Michigan State University
Pavement Research Center of Excellence

Enhancing MDOT's New Pavement Management Tool (PMT) Inputs Through Data-Driven Analysis

SPR-1747

FINAL REPORT

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December 5, 2025

Technical Report Documentation Page

1. Report No. SPR-1747	2. Government Accession No. N/A	3. Recipient's Catalog No. N/A
4. Title and Subtitle Enhancing MDOT's Pavement Management Tool (PMT) Inputs Through Data-Driven Analysis		5. Report Date December 5, 2025 6. Performing Organization Code N/A
7. Author(s) Daniel Castillo, M. Emin Kutay, James Bryce, Syed W. Haider		8. Performing Organization Report No. N/A
9. Performing Organization Name and Address Michigan State University Department of Civil and Environmental Engineering 228 S Shaw Lane, 3546 EB, East Lansing, Michigan 48824		1 Work Unit No. N/A 11. Contract or Grant No. Contract 2021-0288
12. Sponsoring Agency Name and Address Michigan Department of Transportation (MDOT), Research Administration, 8885 Ricks Road, P.O. Box 33049, Lansing, Michigan 48909		13. Type of Report and Period Covered Final Report, 02/02/2021 - 08/31/2025 14. Sponsoring Agency Code N/A
15. Supplementary Notes Conducted in cooperation with the U.S. Department of Transportation, Federal Highway Administration. MDOT research reports are available at www.michigan.gov/mdotresearch.		

16. Abstract

This project was undertaken to support the Michigan Department of Transportation's (MDOT) implementation of a new Pavement Management Tool (PMT), a decision-support system designed to optimize pavement project selection. The goal was to develop data-driven inputs for the PMT using MDOT's extensive historical pavement condition and maintenance data, with a focus on five key General Condition Ratings (GCRs): International Roughness Index (IRI), cracking (CRK), rutting (RUT), faulting (FLT), and the Pavement Distress Score (PDS). The project began with the compilation and preprocessing of condition data from MDOT's *GroupRecords* files, which represent pavement lifecycle histories categorized by treatment type. Condition data were cleaned, harmonized, and filtered to remove post-treatment values and outliers, enabling the development of deterioration models using both discrete (threshold-based) and continuous (mathematical) approaches. Models were calibrated and fitted at the individual-section level, and times to Good/Fair and Fair/Poor thresholds were estimated. Two methods—percentile-based aggregation and group-level curve fitting—were compared to generate representative deterioration trends. In addition, condition improvements were quantified for various fix types by analyzing pre- and post-treatment data, supporting the development of action-benefit profiles. Utility scoring practices from other agencies were reviewed to guide recommendations for scaling and weighting GCRs within the PMT. The analysis also enabled the identification of typical treatment-trigger thresholds to inform network policy decisions. All modeling outputs, thresholds, and supplementary analyses are provided in a digital appendix, including tools to support further customization and application of the results in MDOT's pavement management practice.

17. Key Words Pavement Management System (PMS) Pavement Performance Modeling, General Condition Ratings (GCR), Pavement Deterioration Models, Pavement Utility Scoring, Life-Cycle Cost Analysis, Pavement Treatment Effectiveness		18. Distribution Statement No restrictions. This document is also available to the public through MDOT.	
19. Security Classif. (of this report) Unclassified	2 Security Classif. (of this page) Unclassified	21. No. of Pages 63	22. Price N/A

Form DOT F 1707 (8-72) Reproduction of completed page authorized

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*- Tasks 1 through 8 are covered in a separate report: SPR-1737, "Evaluation of MDOT's Methodologies for both Quantifying Pavement Distress and Modeling Pavement Performance for Life-Cycle Cost and Remaining Service Life Estimation Purposes".

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the financial support provided by the Michigan Department of Transportation (MDOT) for the execution of this study. Special thanks are extended to **Mike Eacker**, who served as the project manager and played a key role throughout the execution of project tasks. Additionally, **Mike Eacker, Ellen Nightingale**, and **Tim Lemon** (all from MDOT) regularly attended bi-weekly research meetings and provided valuable feedback.

The contributions of the advisory panel members and MDOT research managers listed below are also sincerely appreciated for their guidance and insights:
Robert Green, **Lina Chapman**, **Kyle Rudlaff**, **Margaret Szajner**, **Jorind Bardhollari**, **Alison Hamlin**, **Richard Cnossen**, **Tim Lemon**, **Ellen Nightingale**, and **Andre Clover**, (all MDOT).

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INTRODUCTION

In 2020, the Michigan Department of Transportation (MDOT) initiated the development of a new pavement management tool known initially as the Project Identification Tool (PIT). Designed to assist in prioritizing and optimizing pavement project selection across Michigan's road network, the PIT software was expected to be fully operational by early 2024. However, issues arose that, at the time of publication of this report, development had been suspended. Since the future of PIT is unknown at this point, the remainder of this report shall refer to it as the Pavement Management Tool (PMT). The accuracy and utility of this tool depends on the quality of the input data used to characterize pavement deterioration, identify treatment thresholds, and estimate the effects of various maintenance and rehabilitation strategies.

While initial inputs to the PMT were based on engineering experience and expert judgment, there is a clear need to enhance the tool with inputs grounded in historical pavement condition data and maintenance records maintained by MDOT. These inputs will help ensure that the PMT recommendations reflect observed pavement behavior, typical performance trends, and treatment effectiveness over time.

This project aimed to generate such data-driven inputs by analyzing pavement condition trends, maintenance cycles, and treatment outcomes using a comprehensive dataset derived from MDOT's Pavement Analysis, Valuation, Examination, and Tracking (*PAVETrack)* system. The dataset consists of categorized *GroupRecords* files (outputs of PAVETrack), each representing a *parent fix* type. The term *parent fix* refers to the specific type of reconstruction or rehabilitation applied to a pavement section, at which point the pavement's age is reset to zero. After a parent fix, the section is treated as a new pavement for analysis purposes. While the Physical Road (PR) number typically remains the same, the Beginning Mile Point (BMP), and Ending Mile Point (EMP) may differ slightly from the previous project due to changes in project limits or segmentation.

The parent fix types are categorized as follows:

- Flexible and Composite Pavement Parent Fixes:
    - Multi-Course Overlay HMA
    - HMA Reconstruction
    - HMA over Crush & Shape HMA
    - HMA over Rubblized Concrete
    - HMA over Asphalt Stabilized Crack Relief Layer (ASCRL)
- Rigid Pavement Parent Fixes:
    - JPCP reconstruction
    - JRCP reconstruction
    - Concrete Overlay (Unbonded)
    - Thin Concrete Overlay

The research team received nine Excel sheets from MDOT, each containing pavements for a specific parent fix type, and these files are referred to as *GroupRecords* files throughout this report. A snapshot of a list of *GroupRecords* files received from MDOT for this project shown in Figure 1. These records served as the foundation for modeling deterioration and assessing the impacts of treatment.

Figure 1. A snapshot of a list of *GroupRecords* files received from MDOT

The report is organized around four main technical components as listed below.

- **Task 9 – GCR Modeling**: Develop both stepwise and formula-based deterioration models for key pavement condition indicators across surface types.
- **Task 10 – Action Benefits**: Evaluate the effect of specific treatments on condition improvements and estimate how long these treatments defer future maintenance.
- **Task 11 – Utility Scoring**: Review how other state highway agencies apply utility scoring to pavement management, including methods for scaling condition metrics and assigning weights.
- **Task 12 – Network Policy**: Identify statistically supported thresholds and policy rules for determining when specific treatments should be triggered based on pavement condition data.

This project was a continuation of an earlier effort titled *"Evaluation of MDOT's Methodologies for Quantifying Pavement Distress and Modeling Pavement Performance for Life-Cycle Cost and Remaining Service Life Estimation Purposes."* The original project included the first eight tasks, which can be found in the MDOT Report SPR-1737. As a result, the tasks in this phase begin with Task 9 and proceed sequentially through Task 12 to reflect the extended scope of work.

It should be noted that the Pavement Distress Score (PDS), developed during Phase I of this project, is referenced throughout this report. PDS is a composite metric designed to quantify overall pavement surface condition using individual distress measurements collected through MDOT's Surface Defect Survey (SDS) program. It is calculated using a weighted sum of normalized distress quantities, with distinct coefficients assigned to each distress type—such as longitudinal cracking, transverse cracking, block cracking, and patching. The PDS formulation is shown below:

$$TWD = \sum_{i=1}^{n} w_i D_i \quad [1]$$

$$PDS = 25 * (e^{1.386294-(0.045*TWD)}) \quad [2]$$

where, TWD = total weighted distress, n = number of distresses, D_i = quantity at each distress-severity combinations, w_i = weights for each distress, PDS = Pavement Distress Score. Although the PDS is not yet implemented in MDOT's current pavement management system, it serves as a consistent and performance-aligned indicator used throughout this report to support condition-based modeling and facilitate comparisons across pavement types. PDS values for each section were computed using *PDSComp V0.1*, a software tool developed during the earlier phase of this research. Details of this tool and its methodology are documented in the full report titled *"Evaluation of MDOT's Methodologies for Quantifying Pavement Distress and Modeling Pavement Performance for Life-Cycle Cost and Remaining Service Life Estimation Purposes"* (Report RC-1737).

TASK 9: GENERAL CONDITION RATING (GCR) DETERIORATION MODELING

The objective of this task was to develop performance models that characterize the deterioration of key pavement condition metrics, referred to in the PMT as General Condition Ratings (GCRs). The GCRs considered in this project include the International Roughness Index (IRI), cracking (CRK), rutting (RUT), faulting (FLT), and the Pavement Distress Score (PDS). Among these, IRI, CRK, and PDS are evaluated for both flexible and rigid pavement types. In contrast, RUT is applicable only to flexible pavements, while FLT is used exclusively for rigid pavements. It is noted that the cracking (CRK) is the cracking percent (%) that was computed by following Highway Pavement Management System (HPMS) data reporting guidelines[1].

The deterioration models were designed to operate at two levels:

- *Discrete Modeling*: Estimates the time required for a pavement section to transition between predefined condition states—such as from *Good* to *Fair*, or from *Fair* to *Poor*—starting from an idealized initial condition (e.g., 100% Good).

[1] https://www.fhwa.dot.gov/policyinformation/hpms/fieldmanual/page06.cfm#toc249159741

- *Continuous Modeling:* Uses mathematical functions to describe the full progression of a condition metric over time, capturing the continuous degradation of pavement performance throughout its service life.

DATA PREPARATION

The data processing and analysis conducted in this project rely on two primary source files:

- *The "stack" file*: This file is a consolidated compilation of *GroupRecords* data (see Figure 2). Each original *GroupRecords* file corresponds to a specific parent fix type (referred to as "Parent") and contains pavement performance and maintenance data for sections treated with that fix. The parent fixes are categorized as either *flexible* or *rigid*. All *GroupRecords* files were combined into a single, unified dataset—referred to as the "stack"—which serves as the foundational input for all technical tasks in this project. *GroupRecords* files are an output of the PAVETrack application.
- *The pavement list*: This file provides a summary of road network data, roughly corresponding to the "Parent" rows in the stack. It includes key information such as opening year, ending year (if applicable), and reconstruction/rehabilitation identifiers, which are critical for tracking section "connectivity" over time. These lists were maintained by MDOT.

Figure 2 displays a screenshot of the "stack" file, which has been extended to include PDS values. These values were generated using specially prepared pavement lists that includes both Control Section (CS) and *Physical Road (PR)* identifiers. CS and PR are two different versions of MDOT's linear referencing system (LRS). CS is the legacy LRS, while PR is the more modern system that MDOT has transitioned to. While pavement sections in the stack were originally labeled using PR numbers, only the PDS data collected after 2020 could be computed using PR-based identifiers, whereas data from before 2019 follows a CS-based structure. Consequently, accurately merging the PDS values into the stack required establishing a reliable mapping between PR and CS identifiers, including their respective beginning and ending mileposts.

	A	B	C	D	E	I	J	K	L	M	N	O	R	S	T	U	V
1	ID	FLX_RIG	PARENT_FIX	ROUTE	DIR	YEAR	AGE	IRI	RUT	FLT	CRK	PDS	FIX_TYPE	CYCLE	PR	PR_BMP	PR_EMP
2	7	FLX	MULTI-CSE HMA	M-85	NB	2005	0						Multi-Cse HMA	Parent	4700047	0	1.01
3	7	FLX	MULTI-CSE HMA	M-85	NB	2006	1	173	0.2		5	80.5					
4	7	FLX	MULTI-CSE HMA	M-85	NB	2007	2	173	0.18		13	94.6					
5	7	FLX	MULTI-CSE HMA	M-85	NB	2010	5	161	0.17								
6	7	FLX	MULTI-CSE HMA	M-85	NB	2011	6						Recon HMA	End	4700047	0	0.303
7	9	RIG	RECON JRCP	M-59	WB	1995	0						Recon JRCP	Parent	807801	4.433	5.875
8	9	RIG	RECON JRCP	M-59	WB	1997	2										
9	9	RIG	RECON JRCP	M-59	WB	1999	4										
10	9	RIG	RECON JRCP	M-59	WB	2001	6				8	97.7					
11	9	RIG	RECON JRCP	M-59	WB	2003	8				13	89.6					
12	9	RIG	RECON JRCP	M-59	WB	2005	10						Conc FDRs	1	807801	4.129	7.959
13	9	RIG	RECON JRCP	M-59	WB	2007	12	119			14	59					
14	9	RIG	RECON JRCP	M-59	WB	2007	12						Conc FDRs	2	807801	4.129	7.959
15	9	RIG	RECON JRCP	M-59	WB	2009	14	202			7	61.9					
16	9	RIG	RECON JRCP	M-59	WB	2010	15						Conc FDRs	3	807801	3.024	7.959
17	9	RIG	RECON JRCP	M-59	WB	2011	16	180			16	54.8					
18	9	RIG	RECON JRCP	M-59	WB	2013	18	178		0.12	12	52.5					
19	9	RIG	RECON JRCP	M-59	WB	2015	20	228		0.7	26	31.2					
20	9	RIG	RECON JRCP	M-59	WB	2017	22	185		0.16	12	44.1					
21	9	RIG	RECON JRCP	M-59	WB	2018	23						Recon HMA	End	807801	4.203	8.072
22	10	RIG	RECON JRCP	M-59	EB	1995	0						Recon JRCP	Parent	820202	1.454	2.836
23	10	RIG	RECON JRCP	M-59	EB	1997	2										
24	10	RIG	RECON JRCP	M-59	EB	1999	4										
25	10	RIG	RECON JRCP	M-59	EB	2001	6				25	98.4					
26	10	RIG	RECON JRCP	M-59	EB	2003	8										

Figure 2. Partial screenshot of the "stack" file (i.e., compiled *GroupRecords* data). Data corresponding to one section extends over several rows. The first row of each section is highlighted (dark gray for flexible sections, lighter gray for rigid sections)

To facilitate this integration, the unique pavement sections in the 'stack' were consolidated into a new pavement list that includes both *CS*- and *PR*-based identifiers (see Figure 3). To perform the matching between PR and CS, a reference file titled *'hist_cmpst_sgmts_cs_info_2019.csv'*—provided by MDOT—was used. A screenshot of this file is shown in Figure 4. This file contains 0.1-mile segment data from the Highway Pavement Management System (HPMS) and includes both PR-based fields (*PR, PR_BMP, PR_EMP*) and CS-based fields (*CS, CS_DIR, CS_BMP, CS_EMP*), among other attributes. This mapping enabled the integration of PDS data into the correct pavement segments in the stack.

