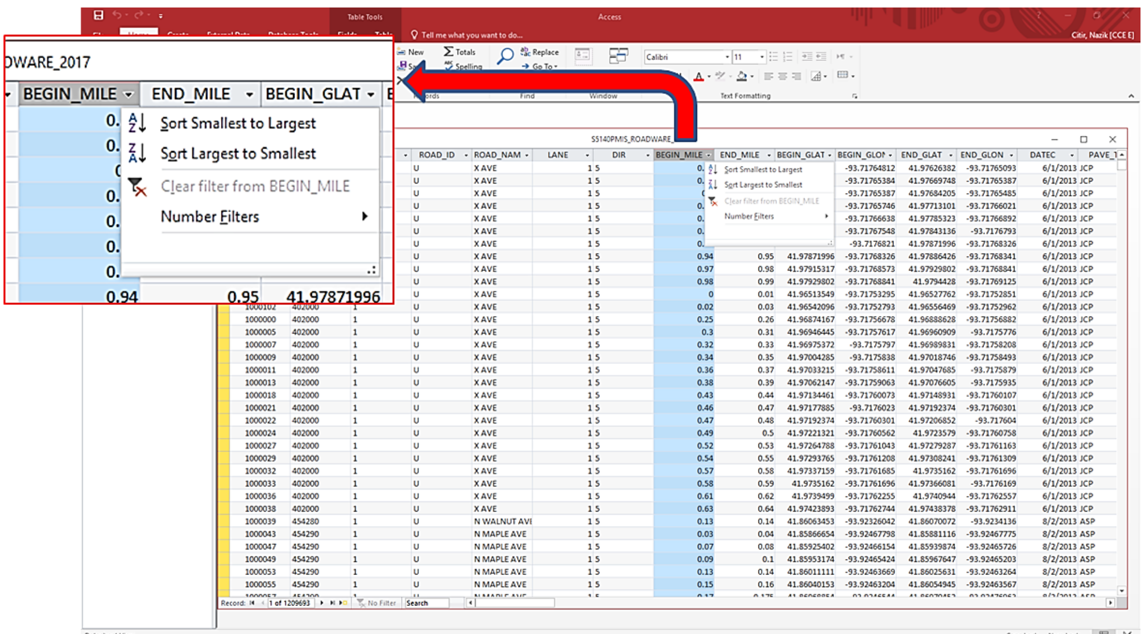


Figure 87. Sorting of county road units

Step 6. Calculation of Total Length of the Road Section

County Records provided the total length of the road section. In order to match it with the ROADWARE_LOCAL raw data, the total length of road sections should be matched. It is calculated using the following equation (equation 6):

Length of road section = END_MILE – BEGIN_MILE (before 2016)

Length of road section = TO_MEASURE – FROM_MEASURE (since 2016) **(6)**

In the above equations, BEGIN_MILE or FROM_MEASURE refers to the beginning mileage value for the first tested road unit, and END_MILE or TO_MEASURE indicates the ending mileage value of the last tested unit, as shown in Figure 88.

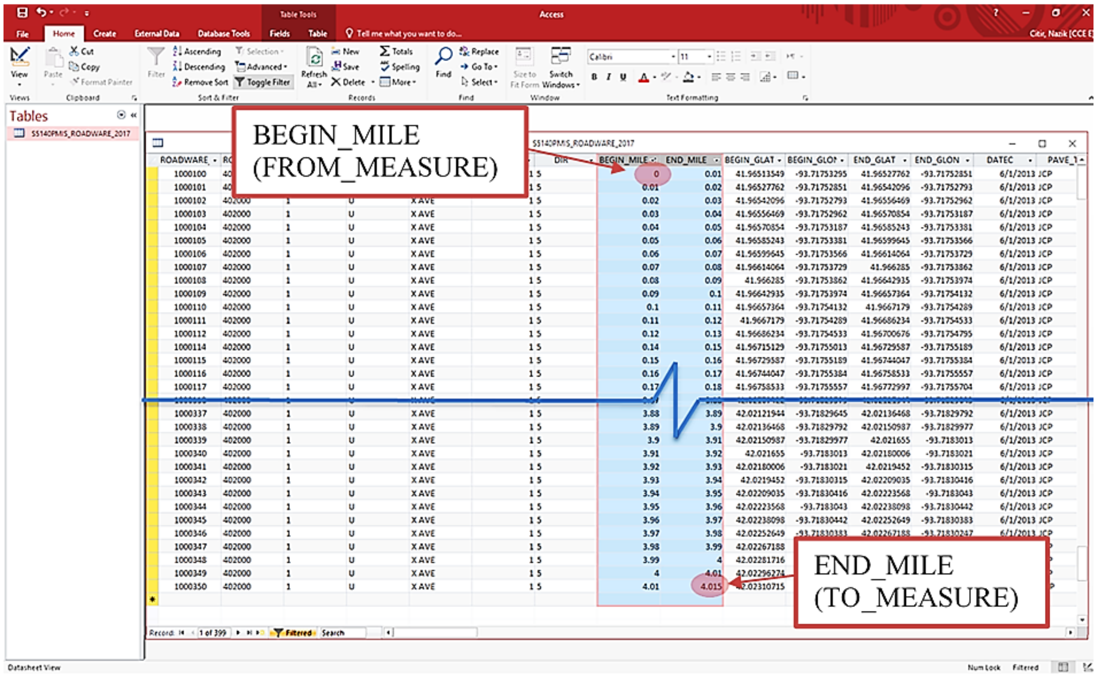


Figure 88. Beginning and ending mileage values of a road section

After a comparison between County Records and ROADWARE_LOCAL, the specified road length is also compared with each year's data. For instance, if the road section has raw data collected in 2013, 2015, and 2017, the road lengths seen in each year should be compared as to whether the same road section was surveyed.

Step 7. Comparison of Pavement Types

The pavement type of a road section selected in County Records should be matched with the filtered raw data taken from ROADWARE_LOCAL. It is found in ROADWARE_LOCAL, as shown in Figure 89.

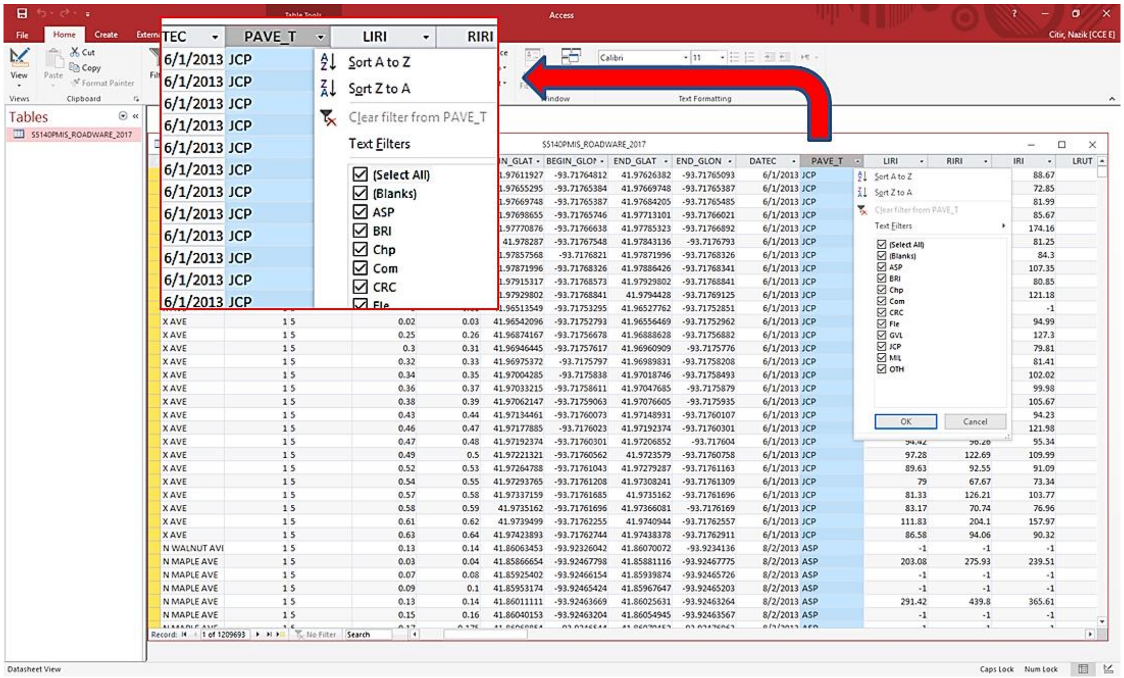


Figure 89. Checking pavement type of a road section

Step 8. Determination of Pavement Type

Based on Step 7, the pavement type of a road section is determined. Then, the identified condition and distress data are processed for this specific pavement type. They are listed as follows:

For rigid pavement:

- International roughness index (IRI)
- Faulting
- High, medium and low severity transverse cracking

For flexible pavement:

- IRI
- Rutting
- High, medium and low severity transverse cracking
- High, medium and low severity longitudinal cracking
- High, medium and low severity wheel path longitudinal cracking

Step 9. Transfer of Arranged Raw Data

The previous steps are completed to arrange the raw data based on the defining characteristics of a road section. In this step, the compared, filtered, checked, and arranged raw data are transferred from Microsoft Access format to an Excel format to reduce the file size and work in detail on it. Thus, the arranged data are selected in the Microsoft Access software and copied to an Excel sheet, as shown in Figure 90.

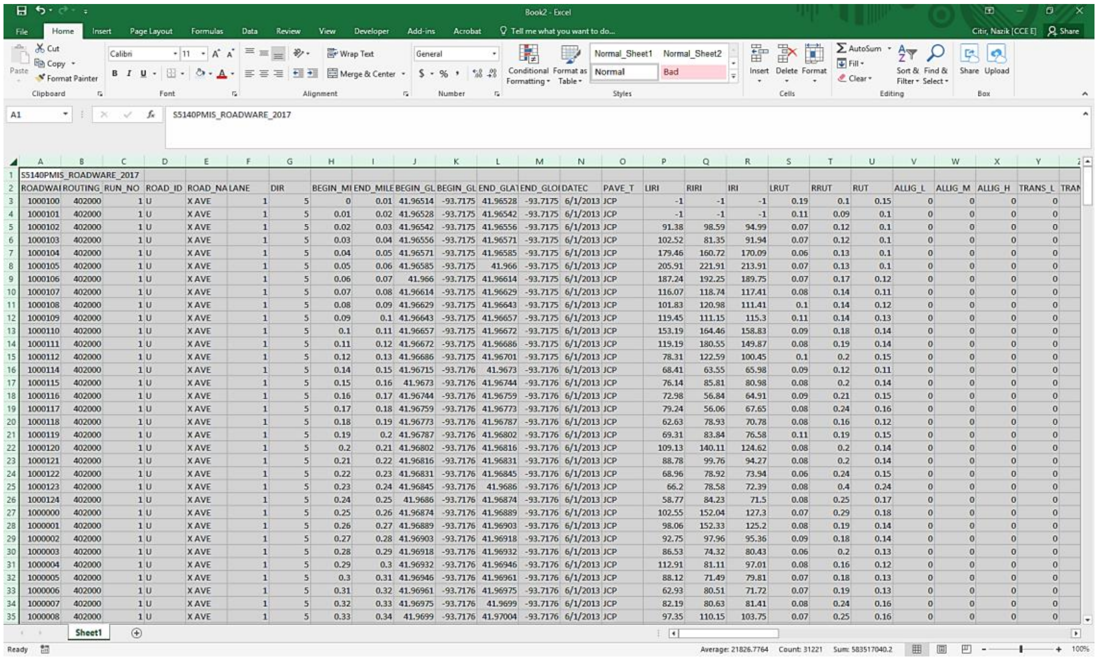


Figure 90. Transfer of arranged data to an Excel sheet

Step 10. Repeating Transfer of Arranged Raw Data for All Years

All transferring processes of the raw data from Microsoft Access to an Excel format is fulfilled for all years that were specified previously. For instance, half the raw data for Iowa is collected in 2013, 2015, and 2017, and the other half is collected in 2014, 2016, and 2018. An example is displayed in Figure 91.

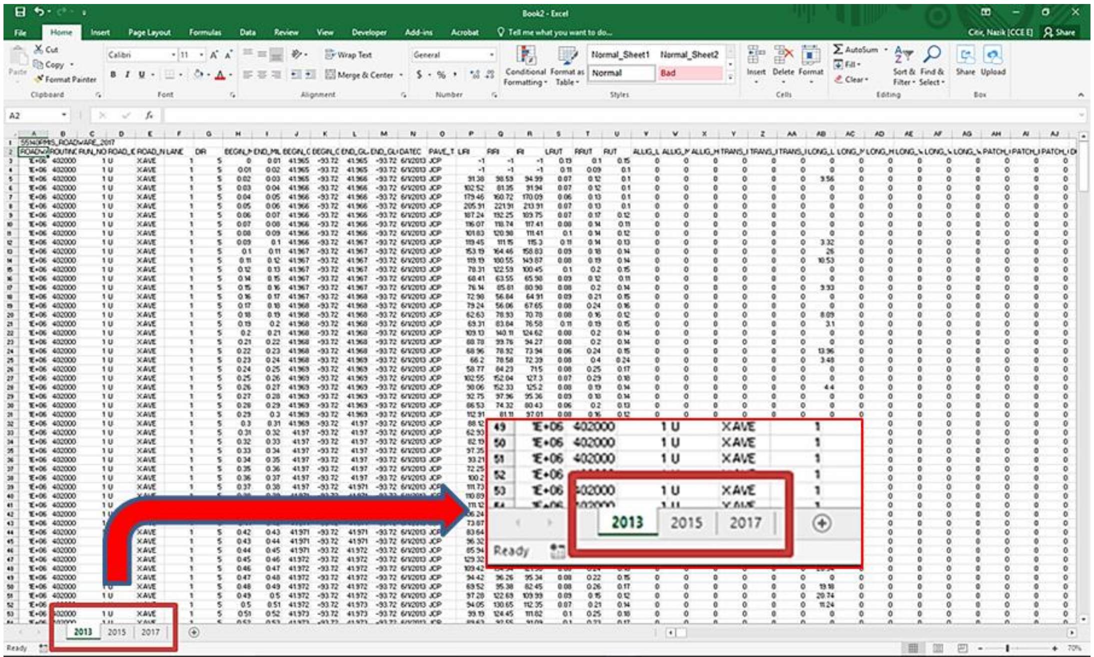
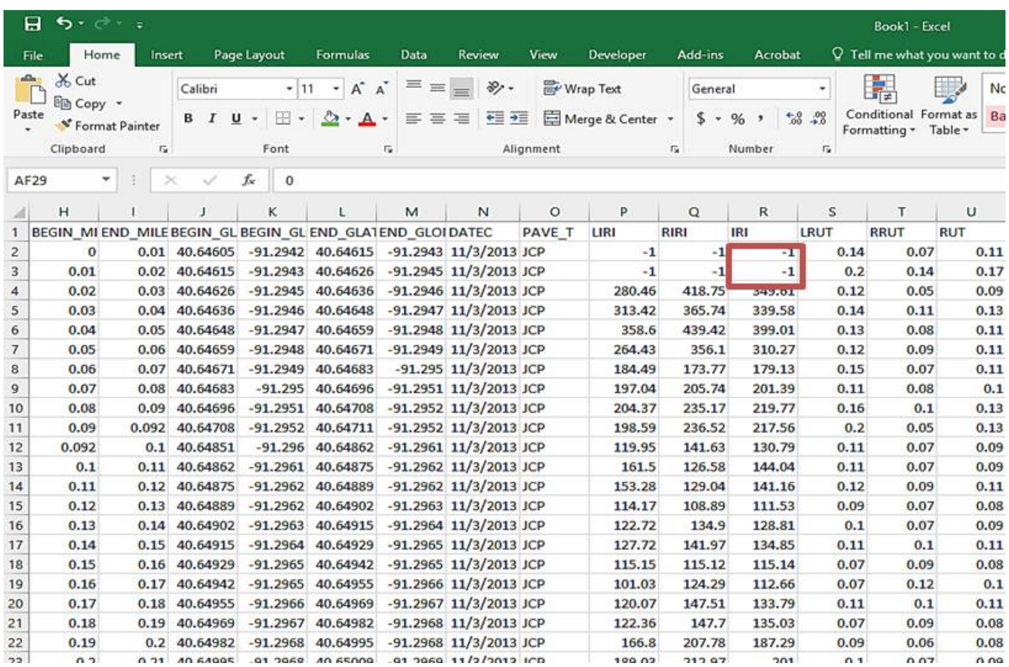


Figure 91. Transfer of arranged data to an Excel sheet for all years

Step 11. Elimination of Nulls in IRI

When the condition and distress data are examined, some null values (e.g., -1), Figure 92, can be observed in the ROADWARE_LOCAL database.



	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
1	BEGIN_MI	END_MILE	BEGIN_GL	BEGIN_GL	END_GLA	END_GLO	DATEC	PAVE_T	LIRI	RIRI	IRI	LRUT	RRUT	RUT
2	0	0.01	40.64605	-91.2942	40.64615	-91.2943	11/3/2013	JCP	-1	-1	-1	0.14	0.07	0.11
3	0.01	0.02	40.64615	-91.2943	40.64626	-91.2945	11/3/2013	JCP	-1	-1	-1	0.2	0.14	0.17
4	0.02	0.03	40.64626	-91.2945	40.64636	-91.2946	11/3/2013	JCP	280.46	418.75	349.61	0.12	0.05	0.09
5	0.03	0.04	40.64636	-91.2946	40.64648	-91.2947	11/3/2013	JCP	313.42	365.74	339.58	0.14	0.11	0.13
6	0.04	0.05	40.64648	-91.2947	40.64659	-91.2948	11/3/2013	JCP	358.6	439.42	399.01	0.13	0.08	0.11
7	0.05	0.06	40.64659	-91.2948	40.64671	-91.2949	11/3/2013	JCP	264.43	356.1	310.27	0.12	0.09	0.11
8	0.06	0.07	40.64671	-91.2949	40.64683	-91.295	11/3/2013	JCP	184.49	173.77	179.13	0.15	0.07	0.11
9	0.07	0.08	40.64683	-91.295	40.64696	-91.2951	11/3/2013	JCP	197.04	205.74	201.39	0.11	0.08	0.1
10	0.08	0.09	40.64696	-91.2951	40.64708	-91.2952	11/3/2013	JCP	204.37	235.17	219.77	0.16	0.1	0.13
11	0.09	0.092	40.64708	-91.2952	40.64711	-91.2952	11/3/2013	JCP	198.59	236.52	217.56	0.2	0.05	0.13
12	0.092	0.1	40.64851	-91.296	40.64862	-91.2961	11/3/2013	JCP	119.95	141.63	130.79	0.11	0.07	0.09
13	0.1	0.11	40.64862	-91.2961	40.64875	-91.2962	11/3/2013	JCP	161.5	126.58	144.04	0.11	0.07	0.09
14	0.11	0.12	40.64875	-91.2962	40.64889	-91.2962	11/3/2013	JCP	153.28	129.04	141.16	0.12	0.09	0.11
15	0.12	0.13	40.64889	-91.2962	40.64902	-91.2963	11/3/2013	JCP	114.17	108.89	111.53	0.09	0.07	0.08
16	0.13	0.14	40.64902	-91.2963	40.64915	-91.2964	11/3/2013	JCP	122.72	134.9	128.81	0.1	0.07	0.09
17	0.14	0.15	40.64915	-91.2964	40.64929	-91.2965	11/3/2013	JCP	127.72	141.97	134.85	0.11	0.1	0.11
18	0.15	0.16	40.64929	-91.2965	40.64942	-91.2965	11/3/2013	JCP	115.15	115.12	115.14	0.07	0.09	0.08
19	0.16	0.17	40.64942	-91.2965	40.64955	-91.2966	11/3/2013	JCP	101.03	124.29	112.66	0.07	0.12	0.1
20	0.17	0.18	40.64955	-91.2966	40.64969	-91.2967	11/3/2013	JCP	120.07	147.51	133.79	0.11	0.1	0.11
21	0.18	0.19	40.64969	-91.2967	40.64982	-91.2968	11/3/2013	JCP	122.36	147.7	135.03	0.07	0.09	0.08
22	0.19	0.2	40.64982	-91.2968	40.64995	-91.2968	11/3/2013	JCP	166.8	207.78	187.29	0.09	0.06	0.08

Figure 92. Null values in IRI column

Specifically, the null values are seen in the IRI condition data since they are collected by sensors. Thus, the null values might come from a data collection error. In that case, these values are deleted and are not taken into account of the data processing for the IRI data. When the cells in Excel that include null values are deleted, the rest of IRI data should be processed for a specified road section.

However, other condition and distress data corresponding to the row that has null value of IRI still can be processed for the same road unit.

Step 12. Filtration of Status

Each raw data field indicates its status under the STATUS column, which is described by the PMIS as the status of segments that should be processed. The metadata for PMIS indicates the status types as follows:

- Bridge
- Construction
- Duplicate
- Failed IRI
- LaneDeviation
- Local
- Matched
- Railroad Crossing (RRX)
- Ramp
- Too short
- NULL

In the ROADWARE_LOCAL raw data, the STATUS column indicates the same categories as the PMIS data. Based on instructions in the PMIS metadata, only data with the STATUS of Matched are considered for data processing, because it is known as a valid point. An example of the filtered data by STATUS is displayed in Figure 93.

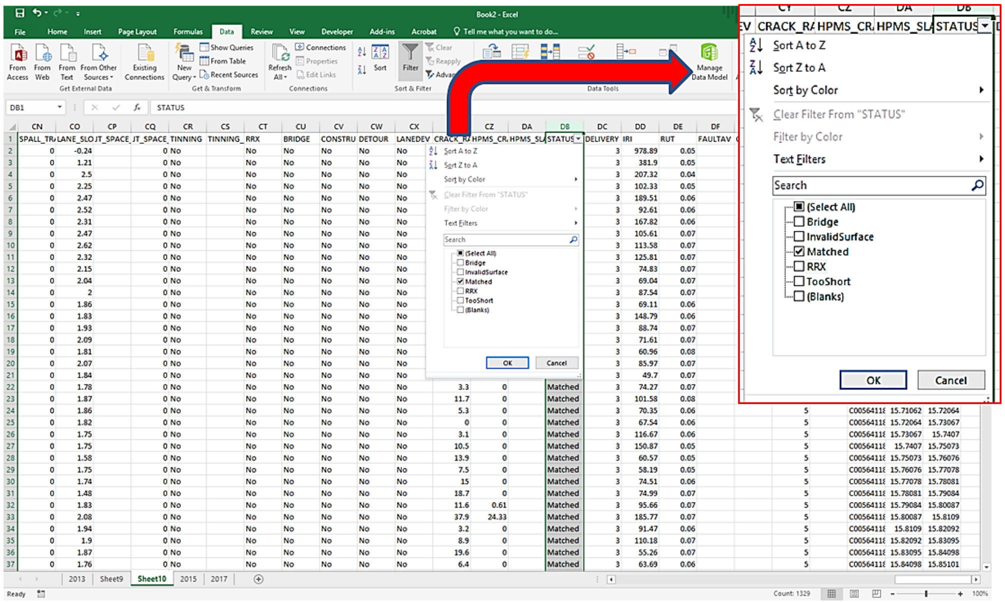


Figure 93. STATUS display

Step 13. Copy of Raw Data Filtered by STATUS

Although raw data are filtered by STATUS, all road units including hidden rows are counted in data processing even in the case of selecting all visible rows in the Excel sheet. In order to prevent any future errors in the calculations, all raw data filtered by STATUS are selected and copied in a new Excel sheet, as seen in Figure 94.

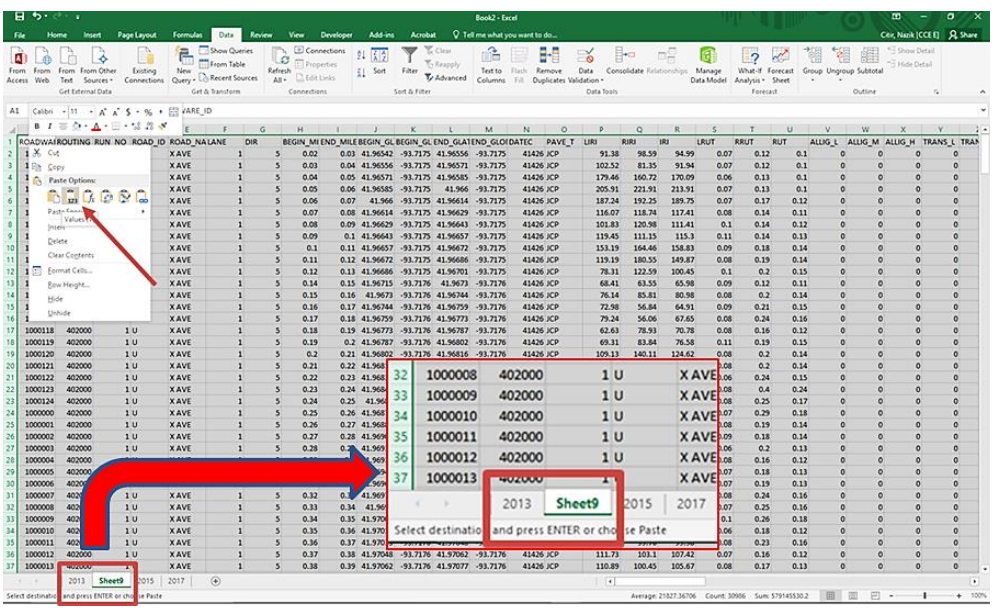


Figure 94. Copying raw data sheet filtered by STATUS

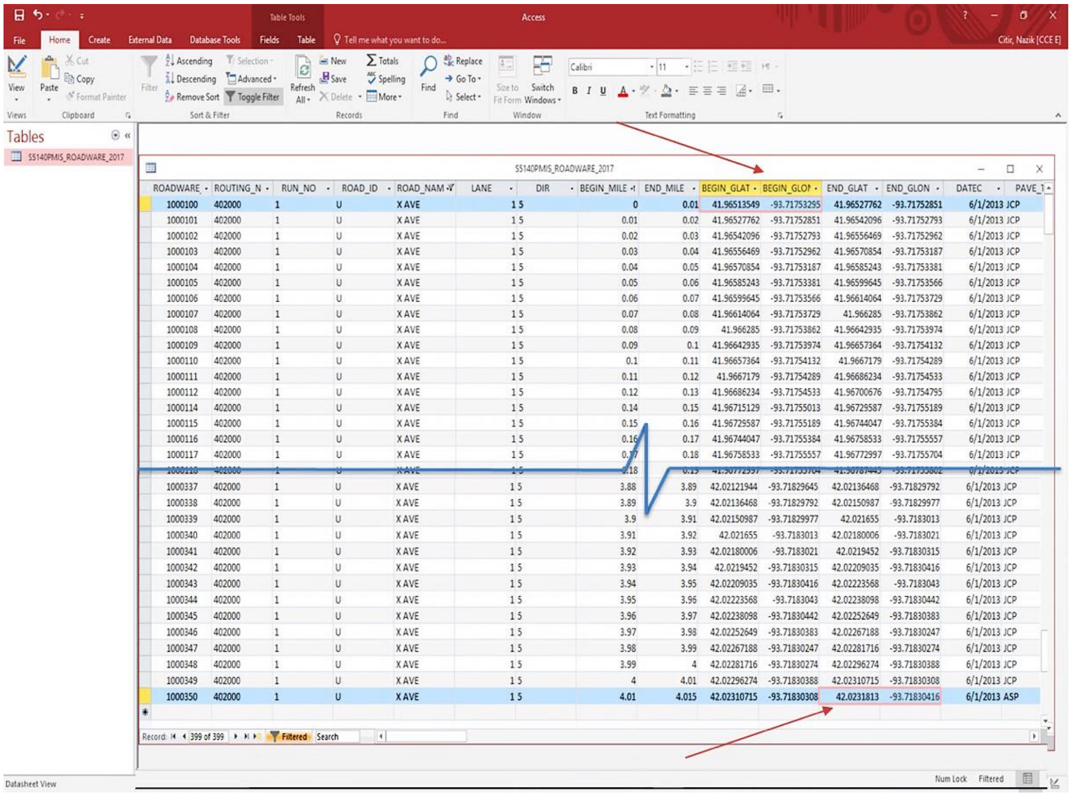
This step is applied on all years.

Step 14. Comparison of Coordinates of a Road Section in Each Year

The coordinates of the beginning of a road section are shown by BEGIN_GLAT and BEGIN_GLON, and the ones for ending of the road section are END_GLAT and END_GLON. These coordinates of beginning and ending point of the road section should always be the same for every other year since the road location never changes. In other words, the coordinates of BEGIN_MILE (FROM_MEASURE) and END_MILE (TO_MEASURE) shown in the ROADWARE_LOCAL database should match for the years even if the beginning and ending mileage values do not.

For example, if the coordinates (BEGIN_GLAT/BEGIN_GLON and END_GLAT/END_GLON) do not match between 2013 and 2015 at the same BEGIN_MILE and END_MILE, find the BEGIN_MILE and END_MILE points by their coordinates identified in ROADWARE_LOCAL_2013 to match with the coordinates in ROADWARE_LOCAL_2015 (e.g., in 2013, BEGIN_MILE of the beginning point is 0 and END_MILE of the ending point is 4.015, but in 2015 BEGIN_MILE and END_MILE might be different than the points given in 2013 shown in Figure 95). The BEGIN_MILE and END_MILE point values between the years do not need to match, only the coordinates.

For the beginning of a road section, BEGIN_GLAT and BEGIN_GLON are checked and END_GLAT and END_GLON are checked for the ending of a road section, as shown in Figure 95.



ROADWARE	ROUTING_N	RUN_NO	ROAD_ID	ROAD_NAM	LANE	DIR	BEGIN_MILE	END_MILE	BEGIN_GLAT	BEGIN_GLON	END_GLAT	END_GLON	DATEC	PAVE_1
1000100	402000	1	U	X AVE	1	5	0	0.01	41.96513549	-93.71753295	41.96527762	-93.71752851	6/1/2013	JCP
1000101	402000	1	U	X AVE	1	5	0.01	0.02	41.96527762	-93.71752851	41.96542096	-93.71752793	6/1/2013	JCP
1000102	402000	1	U	X AVE	1	5	0.02	0.03	41.96542096	-93.71752793	41.96556469	-93.71752962	6/1/2013	JCP
1000103	402000	1	U	X AVE	1	5	0.03	0.04	41.96556469	-93.71752962	41.96570854	-93.71753187	6/1/2013	JCP
1000104	402000	1	U	X AVE	1	5	0.04	0.05	41.96570854	-93.71753187	41.96585243	-93.71753381	6/1/2013	JCP
1000105	402000	1	U	X AVE	1	5	0.05	0.06	41.96585243	-93.71753381	41.96599645	-93.71753566	6/1/2013	JCP
1000106	402000	1	U	X AVE	1	5	0.06	0.07	41.96599645	-93.71753566	41.96614064	-93.71753729	6/1/2013	JCP
1000107	402000	1	U	X AVE	1	5	0.07	0.08	41.96614064	-93.71753729	41.966285	-93.71753862	6/1/2013	JCP
1000108	402000	1	U	X AVE	1	5	0.08	0.09	41.966285	-93.71753862	41.96642935	-93.71753974	6/1/2013	JCP
1000109	402000	1	U	X AVE	1	5	0.09	0.1	41.96642935	-93.71753974	41.96657364	-93.71754132	6/1/2013	JCP
1000110	402000	1	U	X AVE	1	5	0.1	0.11	41.96657364	-93.71754132	41.9667179	-93.71754289	6/1/2013	JCP
1000111	402000	1	U	X AVE	1	5	0.11	0.12	41.9667179	-93.71754289	41.96686234	-93.71754533	6/1/2013	JCP
1000112	402000	1	U	X AVE	1	5	0.12	0.13	41.96686234	-93.71754533	41.96700676	-93.71754795	6/1/2013	JCP
1000114	402000	1	U	X AVE	1	5	0.14	0.15	41.96715129	-93.71755013	41.96729587	-93.71755189	6/1/2013	JCP
1000115	402000	1	U	X AVE	1	5	0.15	0.16	41.96729587	-93.71755189	41.96744047	-93.71755384	6/1/2013	JCP
1000116	402000	1	U	X AVE	1	5	0.16	0.17	41.96744047	-93.71755384	41.96758533	-93.71755557	6/1/2013	JCP
1000117	402000	1	U	X AVE	1	5	0.17	0.18	41.96758533	-93.71755557	41.96772997	-93.71755704	6/1/2013	JCP
1000118	402000	1	U	X AVE	1	5	0.18	0.19	41.96772997	-93.71755704	41.96787445	-93.71755802	6/1/2013	JCP
1000337	402000	1	U	X AVE	1	5	3.88	3.89	42.02121944	-93.71829645	42.02136468	-93.71829792	6/1/2013	JCP
1000338	402000	1	U	X AVE	1	5	3.89	3.9	42.02136468	-93.71829792	42.02150987	-93.71829977	6/1/2013	JCP
1000339	402000	1	U	X AVE	1	5	3.9	3.91	42.02150987	-93.71829977	42.021655	-93.7183013	6/1/2013	JCP
1000340	402000	1	U	X AVE	1	5	3.91	3.92	42.021655	-93.7183013	42.02180006	-93.7183021	6/1/2013	JCP
1000341	402000	1	U	X AVE	1	5	3.92	3.93	42.02180006	-93.7183021	42.0219452	-93.71830315	6/1/2013	JCP
1000342	402000	1	U	X AVE	1	5	3.93	3.94	42.0219452	-93.71830315	42.02209035	-93.71830416	6/1/2013	JCP
1000343	402000	1	U	X AVE	1	5	3.94	3.95	42.02209035	-93.71830416	42.02223568	-93.7183043	6/1/2013	JCP
1000344	402000	1	U	X AVE	1	5	3.95	3.96	42.02223568	-93.7183043	42.02238098	-93.71830442	6/1/2013	JCP
1000345	402000	1	U	X AVE	1	5	3.96	3.97	42.02238098	-93.71830442	42.02252649	-93.71830383	6/1/2013	JCP
1000346	402000	1	U	X AVE	1	5	3.97	3.98	42.02252649	-93.71830383	42.02267188	-93.71830247	6/1/2013	JCP
1000347	402000	1	U	X AVE	1	5	3.98	3.99	42.02267188	-93.71830247	42.02281716	-93.71830274	6/1/2013	JCP
1000348	402000	1	U	X AVE	1	5	3.99	4	42.02281716	-93.71830274	42.02296274	-93.71830388	6/1/2013	JCP
1000349	402000	1	U	X AVE	1	5	4	4.01	42.02296274	-93.71830388	42.02310715	-93.71830308	6/1/2013	JCP
1000350	402000	1	U	X AVE	1	5	4.01	4.015	42.02310715	-93.71830308	42.0231813	-93.71830416	6/1/2013	ASP

Figure 95. Coordinates of a road section to compare between years

Step 15. Conversion of Columns from Text to Value

After the previous steps, the columns that will be used in the processing should be converted from text to value in order to prevent any possible mistakes in the calculations. For this purpose, Text to Columns in Excel is applied to these columns, as shown in Figure 96.

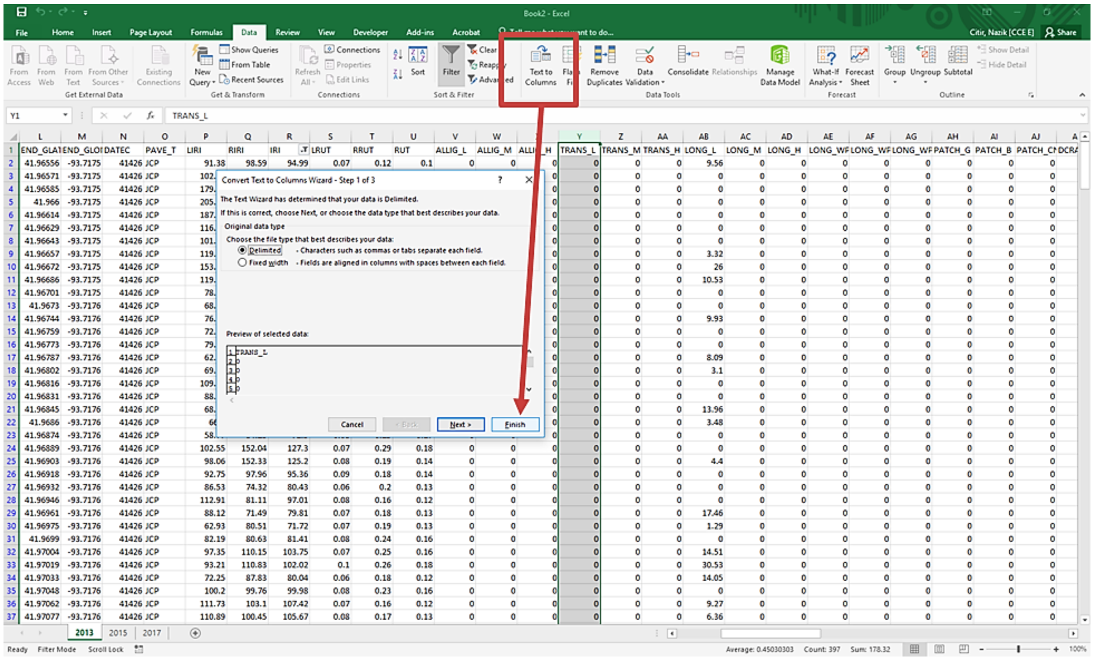


Figure 96. Application of Text to Columns on data columns

Description of Summarization Procedure

Rigid Pavements

Condition and distress data processed for rigid pavements are IRI, faulting, and transverse cracking as mentioned in an earlier section. The following provides more detail on how to process these data.

Condition data for rigid pavements are as follows:

a) IRI

- It is named IRI in all years of data
- It is the average of left wheel IRI and right wheel IRI (e.g., PMIS metadata)
- It is described by inch per mile in both raw data and summarized data, shown in Figure 97
- It is summarized by taking the average of all collected IRI data for a road section

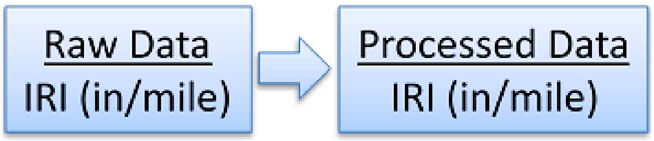


Figure 97. Unit conversion in IRI

b) Faulting

- It is named FAULT before 2015 and FAULTAV since 2015
- FAULT is the average faulting only on faulted joints in a segment, meant as maximum faulting; FAULTAV is the average faulting on all joints in a segment, meant as average faulting (e.g., PMIS metadata)
- It is described by inch in both raw data and summarized data, shown in Figure 98
- It is summarized by taking the average of all collected FAULT or FAULTAV data for a road section

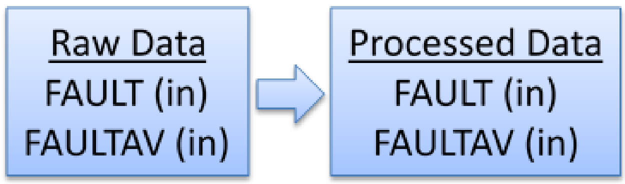


Figure 98. Unit conversion in faulting

Distress data for rigid pavements are as follows:

c) Transverse cracking

- It is named TCRACK_H, TCRACK_M, and TCRACK_L
- TCRACK_H is the area of high severity transverse cracking; TCRACK_M is the area of medium severity transverse cracking; and TCRACK_L is the area of low severity transverse cracking
- It is described by square feet (ft^2) in raw data and by count/mile in summarized data, shown in Figure 99; note that square feet (ft^2) in the raw data can be calculated by multiplying the crack length measured by the 2 ft of crack width assumed
- Its summarization is different before and since 2016; the calculation procedures are explained in detail in the next sections

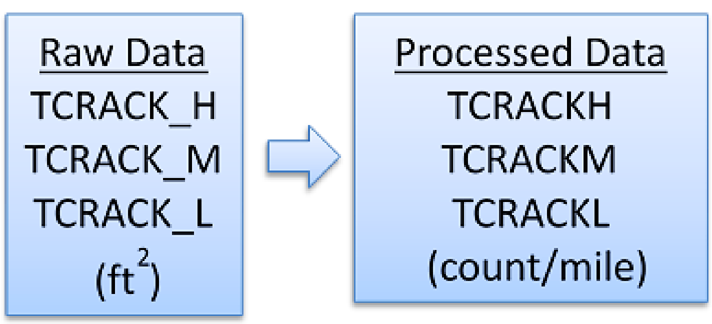


Figure 99. Unit conversion in transverse cracking

Before 2016:

1. Sum of all collected TCRACK_H/M/L data separately (ft^2)
2. Divide it by the length (mi) of road section (ft^2/mi); length of road section is calculated by equation 6
3. Divide it by the unit crack area (ft^2), which is the crack length (ft) by the crack width (ft); a 10 ft lane width is assumed as the crack length (ft) and a 2 ft crack width is assumed as the crack width (ft) for calculating the unit crack area (ft^2)
4. Then, the processed data are recorded as TCRACKH, TCRACKM, and TRCRACKL in count/mi

Since 2016:

The Iowa DOT has stated that it is better to sum transverse cracking with different severity levels. The reason for that is if transverse cracks are sealed, they are categorized as low severity transverse cracks. If seals are no longer in place or not used at all, these transverse cracks are called high severity transverse cracks. This means the data consider whether the transverse cracking is sealed or not in its severities. Thus, the raw transverse cracking data are converted into legacy values before processing data. In order to convert the raw data, the following data columns in ROADWARE_LOCAL are utilized:

- TCRACK_SEAL (ft^2)
- TCRACK_SEAL_H
- TCRACK_SEAL_M
- TCRACK_SEAL_L

Figure 100 provides a schematic diagram that shows how to convert the raw data (ft^2) into the legacy values (ft^2).

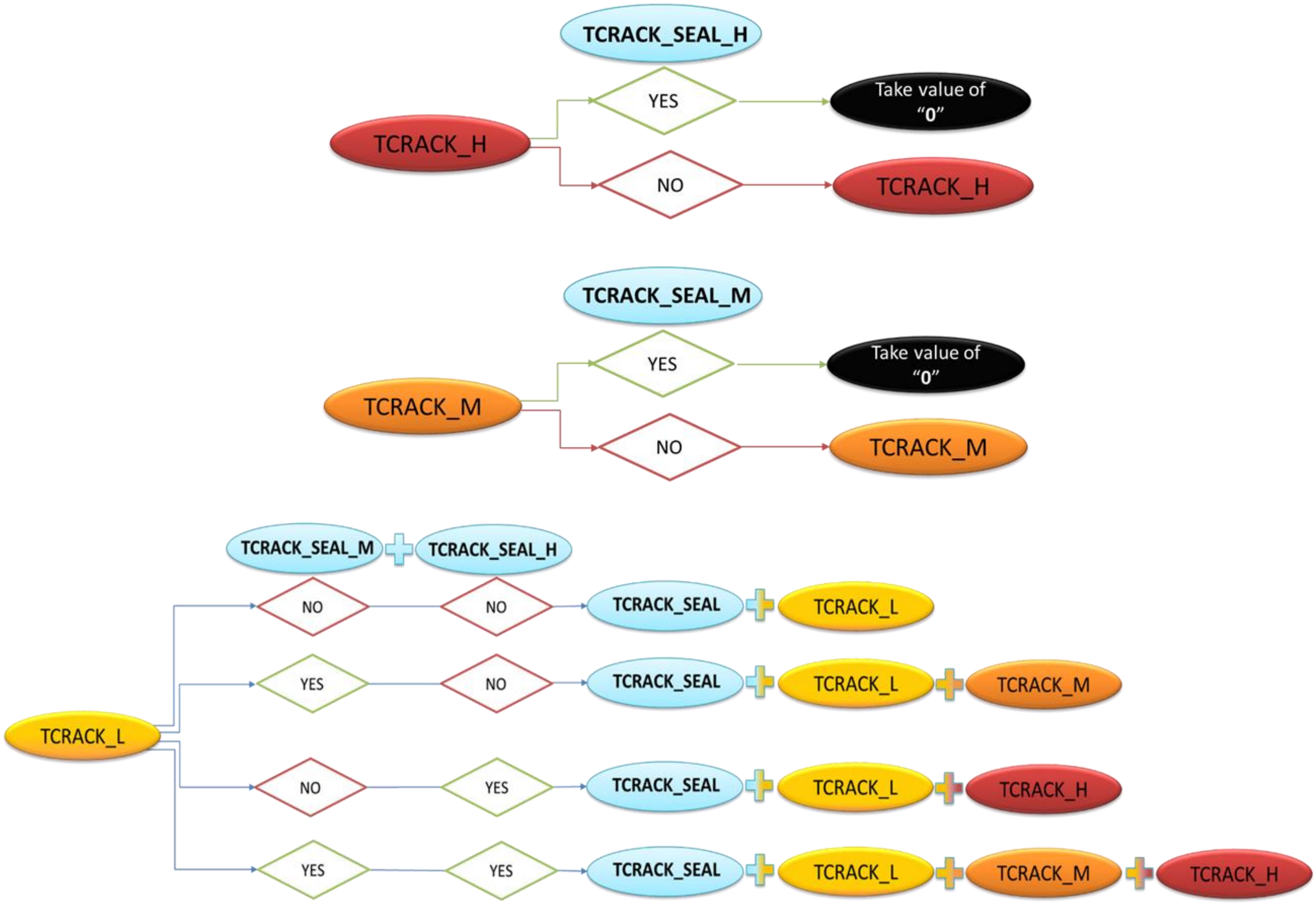


Figure 100. Conversion of transverse cracking in all severities

The columns are explained as follows:

- If high severity transverse cracking has high sealing, this transverse cracking is categorized as low severity transverse cracking. Thus, the value for the area of high severity transverse cracking (TCRACK_H) is taken as 0. However, if there is no high sealing, then the value of area of high severity transverse cracking is directly counted by itself.
- If medium severity transverse cracking has medium sealing, this transverse cracking is categorized as low severity transverse cracking. Thus, the value for the area of medium severity transverse cracking (TCRACK_M) is taken as 0. However, if there is no medium sealing, then the value of area of medium severity transverse cracking is directly counted by itself.
- Low severity transverse cracking has four steps to be converted into legacy values as follows:
  - If low severity transverse cracking does not have either medium or high sealing, the value for the area of low severity transverse cracking (TCRACK_L) is calculated by the sum of the area of sealed transverse cracking (TCRACK_SEAL) and itself.
  - If low severity transverse cracking does not have high sealing but medium sealing, the value for the area of low severity transverse cracking (TCRACK_L) is calculated by the sum of the area of sealed transverse cracking (TCRACK_SEAL), the area of medium severity transverse cracking (TCRACK_M), and itself.
  - If low severity transverse cracking does not have medium sealing but high sealing, the value for the area of low severity transverse cracking (TCRACK_L) is calculated by the sum of the area of sealed transverse cracking (TCRACK_SEAL), area of high severity transverse cracking (TCRACK_H), and itself.
  - If low severity transverse cracking has both high and medium sealing, the value for the area of low severity transverse cracking (TCRACK_L) is calculated by sum of the area of sealed transverse cracking (TCRACK_SEAL), the area of medium severity transverse cracking (TCRACK_M), the area of high severity transverse cracking (TCRACK_H), and itself.

After the conversion of transverse cracking in all severities, they are summarized as follows:

1. Sum of all collected TCRACK_H/M/L data separately (ft^2)
2. Divide it by the length (mi) of road section, (ft^2/mi); length of road section is calculated by equation 6
3. Divide it by the unit crack area (ft^2), which is the unit crack length (ft) by the unit crack width (ft); a 10 ft lane width is assumed as the unit crack length (ft), and a 2 ft crack width is assumed as unit crack width (ft)

Then, the processed data are recorded as TCRACKH, TCRACKM, and TRCRACKL in count/mile.