	B	C	D	K	L	M	N	O	P	Q	R
1	SURFACE	PARENT_FIX	ROUTE	PR	PR_BMP	PR_EMP	CS	DIR	BMP	EMP	LENGTH
2	Flexible	C--S	M-65	3010827	0	3.904	1011	I	0	3.9	3.904
3	Flexible	C--S	M-65	3010827	4.218	10.953	1011	I	4.3	10.953	6.735
4	Flexible	MULTI-CSE-HMA	M-65	1725010	0	4.372	1012	I	0	4.3	4.372
5	Flexible	C--S	M-65	1725010	0.115	4.349	1012	I	0.2	4.3	4.234
6	Flexible	C--S	M-65	3010070	0	0.229	1012	I	9.852	10.081	0.229
7	Flexible	C--S	M-65	1725010	9.415	9.852	1012	I	9.5	9.852	0.437
8	Flexible	C--S	M-72	1725101	0	1.28	1021	I	0	1.2	1.28
9	Flexible	C--S	M-72	1725101	0	1.258	1021	I	0	1.2	1.258
10	Flexible	C--S	M-72	1725101	1.28	4.001	1021	I	1.3	4	2.721
11	Flexible	C--S	M-72	1891001	0	6.934	1022	I	0	6.9	6.934
12	Flexible	C--S	M-72	1725102	0.005	4.321	1023	I	0.1	4.3	4.316
13	Flexible	RECON-HMA	US-23	1725704	10.102	10.425	1051	I	10.2	10.4	0.323
14	Flexible	ASCRL	US-23	1725704	0	6.174	1051	I	0	6.1	6.174
15	Flexible	RUBBLIZE	US-23	1725704	6.213	10.06	1051	I	6.3	10	3.847
16	Flexible	RECON-HMA	US-23	1725704	10.426	10.918	1052	I	0.074	0.474	0.492
17	Flexible	RUBBLIZE	US-23	1725704	10.927	12.9	1052	I	0.574	2.474	1.973
18	Flexible	ASCRL	US-23	1725704	17.563	22.161	1052	I	7.174	11.674	4.598

Figure 3. Partial screenshot of the pavement lists with both PR-based fields (PR, PR_BMP, PR_EMP) and CS-based fields (CS, CS_DIR, CS_BMP, CS_EMP)

	A	B	C	D	E	G	H	I	V	W	X	Y
1	SURVEY_YEAR	RTE_ID_PR	PR_BEG_MP	PR_END_MP	SECT_LGTH	CRACKING_PERCENT_VALUE	CRACKING_PERCENT_GFP	CRACKING_PERCENT_DATE	CS_NUM	CS_PATH_CD	SEG_CS_BEG_MP	SEG_CS_END_MP
7883	2019	354209	16	16.1	0.1	0	Good	5/28/19 16:36	33035	I	3.85	3.95
7884	2019	354209	16.1	16.2	0.1	0	Good	5/28/19 16:36	33035	I	3.95	4.05
7885	2019	354209	16.2	16.3	0.1	1	Good	5/28/19 16:36	33035	I	4.05	4.15
7886	2019	354209	16.3	16.4	0.1	0	Good	5/28/19 16:36	33035	I	4.15	4.25
7887	2019	354209	16.4	16.5	0.1	0	Good	5/28/19 16:36	33035	I	4.25	4.35
7888	2019	354209	16.5	16.6	0.1	0	Good	5/28/19 16:36	33035	I	4.35	4.45
7889	2019	354209	16.6	16.7	0.1	0	Good	5/28/19 16:36	33035	I	4.45	4.55
7890	2019	354209	16.7	16.8	0.1	0	Good	5/28/19 16:36	33035	I	4.55	4.65
7891	2019	354209	16.8	16.9	0.1	1	Good	5/28/19 16:36	33035	I	4.65	4.75
7892	2019	354209	16.9	17	0.1	0	Good	5/28/19 16:36	33035	I	4.75	4.85
7893	2019	354209	17	17.1	0.1	0	Good	5/28/19 16:36	33035	I	4.85	4.95
7894	2019	354209	17.1	17.2	0.1	0	Good	5/28/19 16:36	33035	I	4.95	5.05
7895	2019	354209	17.2	17.3	0.1	1	Good	5/28/19 16:36	33035	I	5.05	5.15
7896	2019	354209	17.3	17.4	0.1	0	Good	5/28/19 16:36	33035	I	5.15	5.25
7897	2019	354209	17.4	17.5	0.1	0	Good	5/28/19 16:36	33035	I	5.25	5.35
7898	2019	354209	17.5	17.6	0.1	0	Good	5/28/19 16:36	33035	I	5.35	5.45
7899	2019	354209	17.6	17.7	0.1	0	Good	5/28/19 16:36	33035	I	5.45	5.55
7900	2019	354209	17.7	17.8	0.1	0	Good	5/28/19 16:36	33035	I	5.55	5.65
7901	2019	354209	17.8	17.9	0.1	0	Good	5/28/19 16:36	33035	I	5.65	5.75
7902	2019	354209	17.9	18	0.1	1	Good	5/28/19 16:36	33035	I	5.75	5.85
7903	2019	354209	18	18.1	0.1	1	Good	5/28/19 16:36	33035	I	5.85	5.95
7904	2019	354209	18.1	18.2	0.1	1	Good	5/28/19 16:36	33035	I	5.95	6.05
7905	2019	354209	18.2	18.3	0.1	1	Good	5/28/19 16:36	33035	I	6.05	6.15
7906	2019	354209	18.3	18.4	0.1	0	Good	5/28/19 16:36	33035	I	6.15	6.25
7907	2019	354209	18.4	18.5	0.1	0	Good	5/28/19 16:36	33035	I	6.25	6.35
7908	2019	354209	18.5	18.6	0.1	0	Good	5/28/19 16:36	33035	I	6.35	6.45

Figure 4. Partial screenshot of the *'hist_cmpst_sgmts_*cs*_info_2019.csv'* file

Additionally, *FLT* values were removed from *flexible* pavement sections, and *RUT* values were removed from *rigid* sections to ensure logical consistency across surface types. A data adjustment and preparation process was also applied to the data, as outlined below:

- *RUT data scaling*: Due to changes in data collection vendors, *RUT (FLX)* measurements showed inconsistencies over time. To address this, a correction factor was applied to RUT data collected during 2006–2011 and 2018–2019 to align it with values from the more stable periods of 2012–2017 and 2021–2023. These timeframes were identified based on year-to-year mean variations exceeding 10%. More details about this adjustment can be found in Report RC-1737.
- *Very high values*: Outliers and unusually high condition metric values were removed from the dataset. Thresholds used for filtering include: *300 in/mile* for *IRI*, *0.5 in* for *RUT*, and *0.3 in* for *FLT*.
- *No Age-0 data*: Some entries in the stack, although not labeled as *"Parent"* sections, contained condition metric values recorded at *Age 0*. These entries were removed to maintain consistency in how initial condition data is interpreted.

Preparation and Evaluation of Condition Metric Records for Model Fitting

Exclusion of Post-Treatment Data

To accurately capture pavement deterioration over time, it is essential to isolate condition data that reflects a continuous period of performance between major treatments. Since the application of a fix interrupts normal deterioration, condition metric values recorded *after* a treatment are excluded from model fitting. This ensures that each performance curve reflects a single, uninterrupted lifecycle phase. Figure 5 illustrates this process using data from a section treated with an *HMA Overlay – Single & Mill*. The chart on the right displays the filtered dataset, retaining only the pre-treatment values for modeling purposes. The vertical dashed line marks the treatment year.

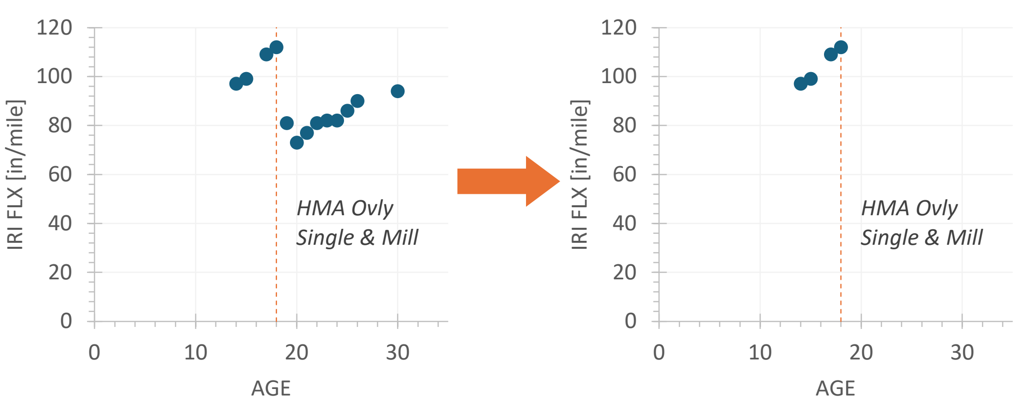


Figure 5. Example of excluding post-treatment data from condition metric records. Left: full record. Right: data retained for modeling. Section ID: 4137.

This filtering process was applied uniformly across all sections and condition metrics. Figure 6 shows the distribution of *IRI FLX* values aggregated across sections after treatment-related values were removed. The general trend of deterioration is visible, while the increasing variability at later ages reflects the smaller number of segments that remain untreated as they age.

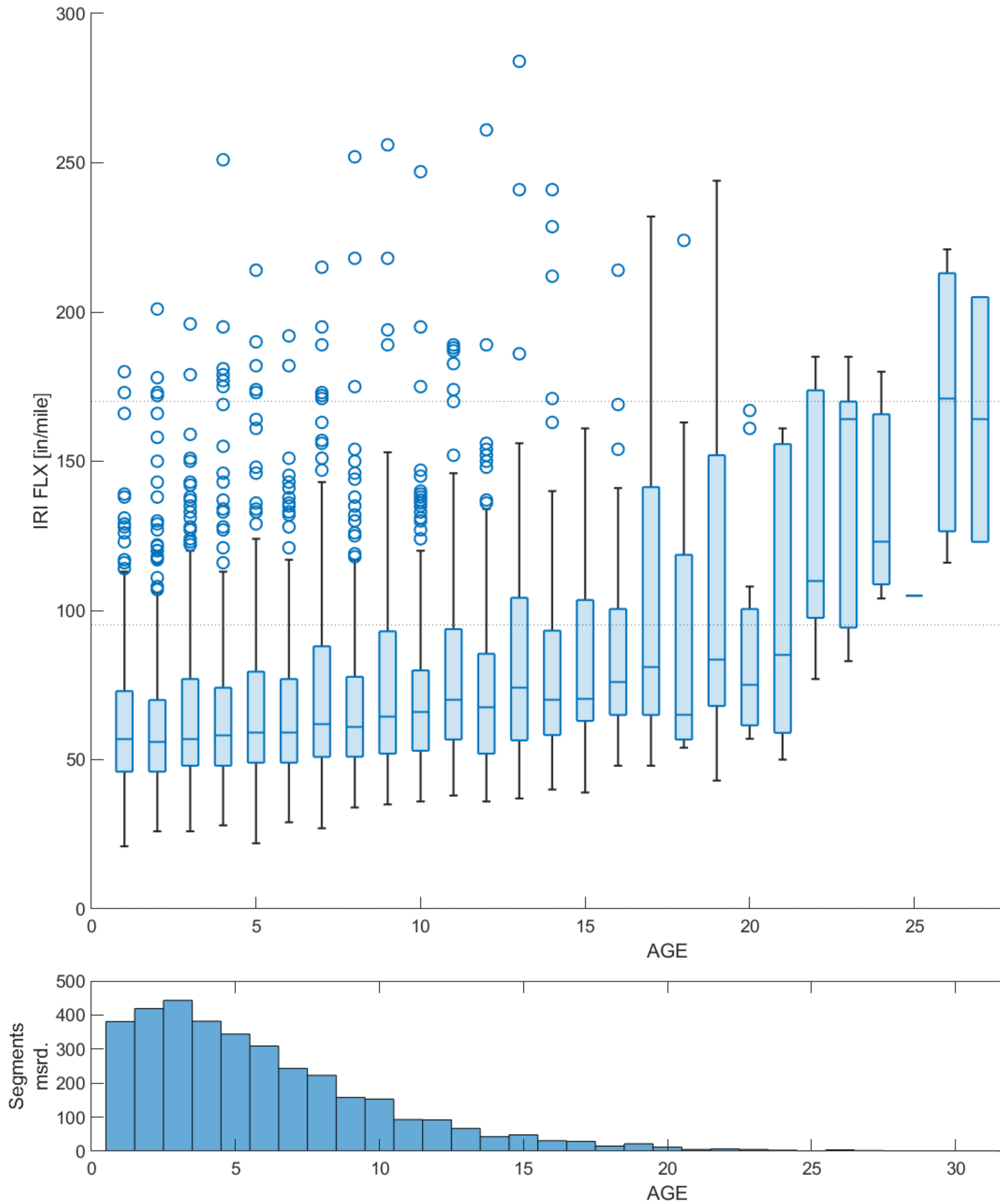


Figure 6. Top: Boxplot of IRI FLX values using only pre-treatment data. Bottom: count of segments contributing data by age.

Screening Condition Records for Fitting

Before condition metric records were used for model fitting, a set of quality control checks was applied to ensure that the data was suitable and representative. These screening criteria helped remove anomalous or insufficient records while maximizing the dataset's usefulness. The following conditions were enforced:

- **Minimum Number of Data Points:** To be eligible for fitting, a section had to include at least:
  - *Three data points* for *IRI*, *CRK*, *RUT*, and *PDS*
  - *Two data points* for *FLT*, due to limited data availability
    In addition, a synthetic data point was added at *Age 0* to represent the initial condition following the most recent treatment. These Age 0 values are explained later in this chapter.
- **Deterioration Trend Requirement:** The overall trend of the condition metric must reflect deterioration over time:
  - For *IRI*, *CRK*, *RUT*, and *FLT*, the linear trend must be *positive*
  - For *PDS*, the trend must be *negative*
    A small tolerance was allowed to include records with near-zero slopes, provided they still represented a plausible aging pattern.
- **Exclusion of Records with Sudden Unexplained Changes:** To avoid fitting unreliable or inconsistent data, any record showing abrupt changes between consecutive points was excluded. The following thresholds were applied:
  - *IRI FLX*: change > *76 in/mile* (80% of Good/Fair threshold)
  - *IRI RIG*: change > *57 in/mile* (60% of Good/Fair threshold)
  - *CRK FLX*: reduction > *20%*
  - *CRK RIG*: reduction > *15%*
  - *RUT*: reduction > *0.16 in* (80% of 0.2 in threshold)
  - *FLT*: change > *0.1 in*
  - *PDS*: improvement > *40 points* (80% of Fair/Poor threshold)

These thresholds were developed and refined through an iterative calibration process. Individual condition records were reviewed to assess the impact of each criterion and ensure the final dataset was both comprehensive and reliable for performance modeling.

MODEL SELECTION AND FITTING OF CONDITION METRIC DATA

Once the condition metric records were filtered according to the criteria described earlier (i.e., post-treatment data removed, validity thresholds applied), each section was evaluated individually to fit a deterioration model appropriate for the corresponding condition metric. This fitting process involves determining the optimal parameters of a selected mathematical model that best represents how the condition metric evolves with pavement age.