Flexible Pavements

Condition and distress data processed for flexible pavements are IRI, rutting, transverse cracking, longitudinal cracking, and wheel path longitudinal cracking as mentioned in an earlier section. The following provides more detail on how to process these data.

Condition data for flexible pavements are as follows:

a) IRI

- It is named IRI in all years of data
- It is the average of left wheel IRI and right wheel IRI (e.g., PMIS metadata)
- It is described by inch per mile in both raw data and summarized data, previously shown in Figure 97
- It is summarized by taking the average of all collected IRI data for a road section

b) Rutting

- It is named RUT in all years of data
- It is the average of left wheel rut and right wheel rut (e.g., PMIS metadata)
- It is described by inch in both raw data and summarized data, shown in Figure 101
- It is summarized by taking the average of all collected RUT data for a road section

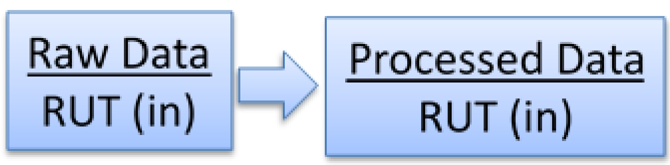


Figure 101. Unit conversion in rutting

Distress data for flexible pavements are as follows:

c) Transverse cracking

- It is named TCRACK_H, TCRACK_M, and TCRACK_L
- TCRACK_H is the area of high severity transverse cracking; TCRACK_M is the area of medium severity transverse cracking; and TCRACK_L is the area of low severity transverse cracking
- It is described by square feet (ft^2) in raw data and by count/mile in summarized data, previously shown in Figure 99; note that square feet (ft^2) in raw data can be calculated by multiplying the crack length measured by the 2 ft of crack width assumed
- Its summarization is different before and since 2016; the calculation procedures are exactly same as the procedure used for processing transverse cracking for rigid pavements

d) Longitudinal cracking

- It is named LCRACK_H, LCRACK_M, and LCRACK_L
- LCRACK_H is the area of high severity longitudinal cracking; LCRACK_M is the area of medium severity longitudinal cracking; and LCRACK_L is the area of low severity longitudinal cracking
- It is described by square feet (ft^2) in raw data and by ft/mi in summarized data, shown in Figure 102; note that square feet (ft^2) in raw data can be calculated by multiplying the crack length measured by the 2 ft of crack width assumed
- Its summarization is different before and since 2016, and the calculation procedures are explained in detail in the next sections

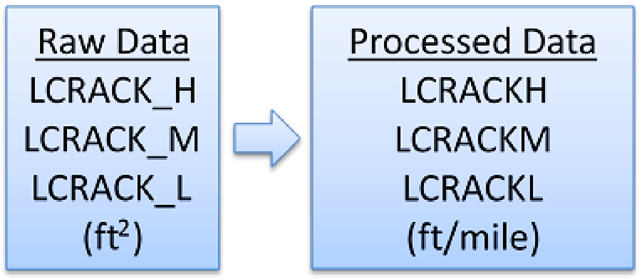


Figure 102. Unit conversion in longitudinal cracking

Before 2016:

1. Sum of all collected LCRACK_H/M/L data separately (ft^2)
2. Divide it by the length (mi) of road section; length of road section is calculated by equation 6
3. Divide it by the 2 ft of crack width (ft)
4. Then, the processed data are recorded as LCRACKH, LCRACKM, and LRCRACKL in ft/mi

Since 2016:

The Iowa DOT has stated that it is better to sum longitudinal cracking with different severity levels. The reason for that is if longitudinal cracks are sealed, they are categorized as low severity longitudinal cracks. If the seals are no longer in place or not used at all, these longitudinal cracks are called high severity longitudinal cracks. This means the data consider whether the longitudinal cracking is sealed or not in all severities. Thus, the raw longitudinal cracking data are converted into legacy values before processing data. In order to convert the raw data, the following data columns in ROADWARE_LOCAL are utilized:

- LCRACK_SEAL (ft^2)
- LCRACK_SEAL_H
- LCRACK_SEAL_M
- LCRACK_SEAL_L

Figure 103 provides a schematic diagram that shows how to convert the raw data (ft^2) into the legacy values (ft^2).

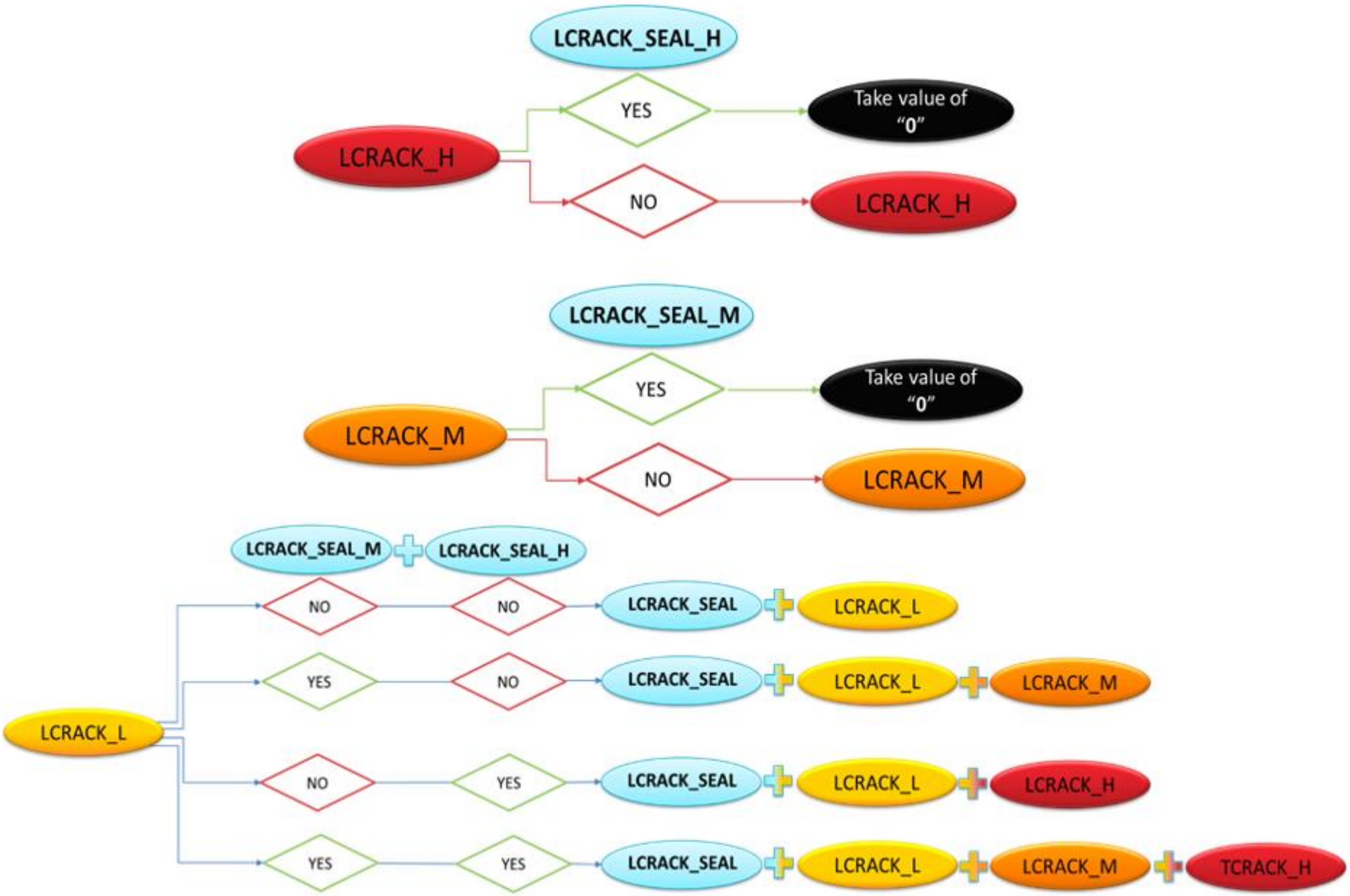


Figure 103. Diagram of conversion of longitudinal cracking in all severities

The columns are explained as follows:

- If high severity longitudinal cracking has high sealing, this longitudinal cracking is categorized as low severity longitudinal cracking. Thus, the value for the area of high severity longitudinal cracking (LCRACK_H) is taken as 0. However, if there is no high sealing, then the value of the area of high severity longitudinal cracking is directly counted by itself.
- If medium severity longitudinal cracking has medium sealing, this longitudinal cracking is categorized as low severity longitudinal cracking. Thus, the value for the area of medium severity longitudinal cracking (LCRACK_M) is taken as 0. However, if there is no medium sealing, then the value of the area of medium severity longitudinal cracking is directly counted by itself.
- Low severity longitudinal cracking has four steps to be converted into legacy values as follows:
  - If low severity longitudinal cracking does not have either medium or high sealing, the value for the area of low severity longitudinal cracking (LCRACK_L) is calculated by the sum of the area of sealed longitudinal cracking (LCRACK_SEAL) and itself.
  - If low severity longitudinal cracking does not have high sealing but medium sealing, the value for the area of low severity longitudinal cracking (LCRACK_L) is calculated by the sum of the area of sealed longitudinal cracking (LCRACK_SEAL), area of medium severity longitudinal cracking (LCRACK_M), and itself.
  - If low severity longitudinal cracking does not have medium sealing but high sealing, the value for the area of low severity longitudinal cracking (LCRACK_L) is calculated by the sum of the area of sealed longitudinal cracking (LCRACK_SEAL), area of high severity longitudinal cracking (LCRACK_H), and itself.
  - If low severity longitudinal cracking has both high and medium sealing, the value for the area of low severity longitudinal cracking (LCRACK_L) is calculated by the sum of the area of sealed longitudinal cracking (LCRACK_SEAL), area of medium severity longitudinal cracking (LCRACK_M), area of high severity longitudinal cracking (LCRACK_H), and itself.

After the conversion of longitudinal cracking in all severities, they are summarized as follows:

1. Sum of all collected LCRACK_H/M/L data separately (ft^2)
2. Divide it by the length (mi) of road section (ft^2/mi); length of road section is calculated by equation 6
3. Divide it by the 2 ft of crack width (ft)

Then, the processed data are recorded as LCRACKH, LCRACKM, and LRCRACKL in ft/mi.

e) Wheel path longitudinal cracking

- It is named LCRACKW_H, LCRACKW_M, and LCRACKW_L

- LCRACKW_H is the area of high severity wheel path longitudinal cracking; LCRACKW_M is the area of medium severity wheel path longitudinal cracking; and LCRACKW_L is the area of low severity wheel path longitudinal cracking
- It is described by square feet (ft^2) in raw data and by ft/mi in summarized data, shown in Figure 104; note that square feet (ft^2) in the raw data can be calculated by multiplying the crack length measured by the 2 ft of crack width assumed
- Its summarization is different before and since 2016, and the calculation procedures are exactly the same as the procedure used for processing longitudinal cracking for flexible pavements and shown in the summarization procedure of longitudinal cracking in flexible pavements

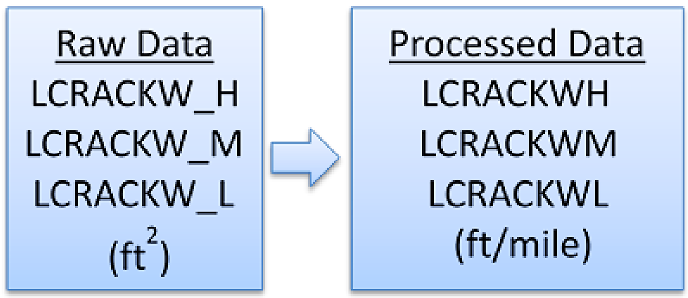


Figure 104. Unit conversion in wheel path longitudinal cracking

Wheel path longitudinal cracking is processed differently than the processing of longitudinal cracking. Thus, the following data columns in ROADWARE_LOCAL are utilized in order to convert the raw data:

- LCRACKW_SEAL (ft^2)
- LCRACKW_SEAL_H
- LCRACKW_SEAL_M
- LCRACKW_SEAL_L

Illustration Example: Lee County Case

An example of data processing for a road section in Lee County is examined in the following steps.

Step 1. Choice of County

Lee County was chosen as an example because there is a construction history that was obtained from County Records, as shown in Figure 105.

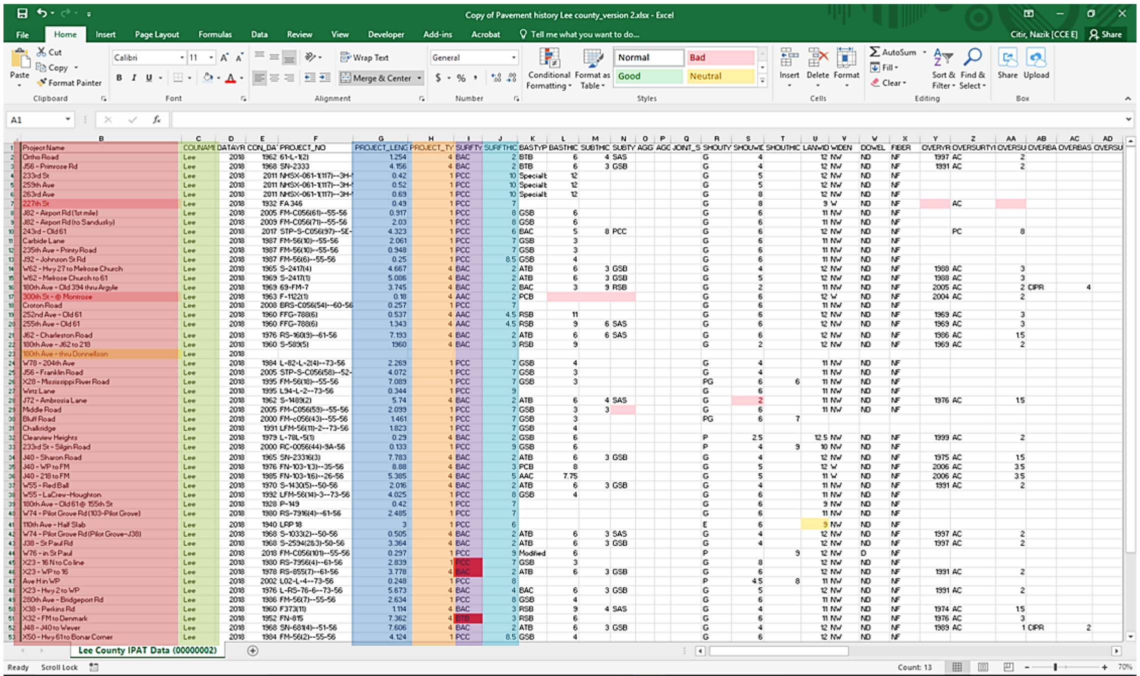


Figure 105. Lee County records

From County Records, the following information is used:

- Project Name
- County Name
- Project Length
- Project Type
- Surface Type
- Surface Thickness

Steps 2 and 3. Preparation of Raw Data and Filtration of Selected Raw Data Based on County ID

The Iowa DOT provided all years of ROADWARE_LOCAL data based on county ID. The Lee County ID is 56. It is in cycle 2 (odd years) (shown previously in Figure 36). Thus, the data were collected for Lee County in 2013, 2015, and 2017. The files of ROADWARE_LOCAL_2013, ROADWARE_LOCAL_2015, and ROADWARE_LOCAL_2017 were processed.

Step 4. Filtration of Selected Raw Data File Based on Road Name

From the County Records of Lee County, the County Highway X38 road system was chosen, as shown in Figure 106.

Project Name	COUNAME	DATAYR	CON_DATE	PROJECT_NO	PROJECT_LENGTH	PROJECT_TYPE	SURFTYP	SURFTHICK	BASTYP	BASTHICK	SUBTHICK	SUBTYP	AGGT	AGGS	JOINT_SPA	SHOUTYP
X38 - Augusta Rd (between J48 Sections)	Lee	2018	1973	L-73-FM-3--73-56	0.631	4	BAC	2	BAC	3	8	RSB				G
X38 - Augusta Rd (J48 N to 16)	Lee	2018	1981	SN-7992(3)--51-56	1.993	1	PCC	7								G
X38 - Augusta Rd (J48 S to Bus 61)	Lee	2018	1981	SN-7996(3)--51-56	3.79	1	PCC	7								G

Figure 106. Selection of road system X38 in Lee County

The road name was checked in ROADWARE_LOCAL_2013, _2015, and _2017 as to whether it was labeled the same in every other year. It was found that the road was called X038 in the 2013 and 2015 databases and called 330th Ave in 2017, which was not mentioned in the County Records database. The designation of 330th Ave in 2017 was found from the Highway and Transportation Map for Lee County, as shown in Figure 107 and Figure 108.

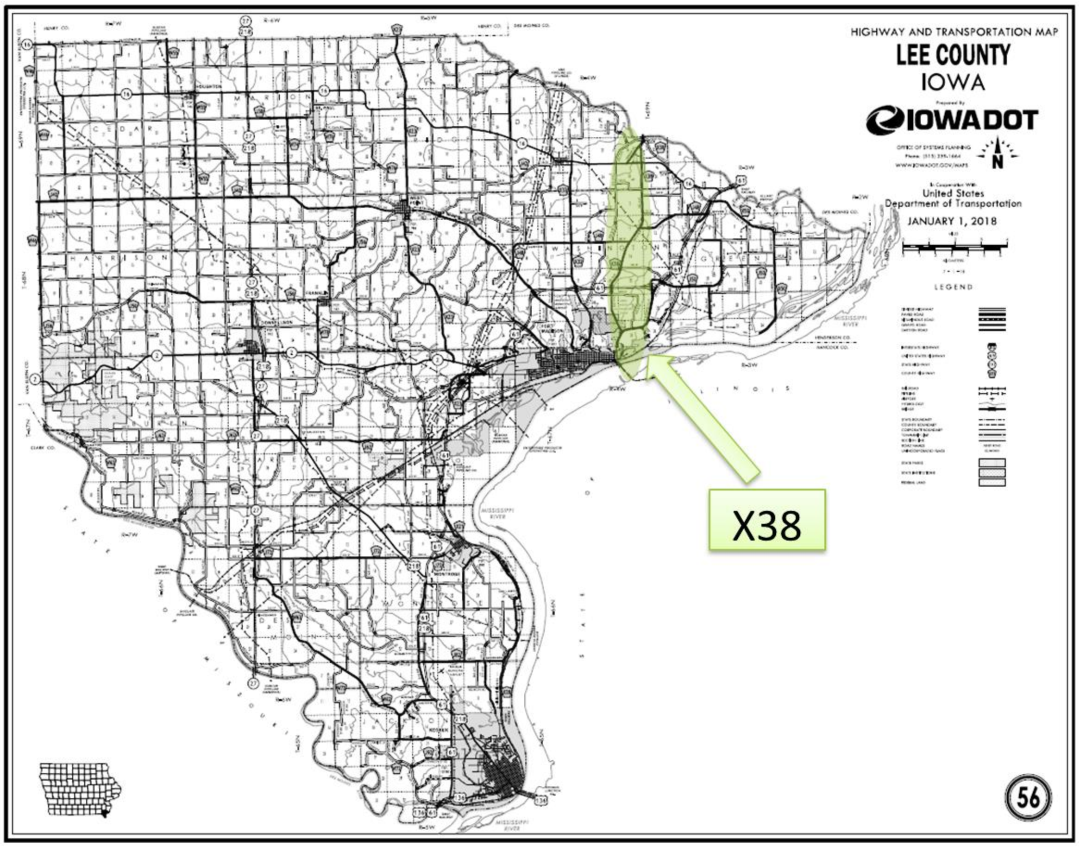


Figure 107. Highway and Transportation Map for Lee County

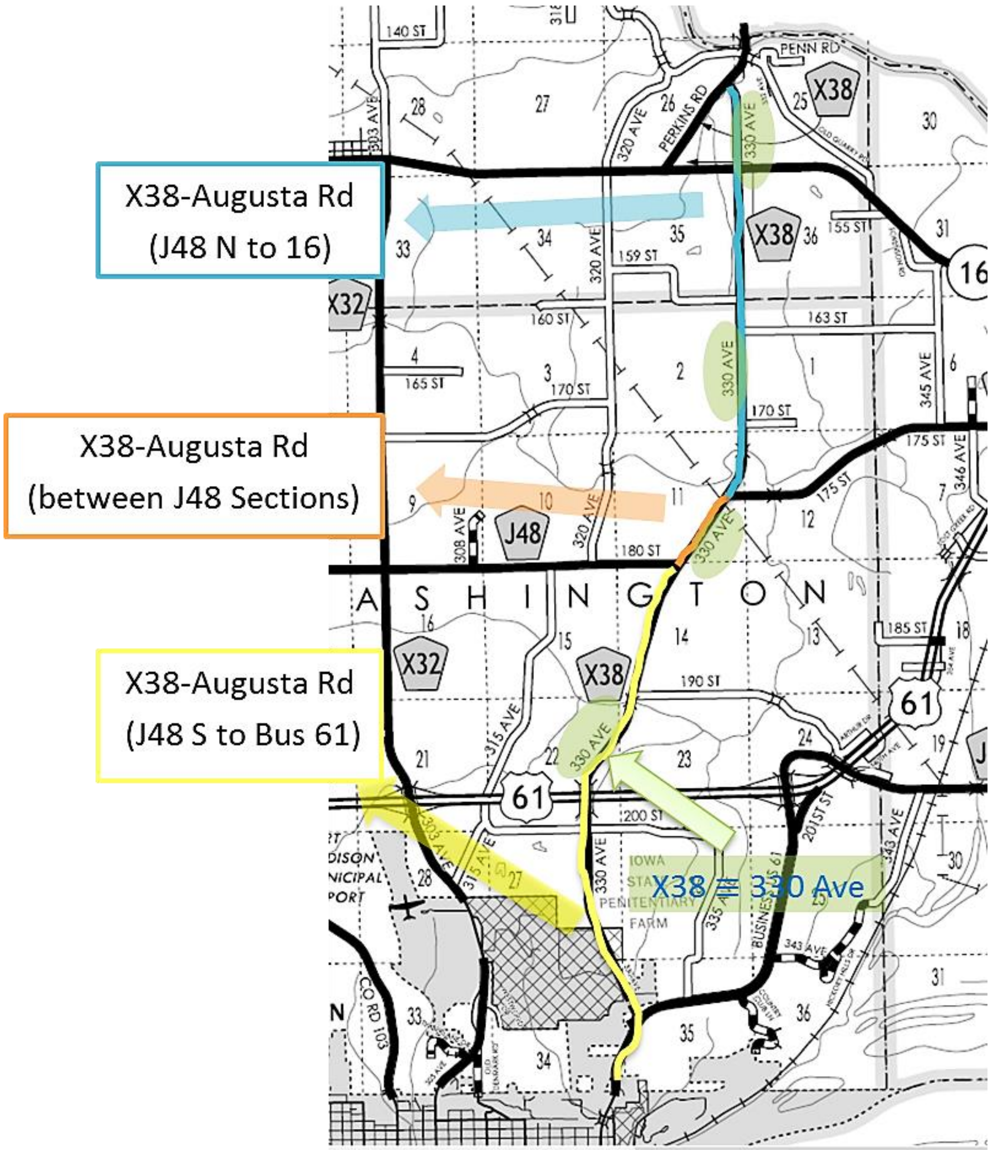


Figure 108. X38 road system in Highway and Transportation Map for Lee County

Also, the County Highway X38 road system was confirmed with Google Maps by using the coordinates of this road.

In County Records, it is clear that the County Highway X38 road system is divided into three road sections as X38-Augusta Rd (from County Highway J48 North to Iowa 16), X38-Augusta Rd (between County Highway J48 sections), and X38-Augusta Rd (from County Highway J48 South to Business US 61) as indicated in Figure 108.

Step 5. Sorting of County Road Units

The road units were sorted in ascending order for the years of 2013, 2015, and 2017, which are shown in Figure 109a, b, and c, respectively.