The primary goal of the fitting process is to develop simple yet versatile models that can capture the full deterioration trend of each condition metric over time. The models were selected based on their ability to:

- Accurately represent a wide range of deterioration patterns,
- Use a minimal number of parameters for ease of implementation,
- Support both interpolation within available data and extrapolation beyond observed data, and
- Conform to expected physical behavior at pavement age zero.

Each condition metric was assigned a distinct model equation, as summarized below:

$$IRI(t) = IRI_0 \times e^{Bt^A} \quad [3]$$

$$CRK(t) = e^{A+Bt} \quad [4]$$

$$RUT(t) = A \times t^B \quad [5]$$

$$FLT(t) = A \times t^B \quad [6]$$

$$PDS(t) = \frac{100}{1 + (t/A)^B} \quad [7]$$

In these equations, *t* represents the pavement age in years. Each model was fit to the condition metric data of individual sections that passed the screening criteria. The resulting parameters (*A*, *B*, and where applicable, IRI_0) were stored for further analysis and reporting.

For Rutting and Faulting, the equations above are the same as one of the models evaluated in the Phase I of this project (power model). For IRI, the equation above is similar to the Dubai model used in the Phase I of the project, with addition of A on the exponent of t to make the fits better. For PDS, the ASigmoid and Logistic equations were too complicated and we thought a two parameter model (simpler) can more easily be modeled in MDOT's internal software tools.

Each model was constrained to follow physically meaningful behavior at age zero:

- IRI_0 (initial IRI) was estimated for each section using a back-casting algorithm described later in the report.
- *CRK(0)* was set to 0.01 %. As a result, the constant *A* in the CRK model is fixed at *ln(0.01)* ≈ -4.6. The model used will not work if Age 0 is exactly 0.
- *RUT(0)* and *FLT(0)* were defined as 0, consistent with the assumption of no initial rutting or faulting post-construction.
- *PDS(0)* was defined as 100, representing perfect condition at the start of the lifecycle.

Figure 7 shows fitted curves for *RUT (FLX)* across selected sections, with thresholds included for visual context. Figure 8a provides some examples of individual fitting results for *IRI FLX* across selected sections, each plot representing three sections and their respective fits. Figure 8b highlights some examples of sections that did not meet the minimum data quality criteria and were excluded from modeling.

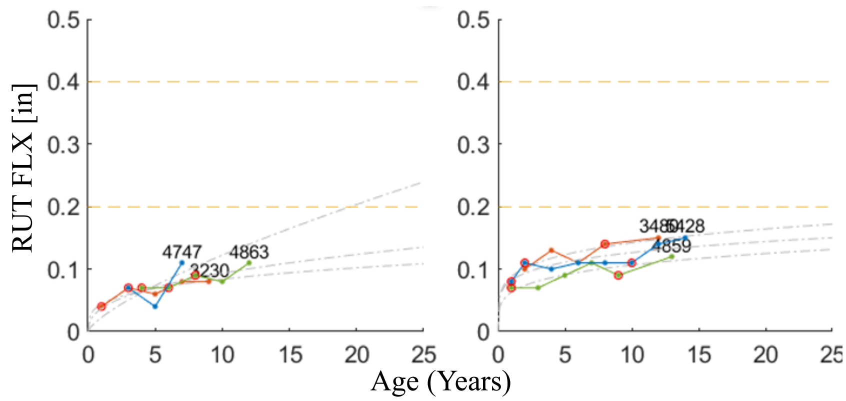
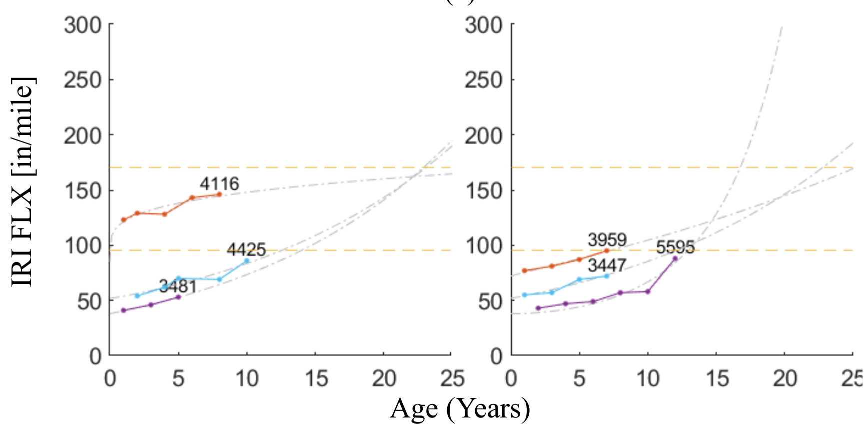


Figure 7. Example fitted RUT (FLX) curves for selected sections. Horizontal axis is section age.

(a)



(b)

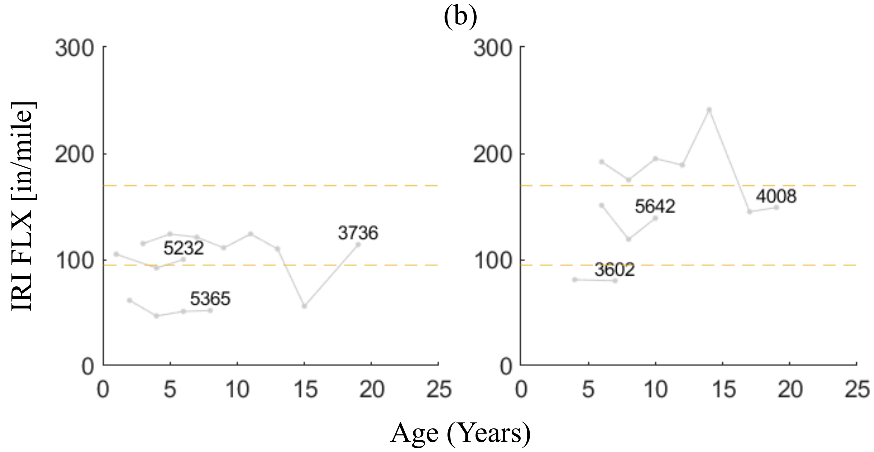


Figure 8. Examples of IRI FLX model fits for selected sections: (a) Passing and (b) failing validation criteria. Horizontal axis is section age

Calculation of times to Good/Fair and Fair/Poor thresholds

Following the model fitting process, the resulting equations and parameters for each section were used to estimate the time required to reach key condition thresholds. Specifically, the *time to reach the Good/Fair threshold (t_GF)* and the *time to reach the Fair/Poor threshold (t_FP)* were calculated for each section using its fitted deterioration model. These times could be determined even for sections whose observed data did not extend far enough to cross either threshold, by using extrapolation beyond the available data.

Two condition thresholds were applied consistently across the project to define pavement performance categories. These thresholds represent the boundaries between Good, Fair, and Poor condition levels for each metric. The specific threshold values used for each condition metric are summarized in Table 1.

Table 1. Thresholds for Good, Fair, and Poor Pavement Condition Classification

Metric	Surface Type	Good / Fair Threshold	Fair / Poor Threshold	Notes
IRI	FLX & RIG	95 in/mile	170 in/mile	International Roughness Index in inches/mile
CRK	FLX	5%	20%	Cracking in percentage
	RIG	5%	15%	
RUT	FLX	0.20 in	0.40 in	Rutting in inches
FLT	RIG	0.10 in	0.15 in	Faulting in inches
PDS	FLX	80	50	Subject to review. Placeholder for comparison
	RIG	80	50	

In many cases, particularly for condition metrics with nearly flat trends, the model predicted extremely long times to threshold crossing. To handle these situations consistently, an upper limit of *111 years* was adopted to represent these values—effectively serving as an *artificial infinity* within the analysis.

A summary spreadsheet was developed to compile key characteristics for each modeled section. This includes identification and network information, the number of valid data points, linear trend slope, model constants (A, B, and where applicable, IRI_0), and the extrapolated threshold times (*t_GF*, *t_FP*). Figure 9 presents a tabular summary of the section properties and fit parameters. Key columns include the number of data points (*N_DATA*), extrapolated times to *Good/Fair (T_GF)* and *Fair/Poor (T_FP)* thresholds, and model constants (A, B, and IRI_0, where applicable). Figure 11 and Figure 12 show examples of fitting results for *CRK FLX* and *PDS FLX*, respectively, illustrating the general performance trends and fitted curves overlaid on the data. The Good/Fair and Fair/Poor thresholds are included for reference.

By rearranging the equations [3] through [7], the times to *Good/Fair (T_GF)* and *Fair/Poor (T_FP)* can be computed by using the following formulations, given the fit coefficients and target GCR values:

$$t = [\frac{\ln(\mathrm{IRI}/\mathrm{IRI}_0)}{B}]^{\frac{1}{A}} \qquad [8]$$

$$t = \frac{\ln(\mathrm{CRK}) - A}{B} \qquad [9]$$

$$t = (\frac{\mathrm{RUT}}{A})^{\frac{1}{B}} \qquad [10]$$

$$t = (\frac{\mathrm{FLT}}{A})^{\frac{1}{B}} \qquad [11]$$

$$t = A \times [\frac{100}{\mathrm{PDS}} - 1]^{\frac{1}{B}} \qquad [12]$$

The last two columns of the sec_fit.xlsx file in the digital appendix contain the implementation of the equations described above. Figure 10 presents a snapshot of these columns, illustrating the formula used to calculate the time to the Good/Fair threshold. This formula is designed to return "n/a" in cases of mathematical errors or invalid inputs and to cap the calculated value at the maximum limit specified in cell AZ1.

	A	B	AB	AE	AF	AG	AI	AJ	AS	AT	AU	AV	AW
1	ID	FLX_RIG	N_DATA	IRI_AVG	IRI_MDN	IRI_MAX	INTRCPT	SLOPE	T_GF	T_FP	A	B	IRI_0
487	4560	FLX	4	51.8	52	53	52.84	-0.24	111.0	111.0	4.6691	0.0000	52.8
488	3676	FLX	3	57.9	58.1	60.3	60.13	-0.55	111.0	111.0	0.7878	0.0000	60.1
489	5530	FLX	3	131.0	131	133	132.50	-0.50	0.0	111.0	0.0000	0.4326	85.0
490	4602	FLX	7	50.9	50	54	53.49	-0.42	111.0	111.0	1.0118	0.0000	53.9
491	4771	FLX	3	34.0	34	36	36.21	-0.47	111.0	111.0	0.8237	0.0000	36.2
492	4772	FLX	3	36.0	36	38	38.21	-0.47	111.0	111.0	0.8219	0.0000	38.2
493	3480	FLX	5	73.8	74	77	76.57	-0.43	111.0	111.0	0.0000	0.1269	65.0
494	3595	FLX	3	53.7	54	54	54.92	-0.25	111.0	111.0	1.1209	0.0000	54.9
495	4366	FLX	5	91.6	90	97	95.36	-0.70	111.0	111.0	0.0000	0.0748	85.0
496	4368	FLX	4	93.8	93.5	96	95.55	-0.45	111.0	111.0	0.0000	0.0980	85.0
497	5475	FLX	4	65.5	65	69	67.98	-0.55	111.0	111.0	1.4604	0.0000	68.0
498	3925	FLX	4	56.0	56.5	57	57.54	-0.34	111.0	111.0	1.4399	0.0000	57.5
499	4856	FLX	5	63.0	64	66	66.00	-0.60	111.0	111.0	0.8504	0.0000	66.0
500	4312	FLX	4	43.3	43.5	45	45.75	-0.50	111.0	111.0	1.0553	0.0000	45.8
501	4825	FLX	3	79.3	79	82	81.58	-0.75	111.0	111.0	0.0000	0.0299	77.0
502	4418	FLX	5	47.7	47	53.8	51.54	-0.80	111.0	111.0	0.7466	0.0000	51.5
503	5638	FLX	3	80.7	80	82	85.17	-0.50	111.0	111.0	0.0000	0.4014	54.0
504	5437	FLX	3	42.3	42	43	43.33	-0.50	111.0	111.0	0.9104	0.0000	43.3

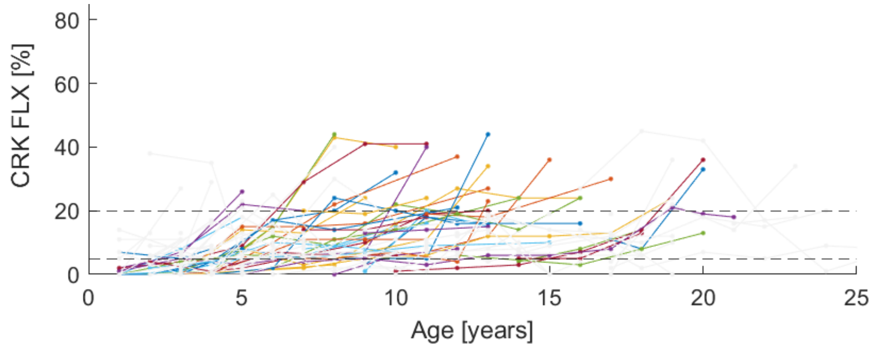
Figure 9. A partial view of the spreadsheet table (see sec_fit.xlsx in digital appendix) of section properties and model parameters, including data count, threshold times (T_GF, T_FP), and fitting constants (A, B, IRI₀).

SUM | =IFERROR(MAX(0, IF((LN(AX$1 / $AW2) / $AV2)^(1 / $AU2) > AZ1,

	A	B	AU	AV	AW	AX	AY	AZ	BA
1	ID	FLX_RIG	A	B	IRI_0	95	170	111	
2	5367	FLX	3.675897903	0.00115816	62.7	=IFERROR(MAX(0, IF((LN(AX$1 / $AW2) / $/			
3	602	FLX	0.630514759	0.255715979	30	10.89355	20.82914		
4	4029	FLX	0.955720781	0.084270006	69	4.036439	11.94201		
5	4565	FLX	0.856265898	0.10550507	65.15	4.427465	13.16753		

Figure 10. A snapshot of the last two columns of 'sec_fit.xlsx' sheet that shows the formulation of the time to Good/Fair threshold.

(a) CRK FLX, condition metric record of selected sections.



(b) CRK FLX, fitted model to the data of the selected sections.