ROADWARE_LOCAL_2013

ROADWARE_	ROUTING_N	RUN_NO	ROAD_ID	ROAD_NAM	LANE	DIR	BEGIN_MILE	END_MILE	BEGIN_GLAT	BEGIN_GLON	END_GLAT	END_GLON	DATEC	PAVE_T
1999131	643710	1	C	X038	1	5	0	0.01	40.64605401	-91.2941918	40.64615426	-91.29432781	11/3/2013	JCP
1999132	643710	1	C	X038	1	5	0.01	0.02	40.64615426	-91.29432781	40.64625786	-91.29445776	11/3/2013	JCP
1999133	643710	1	C	X038	1	5	0.02	0.03	40.64625786	-91.29445776	40.6463647	-91.294584	11/3/2013	JCP
1999134	643710	1	C	X038	1	5	0.03	0.04	40.6463647	-91.294584	40.64647537	-91.29470517	11/3/2013	JCP
1999135	643710	1	C	X038	1	5	0.04	0.05	40.64647537	-91.29470517	40.64659036	-91.2948196	11/3/2013	JCP
1999136	643710	1	C	X038	1	5	0.05	0.06	40.64659036	-91.2948196	40.64670919	-91.29492756	11/3/2013	JCP
1999137	643710	1	C	X038	1	5	0.06	0.07	40.64670919	-91.29492756	40.64683105	-91.29502966	11/3/2013	JCP
1999138	643710	1	C	X038	1	5	0.07	0.08	40.64683105	-91.29502966	40.64695587	-91.29512531	11/3/2013	JCP
1999139	643710	1	C	X038	1	5	0.08	0.09	40.64695587	-91.29512531	40.64708383	-91.29521297	11/3/2013	JCP
1999140	643710	1	C	X038	1	5	0.09	0.092	40.64708383	-91.29521297	40.6471064	-91.29522755	11/3/2013	JCP
1999141	643730	1	C	X038	1	5	0.092	0.1	40.64850985	-91.296024	40.64861957	-91.29608643	11/3/2013	JCP
1999142	643730	1	C	X038	1	5	0.1	0.11	40.64861957	-91.29608643	40.64875245	-91.2961626	11/3/2013	JCP
1999143	643730	1	C	X038	1	5	0.11	0.12	40.64875245	-91.2961626	40.64888541	-91.29623858	11/3/2013	JCP
1999144	643730	1	C	X038	1	5	0.12	0.13	40.64888541	-91.29623858	40.64901849	-91.29631396	11/3/2013	JCP
1999145	643730	1	C	X038	1	5	0.13	0.14	40.64901849	-91.29631396	40.64915187	-91.29638823	11/3/2013	JCP
1999146	643730	1	C	X038	1	5	0.14	0.15	40.64915187	-91.29638823	40.64928538	-91.29646197	11/3/2013	JCP
1999506	643730	1	C	X038	1	5	0.15	0.16	40.64928538	-91.29646197	40.64941895	-91.2965359	11/3/2013	JCP
1999507	643730	1	C	X038	1	5	0.1[illegible]	0.17	40.64941895	-91.2965359	40.64955247	-91.29661015	11/3/2013	JCP
2004915	643750	1	C	X038	1	5	7.73	7.74	40.75048751	-91.27668543	40.75059342	-91.27655437	11/3/2013	ASP
2004916	643750	1	C	X038	1	5	7.74	7.75	40.75059342	-91.27655437	40.75070226	-91.27642728	11/3/2013	ASP
2004917	643750	1	C	X038	1	5	7.75	7.76	40.75070226	-91.27642728	40.75081485	-91.27630585	11/3/2013	ASP
2004918	643750	1	C	X038	1	5	7.76	7.77	40.75081485	-91.27630585	40.75093247	-91.27619265	11/3/2013	ASP
2004919	643750	1	C	X038	1	5	7.77	7.78	40.75093247	-91.27619265	40.75105512	-91.27608919	11/3/2013	ASP
2004920	643750	1	C	X038	1	5	7.78	7.79	40.75105512	-91.27608919	40.75118212	-91.27599542	11/3/2013	ASP
2004921	643750	1	C	X038	1	5	7.79	7.8	40.75118212	-91.27599542	40.75131274	-91.27591064	11/3/2013	ASP
2004922	643750	1	C	X038	1	5	7.8	7.81	40.75131274	-91.27591064	40.75144695	-91.27583692	11/3/2013	ASP
2004923	643750	1	C	X038	1	5	7.81	7.82	40.75144695	-91.27583692	40.7515831	-91.27577192	11/3/2013	ASP
2004924	643750	1	C	X038	1	5	7.82	7.83	40.7515831	-91.27577192	40.75172153	-91.27571517	11/3/2013	ASP
2004925	643750	1	C	X038	1	5	7.83	7.84	40.75172153	-91.27571517	40.7518621	-91.27566621	11/3/2013	ASP
2004926	643750	1	C	X038	1	5	7.84	7.85	40.7518621	-91.27566621	40.75200387	-91.27562323	11/3/2013	JCP
2004927	643750	1	C	X038	1	5	7.85	7.86	40.75200387	-91.27562323	40.75214603	-91.27558369	11/3/2013	JCP
2004928	643750	1	C	X038	1	5	7.86	7.87	40.75214603	-91.27558369	40.7522881	-91.27554448	11/3/2013	JCP
2004929	643750	1	C	X038	1	5	7.87	7.88	40.7522881	-91.27554448	40.75243043	-91.27550687	11/3/2013	JCP
1999172	643750	1	C	X038	1	5	7.88	7.89	40.75243043	-91.27550687	40.75257286	-91.27547267	11/3/2013	JCP
1999173	643750	1	C	X038	1	5	7.89	7.9	40.75257286	-91.27547267	40.75271566	-91.27544231	11/3/2013	JCP
1999174	643750	1	C	X038	1	5	7.9	7.91	40.75271566	-91.27544231	40.75285907	-91.27541701	11/3/2013	CRC
1999175	643750	1	C	X038	1	5	7.91	7.92	40.75285907	-91.27541701	40.75300331	-91.27539709	11/3/2013	CRC
1999176	643750	1	C	X038	1	5	7.92	7.93	40.75300331	-91.27539709	40.75314803	-91.27538329	11/3/2013	CRC
1999177	643750	1	C	X038	1	5	7.93	7.94	40.75314803	-91.27538329	40.75329339	-91.27537573	11/3/2013	CRC
1999178	643750	1	C	X038	1	5	7.94	7.95	40.75329339	-91.27537573	40.75343879	-91.27537262	11/3/2013	CRC
1999179	643750	1	C	X038	1	5	7.95	7.958	40.75343879	-91.27537262	40.75355855	-91.27537285	11/3/2013	CRC

Record: 1 of 798 Filtered Search

(a) 2013

ROADWARE_LOCAL_2015

ROADWARE_	ROUTING_N	RUN_NO	ROAD_ID	ROAD_NAM	LANE	DIR	BEGIN_MILE	END_MILE	BEGIN_GLAT	BEGIN_GLON	BEGIN_GELE	END_GLAT	END_GLON	END_GE
3108219	508610	1	C	X038	1	5	0	0.01	40.64597888	-91.29416209	695	40.64611223	-91.29425951	
3108529	508610	1	C	X038	1	5	0.01	0.02	40.64611223	-91.29425951	694	40.64621308	-91.29439662	
3108530	508610	1	C	X038	1	5	0.02	0.03	40.64621308	-91.29439662	694	40.64631725	-91.29452751	
3108531	508610	1	C	X038	1	5	0.03	0.04	40.64631725	-91.29452751	693	40.64642631	-91.29465174	
3108532	508610	1	C	X038	1	5	0.04	0.05	40.64642631	-91.29465174	693	40.64653876	-91.29477061	
3108533	508610	1	C	X038	1	5	0.05	0.06	40.64653876	-91.29477061	694	40.64665582	-91.29488138	
3108534	508610	1	C	X038	1	5	0.06	0.07	40.64665582	-91.29488138	694	40.64677655	-91.29498519	
3108535	508610	1	C	X038	1	5	0.07	0.08	40.64677655	-91.29498519	694	40.64690067	-91.29508201	
3108536	508610	1	C	X038	1	5	0.08	0.09	40.64690067	-91.29508201	695	40.64702765	-91.29517248	
3108537	508610	1	C	X038	1	5	0.09	0.098	40.64702765	-91.29517248	695	40.64712929	-91.29523907	
3074827	508630	1	C	X038	1	5	0.096	0.106	40.64846934	-91.29600218	701	40.64860208	-91.29607748	
3074828	508630	1	C	X038	1	5	0.106	0.116	40.64860208	-91.29607748	701	40.64873483	-91.29615294	
3074829	508630	1	C	X038	1	5	0.116	0.126	40.64873483	-91.29615294	700	40.64886768	-91.29622791	
3074830	508630	1	C	X038	1	5	0.126	0.136	40.64886768	-91.29622791	700	40.64900066	-91.29630256	
3074831	508630	1	C	X038	1	5	0.136	0.146	40.64900066	-91.29630256	700	40.64913381	-91.29637754	
3074832	508630	1	C	X038	1	5	0.146	0.156	40.64913381	-91.29637754	699	40.64926733	-91.29645223	
3074833	508630	1	C	X038	1	5	0.156	0.166	40.64926733	-91.29645223	699	40.64940111	-91.29652638	
3074834	508630	1	C	X038	1	5	0.1[illegible]6	0.176	40.64940111	-91.29652638	699	40.64953494	-91.29660098	
3055065	508650	1	C	X038	1	5	7.776	7.786	40.75089333	-91.27622627	550	40.75101419	-91.27612037	
3055066	508650	1	C	X038	1	5	7.786	7.796	40.75101419	-91.27612037	549	40.75113963	-91.27602388	
3055067	508650	1	C	X038	1	5	7.796	7.806	40.75113963	-91.27602388	548	40.75126898	-91.27593675	
3055068	508650	1	C	X038	1	5	7.806	7.816	40.75126898	-91.27593675	548	40.75140165	-91.27585902	
3055069	508650	1	C	X038	1	5	7.816	7.826	40.75140165	-91.27585902	548	40.75153747	-91.27579088	
3055070	508650	1	C	X038	1	5	7.826	7.836	40.75153747	-91.27579088	548	40.75167623	-91.27573413	
3055071	508650	1	C	X038	1	5	7.836	7.846	40.75167623	-91.27573413	548	40.75181666	-91.2756862	
3055072	508650	1	C	X038	1	5	7.846	7.856	40.75181666	-91.2756862	548	40.75195797	-91.27564372	
3055073	508650	1	C	X038	1	5	7.856	7.866	40.75195797	-91.27564372	549	40.75209946	-91.27560343	
3055074	508650	1	C	X038	1	5	7.866	7.876	40.75209946	-91.27560343	549	40.75224106	-91.27556412	
3055385	508650	1	C	X038	1	5	7.876	7.886	40.75224106	-91.27556412	550	40.75238256	-91.27552398	
3055386	508650	1	C	X038	1	5	7.886	7.896	40.75238256	-91.27552398	551	40.75252471	-91.2754867	
3055387	508650	1	C	X038	1	5	7.896	7.906	40.75252471	-91.2754867	552	40.75266755	-91.27545396	
3055388	508650	1	C	X038	1	5	7.906	7.916	40.75266755	-91.27545396	552	40.75281121	-91.27542763	
3055389	508650	1	C	X038	1	5	7.916	7.926	40.75281121	-91.27542763	554	40.75295531	-91.27540684	
3055390	508650	1	C	X038	1	5	7.926	7.936	40.75295531	-91.27540684	554	40.75309998	-91.27539182	
3055391	508650	1	C	X038	1	5	7.936	7.946	40.75309998	-91.27539182	555	40.75324476	-91.27538116	
3055392	508650	1	C	X038	1	5	7.946	7.956	40.75324476	-91.27538116	555	40.75338968	-91.27537493	
3055393	508650	1	C	X038	1	5	7.956	7.966	40.75338968	-91.27537493	555	40.75353472	-91.27537307	
3055394	508650	1	C	X038	1	5	7.966	7.969	40.75353472	-91.27537307	555	40.75357454	-91.27537357	

Record: 1 of 798 Filtered Search

(b) 2015

ROADWARE_LOCAL_2017

ROADWARE_ID	ROUTE_NAME	SYST	NHS	CALC_LGTH	ROUTE_ID	FROM_MEASURE	TO_MEASUR	BEGIN_GLAT	BEGIN_GLON	END_GLAT	END_GLON	DIR	BEARING	COUNTY_ID	DA
14885250	330TH AVENUE	0	N	56.0364539317	M269741710N	0	0.00996	40.64707641	-91.29521253	40.64721609	-91.29529713	I	335.32	56	
14874012	330TH AVENUE	0	N	52.8924101759	C005642570N	0.001	0.01087	40.64596563	-91.29413689	40.64608929	-91.29423679	I	328.49	56	
14885249	330TH AVENUE	0	N	52.1402847825	M269741710N	0.00996	0.01992	40.64721609	-91.29529713	40.64734699	-91.29537314	I	336.22	56	
14874013	330TH AVENUE	0	N	51.4754330064	C005642570N	0.01087	0.02074	40.64608929	-91.29423679	40.64618579	-91.29437231	I	313.18	56	
14885248	330TH AVENUE	0	N	50.8194304517	M269741710N	0.01992	0.02989	40.64734699	-91.29537314	40.64747531	-91.295445	I	336.98	56	
14874014	330TH AVENUE	0	N	56.1007147374	C005642570N	0.02074	0.03061	40.64618579	-91.29437231	40.64629728	-91.29451179	I	316.49	56	
14885247	330TH AVENUE	0	N	52.5951339199	M269741710N	0.02989	0.03985	40.64747531	-91.295445	40.64760814	-91.29551929	I	337	56	
14874015	330TH AVENUE	0	N	52.227914315	C005642570N	0.03061	0.04047	40.64629728	-91.29451179	40.64640605	-91.29463442	I	319.46	56	
14885246	330TH AVENUE	0	N	54.5547239581	M269741710N	0.03985	0.04981	40.64760814	-91.29551929	40.64774569	-91.29559705	I	336.78	56	
14874016	330TH AVENUE	0	N	51.0873283837	C005642570N	0.04047	0.05034	40.64640605	-91.29463442	40.64651729	-91.29474654	I	322.59	56	
14885245	330TH AVENUE	0	N	52.1337759100	M269741710N	0.04981	0.05977	40.64774569	-91.29559705	40.64787708	-91.29567153	I	336.73	56	
14874017	330TH AVENUE	0	N	51.7057611352	C005642570N	0.05034	0.06021	40.64651729	-91.29474654	40.64663277	-91.29485489	I	324.55	56	
14885244	330TH AVENUE	0	N	50.2923917706	M269741710N	0.05977	0.06973	40.64787708	-91.29567153	40.64800397	-91.29574295	I	336.88	56	
14874018	330TH AVENUE	0	N	54.1347711273	C005642570N	0.06021	0.07008	40.64663277	-91.29485489	40.64675595	-91.29496403	I	326.09	56	
14885243	330TH AVENUE	0	N	53.4147561407	M269741710N	0.06973	0.0797	40.64800397	-91.29574295	40.64813906	-91.29581781	I	337.2	56	
14874019	330TH AVENUE	0	N	52.755338373	C005642570N	0.07008	0.07995	40.64675595	-91.29496403	40.64687761	-91.29506717	I	327.25	56	
14885242	330TH AVENUE	0	N	53.8546660753	M269741710N	0.0797	0.08966	40.64813906	-91.29581781	40.64827521	-91.29589345	I	337.14	56	
14874020	330TH AVENUE	0	N	51.2133742285	C005642570N	0.07995	0.089[illegible]2	40.64687761	-91.29506717	40.64699864	-91.29516108	I	329.51	56	
14874740	330TH AVENUE	0	N	51.6832314279	C005642570N	7.25661	7.2666	40.74632311	-91.27694341	40.74646499	-91.2769433	I	0.04	56	
14874741	330TH AVENUE	0	N	52.8575664742	C005642570N	7.2666	7.27659	40.74646499	-91.2769433	40.74661009	-91.27694192	I	0.41	56	
14874742	330TH AVENUE	0	N	52.2922196003	C005642570N	7.27659	7.28658	40.74661009	-91.27694192	40.74675364	-91.27694097	I	0.29	56	
14874743	330TH AVENUE	0	N	55.7887665195	C005642570N	7.28658	7.29657	40.74675364	-91.27694097	40.74690679	-91.27694148	I	359.85	56	
14874744	330TH AVENUE	0	N	51.7940592399	C005642570N	7.29657	7.30656	40.74690679	-91.27694148	40.74704896	-91.27694413	I	359.19	56	
14874745	330TH AVENUE	0	N	52.9869760953	C005642570N	7.30656	7.31656	40.74704896	-91.27694413	40.74719436	-91.27694958	I	358.37	56	
14874746	330TH AVENUE	0	N	55.7887711441	C005642570N	7.31656	7.32655	40.74719436	-91.27694958	40.74734734	-91.27695908	I	357.31	56	
14874747	330TH AVENUE	0	N	50.7559403102	C005642570N	7.32655	7.33654	40.74734734	-91.27695908	40.74748632	-91.27697214	I	355.93	56	
14874748	330TH AVENUE	0	N	53.4749106267	C005642570N	7.33654	7.34653	40.74748632	-91.27697214	40.74763214	-91.27699439	I	353.41	56	
14874749	330TH AVENUE	0	N	53.1016054391	C005642570N	7.34653	7.35652	40.74763214	-91.27699439	40.74777513	-91.27703167	I	348.83	56	
14874750	330TH AVENUE	0	N	54.6632615466	C005642570N	7.35652	7.36651	40.74777513	-91.27703167	40.747919	-91.27708776	I	343.55	56	
14874751	330TH AVENUE	0	N	51.8129891992	C005642570N	7.36651	7.37651	40.747919	-91.27708776	40.74805162	-91.27715536	I	338.89	56	
14874752	330TH AVENUE	0	N	51.3409728802	C005642570N	7.37651	7.3865	40.74805162	-91.27715536	40.74817943	-91.27723347	I	335.16	56	
14874753	330TH AVENUE	0	N	53.6893814665	C005642570N	7.3865	7.39649	40.74817943	-91.27723347	40.74830938	-91.27732491	I	331.94	56	
14874754	330TH AVENUE	0	N	52.4918793662	C005642570N	7.39649	7.40648	40.74830938	-91.27732491	40.74843258	-91.27742319	I	328.85	56	
14874755	330TH AVENUE	0	N	52.5212098496	C005642570N	7.40648	7.41647	40.74843258	-91.27742319	40.74855365	-91.27752614	I	327.21	56	
14874756	330TH AVENUE	0	N	52.5771976176	C005642570N	7.41647	7.42646	40.74855365	-91.27752614	40.74867344	-91.27763201	I	326.2	56	
14874757	330TH AVENUE	0	N	52.6768762509	C005642570N	7.42646	7.43645	40.74867344	-91.27763201	40.7487917	-91.27774144	I	324.97	56	
14874758	330TH AVENUE	0	N	52.7317830391	C005642570N	7.43645	7.44645	40.7487917	-91.27774144	40.74890928	-91.27785247	I	324.42	56	
14874759	330TH AVENUE	0	N	52.7812904	C005642570N	7.44645	7.45644	40.74890928	-91.27785247	40.74902712	-91.27796333	I	324.52	56	
14874760	330TH AVENUE	0	N	52.8044486694	C005642570N	7.45644	7.46643	40.74902712	-91.27796333	40.74914638	-91.27807168	I	325.46	56	
14874761	330TH AVENUE	0	N	52.8102668944	C005642570N	7.46643	7.47642	40.74914638	-91.27807168	40.74926529	-91.27818073	I	325.21	56	
14874762	330TH AVENUE	0	N	8.32689001873	C005642570N	7.47642	7.478	40.74926529	-91.27818073	40.74928212	-91.27820107	I	317.52	56	

Record: 1 of 762 Filtered Search

(c) 2017

Figure 109. Sorting of X38 county road units

Step 6. Calculation of Total Length of the Road Section

By using equation 6, the total length of the road section in the ROADWARE_LOCAL database is determined as follows:

- For ROADWARE_LOCAL_2013: END_MILE–BEGIN_MILE = 7.958–0 = 7.958 mi
- For ROADWARE_LOCAL_2015: END_MILE–BEGIN_MILE = 7.969–0 = 7.969 mi
- For ROADWARE_LOCAL_2017: TO_MEASURE–FROM_MEASURE = 7.478–0 = 7.478 mi

The total length of the X38 road section in the County Records database is as follows:

$\sum PROJECT\_LENGTH$ = 1.993 + 0.631 + 3.79 = 6.414 mi

The total length of the road section shows a slight difference between every other year in the ROADWARED_LOCAL database and quite a large difference between the lengths in the ROADWARE_LOCAL and County Records databases. Thus, the coordinates of BEGIN_MILE (FROM_MEASURE) and END_MILE (TO_MEASURE) need to be checked and also matched with each other.

Step 7. Comparison of Pavement Types

The pavement types indicated in the ROADWARE_LOCAL and County Records databases matched with each other without issue, as shown in Figure 110.

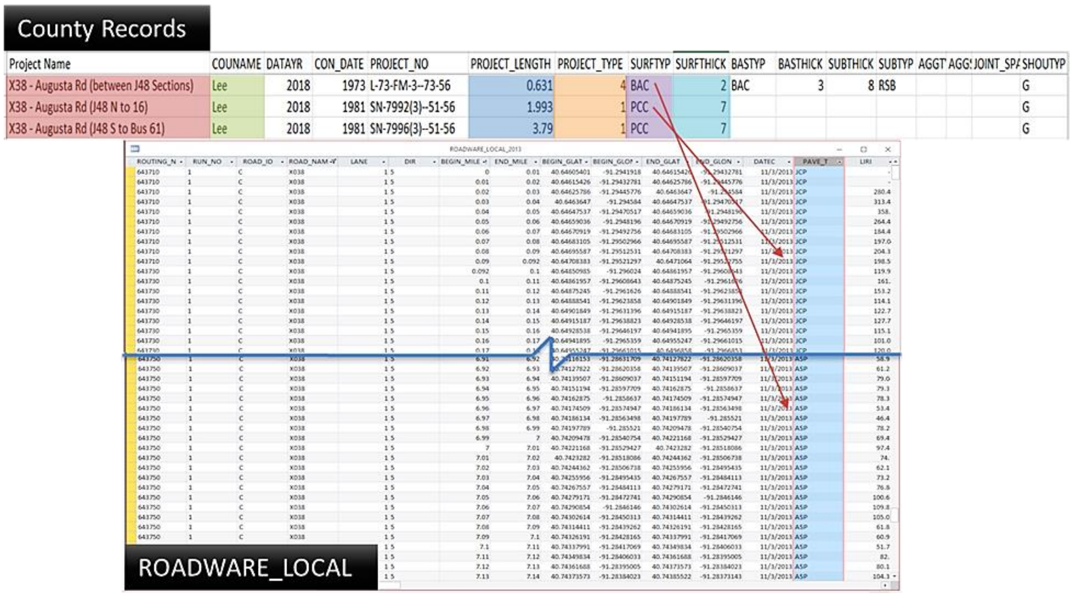


Figure 110. Database comparison of pavement types

Step 8. Determination of Pavement Type

After checking pavement types, the condition and distress data used in the data processing were determined. They are listed as follows and also shown previously in Figure 108.

For X38-Augusta Rd (from J48 North to Iowa 16), it is rigid pavement. Thus, the data are as follows:

- IRI
- Faulting
- Transverse cracking

For X38-Augusta Rd (between J48 sections), it is flexible pavement. Thus, the data are as follows:

- IRI
- Rutting
- Transverse cracking
- Longitudinal cracking
- Wheel path longitudinal cracking

For X38-Augusta Rd (from J48 South to Business US 61), it is rigid pavement. Thus, the data are as follows:

- IRI
- Faulting
- Transverse cracking

Steps 9 and 10. Transfer of Arranged Raw Data and Repeating It for All Years

Each year of ROADWARE_LOCAL was copied into an Excel sheet, as shown in Figure 111.