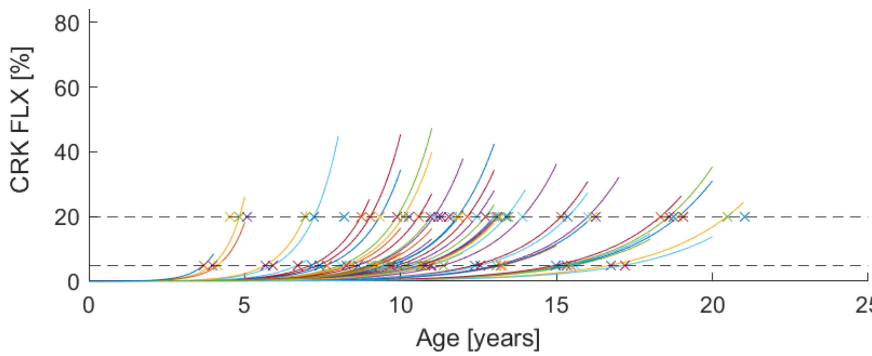
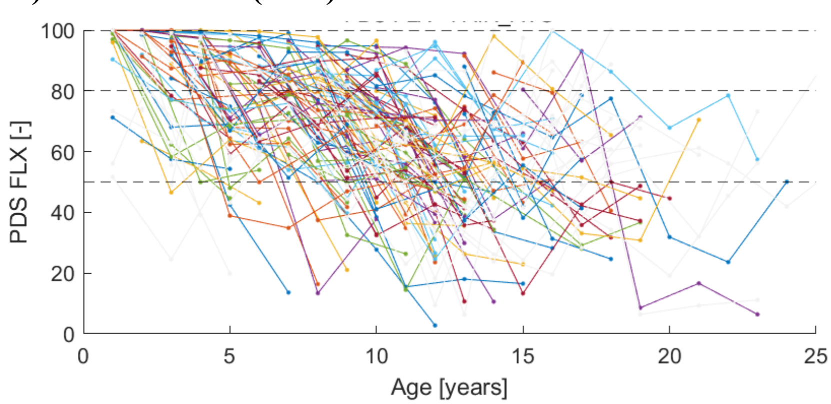


Figure 11. Fitted deterioration curves for selected sections using CRK FLX. Good/Fair (5%) and Fair/Poor (20%) thresholds are shown.

(a) PDS FLX, condition metric record of selected sections.



(b) PDS FLX, fitted model to the data of the selected sections.

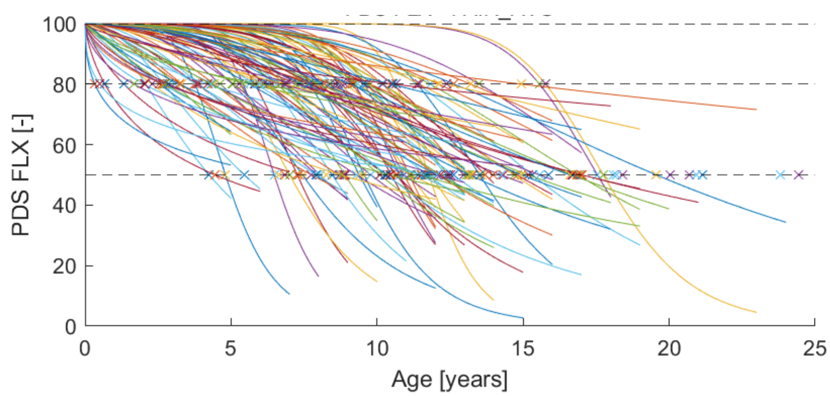


Figure 12. Fitted deterioration curves for selected sections using PDS FLX. Good/Fair (80%) and Fair/Poor (50%) thresholds are shown.

Comparison of two modeling approaches for representative deterioration trends

With threshold times (*t_GF* and *t_FP*) estimated for each section and condition metric records available, two complementary approaches were applied to generate representative deterioration trends for selected subsets of pavement sections. These subsets can be defined broadly (e.g., all *flexible* sections) or more specifically by *parent fix type* or *region*.

Approach 1 is based on individual threshold times derived from section-level model fits. For each subset, the *time to Good/Fair* and *time to Fair/Poor* are aggregated and summarized using the *median* (50^{th} percentile). This statistical approach provides a straightforward way to characterize deterioration trends without fitting a new curve across the group. For example, as shown in Figure 13, the histogram distributions of *IRI FLX* threshold times for all flexible sections yield characteristic values of *24.4 years* to the *Good/Fair* threshold and *60.1 years* to the *Fair/Poor* threshold (the time to Fair/Poor extends beyond the horizontal axis). A summary of results for all condition metrics using this method is presented in Table 2.**Error! Reference source not found.**

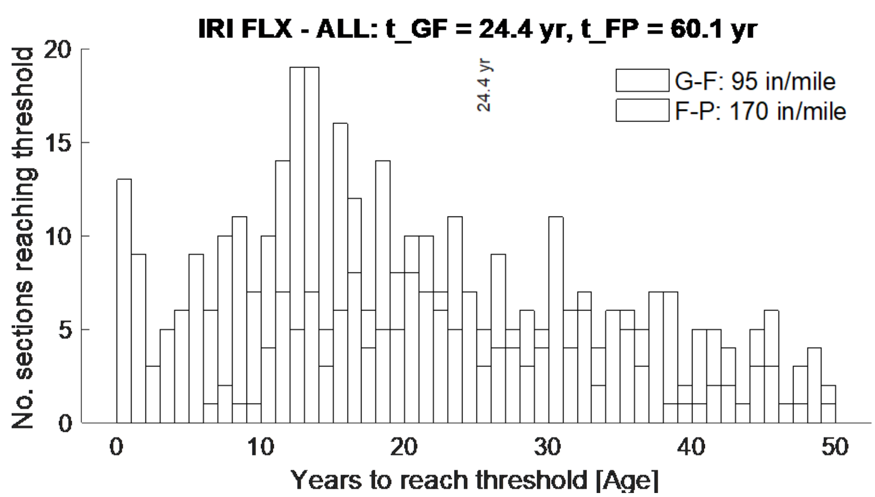


Figure 13. Approach 1: Distribution of threshold times for IRI FLX. The time to Fair/Poor extends beyond the horizontal axis.

In contrast, *Approach 2* applies a single deterioration model to the aggregated condition metric data from all sections in the subset that passed the fitting criteria. Rather than relying on section-level results, this method generates a continuous, representative curve for the entire group. Threshold times are then estimated directly from this curve. As shown in Figure 14, the curve fitted to the combined *IRI FLX* data from all flexible sections indicates a time of *19.0 years* to the *Good/Fair* threshold and *45.1 years* to the *Fair/Poor* threshold. Full results for this approach are provided in Table 2.

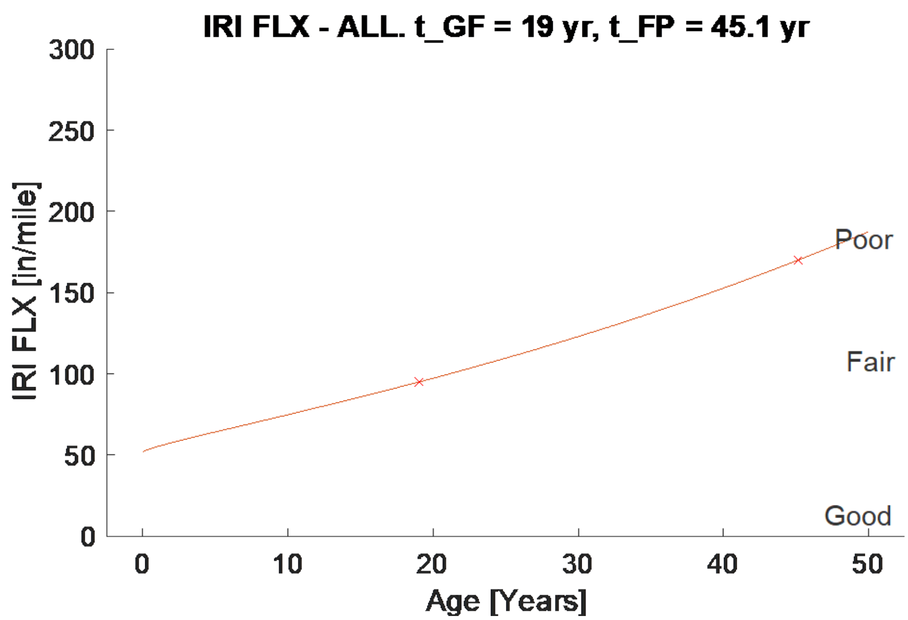


Figure 14. Approach 2: Characteristic curve fitted to combined IRI FLX data.

Table 2. Summary of results from Approaches 1 and 2. Subset: All sections, all condition metrics

GCR	Times to thresholds				Initial IRI	Fitting constants	
	T_GF		T_FP			A2	
	A1	A2	A1	A2	IRI0	A	B
IRI FLX	24.4	19	60.1	45.1	51.9	0.7805	0.0606
IRI RIG	36.2	15	111	111	73.5	0.2182	0.1422
CRK FLX	15.2	19.5	18.6	23.8	N/A	-4.6052	0.3192
CRK RIG	34.9	19.3	41	22.7	N/A	-4.6052	0.3222
RUT FLX	62.2	41.8	111	111	N/A	0.0578	0.3323
FLT RIG	111	111	111	111	N/A	0.031	0.0094
PDS FLX	15.9	12.9	28.7	28.9	N/A	28.9145	1.7216
PDS RIG	82.2	14.3	111	64.7	N/A	64.7059	1.9546

Notes: A1 = Approach 1: 50th percentile (median) = Quartile 2 (Q2) of times to Good/Fair, times to Fair/Poor. Fits are performed individually, for each section. A2 = Approach 2: A characteristic curve is fitted over the condition metric record of the subset.

While both approaches aim to characterize deterioration behavior, their results are not always identical. Differences reflect the nature of each method: *Approach 1* captures variability across individual sections, while *Approach 2* reflects the overall trend of the group. Interestingly, the results suggest that the use of the 50th percentile in *Approach 1* may sometimes overestimate threshold times compared to *Approach 2*. Adjusting this percentile downward may improve alignment between the two methods. Ultimately, both approaches provide valuable insight and can be used in complementary ways to support pavement management decision-making.

It should be noted that the "Histograms" folder in the digital appendix includes several excel sheets that can be used to compute the *time to Good/Fair* and *time to Fair/Poor* values based on different percentiles, instead of the 50^{th} percentile. Figure 15 shows one of the histogram excel sheets where the user can enter the desired percentile in cell E19 in fraction format to see the percentile result in cell D19.

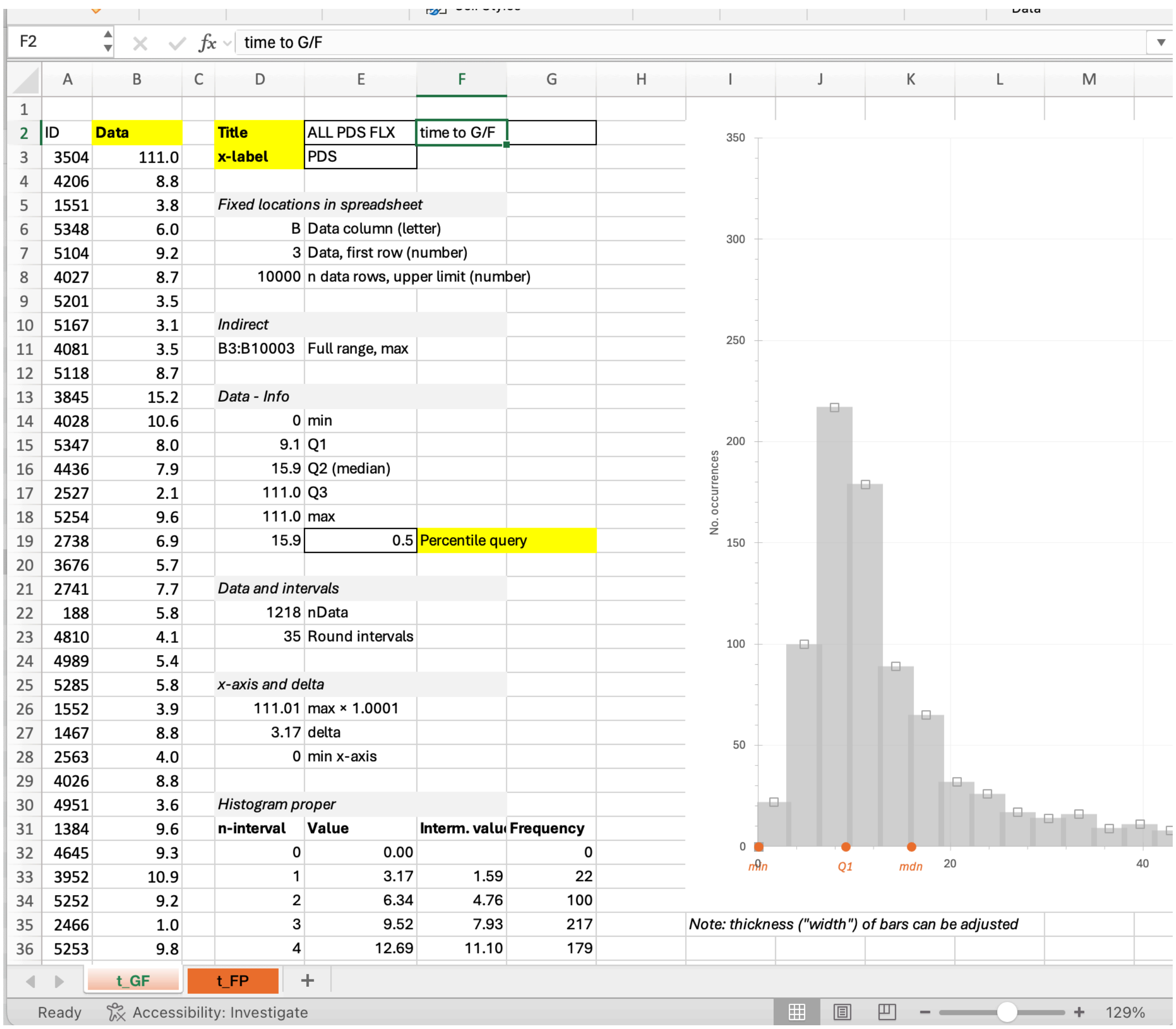


Figure 15. An example histogram excel sheet provided in the digital appendix, "Histograms" folder.

Subset analysis by parent fix type and region

The previous results were based on the entire set of *flexible* or *rigid* pavement sections contained in the *GroupRecords* dataset. However, the road network data associated with each section includes additional attributes—such as *parent fix type* and *region*—which can be used to filter the data into meaningful subsets. Applying the two modeling approaches (Approach 1 and Approach 2) to these subsets enables a more targeted evaluation of pavement performance within specific treatment categories or geographic areas.

The following analysis focuses on the *IRI* condition metric and summarizes results obtained using *Approach 2* for various subsets. Sections were filtered first by *parent fix type*—with flexible results shown in Figure 16 and rigid results in Figure 17—and then by *region*—with flexible sections shown in Figure 18 and rigid sections in Figure 19. This allows for the comparison of deterioration trends across different treatment strategies and locations.

The results from both approaches, applied to these filtered subsets for *IRI FLX* and *IRI RIG*, are provided in Table 3 and Table 4 for Approach 1 and Approach 2, respectively.