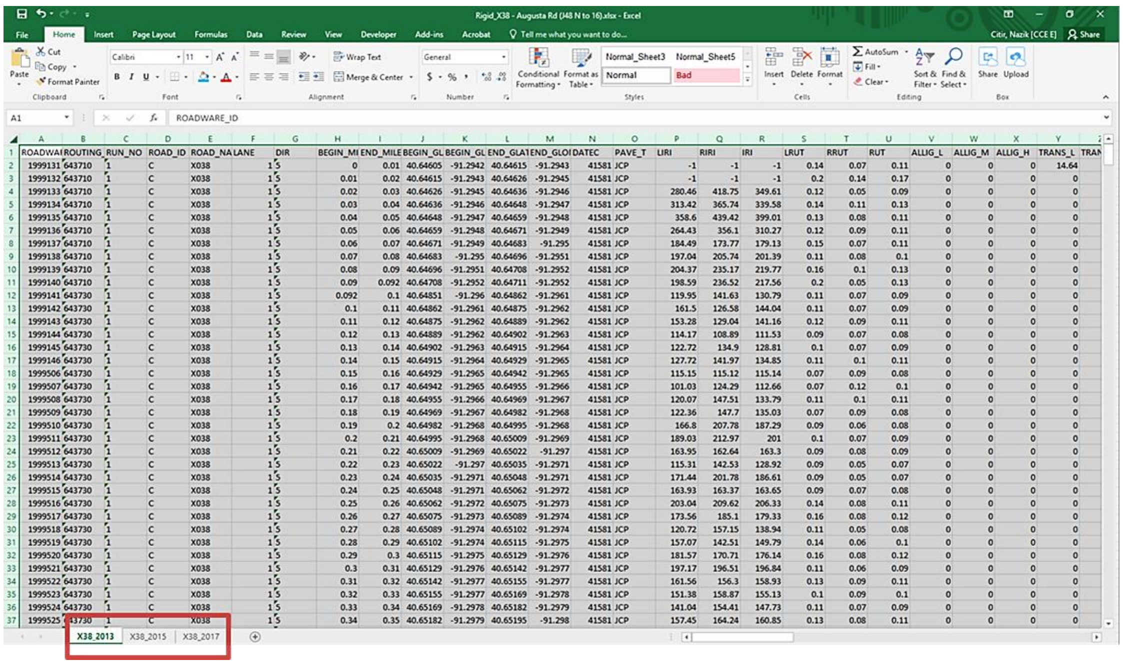


Figure 111. Transfer of arranged raw data for all years

Step 11. Elimination of Nulls in IRI

The IRI column was checked as to whether the field had null value or not. If there was, the null value would be eliminated in the IRI data processing; however, there were none. An example of an Excel sheet with null values to remove is shown in Figure 112.

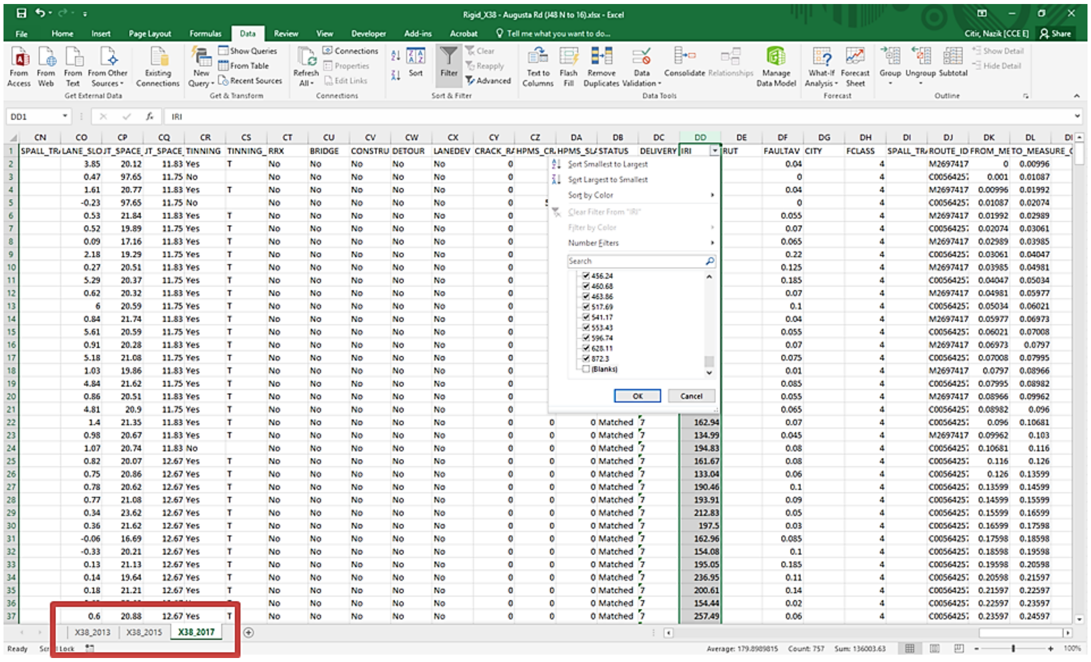
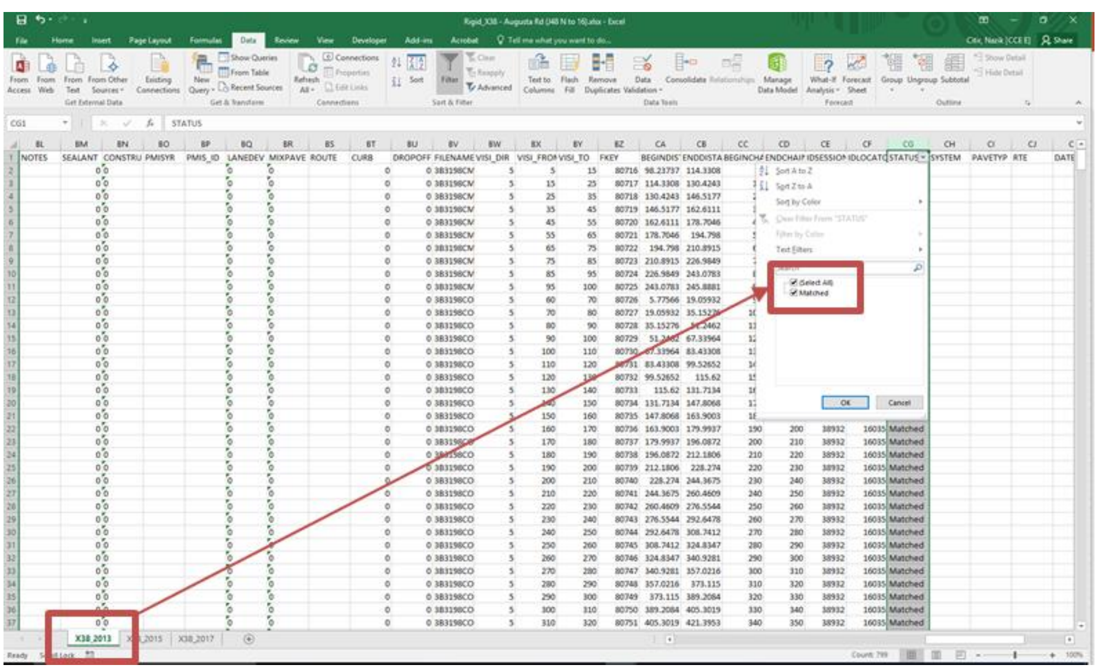


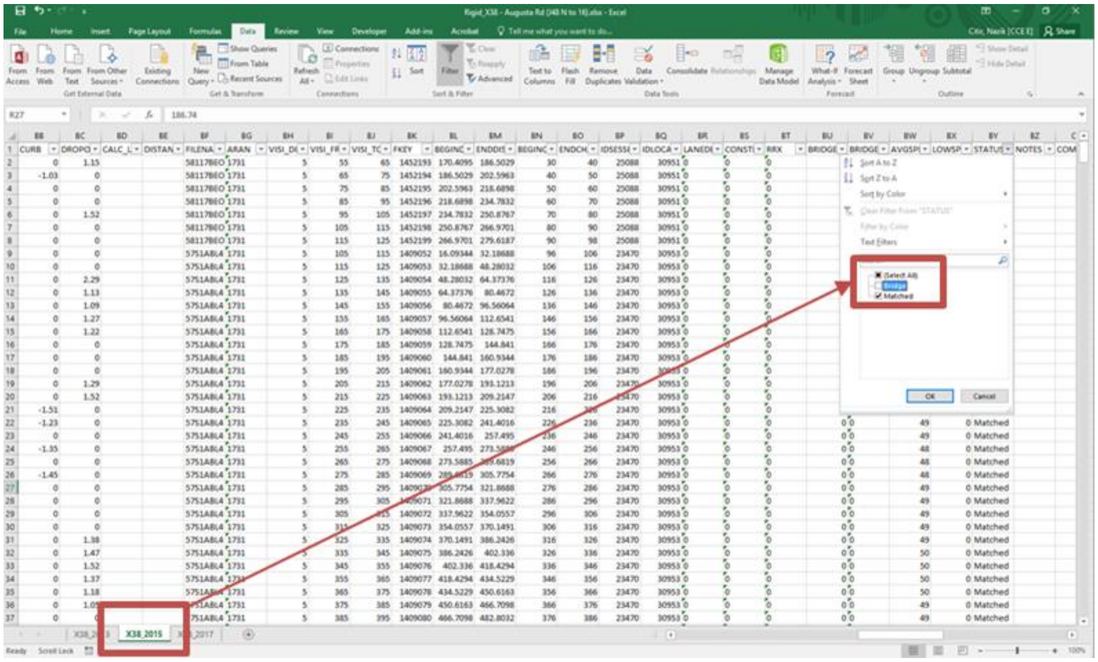
Figure 112. Elimination of nulls in IRI

Step 12. Filtration of Status

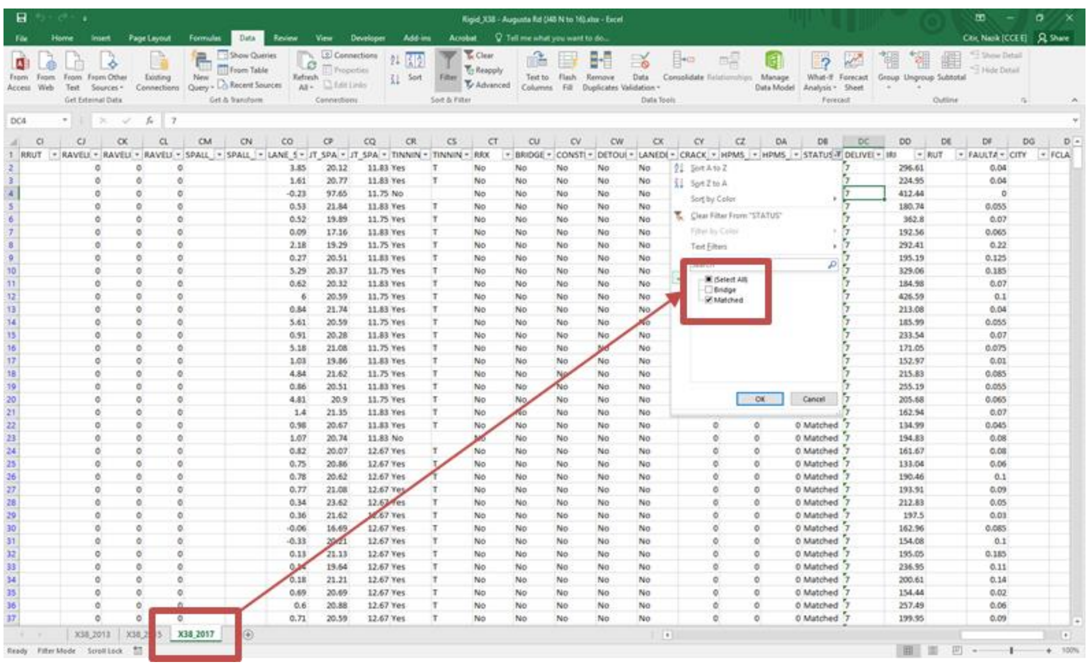
The STATUS of the road sections was filtered by selecting only the Matched type, as shown in Figure 113a, b, and c for the years of 2013, 2015, and 2017, respectively.



(a) 2013



(b) 2015



(c) 2017

Figure 113. Filtration of STATUS

Step 13. Copy of Raw Data Filtered by STATUS

The filtered data by STATUS were copied into a new Excel sheet for each year, as shown in Figure 114.

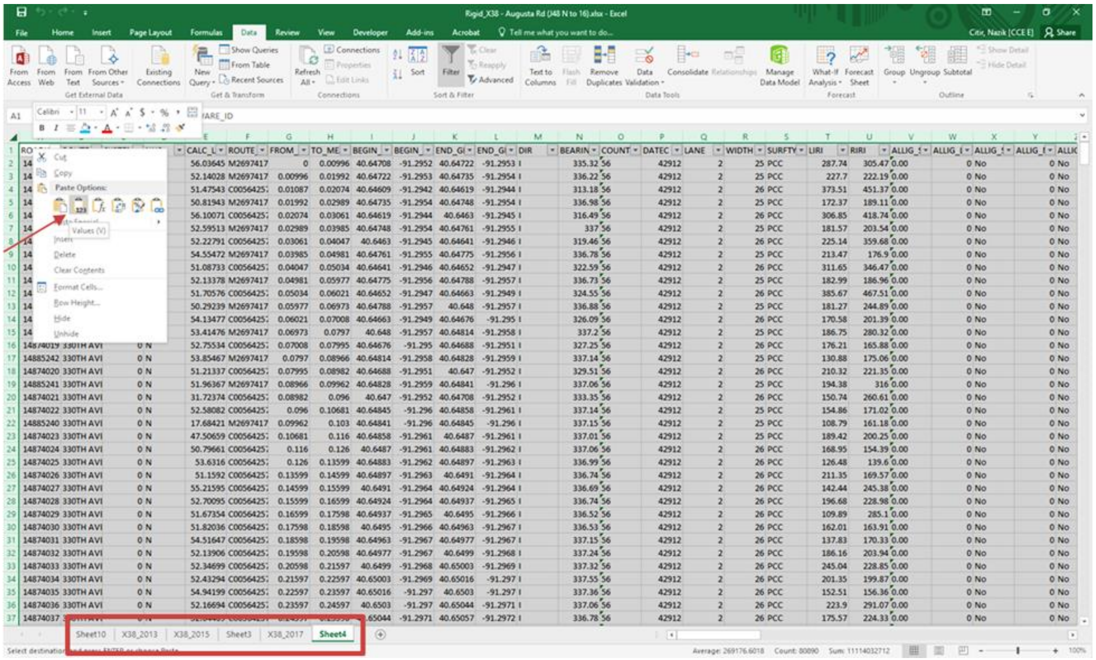


Figure 114. Copy of raw data filtered by STATUS for all years

Step 14. Comparison of Coordinates of a Road Section in Each Year

The coordinates of road sections were compared for all years.

This step requires close attention, as many different situations might be encountered. A sample situation is given in the Lee County case as explained in this section.

The beginning and ending miles and coordinates of the road sections can be combined in one Excel sheet for each year to be able to compare them easily. The sample Excel sheet is shown in Figure 115.

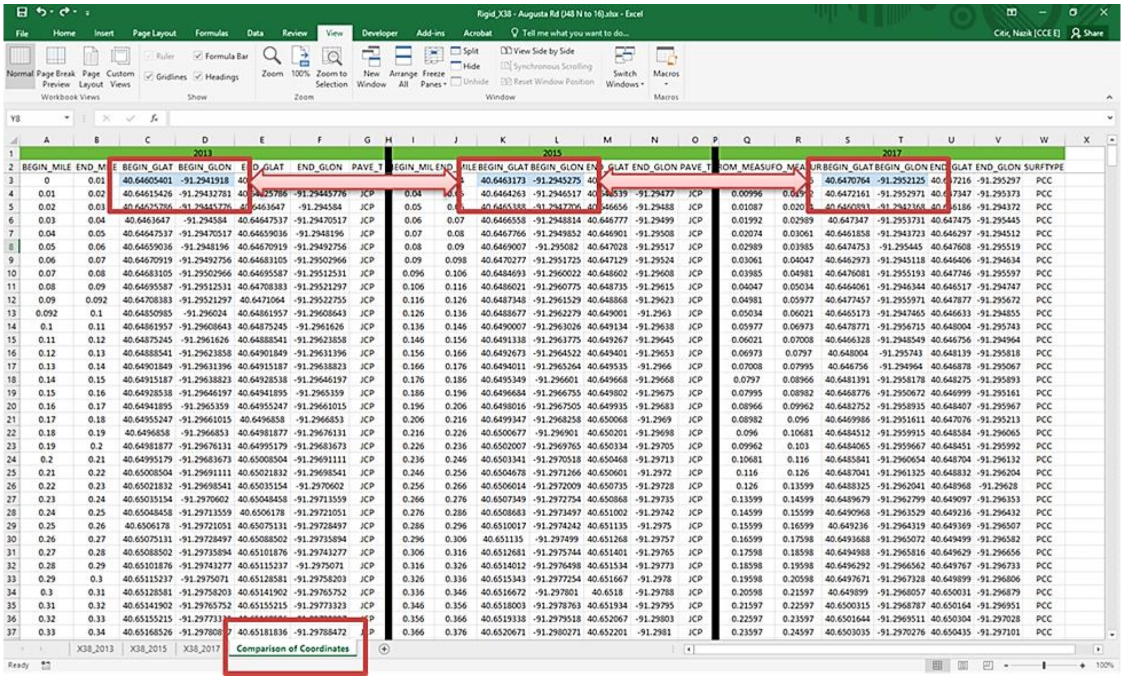


Figure 115. Combination of road sections for all years

As shown, the coordinates of the beginning of the road section did not match, which means that the beginning points for collecting distress data are different. Therefore, the same (or as close as possible) points for the beginning coordinate were found for each year, as shown in Figure 116.

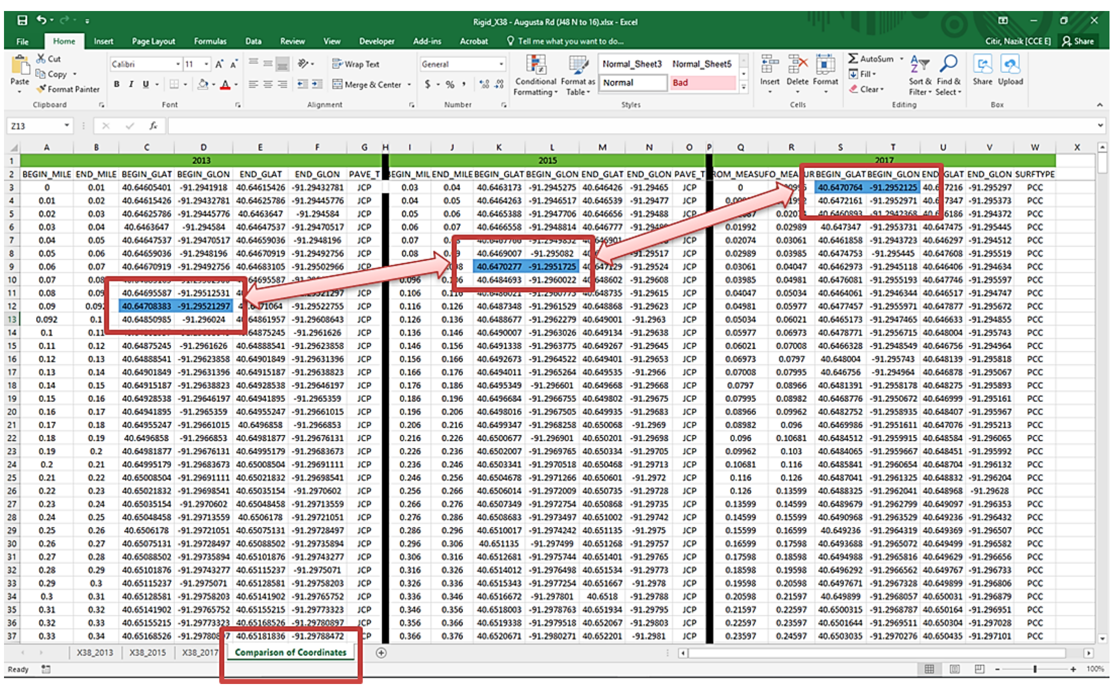


Figure 116. Matching the beginning coordinates for each year

Then, the found beginning coordinate was set in Google Maps, shown in Figure 117, to confirm the location of the beginning of the road section.

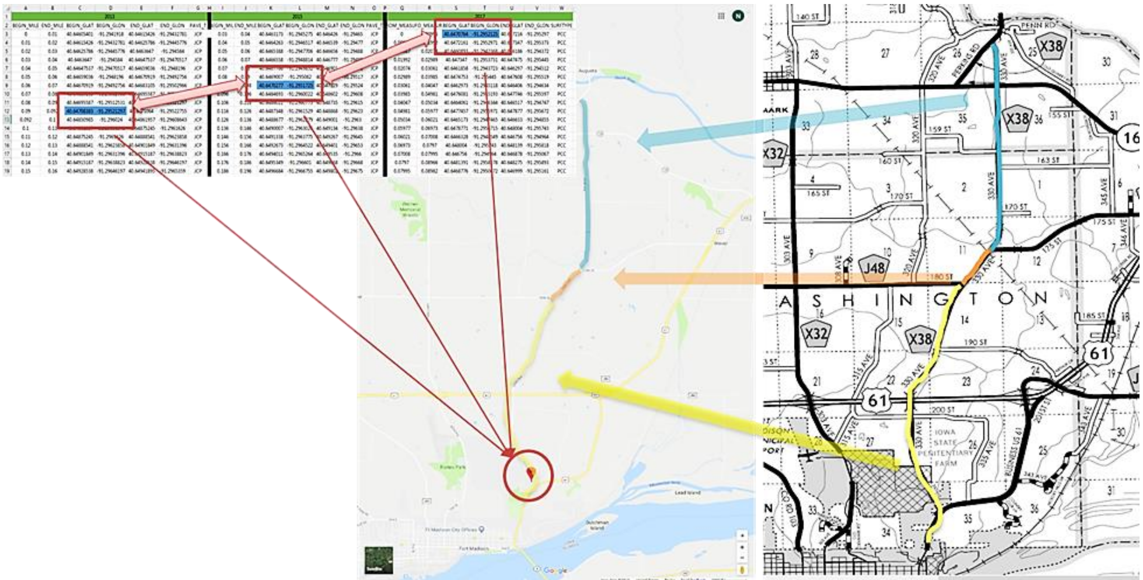


Figure 117. Beginning coordinate of the road section in Google Maps

For every other year, the same process was carried out to find the beginning and ending points of each road section and to match them with each other. The detail on them is explained as follows:

- For the road section of X38-Augusta Rd (from J48 South to Business US 61), the coordinates and total length (by equation 6) are shown in Table 20 for 2013, 2015, and 2017.

Table 20. Length and coordinates of X38-Augusta Rd (from J48 South to Business US 61)

Year	BEGIN_ MILE	END_ MILE	BEGIN_ GLAT	BEGIN_ GLON	END_ GLAT	END_ GLON	Total length
2013	**0.09**	0.092	**40.6470838**	**-91.2952130**	40.647106	-91.295227	3.53
	3.610	**3.620**	40.6959646	-91.2871205	**40.696083**	**-91.287010**	
2015	**0.09**	0.098	**40.6470277**	**-91.2951725**	40.647129	-91.295240	3.53
	3.616	**3.626**	40.6959620	-91.2871212	**40.696080**	**-91.287010**	
2017	**0.00**	0.009	**40.6470764**	**-91.2952125**	40.647216	-91.295297	3.63
	3.627	**3.632**	40.6960414	-91.2870431	**40.696103**	**-91.286985**	

After matching the coordinates and confirming the location of the road section in Google Maps (Figure 118), the pavement type in ROADWARE_LOCAL and County Records was re-matched, which is rigid pavement.