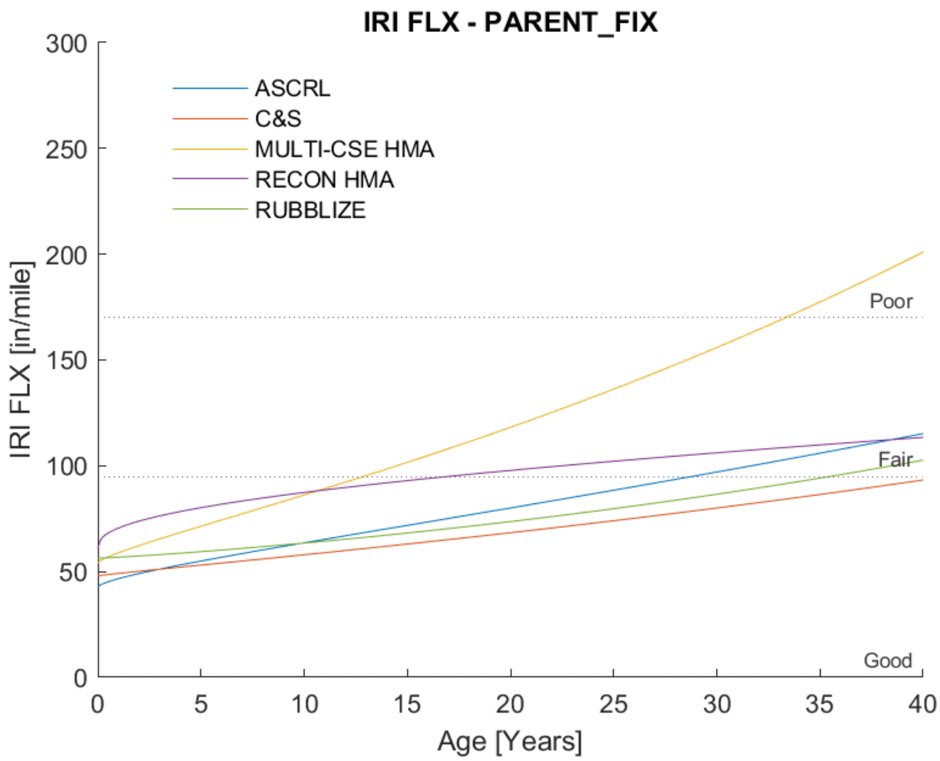


Figure 16. Approach 2 results for IRI FLX by parent fix type.

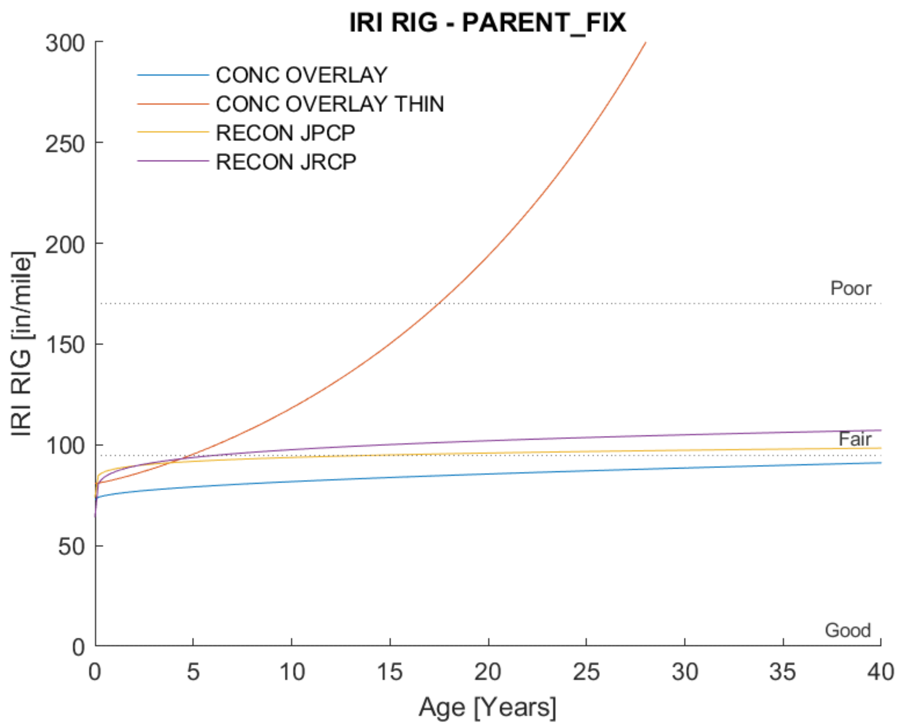


Figure 17. Approach 2 results for IRI RIG by parent fix type.

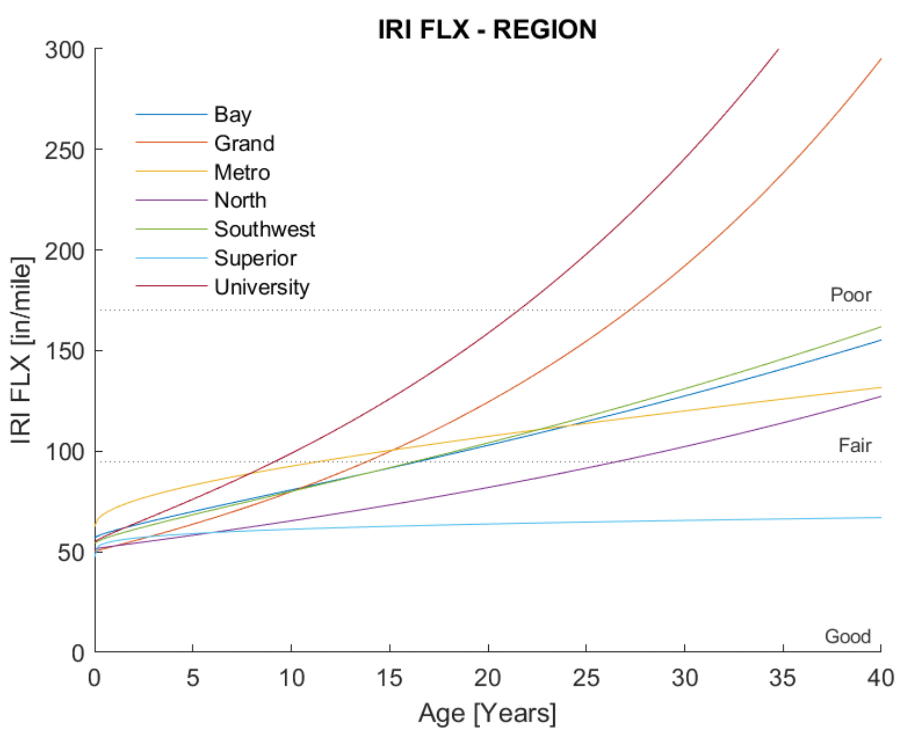


Figure 18. Approach 2 results for IRI FLX by region.

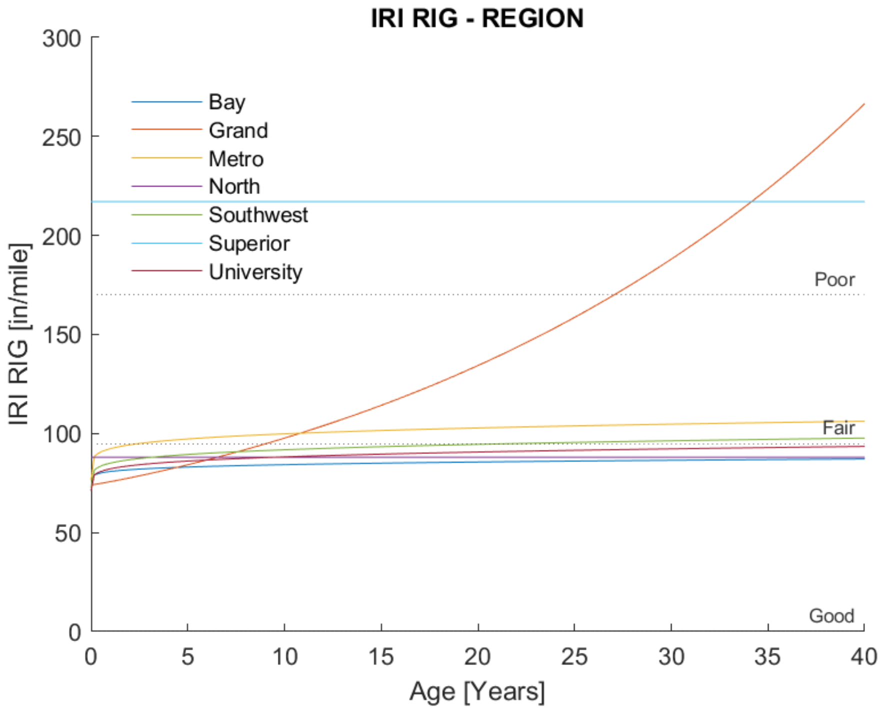


Figure 19. Approach 2 results for IRI RIG by region.

Table 3. Summary of results of Approach 1. Samples: Sections filtered by Parent fix. Condition metric: IRI (FLX and RIG)

GCR	PARENT_FIX	Approach 1 *		
		Thresholds		
		T_GF (Q2)	T_FP (Q2)	IRI_0 (Q2)
IRI FLX	ASCRL	24.4	47.4	42.8
IRI FLX	C&S	50.8	111	48.0
IRI FLX	MULTI-CSE HMA	15.4	35.9	54.2
IRI FLX	RECON HMA	25.4	104.5	61.1
IRI FLX	RUBBLIZE	34.3	72.4	56.3
IRI RIG	CONC OVERLAY	111	111	72.7
IRI RIG	CONC OVERLAY THIN	5.2	30.0	80.8
IRI RIG	RECON JPCP	111	111	74.0
IRI RIG	RECON JRCP	11.7	91.7	64.1

Table 4. Summary of results of Approach 2. Samples: Sections filtered by Parent fix. Condition metric: IRI (FLX and RIG)

GCR	PARENT_FIX	Approach 2 *				
		Fitting constants			Thresholds	
		A	B	IRI_0	T_GF_FIT	T_FP_FIT
IRI FLX	ASCRL	0.6601	0.0868	42.8	28.8	66.1
IRI FLX	C&S	0.9097	0.0232	48.0	41.2	81.2
IRI FLX	MULTI-CSE HMA	0.7492	0.0826	54.2	12.9	33.3
IRI FLX	RECON HMA	0.3951	0.1441	61.1	17.0	111
IRI FLX	RUBBLIZE	1.1650	0.0082	56.3	35.5	67.5
IRI RIG	CONC OVERLAY	0.4719	0.0395	72.7	57.5	111
IRI RIG	CONC OVERLAY THIN	1.1995	0.0241	80.8	4.9	17.5
IRI RIG	RECON JPCP	0.1342	0.1735	74.0	15.1	111
IRI RIG	RECON JRCP	0.1454	0.3013	64.1	6.4	111

ESTIMATING INITIAL IRI (IRI_0)

For the *IRI* condition metric, an initial IRI value (IRI_0) was estimated individually for each pavement section. This estimation was performed using a backcasting algorithm based on the methodology described in *"Backcasting Initial IRI for Surface Roughness Model Local Calibration"* (Singh and Haider 2024). This methodology is also described in the final report of the *"Testing Protocol, Data Storage, and Recalibration for Pavement-ME Design"* project (Haider et al. 2023: SPR-1723). Several methods were applied to backcast IRI_0 to year zero:

- Linear backcasting using the first ten years of IRI measurements
- Linear backcasting using all available IRI data
- Reducing the first measured IRI by 5 in/mile per year to age zero
- Threshold-based reduction:
  - Reduce by 5 in/mile/year if the first measured IRI > 100
  - Reduce by 4 in/mile/year if IRI is between 70 and 100
  - Reduce by 3 in/mile/year if IRI is below 70

The final IRI_0 value for each section was selected based on the following rules:

- Choose the back casted IRI from the above methods that is *closest to but below* the limit of 70 in/mile for flexible and rigid pavements, respectively.
- If all the back casted IRI from the above methods exceed the limit, select the one that is *closest above* the limit.
- For a small number of flexible pavement sections where the resulting IRI_0 was unreasonably low (e.g., below 30 in/mile), a default value of *30 in/mile* was assigned. This threshold may be adjusted in future work to better reflect recent observations of very smooth new pavements.

TASK 10. ACTION BENEFITS

The objective of Task 10 was to quantify the changes in pavement condition metrics resulting from the application of specific fixes. This task is closely linked to Task 12 (*Network Policy*), as both rely on analyzing condition metrics before and after maintenance/rehabilitation events.

To accomplish this, condition metrics were extracted at two key points for each fix event: the *last available measurement before* the fix ("before" or time 0), and the *first available measurement after* the fix ("after" or time 1). For a valid comparison, these measurements must directly precede and follow the fix without any other fix event occurring between them. In cases where a section was reconstructed, continuity between segments was maintained using *connectivity data* from the pavement list. The term *connectivity data* refers to information used to maintain continuity of pavement records through major fixes, such as rehabilitation (RHB) or reconstruction (RCN). When such a “large” fix is applied, the maintained section is often assigned a new segment ID in the database. As a result, any condition measurements taken after the fix—even if collected over the exact same physical location—are stored under this new ID rather than the original one. The pavement list includes fields identifying the *preceding* and *following* segment IDs, which represent the same physical location before and after the large fix. By using this connectivity information, it is possible to link the “before” condition data from the original ID with the “after” data from the new ID. This ensures that the computed improvements for RHB and RCN activities reflect true changes in condition across the same location, despite the change in segment ID.A comprehensive spreadsheet was developed to support this analysis, based on the *PDS-expanded stack* described in Task 9. This summary file includes a complete list of fix events along with the corresponding condition metric values (*IRI, CRK, RUT, FLT,* and *PDS*) immediately before and after each fix. It also includes road network data such as section ID, fix type, fix category (*CPM, Reconstruction,* or *Rehabilitation*), parent fix type, region, route, direction, tier, and job number.

Additional information recorded for each fix event includes:

- *Year* and *age* of the pavement at the time of the fix
- *Cycle number* of the treatment
- *Dates* of before and after measurements, used to calculate the measurement interval (*MAX_D_YR*), limited to a maximum of four years
- *Years since the previous fix* (*YR_2_PRE*) and *years until the next fix* (*YR_2_NXT*)

If both before and after measurements are available, the change (or improvement) in each condition metric is computed for that fix event. A screenshot of the spreadsheet is shown in Figure 20.

	ID	FLX_RIG	PARENT_FIX	TIER	YEAR	AGE	FIX_TYPE	FIX_CAT	CYCLE	IRI0	IRI1	I_IRI	CRK0	CRK1	I_CRK	RUT0	RUT1	I_RUT	FLT0	FLT1	I_FLT	PDS0	PDS1	I_PDS
2	391	FLX	MULTI-CSE HMA	4	2010	22	ASCRL	RHB	End	110	42	68	4	1	3	0.34	0.06	0.28				82.1	99.4	17.31
3	515	FLX	MULTI-CSE HMA	3	2008	17	ASCRL	RHB	End	139	84	55	19	0	19	0.3	0.07	0.23				82.8	100	17.16
4	1073	FLX	MULTI-CSE HMA	4	2011	12	ASCRL	RHB	End	121	44	77	7	0	7	0.13	0.06	0.07				55.2	100	44.8
5	2464	FLX	MULTI-CSE HMA	1	2006	14	ASCRL	RHB	End		42		4	1	3		0.05					50.7	100	49.28
6	2465	FLX	MULTI-CSE HMA	1	2006	14	ASCRL	RHB	End		39		6	1	5		0.05					44.4	100	55.65
7	3307	FLX	ASCRL	3	2003	0	ASCRL	RHB	Parent		43			0			0.05						100	
8	3455	FLX	ASCRL	4	2007	0	ASCRL	RHB	Parent		43			0			0.07						99.9	
9	3456	FLX	ASCRL	4	2007	0	ASCRL	RHB	Parent		37			0			0.07						100	
10	3457	FLX	ASCRL	4	2007	0	ASCRL	RHB	Parent		40			0			0.07						95.4	
11	3465	FLX	ASCRL	4	2014	0	ASCRL	RHB	Parent		52			0			0.06						100	
12	3527	FLX	ASCRL	3	2009	0	ASCRL	RHB	Parent		45			0			0.07						100	
13	3528	FLX	ASCRL	3	2009	0	ASCRL	RHB	Parent		56			0			0.07						100	
14	3535	FLX	ASCRL	1	2006	0	ASCRL	RHB	Parent		42		4	1	3		0.05					50.7	100	49.28
15	3536	FLX	ASCRL	1	2006	0	ASCRL	RHB	Parent		39		6	1	5		0.05					44.4	100	55.65
16	3579	FLX	ASCRL	2	2008	0	ASCRL	RHB	Parent		37			0			0.07						100	
17	3580	FLX	ASCRL	2	2008	0	ASCRL	RHB	Parent		41			0			0.07						100	
18	3581	FLX	ASCRL	2	2008	0	ASCRL	RHB	Parent		51			0			0.08						100	
19	3582	FLX	ASCRL	2	2008	0	ASCRL	RHB	Parent		49			1			0.08						100	
20	3677	FLX	ASCRL	3	2016	0	ASCRL	RHB	Parent		59			0			0.16						100	

Figure 20. Partial view of "Before-and-after" spreadsheet (bef_aft.xlsx). Each row corresponds to a fix-event. The "improvement" columns of the condition metrics are highlighted.