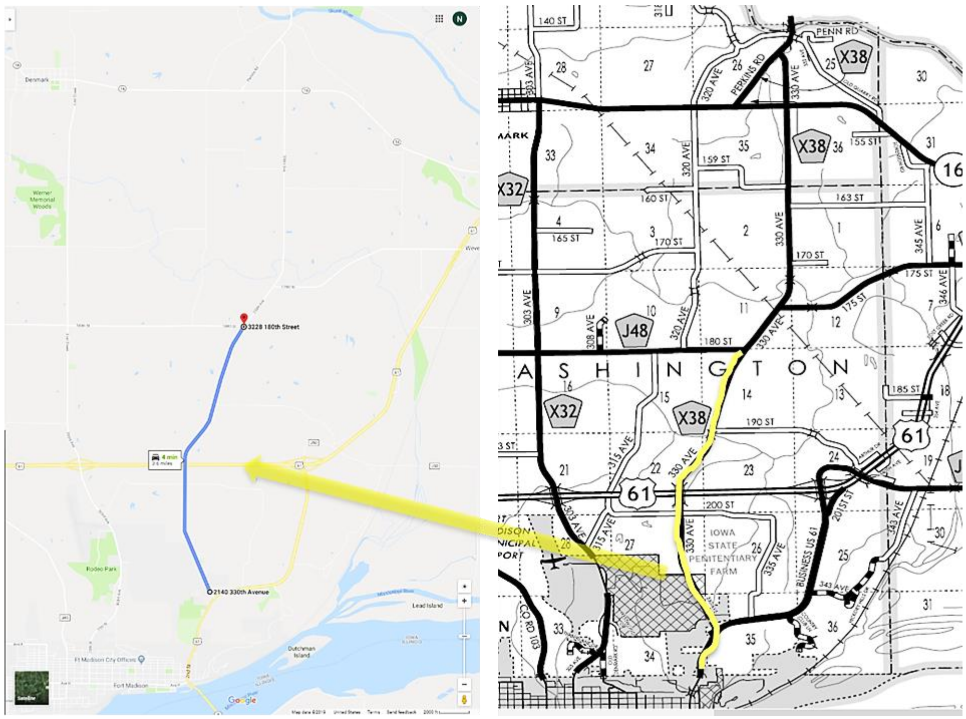


Figure 118. Location of X38-Augusta Rd (J48 S to Bus 61) in Google Maps and in Highway and Transportation Map for Lee County

From Table 20, the total length in ROADWARE_LOCAL was calculated as 3.53 mi for 2013 and 2015; 3.63 mi for 2017; and it is shown as 3.79 mi in County Records. It is almost the same value, so it is acceptable.

- For the road section of X38-Augusta Rd (between J48 sections), the coordinates and total length (by equation 6) are indicated in Table 21 for 2013, 2015, and 2017.

Table 21. Length and coordinates of X38-Augusta Rd (between J48 sections)

Year	BEGIN_ MILE	END_ MILE	BEGIN_ GLAT	BEGIN_ GLON	END_ GLAT	END_ GLON	Total length
2013	**3.62**	3.63	**40.6960826**	**-91.2870095**	40.696200	-91.2868967	0.63
	4.250	**4.260**	40.7034462	-91.2799036	**40.703563**	**-91.2797937**	
2015	**3.626**	3.636	**40.6960802**	**-91.2870113**	40.696197	-91.2868991	0.63
	4.246	**4.256**	40.7033229	-91.28002	**40.703440**	**-91.2799084**	
2017	**3.632**	3.642	**40.6961029**	**-91.286985**	40.696220	-91.2868718	0.63
	4.252	**4.262**	40.7033508	-91.2799942	**40.70347**	**-91.2798828**	

After matching the coordinates and confirming the location of the road section in Google Maps (Figure 119), the pavement types in ROADWARE_LOCAL and County Records were not re-matched and are rigid and flexible pavement, respectively.

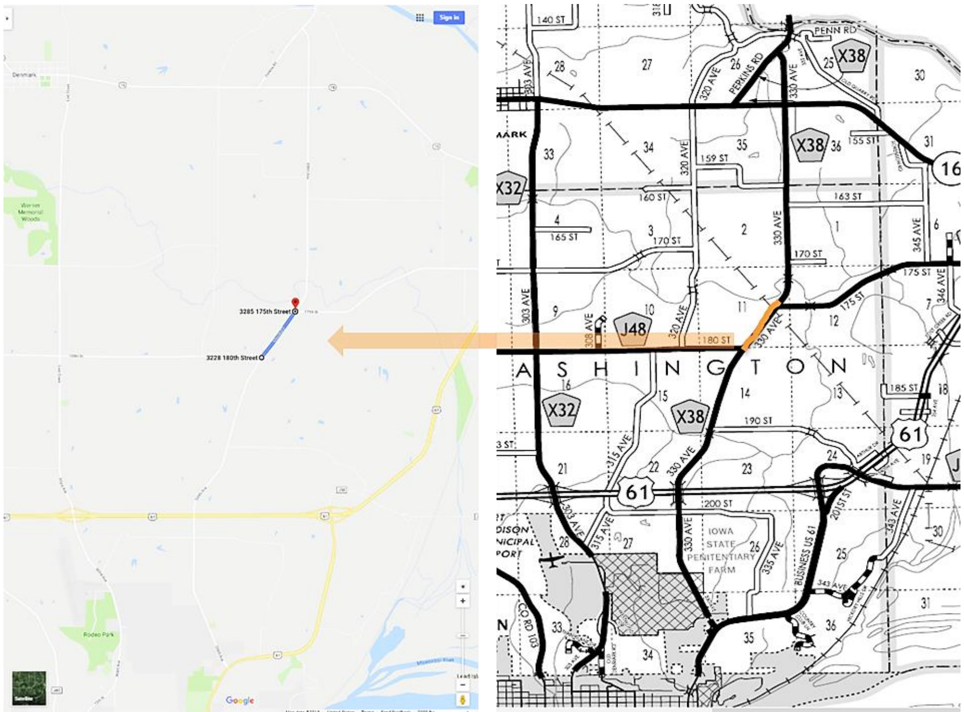


Figure 119. X38-Augusta Rd (between J48 sections) in Google Maps and in Highway and Transportation Map for Lee County

From Table 21, the total length in ROADWARE_LOCAL was calculated as 0.63 mi, and it is shown as 0.631 mi in County Records. It is essentially the same value, so it is acceptable.

- For the road section of X38-Augusta Rd (from J48 North to Iowa 16), the coordinates and total length (by equation 6) are indicated in
- Table 22 for 2013, 2015, and 2017.

Table 22. Length and coordinates of X38-Augusta Rd (from J48 North to Iowa 16)

Year	BEGIN_ MILE	END_ MILE	BEGIN_ GLAT	BEGIN_ GLON	END_ GLAT	END_ GLON	Total length
2013	4.25	4.26	40.7034462	-91.2799031	40.703563	-91.2797937	2.53
	6.77	6.78	40.7394411	-91.2769560	40.739587	-91.2769529	
2015	4.256	4.266	40.70344	-91.2799084	40.70356	-91.2797964	2.50
	6.746	6.756	40.739001	-91.2769397	40.739147	-91.2769384	
2017	4.262	4.272	40.7034689	-91.2798828	40.703590	-91.2797685	2.51
	6.760	6.769	40.7391228	-91.2769551	40.739265	-91.2769546	

After matching the coordinates and confirming the location of the road section in Google Maps (Figure 120), the pavement type in ROADWARE_LOCAL and County Records was re-matched, which is rigid pavement.

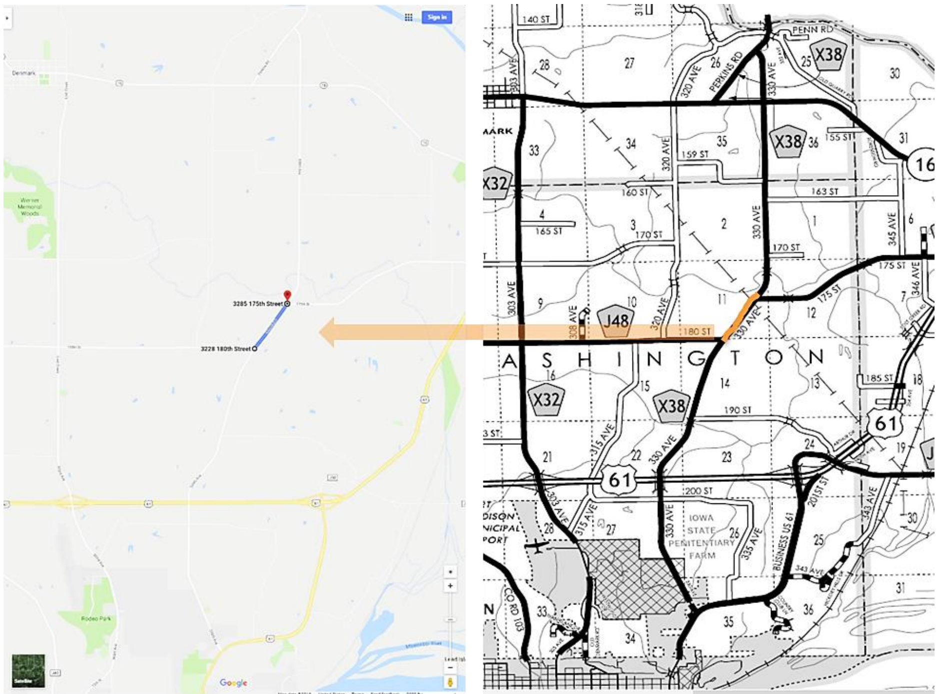


Figure 120. X38-Augusta Rd (from J48 North to Iowa 16) in Google Maps and in Highway and Transportation Map for Lee County

From
Table 22, the total length in ROADWARE_LOCAL was calculated as 2.53, 2.50, and 2.51 mi for 2013, 2015, and 2017, respectively, while it is shown as 1.993 mi in County Records. It is almost the same value, so it is acceptable.

The results deduced from Step 14 are as follows:

- *Summary*: After examinations of data taken from ROADWARE_LOCAL and County Records, it was seen that one county road section of X38 was recorded as flexible pavement in County Records while it was shown as rigid pavement in ROADWARE_LOCAL.
  - This means that there is an inconsistency in database.
  - The data should be verified with county engineers and/or Iowa DOT.
- *Assumption*: County Records data were collected in 2018.
  - The mentioned road section might have been overlaid with asphalt in 2018. Thus, ROADWARE_LOCAL, which was collected in 2013, 2015, and 2017, might not represent it as flexible pavement.
- *Suggestion*: Each road section can have different scenarios in its history. Thus, the segmentation process should be carefully performed to be able to verify all the road sections that were inspected.

Step 15. Conversion of Columns from Text to Value

All columns that are used in data processing were converted from text to value, as shown in

Figure 121.

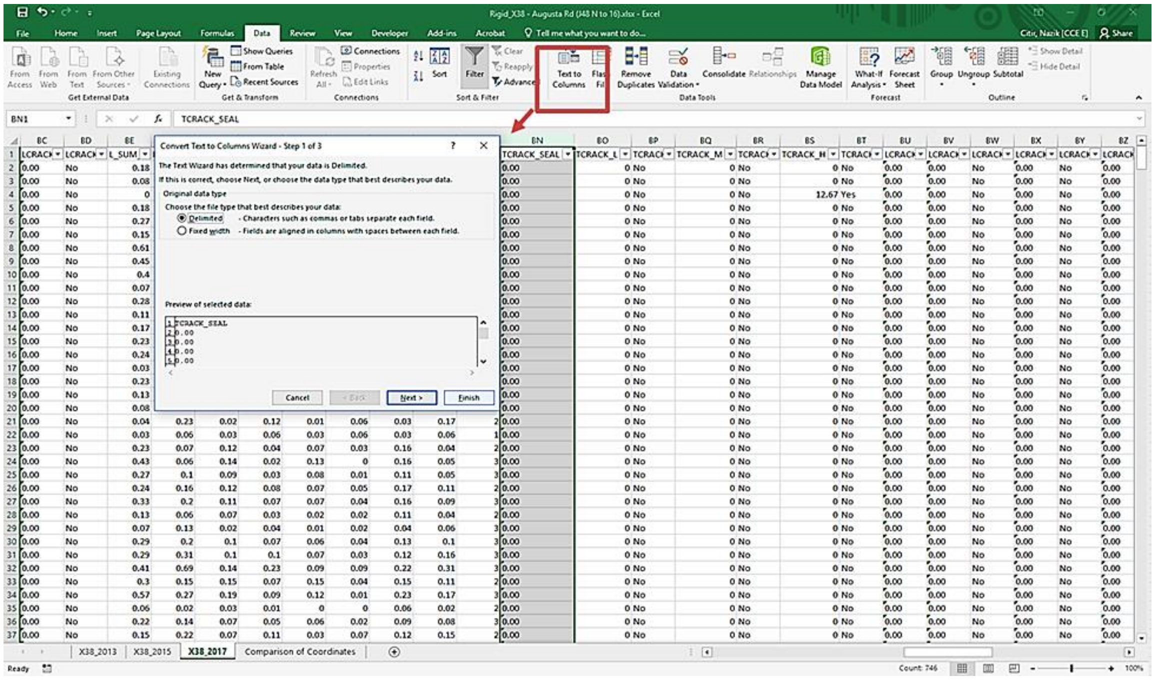


Figure 121. Application of text to columns for road sections of X38

Step 16. Summarization Procedure for Rigid Pavements

a) IRI

IRI data were processed for X38. The results are shown in Figure 122.

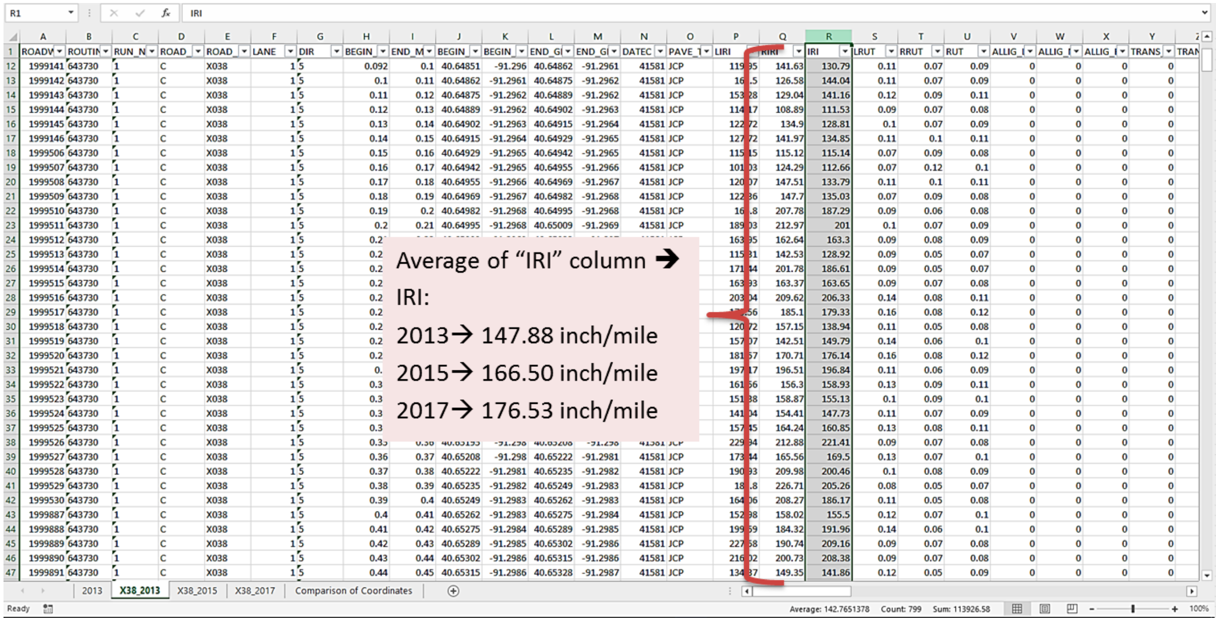


Figure 122. Summarization of IRI data for X38

b) Faulting

Faulting data were processed for X38. The results are shown in Figure 123.

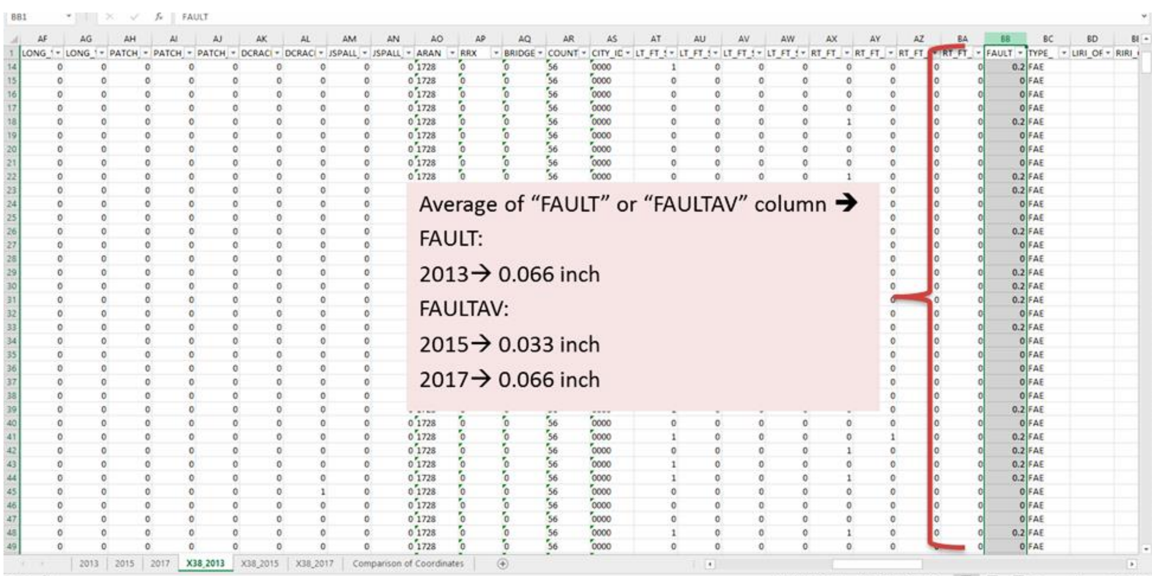
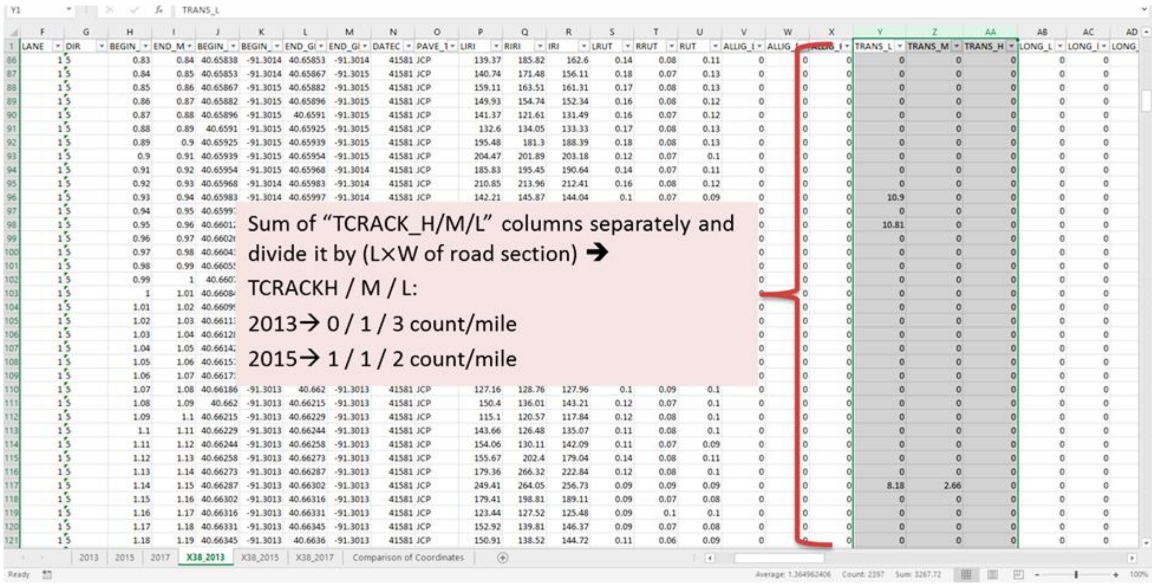


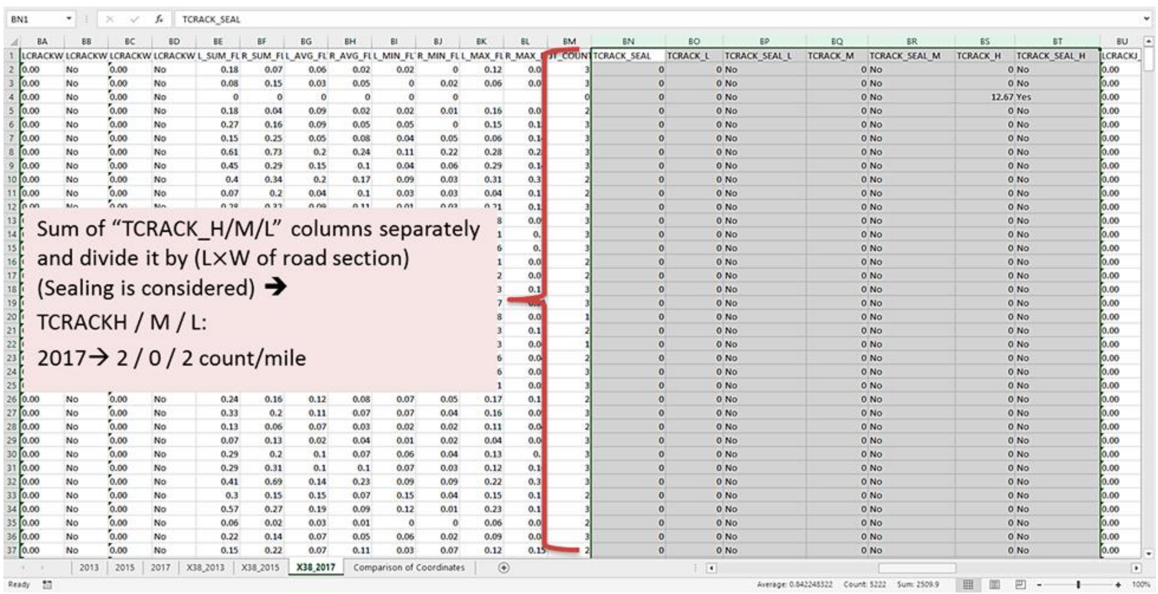
Figure 123. Summarization of faulting data for X38

c) Transverse Cracking

Transverse cracking data were processed for X38. The results are shown in Figure 124a and b for 2013/2015 and 2017, respectively.



(a) 2013 and 2015



(b) 2017

Figure 124. Summary of transverse cracking data for X38

Overall Summary

In this standard procedure, the process was presented to develop an Iowa county pavement HPD. Based on all steps provided in the earlier sections, the following summary is provided:

- IPMP utilizes the dynamic segmentation approach to process and assimilate raw distress data collected by third-party vendor (i.e., Pathway Services Inc.).
- The framework of an Iowa county pavement HPD is identified and developed with reference to a dynamic segmentation approach with two main aims: (1) to validate and refine the

simplified pavement performance and remaining service life (RSL) prediction models (developed using primary road PMIS data) in use of Iowa county road applications and (2) to develop a user manual for creating an Iowa county pavement HPD for Iowa county engineers who will need inputs for the IPAT tool for their own analysis.

- The related data sources for developing an Iowa county pavement HPD include the following:
  - Iowa DOT ROADWARE_LOCAL data: raw condition and distress data (collected by third-party vendor) obtained from the Office of Analytics at Iowa DOT.
  - County Records data: county road construction history obtained from some county engineer offices (e.g., Lee County) during the IPAT project.
  - Traffic-related data: annual average daily truck traffic (AADTT) and equivalent single axle load (ESAL) obtained from the Iowa DOT RAMS/open data web portal.
- The detailed steps identified for developing an Iowa county pavement HPD can be categorized into two groups: segmentation and summarizing of condition and distress data.
- Raw condition and distress data (i.e., ROADWARE_LOCAL) taken from the Iowa DOT may need improvements on the following subjects:
  - Designations may change from year to year.
    - The descriptions of designations should be clearer if there is a change.
  - County road sections' names can change year by year.
    - If so, a descriptive column named previous road name may be added into the database so that it makes segmentation faster
  - Length of county road sections
    - The beginning mile and ending mile should be the same each year.
    - The location of county road sections should not be changed for each year.
- County road construction history data (i.e., County Records) taken from county engineers may need improvements on the following subjects:
  - The database should have at least the beginning and ending coordinates (latitude and longitude) to be able to achieve more accurate results by confirming it with raw condition and distress data (i.e., ROADWARE_LOCAL).
  - All County Records should have the same terminology in their database to prevent any confusion while transferring data.
  - The project name and descriptions for each county road section should be recorded with more information. They may be indicated by Global Positioning System (GPS) coordinates in a new column in the datasheet instead of describing the direction of county road sections as "from … to."
  - After collecting data, the records should be performed with caution (e.g., surface type of pavement and so on).
  - The county road sections should be updated whenever road alignments change.
  - The maintenance applications should be recorded carefully to maintain the integrity of the database.

APPENDIX B. PROTOTYPE ANALYSIS TOOLS FOR PRESERVATION AND REHABILITATION TECHNIQUES

Rigid Pavement

The Microsoft Excel macro-based network-level pavement performance prediction automation tool was improved to be used for future post-treatment pavement performance estimation using the developed artificial neural network (ANN) model (international roughness index [IRI] approach 1). Figure 125 shows the interface of a sample automation tool predicting network-level pavement post-treatment performance.

Figure 125. Pavement performance prediction automation and decision-making tool using ANN-based IRI approach 1 model for rigid pavements

In the section of pretreatment IRI predictions, the tool calculates the future IRI predictions as stated previously. Once the IRI prediction exceeds the treatment trigger value, the pavement performance prediction can be reset by clicking the reset pretreatment IRI button. By using the last predicted pretreatment IRI value and user-defined recovery percentage, post-treatment IRI $_{(i-2)\ year}$ is calculated. The increase rate between first IRI $_{(i-2)\ year}$ and IRI $_{(i-1)\ year}$ at post-treatment (red cells) is determined based on the increase rate between first IRI $_{(i-2)\ year}$ and IRI $_{(i-1)\ year}$ at pretreatment (blue cells), multiplying it with the average ratio of growth rate (0.86). For post-treatment IRI predictions, input parameters are fed into the tool by starting from the age when the treatment was applied. Then, the tool calculates future post-treatment IRI predictions by considering the growth rate of IRI after application of the treatment upon clicking the calculate future post-treatment IRI button. The post-treatment section also utilizes extracted weight and biases for the ANN-based IRI approach 1 model.

Flexible Pavement

In this part of the study, a Microsoft Excel macro-based network-level pavement performance prediction automation tool whose interface is shown in Figure 126 was improved for use as a decision-making tool for future post-treatment IRI using the developed ANN model.

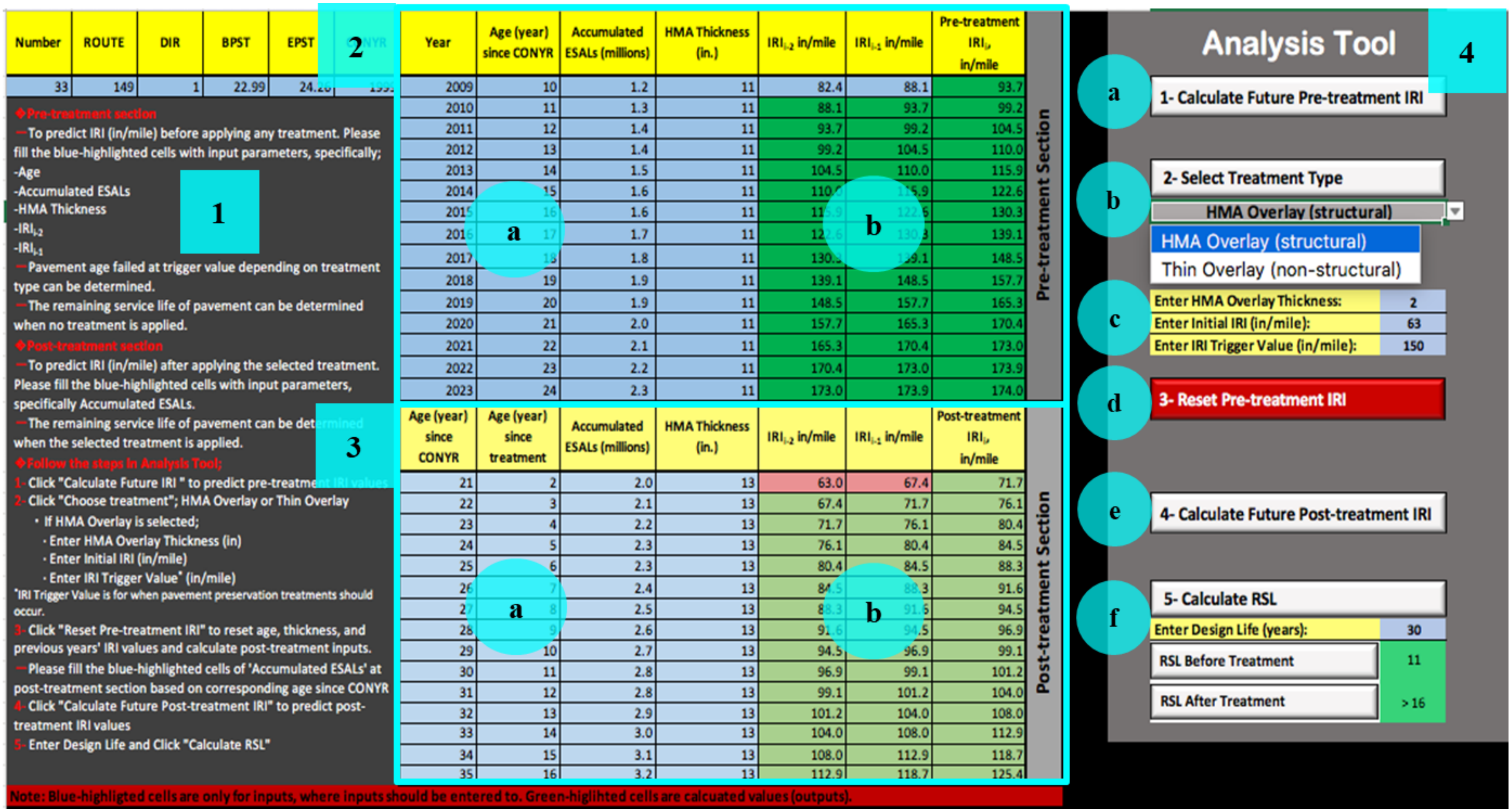


Figure 126. Pavement performance prediction automation and decision-making tool using ANN-based IRI approach 1 model for flexible pavements

Detailed steps for use of this tool are as follows:

1. *User manual panel*: Black-colored panel including descriptions for tool and how-to-use it.
2. *Pretreatment section*: First block including pavement input parameters and performance predictions before applying any treatment.
    a. *Input parameters*: Blue-highlighted columns representing inputs to be entered, including pavement age, accumulated equivalent single axle load (ESAL), hot-mixed asphalt (HMA) thickness, and previous two-year IRI values for the first age entered (e.g., age of 10).
    b. *ANN predictions*: Green-highlighted columns representing IRI predictions by ANN. No need to enter the previous year's IRIs for each age; the ANN model predicts them. The last column indicates the predicted pretreatment IRI corresponding to each pavement age.
3. *Post-treatment section*: Second block including pavement input parameters and performance predictions after applying any treatment.
    a. *Input parameters*: Blue-highlighted columns representing inputs to be entered, including pavement age since construction and treatment, accumulated ESAL, HMA thickness, and previous two-year IRI values for the first age entered (e.g., age of 21). Thin overlay treatments were considered to be 1 in. thick. In the case of structural HMA overlay, the thickness changes based on the entered overlay thickness, which is added to the existing HMA thickness.
    b. *ANN predictions*: Green-highlighted columns representing IRI predictions by ANN. The last column indicates the predicted post-treatment IRI corresponding to each pavement age.
4. *Analysis tool panel*:
    a. Button to calculate future pretreatment IRI predictions
    b. Button to select a treatment type
        i. HMA overlay (structural)
        ii. Thin overlay (non-structural)
    c. Information panel to be entered when selecting HMA overlay treatment, including overlay thickness, initial IRI, and IRI trigger value. It becomes inactivated when selecting thin overlay treatment.
    d. Button to reset pretreatment IRI when it reaches the IRI trigger value, and to calculate initial post-treatment IRI, new HMA thickness, age since construction and treatment.
    e. Button to calculate future post-treatment IRI predictions after applying a treatment. Clicking this button calculates the deterioration rate between IRI_{i-2} and IRI_{i-1} in the pretreatment section (blue cells) and applies it to between IRI_{i-2} and IRI_{i-1} in the post-treatment section (red cells).
    f. Button to calculate the remaining service life (RSL). RSL before treatment is calculated by subtracting the failed age of the pavement based on the IRI trigger value from the entered design life. RSL after treatment is calculated by subtracting the failed age of the treated pavement based on the IRI trigger value from the stated design life.

The life extension per treatment based on the calculated RSL before and after treatment can be determined. The statewide preservation and rehabilitation decision-making tool using ANN provides flexibility to choose two different treatment types with the capability of trying different parameters, such as thickness and threshold IRI value-triggered treatment.

APPENDIX C. PROGRAMMING CODE OF IOWA PAVEMENT ANALYSIS TECHNIQUES (IPAT)

Example of Source Code by MATLAB Software to Develop Artificial Neural Network (ANN) Models

```
% This script assumes these variables are defined:
%
% x - input data.
% t - target data.

x = Input';
t = Output';

% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging problems.
% 'trainscg' uses less memory. SuiTable in low memory situations.
trainFcn = 'trainlm'; % Levenberg-Marquardt backpropagation.

% Create a Fitting Network
hiddenLayerSize = 5;
net = fitnet(hiddenLayerSize,trainFcn);

% Choose Input and Output Pre/Post-Processing Functions
% For a list of all processing functions type: help nnprocess
net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns = {'removeconstantrows','mapminmax'};

% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand'; % Divide data randomly
net.divideMode = 'sample'; % Divide up every sample
net.divideParam.trainRatio = 60/100;
net.divideParam.valRatio = 30/100;
net.divideParam.testRatio = 10/100;
net.trainParam.epochs = 1000;
net.trainParam.max_fail = 500;

% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
net.performFcn = 'mse'; % Mean Squared Error

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
```

```
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
 'plotregression', 'plotfit'};

% Train the Network
[net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)

% Recalculate Training, Validation and Test Performance for Performance
% Indicator (PI)
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformancePI = perform(net,trainTargets(1,:),y(1,:))

valPerformancePI = perform(net,valTargets(1,:),y(1,:))

testPerformancePI = perform(net,testTargets(1,:),y(1,:))

PIPerform=[trainPerformancePI,testPerformancePI,valPerformancePI]

TrainPredict=y;
TestPredict=y;
ValPredict=y;

[row, col] = find(isnan(trainTargets));
   TrainPredict(:,col)= [];
   trainTargets(:,col)=[];
[row1, col1] = find(isnan(testTargets));
   TestPredict(:,col1)= [];
   testTargets(:,col1)=[];
[row2, col2] = find(isnan(valTargets));
   ValPredict(:,col2)= [];
   valTargets(:,col2)=[];
 %% Rsquare (Performance Indicator)
  PITrainSELine=sum((TrainPredict(1,:)-trainTargets(1,:)).^2)
  PITrainSEY=sum((TrainPredict(1,:)-mean2(TrainPredict(1,:))).^2)
  PIR2LOETrain=1-(PITrainSELine/PITrainSEY)

  PIValidSELine= sum((ValPredict(1,:)-valTargets(1,:)).^2)
  PIValidSEY= sum((ValPredict(1,:)-mean2(ValPredict(1,:))).^2)
  PIR2LOEVal= 1-(PIValidSELine/PIValidSEY)
```

```
  PITestSELine= sum((TestPredict(1,:)-testTargets(1,:)).^2)
  PITestSEY=sum((TestPredict(1,:)-mean2(TestPredict(1,:))).^2)
  PIR2LOETest=1-(PITestSELine/PITestSEY)

  PI_R2=[PIR2LOETrain,PIR2LOETest,PIR2LOEVal];

% Deployment
% Change the (false) values to (true) to enable the following code blocks.
% See the help for each generation function for more information.
if (false)
 % Generate MATLAB function for neural network for application
 % deployment in MATLAB scripts or with MATLAB Compiler and Builder
 % tools, or simply to examine the calculations your trained neural
 % network performs.
 genFunction(net,'myNeuralNetworkFunction');
 y = myNeuralNetworkFunction(x);
end
if (false)
 % Generate a matrix-only MATLAB function for neural network code
 % generation with MATLAB Coder tools.
 genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
 y = myNeuralNetworkFunction(x);
end
if (false)
 % Generate a Simulink diagram for simulation or deployment with.
 % Simulink Coder tools.
 gensim(net);
end
```