ANALYSIS BASED ON FIX CATEGORIES: RCN, RHB AND CPM

To analyze changes in each GCR across different improvement categories (RCN, RHB, or CPM), histograms were generated using the histogram Excel template developed in Task 9 (Figure 15). The process involved the following steps:

1. **Filter by pavement surface type** – Use the `FLX_RIG` column in `bef_aft.xlsx` excel sheet to select either FLX or RIG (see Figure 21).
2. **Filter by fix category** – Use the `FIX_CAT` column (see Figure 22).
3. **Exclude blank values** – For the selected GCR (e.g., I_IRI, representing improvement in IRI; see Figure 23), remove rows with blank cells.
4. **Generate histogram** – Copy the filtered GCR data (e.g., I_IRI) into the histogram template sheet (Figure 24) to create the histogram and calculate percentile values. Enter the desired percentile (as a fraction) in cell E19; the corresponding percentile value will appear in cell D19.

These steps were repeated for each GCR within each fix category. The resulting histogram Excel files are listed in Figure 25 and provided in the digital appendix. For each histogram, the 25th, 50th, and 75th percentiles were calculated and compiled in the file `FIX_CAT_Histograms_summary.xlsx`, under the sheet “`DistressI`”, whose contents are shown in Table 5.

It is important to note that some GCRs have a limited number of available data points, and their results should be interpreted with caution. For example, Table 5 shows that the 50th percentile improvement in cracking (I_CRK) for rigid pavement (RIG) rehabilitation (RHB) is 79.5%, but this is based on only 20 data points. In contrast, the corresponding value for flexible pavement (FLX) rehabilitation (RHB) is 9%, calculated from 283 data points.

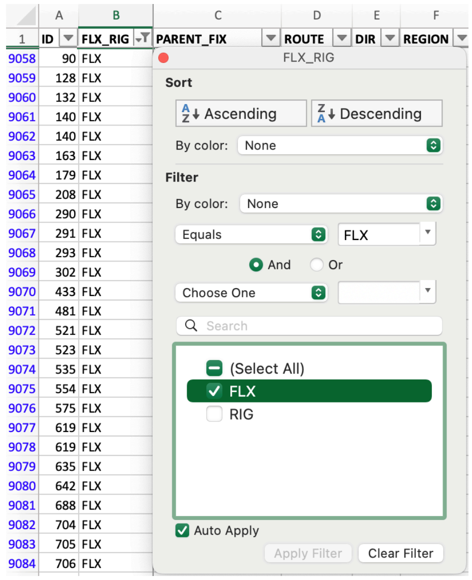


Figure 21. Filtering “bef_aft.xlsx” sheet based on “FLX_RIG” column

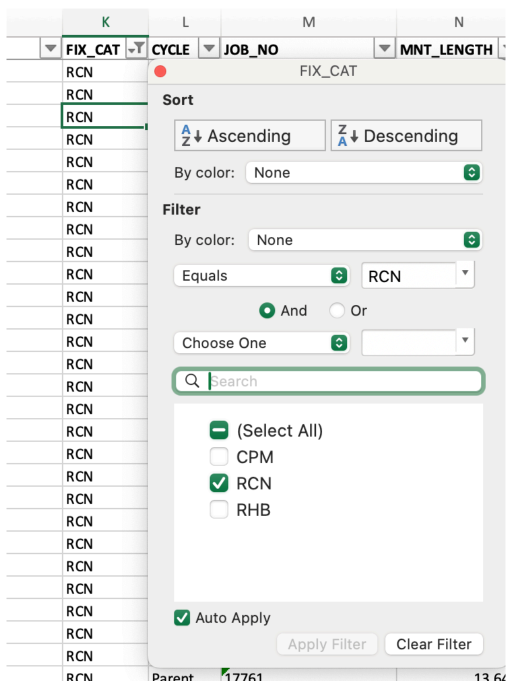


Figure 22. Filtering “bef_aft.xlsx” sheet based on “FIX_CAT” column

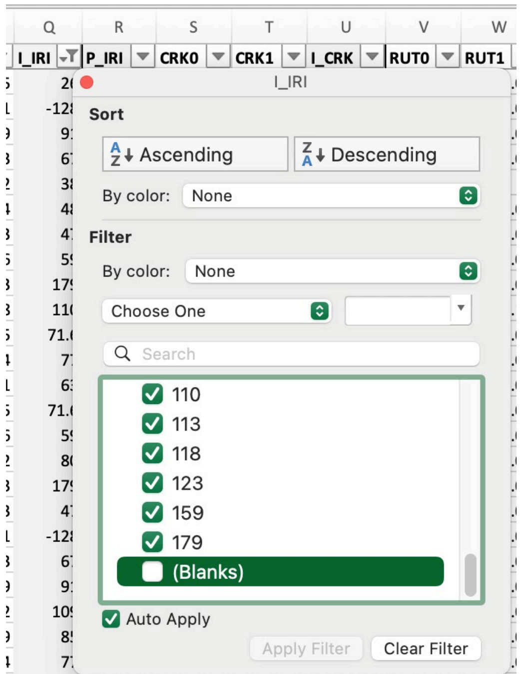


Figure 23. Filtering "bef_aft.xlsx" sheet based on "I_IRI" column to exclude the blank cells

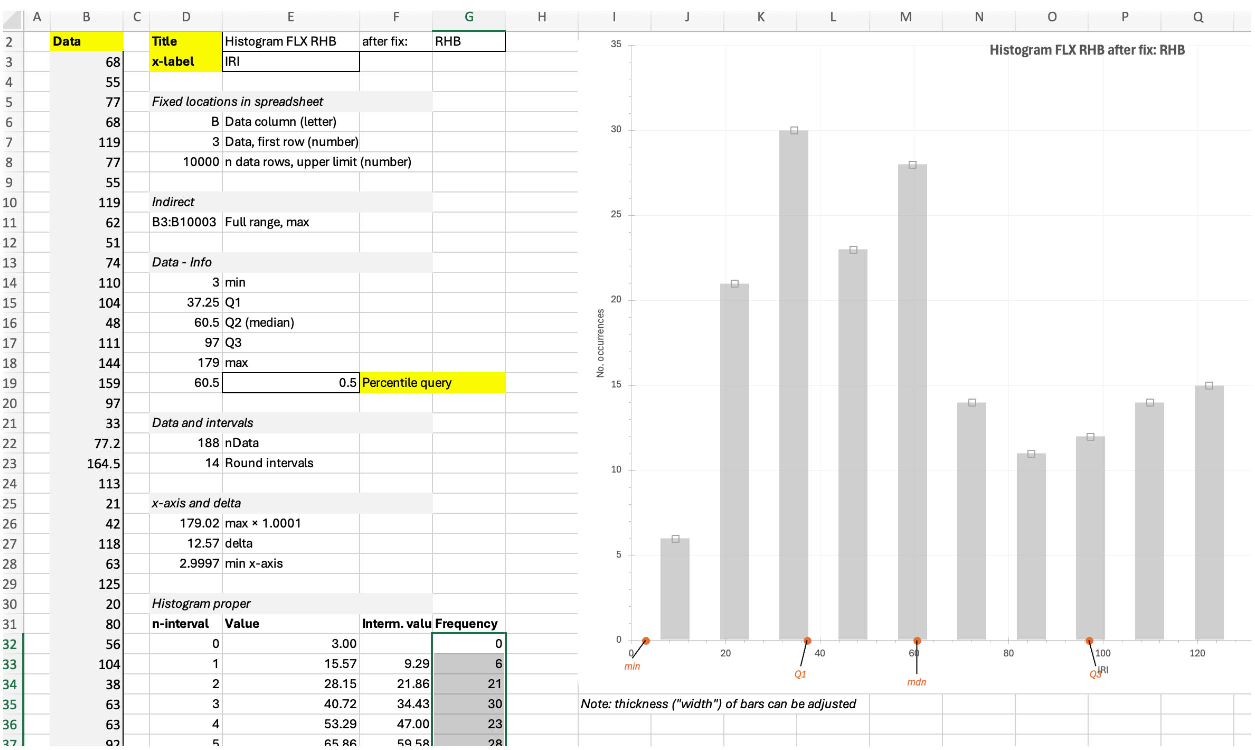


Figure 24. Pasting data into the histogram excel sheet template to compute the histogram and the desired percentile: for I_IRI.

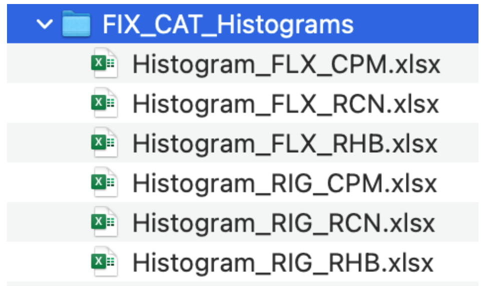


Figure 25. Histogram excel sheets prepared for each of the fix categories.

Table 5. Contents of the "DistressI" tab of "FIX_CAT_Histograms_summary.xlsx" excel sheet showing the improvements in each GCR

Surface	FIX_CAT	Improvement in GCR	25th Percentile	50th Percentile	75th Percentile	Units
FLX	1_CPM	I_CRK	-2	0	2	%
FLX	2_RHB	I_CRK	3	9	23	%
FLX	3_RCN	I_CRK	1.25	5	16.75	%
RIG	1_CPM	I_CRK	-2	0	7	%
RIG	2_RHB	I_CRK	19	79.5	93.25	%
RIG	3_RCN	I_CRK	6.5	32.5	76	%
RIG	1_CPM	I_FLT	-0.01	0.01	0.03	in
RIG	3_RCN	I_FLT	0.035	0.11	0.13	in
FLX	1_CPM	I_IRI	-6	-1	10	in/mile
FLX	2_RHB	I_IRI	37.75	60.5	97	in/mile
FLX	3_RCN	I_IRI	38	66.5	91	in/mile
RIG	1_CPM	I_IRI	-7	-1	5	in/mile
RIG	2_RHB	I_IRI	64	113	140	in/mile
RIG	3_RCN	I_IRI	33	61	118.7	in/mile
FLX	1_CPM	I_PDS	-4.2	0.0	8.4	-
FLX	2_RHB	I_PDS	12.7	34.5	58.7	-
FLX	3_RCN	I_PDS	4.0	31.2	55.3	-
RIG	1_CPM	I_PDS	-5.4	-0.4	1.9	-
RIG	2_RHB	I_PDS	10.1	14.4	28.7	-
RIG	3_RCN	I_PDS	7.1	17.3	37.5	-
FLX	1_CPM	I_RUT	-0.02	0	0.03	in
FLX	2_RHB	I_RUT	0.06	0.09	0.14	in
FLX	3_RCN	I_RUT	0.04	0.07	0.14	in

Figure 26 presents the 50th percentile improvement in IRI for each fix category, separated by pavement type. Among flexible pavements, reconstruction (RCN) and rehabilitation (RHB) show substantial median IRI reductions of approximately 66.5 in/mi and 60.5 in/mi, respectively, while CPM shows no meaningful improvement (−1 in/mi). For rigid pavements, rehabilitation (RHB) yields the highest improvement at roughly 113 in/mi, followed by reconstruction (RCN) at about 61 in/mi, with CPM again showing negligible change (−1 in/mi).

Importantly, there are two reasons why some combinations of fix categories and GCRs demonstrate very little or no change. The first is that the fix type does not cause a change in the specific GCR value, such as the case for IRI and CPM. Many studies (e.g., Rada et al., 2016) show that the majority of preservation treatments do not cause an immediate change in IRI. The second reason is that a fix type is applied to a pavement in good condition, so the maximum possible change is small. CPM is expected to be performed on pavements in relatively good condition, so the possible percentage improvement in condition is also small. For example, if a CPM is placed on a pavement with a PDS of 90, then the most it can improve is 10 percent.

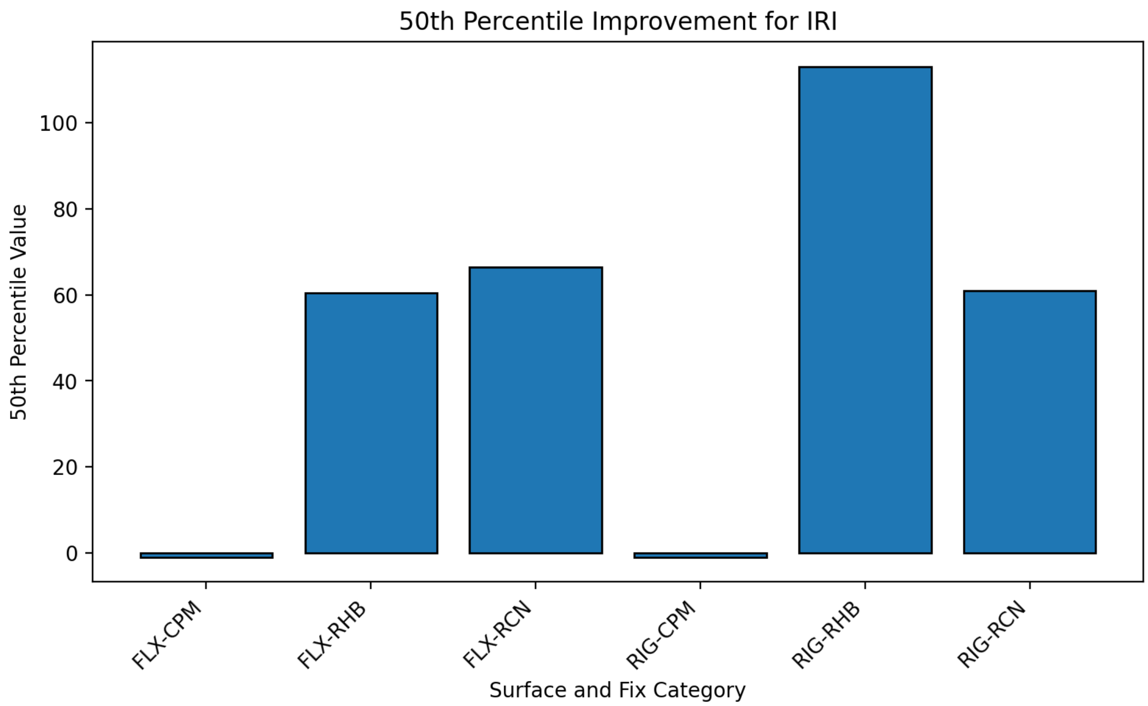


Figure 26. IRI improvement for each fix category

Figure 27 shows the 50th percentile improvement in PDS for each fix category by pavement type. For flexible pavements, the median PDS improvement is highest for rehabilitation (RHB) at about 34.5 points, followed closely by reconstruction (RCN) at 31.2 points, while CPM shows no change (0 points). For rigid pavements, reconstruction (RCN) yields the largest median improvement at roughly 17.3 points, rehabilitation (RHB) achieves 14.4 points, and CPM results in a slight decrease (−0.4 points)

Figure 28 illustrates the 50th percentile improvement in cracking (I_CRK) for each fix category, separated by pavement type. For flexible pavements, rehabilitation (RHB) achieves the highest median improvement at 9%, followed by reconstruction (RCN) at 5%, while CPM shows no change (0%). In contrast, rigid pavements exhibit substantially larger gains from major interventions, with rehabilitation (RHB) producing a median improvement of 79.5% and reconstruction (RCN) yielding 32.5%. CPM for rigid pavements shows no measurable improvement (0%).

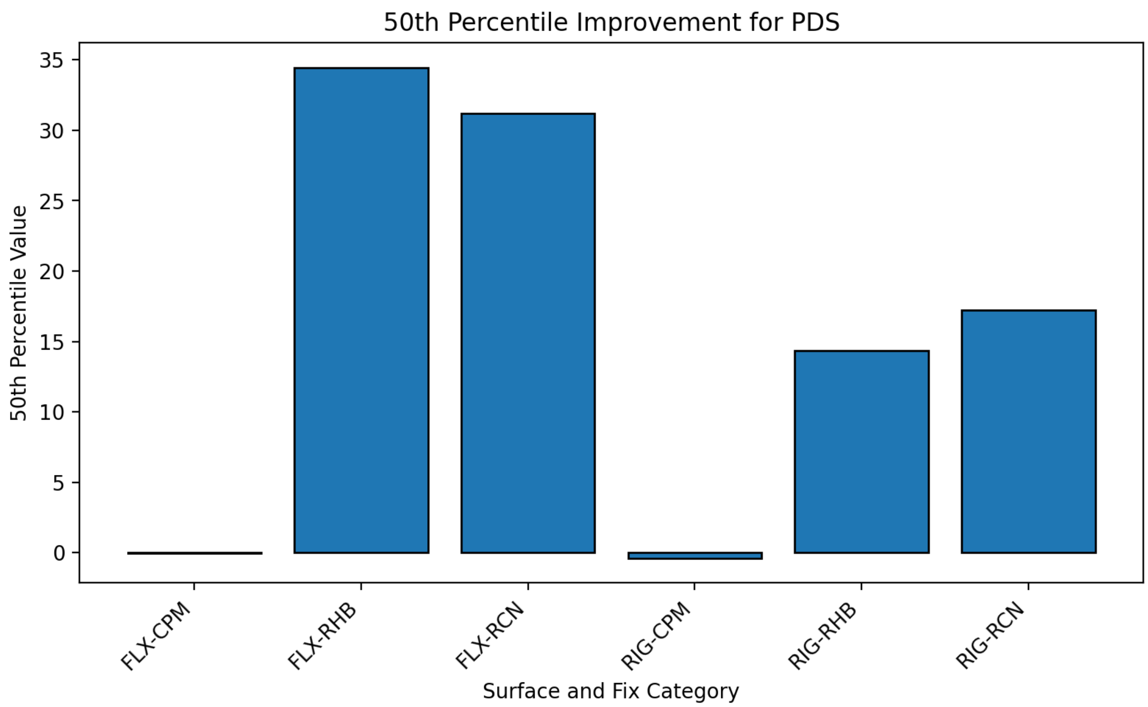


Figure 27. PDS improvement for each fix category

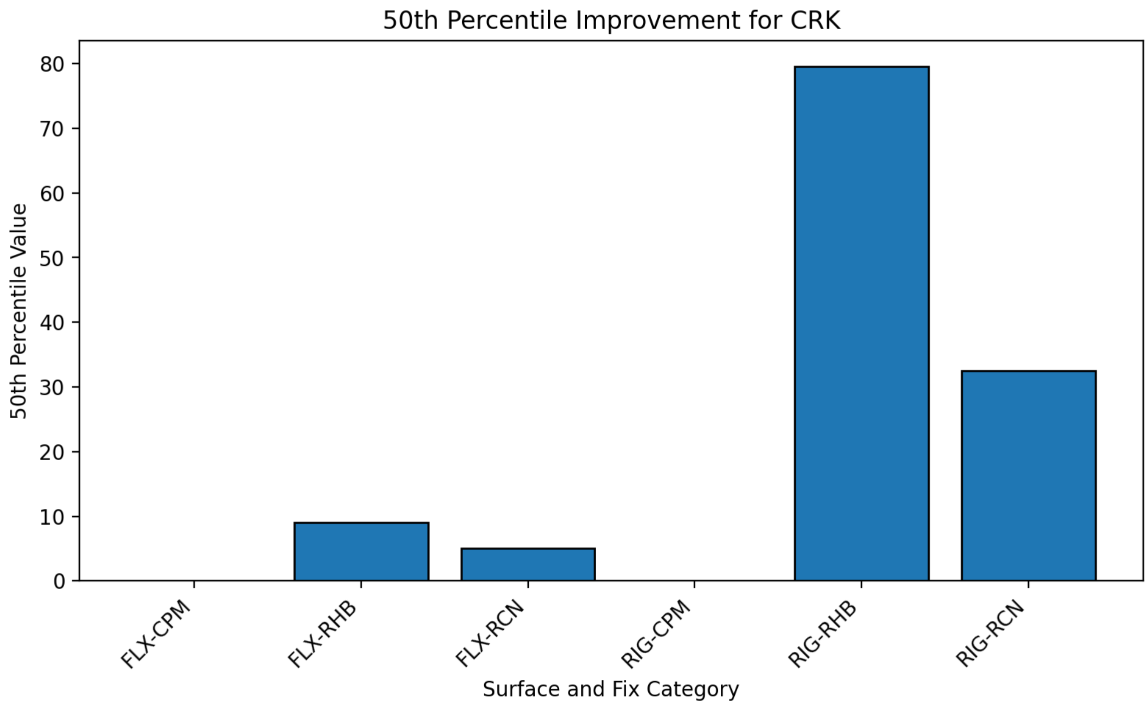


Figure 28. CRK improvement for each fix category

Figure 29 presents the 50th percentile improvement in rutting (I_RUT) for each fix category in flexible pavements. Rehabilitation (RHB) achieves the highest median improvement at approximately 0.09 inches, followed closely by reconstruction (RCN) at 0.07 inches, while CPM shows no change (0 inches).

Figure 30 shows the 50th percentile improvement in faulting (I_FLT) for each fix category in rigid pavements. Reconstruction (RCN) delivers the highest median improvement at approximately 0.11 inches, followed by CPM at 0.01 inches. Rehabilitation (RHB) values are not reported for I_FLT in the available dataset due to lack of before-fix and/or after-fix faulting data for all projects.

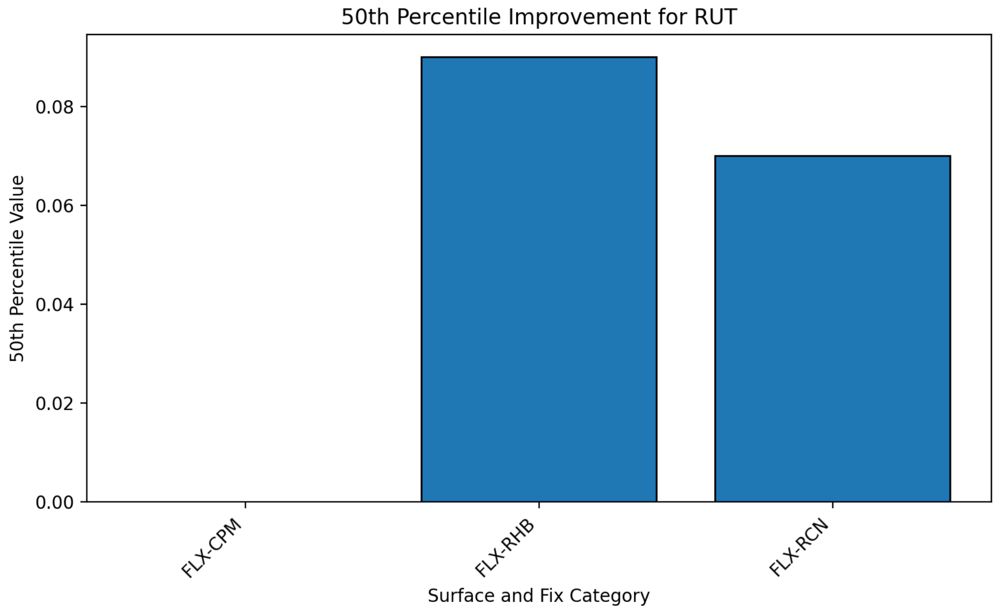


Figure 29. RUT improvement for each fix category

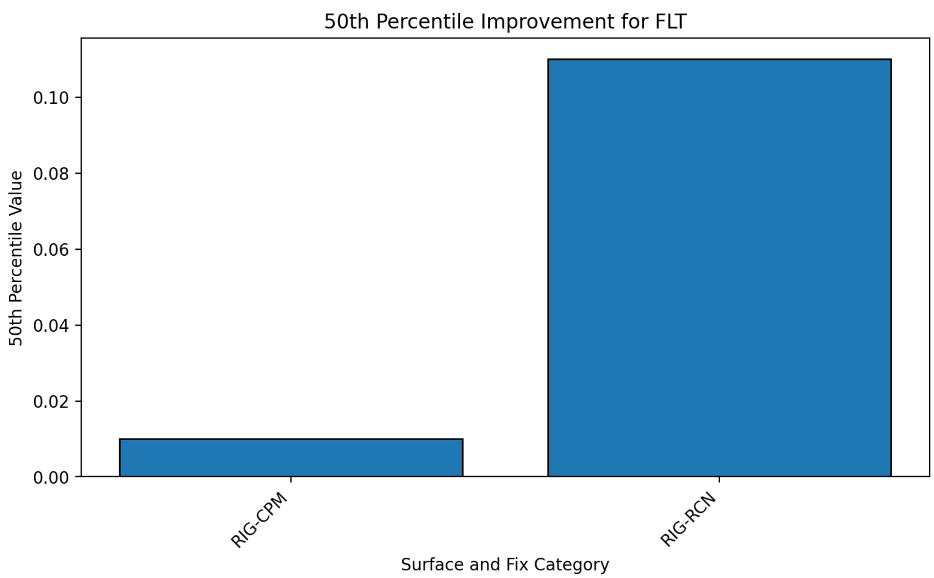


Figure 30. FLT improvement for each fix category

ANALYSIS BASED ON EACH INDIVIDUAL FIX TYPE

The procedure described in the previous section was repeated for each specific fix type (as listed in the FIX_TYPE column) rather than for the broader fix categories (FIX_CAT). The resulting histogram Excel sheets are provided in the "FLX_Histograms" and "RIG_Histograms" folders in the digital appendix. As examples, Figure 31 and Figure 32 present these histograms as boxplots for IRI FLX and PDS FLX, respectively. The full set of before-and-after data, calculated improvements, and summary figures is included in the digital appendix for further analysis.

The digital appendix also contains two summary files—*FLX_Histograms_summary.xlsx* and *RIG_Histograms_summary.xlsx*—which list the 25th, 50th, and 75th percentiles for each fix type (like Table 5 but for reach fix type). Due to the length of these lists, they are not reproduced in this report to maintain brevity.

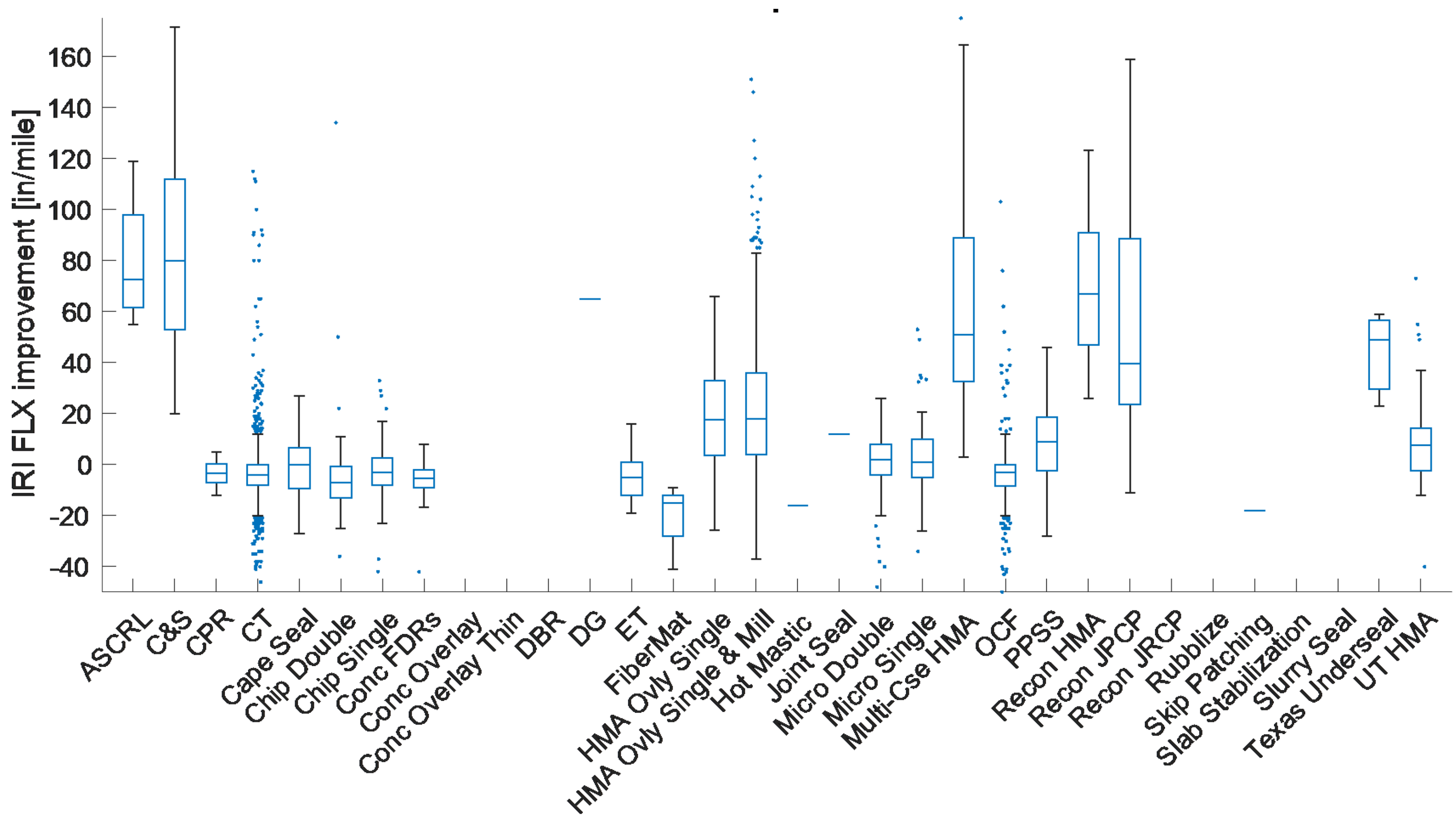


Figure 31. Improvement in IRI FLX by fix type.