Example of Script by Visual Basic for Applications (VBA) in Excel to Develop IPAT Main Tool

```
Private Sub flexiblepic_Click()
End Sub
Private Sub Frame2_Click()
End Sub
Private Sub Label20_Click()
End Sub
Private Sub Label14_Click()
End Sub
Private Sub Label15_Click()
End Sub
Private Sub Label28_Click()
End Sub
Private Sub Label31_Click()
End Sub
```

```
Private Sub Label38_Click()
End Sub
Private Sub Label46_Click()
End Sub
Private Sub Label5_Click()
End Sub
Private Sub Label26_Click()
End Sub
Private Sub PLpage_Click()
End Sub
Private Sub Label58_Click()
End Sub
Private Sub Label59_Click()
End Sub
Private Sub Label61_Click()
End Sub
Private Sub Label63_Click()
End Sub
Private Sub Label65_Click()
End Sub
Private Sub Label73_Click()
End Sub
Private Sub Label76_Click()
End Sub
Private Sub MultiPage_NL_PI_RUT_Change()
End Sub
Private Sub MultiPage_NL_PI_TCRACK_Change()
End Sub
Private Sub UserForm_Click()
End Sub
Private Sub MultiPage_NL_PI_IRI_Change()
End Sub
Private Sub Back2_NLAsphalt_Click()
 NLpage_Asphalt_PI.Hide
 NLpage_PT.Show
End Sub

Private Sub UserForm_Initialize()
 Me.MultiPage_NL_PI_IRI.Visible = False
 Me.MultiPage_NL_PI_RUT.Visible = False
 Me.MultiPage_NL_PI_TCRACK.Visible = False
 Me.MultiPage_NL_PI_LCRACK.Visible = False
 Me.flexiblepic.Visible = True

 With Me.PLPPI
 .Clear ' clear previous items (not to have "doubles")
```

```
 .AddItem "Select"
 .AddItem "IRI"
 .AddItem "Rutting"
 .AddItem "Transverse Cracking"
 .AddItem "Longitudinal Cracking"
 End With

End Sub

Private Sub PLPPI_Change()

 If Me.PLPPI.Value = "Select" & "" Then
  Me.flexiblepic.Visible = True
  Me.MultiPage_NL_PI_IRI.Visible = False
  Me.MultiPage_NL_PI_RUT.Visible = False
  Me.MultiPage_NL_PI_TCRACK.Visible = False
  Me.MultiPage_NL_PI_LCRACK.Visible = False
 End If
 '***********************************IRI**************************************
If Me.PLPPI.Value = "IRI" Then
  Me.MultiPage_NL_PI_IRI.Visible = True
  Me.MultiPage_NL_PI_RUT.Visible = False
  Me.MultiPage_NL_PI_TCRACK.Visible = False
  Me.MultiPage_NL_PI_LCRACK.Visible = False
  Me.flexiblepic.Visible = False
'  Me.MultiPage_NL_PI_IRI.BackColor = vbBlack
 End If

 With MultiPage_NL_PI_IRI
 'The next 2 lines disable Page2 & Page3
 .Pages(1).Enabled = False
 .Pages(2).Enabled = False
 'Make Page1 the active page
 .Value = 0

 Yes.Value = False
 No.Value = False

 Me.trf1.Visible = False
 Me.trf2.Visible = False
 Me.trf3.Visible = False
 Me.Yes_trf.Visible = False
 Me.No_trf.Visible = False
 Me.Yes_trf1.Visible = False
 Me.No_trf1.Visible = False
 Me.ESAL.Visible = False
```

```
 Me.AADT.Visible = False
 End With
'********************************RUTTING*************************************
 If Me.PLPPI.Value = "Rutting" Then
  Me.MultiPage_NL_PI_IRI.Visible = False
  Me.MultiPage_NL_PI_RUT.Visible = True
  Me.MultiPage_NL_PI_TCRACK.Visible = False
  Me.MultiPage_NL_PI_LCRACK.Visible = False
  Me.flexiblepic.Visible = False
 End If

 With MultiPage_NL_PI_RUT
 'The next 2 lines disable Page2 & Page3
 .Pages(1).Enabled = False
 .Pages(2).Enabled = False
 'Make Page1 the active page
 .Value = 0

 Yes_rut.Value = False
 No_rut.Value = False

 Me.trf2_rut.Visible = False
 Me.ESAL_rut.Visible = False
 Me.AADT_rut.Visible = False
 End With
'**********************TRANSVERSE CRACKING*****************************
 If Me.PLPPI.Value = "Transverse Cracking" Then
  Me.MultiPage_NL_PI_IRI.Visible = False
  Me.MultiPage_NL_PI_RUT.Visible = False
  Me.MultiPage_NL_PI_TCRACK.Visible = True
  Me.MultiPage_NL_PI_LCRACK.Visible = False
  Me.flexiblepic.Visible = False
 End If

 With MultiPage_NL_PI_TCRACK
 'The next 2 lines disable Page2 & Page3
 .Pages(1).Enabled = False
 .Pages(2).Enabled = False
 'Make Page1 the active page
 .Value = 0

 Yes_tcrack.Value = False
 No_tcrack.Value = False

 Me.trf2_tcrack.Visible = False
 Me.ESAL_tcrack.Visible = False
```

```
 Me.AADT_tcrack.Visible = False
 End With
'*************************LONGITUDINAL CRACKING**************************
 If Me.PLPPI.Value = "Longitudinal Cracking" Then
  Me.MultiPage_NL_PI_IRI.Visible = False
  Me.MultiPage_NL_PI_RUT.Visible = False
  Me.MultiPage_NL_PI_TCRACK.Visible = False
  Me.MultiPage_NL_PI_LCRACK.Visible = True
  Me.flexiblepic.Visible = False
 End If

 With MultiPage_NL_PI_LCRACK
 'The next 2 lines disable Page2 & Page3
 .Pages(1).Enabled = False
 .Pages(2).Enabled = False
 'Make Page1 the active page
 .Value = 0

 Yes_lcrack.Value = False
 No_lcrack.Value = False

 Me.trf2_lcrack.Visible = False
 Me.ESAL_lcrack.Visible = False
 Me.AADT_lcrack.Visible = False
 End With

End Sub
'******************************************************************************
'************************************IRI*************************************
'******************************************************************************
Private Sub Yes_Click()
 Me.trf1.Visible = True
 Me.Yes_trf.Visible = True
 Me.No_trf.Visible = True
 Me.trf2.Visible = False
 Me.ESAL.Visible = False
 Me.AADT.Visible = False
 Me.trf3.Visible = False
 Me.Yes_trf1.Visible = False
 Me.No_trf1.Visible = False

 With MultiPage_NL_PI_IRI
  .Pages(1).Enabled = False
  .Pages(2).Enabled = False
 End With
```

```
End Sub
Private Sub No_Click()
 With MultiPage_NL_PI_IRI
  .Pages(1).Enabled = False
  .Pages(2).Enabled = False
 End With
 MsgBox "You need the required data to launch the tool."

End Sub
Private Sub Yes_trf_Click()
 Me.trf2.Visible = True
 Me.ESAL.Visible = True
 Me.AADT.Visible = True
 Me.trf3.Visible = False
 Me.Yes_trf1.Visible = False
 Me.No_trf1.Visible = False

 With MultiPage_NL_PI_IRI
  .Pages(1).Enabled = False
  .Pages(2).Enabled = False
 End With
 ESAL.Enabled = True
 AADT.Enabled = True
 trf2.Enabled = True
 ESAL.Object.Value = False
 AADT.Object.Value = False
End Sub
Private Sub No_trf_Click()
 Me.trf3.Visible = True
 Me.Yes_trf1.Visible = True
 Me.No_trf1.Visible = True
 With MultiPage_NL_PI_IRI
  .Pages(1).Enabled = False
  .Pages(2).Enabled = False
 End With
 Yes_trf1.Enabled = True
 No_trf1.Enabled = True
 trf3.Enabled = True
 Yes_trf1.Object.Value = False
 No_trf1.Object.Value = False
End Sub
Private Sub Yes_trf1_Click()
 Me.trf3.Visible = True
 Me.Yes_trf1.Visible = True
 Me.No_trf1.Visible = True
```

```
 With MultiPage_NL_PI_IRI
  .Pages(0).Enabled = False
  .Pages(1).Enabled = True
  .Pages(2).Enabled = True
  .Value = 1
 Me.CommandButton1.Enabled = False
 Me.CommandButton2.Enabled = True
 Me.CommandButton3.Enabled = False
 End With

 Me.trf2.Enabled = False
 Me.ESAL.Enabled = False
 Me.AADT.Enabled = False
 trf3.Enabled = True
 Yes_trf1.Enabled = True
 No_trf1.Enabled = True

End Sub
Private Sub No_trf1_Click()
 With MultiPage_NL_PI_IRI
  .Pages(1).Enabled = False
  .Pages(2).Enabled = False
 End With
 MsgBox "You need the required data to launch the tool."

 Me.trf1.Visible = True
 Me.Yes_trf.Visible = True
 Me.No_trf.Visible = True
 Me.trf3.Visible = True
 Me.Yes_trf1.Visible = True
 Me.No_trf1.Enabled = False

End Sub
Private Sub ESAL_Click()
 If ESAL.Value = True Then
  AADT.Value = False
  AADT.Enabled = False
 Else
  AADT.Enabled = True
 End If

 With MultiPage_NL_PI_IRI
  .Pages(0).Enabled = False
  .Pages(1).Enabled = True
  .Pages(2).Enabled = True
  .Value = 1
```

```
 Me.CommandButton1.Enabled = False
 Me.CommandButton2.Enabled = False
 Me.CommandButton3.Enabled = True

 End With
End Sub
Private Sub AADT_Click()
 If AADT.Value = True Then
  ESAL.Value = False
  ESAL.Enabled = False
 Else
  ESAL.Enabled = True
 End If

 With MultiPage_NL_PI_IRI
  .Pages(0).Enabled = False
  .Pages(1).Enabled = True
  .Pages(2).Enabled = True
  .Value = 1
 Me.CommandButton1.Enabled = True
 Me.CommandButton2.Enabled = False
 Me.CommandButton3.Enabled = False

 End With
End Sub

'Location of EXCEL tool and transferring data to this tool_LAUNCH TOOL 1
Private Sub CommandButton1_Click()
 Me.CommandButton2.Enabled = False
 Me.CommandButton3.Enabled = False

 Dim xWB As Workbook
 Dim wbName As String
 Dim wbSheet As Worksheet
 Dim iRow As Long

 On Error Resume Next
 Set xWB = Workbooks.Open(ThisWorkbook.Path & "\" & " County_HMA_IRI_Approach 1-
ANN Tool.xlsm") 'UPDATE filename
 wbName = xWB.Name
  If Err.Number <> 0 Then
   MsgBox "Tool does not exist!"
   Err.Clear
  End If

 Set wbSheet = xWB.Sheets("Interface")
```

```
  With wbSheet
   .Unprotect
    Contents = True
   .Range("A2").Value = Me.TextBox1.Value
   .Range("B2").Value = Me.TextBox2.Value
   .Range("C2").Value = Me.TextBox3.Value
   .Range("D2").Value = Me.TextBox4.Value
   .Range("E2").Value = Me.TextBox5.Value
   .Range("F2").Value = Me.TextBox6.Value
  End With

End Sub
'Location of EXCEL tool and transferring data to this tool_LAUNCH TOOL 2
Private Sub CommandButton2_Click()
 Me.CommandButton1.Enabled = False
 Me.CommandButton3.Enabled = False

 Dim xWB As Workbook
 Dim wbName As String
 Dim wbSheet As Worksheet
 Dim iRow As Long

 On Error Resume Next
 Set xWB = Workbooks.Open(ThisWorkbook.Path & "\" & "
CountyandPMIS_HMA_IRI_Approach 2-ANN Tool.xlsm") 'UPDATE filename
 wbName = xWB.Name
  If Err.Number <> 0 Then
   MsgBox "Tool does not exist!"
   Err.Clear
  End If

 Set wbSheet = xWB.Sheets("Interface")
  With wbSheet
   .Unprotect
    Contents = True
   .Range("A2").Value = Me.TextBox1.Value
   .Range("B2").Value = Me.TextBox2.Value
   .Range("C2").Value = Me.TextBox3.Value
   .Range("D2").Value = Me.TextBox4.Value
   .Range("E2").Value = Me.TextBox5.Value
   .Range("F2").Value = Me.TextBox6.Value
 End With

End Sub

'Location of EXCEL tool and transferring data to this tool_LAUNCH TOOL 3
```

```
Private Sub CommandButton3_Click()
 Me.CommandButton1.Enabled = False
 Me.CommandButton2.Enabled = False
' Me.Visible = True

 Dim xWB As Workbook
 Dim wbName As String
 Dim wbSheet As Worksheet
 Dim iRow As Long

 On Error Resume Next
 Set xWB = Workbooks.Open(ThisWorkbook.Path & "\" & " PMIS_HMA_IRI_Approach 1-
ANN Tool.xlsm") 'UPDATE filename
 wbName = xWB.Name
  If Err.Number <> 0 Then
   MsgBox "Tool does not exist!"
   Err.Clear
  End If

 Set wbSheet = xWB.Sheets("Interface")
 With wbSheet
   .Unprotect
    Contents = True
   .Range("A2").Value = Me.TextBox1.Value
   .Range("B2").Value = Me.TextBox2.Value
   .Range("C2").Value = Me.TextBox3.Value
   .Range("D2").Value = Me.TextBox4.Value
   .Range("E2").Value = Me.TextBox5.Value
   .Range("F2").Value = Me.TextBox6.Value
 End With

End Sub

Private Sub Back1_Click()
 ESAL.Value = False
 AADT.Value = False
 Yes.Value = False
 No.Value = False
 Yes_trf1.Value = False
 No_trf1.Value = False
 TextBox1.Text = ""
 TextBox2.Text = ""
 TextBox3.Text = ""
 TextBox4.Text = ""
 TextBox5.Text = ""
 TextBox6.Text = ""
```

```
 MultiPage_NL_PI_IRI.Pages(0).Enabled = True
 Me.MultiPage_NL_PI_IRI.Value = 0

 trf1.Visible = False
 Yes_trf.Visible = False
 No_trf.Visible = False
 trf2.Visible = False
 AADT.Visible = False
 ESAL.Visible = False
 trf3.Visible = False
 Yes_trf1.Visible = False
 No_trf1.Visible = False

End Sub

'Private Sub Back2_Click()
' Me.MultiPage_NL_PI_IRI.Value = 1
'End Sub

'Private Sub Next2_Click()
' Me.MultiPage_NL_PI_IRI.Value = 2
'End Sub
'Me.MultiPage_NL_PI_IRI_Next2.Hide

'****************************************************************************************
'**********************************RUTTING*****************************************
'****************************************************************************************
Private Sub Yes_rut_Click()
 Me.trf2_rut.Visible = True
 Me.ESAL_rut.Visible = True
 Me.AADT_rut.Visible = True
 With MultiPage_NL_PI_RUT
  .Pages(1).Enabled = False
  .Pages(2).Enabled = False
 End With
 ESAL_rut.Enabled = True
 AADT_rut.Enabled = True
 trf2_rut.Enabled = True
 ESAL_rut.Object.Value = False
 AADT_rut.Object.Value = False
End Sub
Private Sub No_rut_Click()
 With MultiPage_NL_PI_RUT
  .Pages(1).Enabled = False
  .Pages(2).Enabled = False
```

```
 End With
 MsgBox "You need the required data to launch the tool."

End Sub

Private Sub ESAL_rut_Click()
 If ESAL_rut.Value = True Then
  AADT_rut.Value = False
  AADT_rut.Enabled = False
 Else
  AADT_rut.Enabled = True
 End If

 With MultiPage_NL_PI_RUT
  .Pages(1).Enabled = True
  .Pages(2).Enabled = True
  .Value = 1
 Me.CommandButton4.Enabled = False
 Me.CommandButton5.Enabled = True

 End With
End Sub
Private Sub AADT_rut_Click()
 If AADT_rut.Value = True Then
  ESAL_rut.Value = False
  ESAL_rut.Enabled = False
 Else
  ESAL_rut.Enabled = True
 End If

 With MultiPage_NL_PI_RUT
  .Pages(1).Enabled = True
  .Pages(2).Enabled = True
  .Value = 1
 Me.CommandButton4.Enabled = True
 Me.CommandButton5.Enabled = False

 End With
End Sub
'Location of EXCEL tool and transferring data to this tool_LAUNCH TOOL 1
Private Sub CommandButton4_Click()
 Dim xWB As Workbook
 Dim wbName As String
 Dim wbSheet As Worksheet
 Dim iRow As Long
```

```
 On Error Resume Next
 Set xWB = Workbooks.Open(ThisWorkbook.Path & "\" & " County_HMA_Rut-ANN
Tool.xlsm") 'UPDATE filename
 wbName = xWB.Name
  If Err.Number <> 0 Then
   MsgBox "Tool does not exist!"
   Err.Clear
  End If

 Set wbSheet = xWB.Sheets("Interface")
 With wbSheet
   .Unprotect
    Contents = True
   .Range("A2").Value = Me.TextBox8.Value
   .Range("B2").Value = Me.TextBox9.Value
   .Range("C2").Value = Me.TextBox10.Value
   .Range("D2").Value = Me.TextBox11.Value
   .Range("E2").Value = Me.TextBox12.Value
   .Range("F2").Value = Me.TextBox13.Value
 End With

End Sub
'Location of EXCEL tool and transferring data to this tool_LAUNCH TOOL 2
Private Sub CommandButton5_Click()
 Dim xWB As Workbook
 Dim wbName As String
 Dim wbSheet As Worksheet
 Dim iRow As Long

 On Error Resume Next
 Set xWB = Workbooks.Open(ThisWorkbook.Path & "\" & " PMIS_HMA_Rut-ANN
Tool.xlsm") 'UPDATE filename
 wbName = xWB.Name
  If Err.Number <> 0 Then
   MsgBox "Tool does not exist!"
   Err.Clear
  End If

 Set wbSheet = xWB.Sheets("Interface")
 With wbSheet
   .Unprotect
    Contents = True
   .Range("A2").Value = Me.TextBox8.Value
   .Range("B2").Value = Me.TextBox9.Value
   .Range("C2").Value = Me.TextBox10.Value
   .Range("D2").Value = Me.TextBox11.Value
```

```
  .Range("E2").Value = Me.TextBox12.Value
  .Range("F2").Value = Me.TextBox13.Value
 End With

End Sub
Private Sub Back1_rut_Click()
 ESAL_rut.Value = False
 AADT_rut.Value = False
 Yes_rut.Value = False
 No_rut.Value = False
 TextBox8.Text = ""
 TextBox9.Text = ""
 TextBox10.Text = ""
 TextBox11.Text = ""
 TextBox12.Text = ""
 TextBox13.Text = ""

 Me.MultiPage_NL_PI_RUT.Value = 0

 AADT_rut.Visible = False
 ESAL_rut.Visible = False
 trf2_rut.Visible = False

End Sub

'Private Sub Back2_rut_Click()
' Me.MultiPage_NL_PI_RUT.Value = 1
'End Sub

Private Sub Next2_rut_Click()
 Me.MultiPage_NL_PI_RUT.Value = 2
End Sub

'*****************************************************************************
'*********************TRANSVERSE CRACKING*********************************
'*****************************************************************************
Private Sub Yes_tcrack_Click()
 Me.trf2_tcrack.Visible = True
 Me.ESAL_tcrack.Visible = True
 Me.AADT_tcrack.Visible = True
 With MultiPage_NL_PI_TCRACK
  .Pages(1).Enabled = False
  .Pages(2).Enabled = False
 End With
 ESAL_tcrack.Enabled = True
 AADT_tcrack.Enabled = True
```

```
 trf2_tcrack.Enabled = True
 ESAL_tcrack.Object.Value = False
 AADT_tcrack.Object.Value = False
End Sub
Private Sub No_tcrack_Click()
 With MultiPage_NL_PI_TCRACK
  .Pages(1).Enabled = False
  .Pages(2).Enabled = False
 End With
 MsgBox "You need the required data to launch the tool."

End Sub

Private Sub ESAL_tcrack_Click()
 If ESAL_tcrack.Value = True Then
  AADT_tcrack.Value = False
  AADT_tcrack.Enabled = False
 Else
  AADT_tcrack.Enabled = True
 End If

 With MultiPage_NL_PI_TCRACK
  .Pages(1).Enabled = True
  .Pages(2).Enabled = True
  .Value = 1
 Me.CommandButton6.Enabled = False
 Me.CommandButton7.Enabled = True

 End With
End Sub
Private Sub AADT_tcrack_Click()
 If AADT_tcrack.Value = True Then
  ESAL_tcrack.Value = False
  ESAL_tcrack.Enabled = False
 Else
  ESAL_tcrack.Enabled = True
 End If

 With MultiPage_NL_PI_TCRACK
  .Pages(1).Enabled = True
  .Pages(2).Enabled = True
  .Value = 1
 Me.CommandButton6.Enabled = True
 Me.CommandButton7.Enabled = False

 End With
```

```
End Sub
'Location of EXCEL tool and transferring data to this tool_LAUNCH TOOL 1
Private Sub CommandButton6_Click()
 Dim xWB As Workbook
 Dim wbName As String
 Dim wbSheet As Worksheet
 Dim iRow As Long

 On Error Resume Next
 Set xWB = Workbooks.Open(ThisWorkbook.Path & "\" & " County_HMA_TCrack-ANN
Tool.xlsm") 'UPDATE filename
 wbName = xWB.Name
  If Err.Number <> 0 Then
   MsgBox "Tool does not exist!"
   Err.Clear
  End If

 Set wbSheet = xWB.Sheets("Interface")
 With wbSheet
   .Unprotect
    Contents = True
   .Range("A2").Value = Me.TextBox15.Value
   .Range("B2").Value = Me.TextBox16.Value
   .Range("C2").Value = Me.TextBox17.Value
   .Range("D2").Value = Me.TextBox18.Value
   .Range("E2").Value = Me.TextBox19.Value
   .Range("F2").Value = Me.TextBox20.Value
 End With

End Sub
'Location of EXCEL tool and transferring data to this tool_LAUNCH TOOL 2
Private Sub CommandButton7_Click()
 Dim xWB As Workbook
 Dim wbName As String
 Dim wbSheet As Worksheet
 Dim iRow As Long

 On Error Resume Next
 Set xWB = Workbooks.Open(ThisWorkbook.Path & "\" & " PMIS_HMA_TCrack-ANN
Tool.xlsm") 'UPDATE filename
 wbName = xWB.Name
  If Err.Number <> 0 Then
   MsgBox "Tool does not exist!"
   Err.Clear
  End If
```

```
 Set wbSheet = xWB.Sheets("Interface")
 With wbSheet
   .Unprotect
    Contents = True
   .Range("A2").Value = Me.TextBox15.Value
   .Range("B2").Value = Me.TextBox16.Value
   .Range("C2").Value = Me.TextBox17.Value
   .Range("D2").Value = Me.TextBox18.Value
   .Range("E2").Value = Me.TextBox19.Value
   .Range("F2").Value = Me.TextBox20.Value
 End With

End Sub
Private Sub Back1_tcrack_Click()
 ESAL_tcrack.Value = False
 AADT_tcrack.Value = False
 Yes_tcrack.Value = False
 No_tcrack.Value = False
 TextBox15.Text = ""
 TextBox16.Text = ""
 TextBox17.Text = ""
 TextBox18.Text = ""
 TextBox19.Text = ""
 TextBox20.Text = ""

 Me.MultiPage_NL_PI_TCRACK.Value = 0

 AADT_tcrack.Visible = False
 ESAL_tcrack.Visible = False
 trf2_tcrack.Visible = False

End Sub

'Private Sub Back2_tcrack_Click()
' Me.MultiPage_NL_PI_TCRACK.Value = 1
'End Sub

'********************************************************************************
'********************LONGITUDINAL CRACKING******************************
'********************************************************************************
Private Sub Yes_lcrack_Click()
 Me.trf2_lcrack.Visible = True
 Me.ESAL_lcrack.Visible = True
 Me.AADT_lcrack.Visible = True
 With MultiPage_NL_PI_LCRACK
  .Pages(1).Enabled = False
```

```
  .Pages(2).Enabled = False
 End With
 ESAL_lcrack.Enabled = True
 AADT_lcrack.Enabled = True
 trf2_lcrack.Enabled = True
 ESAL_lcrack.Object.Value = False
 AADT_lcrack.Object.Value = False
End Sub
Private Sub No_lcrack_Click()
 With MultiPage_NL_PI_LCRACK
  .Pages(1).Enabled = False
  .Pages(2).Enabled = False
 End With
 MsgBox "You need the required data to launch the tool."

End Sub

Private Sub ESAL_lcrack_Click()
 If ESAL_lcrack.Value = True Then
  AADT_lcrack.Value = False
  AADT_lcrack.Enabled = False
 Else
  AADT_tcrack.Enabled = True
 End If

 With MultiPage_NL_PI_LCRACK
  .Pages(1).Enabled = True
  .Pages(2).Enabled = True
  .Value = 1
 Me.CommandButton10.Enabled = False
 Me.CommandButton11.Enabled = True

 End With
End Sub
Private Sub AADT_lcrack_Click()
 If AADT_lcrack.Value = True Then
  ESAL_lcrack.Value = False
  ESAL_lcrack.Enabled = False
 Else
  ESAL_lcrack.Enabled = True
 End If

 With MultiPage_NL_PI_LCRACK
  .Pages(1).Enabled = True
  .Pages(2).Enabled = True
  .Value = 1
```

```
 Me.CommandButton10.Enabled = True
 Me.CommandButton11.Enabled = False

 End With
End Sub
'Location of EXCEL tool and transferring data to this tool_LAUNCH TOOL 1
Private Sub CommandButton10_Click()
 Dim xWB As Workbook
 Dim wbName As String
 Dim wbSheet As Worksheet
 Dim iRow As Long

 On Error Resume Next
 Set xWB = Workbooks.Open(ThisWorkbook.Path & "\" & " County_HMA_LCrack-ANN
Tool.xlsm") 'UPDATE filename
 wbName = xWB.Name
  If Err.Number <> 0 Then
   MsgBox "Tool does not exist!"
   Err.Clear
  End If

 Set wbSheet = xWB.Sheets("Interface")
 With wbSheet
   .Unprotect
    Contents = True
   .Range("A2").Value = Me.TextBox22.Value
   .Range("B2").Value = Me.TextBox23.Value
   .Range("C2").Value = Me.TextBox24.Value
   .Range("D2").Value = Me.TextBox25.Value
   .Range("E2").Value = Me.TextBox26.Value
   .Range("F2").Value = Me.TextBox27.Value
 End With

End Sub
'Location of EXCEL tool and transferring data to this tool_LAUNCH TOOL 2
Private Sub CommandButton11_Click()
 Dim xWB As Workbook
 Dim wbName As String
 Dim wbSheet As Worksheet
 Dim iRow As Long

 On Error Resume Next
 Set xWB = Workbooks.Open(ThisWorkbook.Path & "\" & " PMIS_HMA_LCrack-ANN
Tool.xlsm") 'UPDATE filename
 wbName = xWB.Name
  If Err.Number <> 0 Then
```

```
  MsgBox "Tool does not exist!"
  Err.Clear
 End If

Set wbSheet = xWB.Sheets("Interface")
With wbSheet
  .Unprotect
   Contents = True
  .Range("A2").Value = Me.TextBox22.Value
  .Range("B2").Value = Me.TextBox23.Value
  .Range("C2").Value = Me.TextBox24.Value
  .Range("D2").Value = Me.TextBox25.Value
  .Range("E2").Value = Me.TextBox26.Value
  .Range("F2").Value = Me.TextBox27.Value
End With

End Sub
Private Sub Back1_lcrack_Click()
 ESAL_lcrack.Value = False
 AADT_lcrack.Value = False
 Yes_lcrack.Value = False
 No_lcrack.Value = False
 TextBox22.Text = ""
 TextBox23.Text = ""
 TextBox24.Text = ""
 TextBox25.Text = ""
 TextBox26.Text = ""
 TextBox27.Text = ""

 Me.MultiPage_NL_PI_LCRACK.Value = 0

 AADT_lcrack.Visible = False
 ESAL_lcrack.Visible = False
 trf2_lcrack.Visible = False

End Sub

'Private Sub Back2_lcrack_Click()
' Me.MultiPage_NL_PI_LCRACK.Value = 1
'End Sub

Private Sub UserForm1_Click()

End Sub
```

Example of Script by Macro in Excel to Develop IPAT Sub-Tools for Predicting Each Performance Indicator

```
Sub BackMain()
End Sub
*******************************View_IRI_Model Macro************************

Sub ViewIRIModel()
Sheets("IRI").Select
End Sub

******************************* Goback_IRI Macro ***************************
Sub GoBackIRI()
Sheets("Interface").Select
End Sub

************************* CalculateFutureRSL Macro ***************************
Sub CalculateFutureRSL()
'To hide screen during macro run
 Application.ScreenUpdating = False

'To unprotect locked cells
Sheets("Interface").Unprotect

'Automate 'Calculate Sheet'
Sheets("Interface").Select
ActiveSheet.Calculate
Sheets("RSL").Select
ActiveSheet.Calculate

Sheets("Interface").Select
Range("J3:M16").Font.Color = RGB(0, 0, 0)
Range("L2:M2").Font.Color = RGB(0, 0, 0)
Range("B14:D23").Font.Color = RGB(0, 0, 0)
Range("B14:D23").Font.Bold = True
Range("B14:D15").Font.Size = 13
Range("B16:D23").Font.Italic = True
Range("B16:D23").Font.Size = 13

Sheets("Interface").Select
Range("B14:D23").Interior.Color = RGB(146, 208, 80)

Sheets("Interface").Range("B14:D15").Select
 With Selection
  .HorizontalAlignment = xlCenter
  .VerticalAlignment = xlCenter
```

```
  .Merge
 End With
Sheets("RSL").Select
Range("O15").Select
Selection.Copy
Sheets("Interface").Select
Range("B14").Select
ActiveSheet.Paste Link:=True
Sheets("Interface").Select

Sheets("Interface").Range("B16:D23").Select
 With Selection
  .HorizontalAlignment = xlCenter
  .VerticalAlignment = xlCenter
  .WrapText = True
  .Merge
 End With
Sheets("RSL").Select
Range("O16").Select
Selection.Copy
Sheets("Interface").Select
Range("B16:D23").Select
On Error Resume Next
ActiveSheet.Paste Link:=True
On Error GoTo 0
Sheets("Interface").Select

"To protect locked cells
'Sheets("Inputs").Protect
' Contents = True

'To show screen after macro run
Application.ScreenUpdating = True

End Sub

************************* Reset Macro ***************************
Sub Reset()

"To unprotect locked cells
'Sheets("Interface").Unprotect

Sheets("Interface").Select
 Range("A2:F2").Clear
 Range("A2:F2").Interior.Color = RGB(155, 194, 230)
 Range("G2:I16").Clear
```

```
 Range("G2:I16").Interior.Color = RGB(155, 194, 230)
 Range("J2:K2").Clear
 Range("J2:K2").Interior.Color = RGB(155, 194, 230)
 Range("J3:K16").Clear

 Range("J3:M16").Interior.Color = RGB(146, 208, 80)
 Range("L2:M2").Interior.Color = RGB(146, 208, 80)
 Range("L2:M16").Font.Color = RGB(146, 208, 80)

Dim myRange1 As Range
Set myRange1 = Range("A2:F2")
With myRange1.Borders
 .LineStyle = xlContinuous
 .ColorIndex = 0
 .TintAndShade = 0
 .Weight = xlThin
End With

Dim myRange2 As Range
Set myRange2 = Range("G2:K16")
With myRange2.Borders
 .LineStyle = xlContinuous
 .ColorIndex = 0
 .TintAndShade = 0
 .Weight = xlThin
End With
'Range("J3:M16").Font.Color = RGB(146, 208, 80)
'Range("L2:M2").Font.Color = RGB(146, 208, 80)

Range("B14:D23").Clear
Range("B14:D23").Interior.Color = RGB(27, 55, 114)

''To protect locked cells
'Sheets("Interface").Protect
' Contents = True
End Sub

************************* CalculateFutureIRI Macro ***************************

Sub CalculateFutureIRI()

'To hide screen during macro run
 Application.ScreenUpdating = False
'
''To unprotect locked cells
'Sheets("Interface").Unprotect
```

```
Sheets("Interface").Select
Range("L2:M2").Font.Color = RGB(0, 0, 0)
Range("J3:M16").Font.Color = RGB(0, 0, 0)

''Automate 'Calculate Sheet'
'
'Sheets("RSL").Select
'ActiveSheet.Calculate
''Sheets("Interface").Select
'''ActiveSheet.Calculate
'
' Sheets("RSL").Select
' Range("H2:H16").Select
' Application.CutCopyMode = False
' Selection.Copy
' Sheets("Interface").Select
' Range("L2:L16").Select
' Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
'  :=False, Transpose:=False

 Range("K2").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("J3").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False
 Range("M2").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("K3").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False

Range("K3").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("J4").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False
 Range("M3").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("K4").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False
```

```
Range("K4").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("J5").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False
 Range("M4").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("K5").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False

Range("K5").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("J6").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False
 Range("M5").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("K6").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False

Range("K6").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("J7").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False
 Range("M6").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("K7").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False

Range("K7").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("J8").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False
```

```
Range("M7").Select
Application.CutCopyMode = False
Selection.Copy
Range("K8").Select
Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
 :=False, Transpose:=False

Range("K8").Select
Application.CutCopyMode = False
Selection.Copy
Range("J9").Select
Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
 :=False, Transpose:=False
Range("M8").Select
Application.CutCopyMode = False
Selection.Copy
Range("K9").Select
Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
 :=False, Transpose:=False

Range("K9").Select
Application.CutCopyMode = False
Selection.Copy
Range("J10").Select
Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
 :=False, Transpose:=False
Range("M9").Select
Application.CutCopyMode = False
Selection.Copy
Range("K10").Select
Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
 :=False, Transpose:=False

Range("K10").Select
Application.CutCopyMode = False
Selection.Copy
Range("J11").Select
Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
 :=False, Transpose:=False
Range("M10").Select
Application.CutCopyMode = False
Selection.Copy
Range("K11").Select
Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
 :=False, Transpose:=False
```

```
 Range("K11").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("J12").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False
 Range("M11").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("K12").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False

 Range("K12").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("J13").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False
 Range("M12").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("K13").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False

Range("K13").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("J14").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False
 Range("M13").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("K14").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False

Range("K14").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("J15").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False
 Range("M14").Select
```

```
 Application.CutCopyMode = False
 Selection.Copy
 Range("K15").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False

Range("K15").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("J16").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False
 Range("M15").Select
 Application.CutCopyMode = False
 Selection.Copy
 Range("K16").Select
 Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
  :=False, Transpose:=False

"To protect locked cells
'Sheets("Interface").Protect
' Contents = True
'To show screen after macro run
Application.ScreenUpdating = True

End Sub
```

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