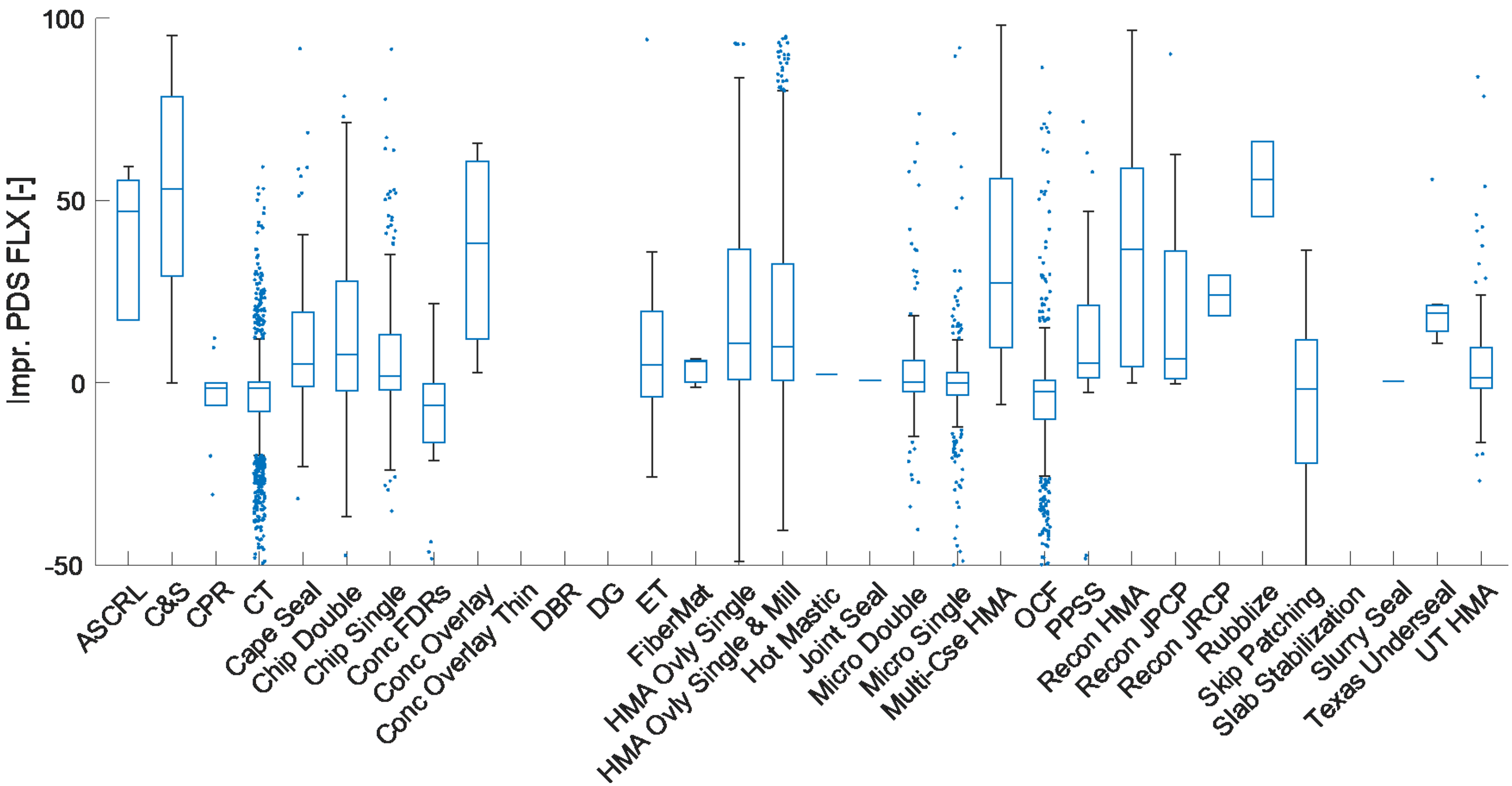


Figure 32. Improvement in PDS FLX by fix type.

TASK 11. UTILITY SCORING

The potential new PMT utilizes the concept of utility, where utility is a scaled value from 100 to 0, with 100 representing a “perfect” pavement and 0 representing the absolute worst. Each GCR is measured on a different scale with units that are not directly comparable to one another, and therefore, the utility score allows for a direct comparison of the GCR values. The change in utility score from just before an action to after the action is used to calculate a cost/benefit value. Furthermore, the utility scores are incorporated into a weighted overall decision tree to calculate a weighted utility score for each pavement segment.

This chapter presents the results of work conducted to develop a more systematic approach to constructing the utility curves for the GCRs. This task began with a review of practices used by other DOTs to calculate utility and scaling values to develop recommendations for MDOT. Then, a simple Excel® based tool was developed to implement the recommendations. The remainder of this chapter presents the review's results and the resulting recommendations.

REVIEW OF PRACTICES IN UTILITY THEORY

Utility theory is a concept that is extensively used in applications involving complex decision-making (Edwards, 1954; Fishburn, 1990; Dyer et al., 1992). More recently, the use of cross-asset utility theory in transportation asset management has highlighted the application of utility theory (Maggiore & Ford, 2015). Bryce *et al.* (2014) demonstrated how utility theory can be applied to investigate the tradeoff between the condition of a pavement network, its maintenance and rehabilitation budget, and the environmental impacts of managing that pavement network.

Utility theory is a method in which a decision maker's values are quantified over a range of feasible outcomes. Then, the values are combined with the corresponding probabilities of each outcome to form a set of utility values. The motivating factor behind utility theory is that if an appropriate utility is assigned to each possible outcome and the expected utility of each alternative is calculated, the best alternative is the one that maximizes the overall utility (Keeney and Raiffa, 1993). The strength of utility theory lies in the use of the relative scale of preference between possible outcomes for each variable to determine the best alternative from the set of feasible alternatives. In other words, the range of values and differences in potential values are used to scale preferences. For example, it is not assumed that increasing a variable four times the original amount is preferred twice as much as increasing it by a factor of two.

For uni-dimensional utility theory, the utility value describes one attribute, such as a single GCR. However, the condition of a pavement is generally defined by many attributes taken together. Thus, multidimensional utility theory is employed, and the individual utility values are combined to describe multiple attributes (i.e., multiple GCR values) in a given state.

The majority of applications of utility theory in the transportation engineering literature are for use in cross-asset resource allocation, as detailed in the National Cooperative Highway Research Program (NCHRP) Report 806 (Maggiore & Ford, 2015). Spy Pond Partners, LLC*, et al.* (2019) and Nicolosi, *et al*. (2023) present case studies of cross-asset resource allocation. Cross-asset resource allocation is the application of decision analysis techniques to address the question of how to best allocate resources (e.g., finances) from a single source among the various types of assets an agency manages. For example, the NCHRP Report 806 demonstrates the application of common decision analysis techniques, such as utility theory and the Analytical Hierarchy Process (AHP), to scale and apply weights to the outcomes of individual management systems, thereby determining the amount of resources to distribute to the assets under consideration.

The Texas DOT utilizes utility theory to calculate its Distress Score (Gharaibeh et al., 2012). Each severity for each distress is measured using a density, such as the quantity of distress per section area, and then a utility score is assigned based on the density. The calculation of a distress density is not the same for each distress, but follows a similar structure to American Society of Testing Materials (ASTM) Standard 6433 for the calculation of the Pavement Condition Index (PCI). A utility score is calculated for each distress-severity combination for each family of pavements. The Distress Score is calculated as 100 times the product of all relevant utility values. Figure 33 shows an example utility curve used by Texas DOT, and can be interpreted as follows:

- For density values between zero and 15, the utility value is maximum, meaning that the given distress and severity does not reduce the distress score
- For density values 15 to 30, small increases in density lead to significant decreases in utility values
- Density values above 40 remain near the minimal utility value, meaning that there is practically no difference between a severity of 40 and a severity of 100.

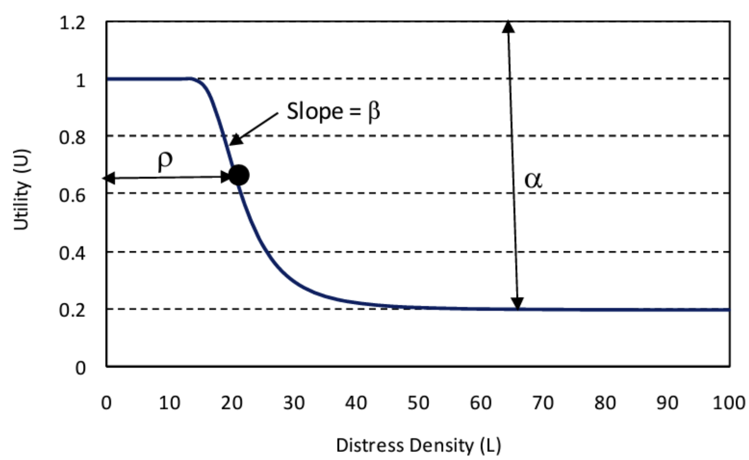


Figure 33. Example utility curve (Gharaibeh, et al. 2012)

The utility scores used by the Texas DOT were developed based on expert opinion and have been recalibrated based on evaluations from the Performance Management System (PMS). Abu-Samra *et al.* (2017) describe another approach developed for utilizing utility theory in pavement condition data analysis and demonstrate its application with data from the Nebraska DOT. The approach of Abu-Samra *et al.* (2017) is similar to that of the Texas DOT, and the utility curves were also developed using expert opinion.

Li and Sinha (2004) described the use of utility theory for informing tradeoff analysis across highway assets. Several performance measures were defined, including pavement condition and utility curves were developed for each of these measures. Similar to Gharaibeh, *et al*. (2012) and Abu-Samra *et al.* (2017), Li and Sinha (2004) developed the utility curves based on expert opinion.

There is no standard method in the literature for developing utility curves; however, several steps can help guide the procedure. Keeney and Raiffa (1993) present a five-step process to help guide the process. Each of the five steps is discussed in further detail next.

Step 1 – Preparing for the Assessment

This step involves explaining the reasons for developing the utility curves, which describe the decision makers' preferences, and other initial steps to prepare the decision maker for the assessment. Another aspect of this step is defining the range over which the preferences will be evaluated. The range of values is critical because a range that is significantly larger than the scale of achievable values will minimize the impact of the achievable values in the decision-making process. However, it is important to note that the upper bound on the utility curve does not necessarily need to reflect what is currently achievable, only that the range of values for the utility curve are feasible estimates for the variable being modeled. An example given in Keeney and Raiffa (1993) is that given a range of criteria from 0 to 8.75, setting the bound of the utility curve at 0 and 10 is reasonable, whereas setting the upper bound at 10,000 would have very little meaning to the decision maker.

Step 2 – Identify the Relevant Qualitative Characteristics

Some key steps in identifying the relevant criteria are to determine whether the utility curve is concave or convex and to identify the range of values to which the utility curve is most sensitive. For the example shown in Figure 33, the utility curve is not sensitive to changes in density between 0 and 15 or above 40.

Step 3 – Specifying Quantitative Restrictions

This step involves addressing multiple points along the utility curve, including identifying the midpoint of the curve. Qualitative preferences can be translated to quantitative constraints during this step. For example, the analyst can specify the following:

- Changes in PDS from 80 to 70 should have twice the impact as changes in PDS from 100 to 90
- A PDS of 70 should have a utility of 0.5

Figure 34 shows an example utility curve that meets the above-specified criteria: the change in utility values when PDS changes from 100 to 90 is approximately 0.1, and the change in utility values when PDS changes from 80 to 70 is approximately 0.2.

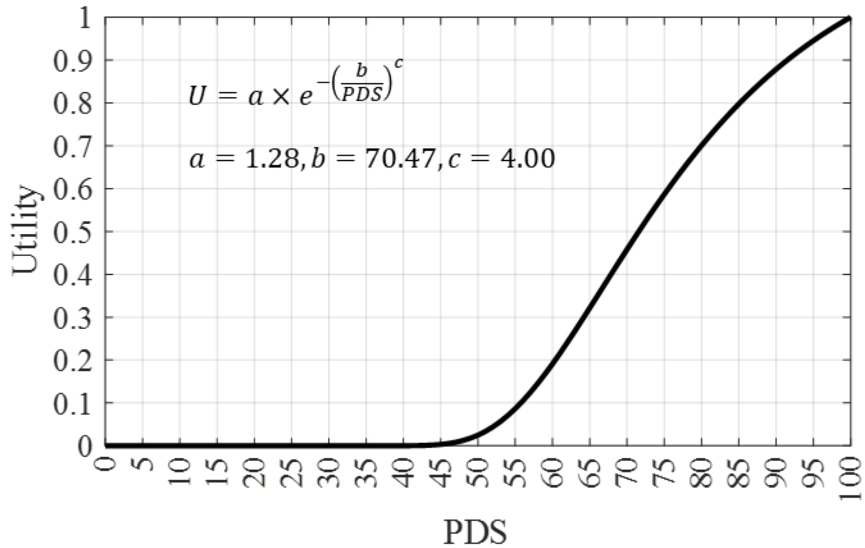


Figure 34. Example PDS Utility Curve

This step also includes checks for consistency among the expert opinions, typically by asking questions where the answer can be verified using previous responses provided by the decision-makers. For example, if an IRI value of 140 inches per mile is selected as having a utility value of 0.5, then an IRI value of 160 inches per mile cannot be assigned a value of 0.6.

Step 4 – Choosing Utility Curve

Choosing the utility curve involves more than just fitting a curve to the data points; it is also important for the curve to match the preferences of the experts. Examples of multiple different utility curves are demonstrated later in this chapter.

Step 5 – Checking for Consistency

Several checks for consistency can be used to validate the curve and preferences developed by the decision maker. Many of these checks are made in real time as the curve is defined. This step should also include a sensitivity analysis, such as the simple sensitivity analysis shown later in this chapter.

DEVELOPMENT OF SIMPLE UTILITY CURVE TOOL

A simple Excel-based tool was developed for MDOT to update its utility curves for the GCRs and PDS. The objectives of the tool are to:

- Present many example utility curves for percent cracking, rutting, faulting, and IRI.
- Provide users with the ability to update performance curves and visualize the results.
- Allow users to specify different levels of importance to each GCR and display the results by combining the utility values.

- Be constructed in such a way that future users can simply update it and that it does not require external add-ins or macros to use.

The following are the sheets included in the Excel® tool:

- **Instructions** sheet provides very basic instructions to using the tool
- **Util_Calculation AC** sheet is where GCR values are input, each GCR is weighted and the overall utility values are calculated for asphalt pavements
- **Util_Calculation PCC** sheet is where GCR values are input, each GCR is weighted and the overall utility values are calculated for concrete pavements
- **IRI_Util** is where the analyst modifies the coefficients for equation [13] or equation [14] to define the preferred utility curve. The following sheets serve the same purpose for different GCRs: **Rutting_Util**, **Cracking_Util**, **Faulting_Util** and **PDS_Util**.
- **IRI_ExampleCurves** provides a set of utility curves for IRI using equation 1 and equation 2 for the analyst to use as guidance. The following sheets serve the same purpose for different GCRs: **Rutting_ExampleCurves**, **Cracking_ExampleCurves**, **Faulting_ExampleCurves** and **PDS_ExampleCurves**.

The next sections of this chapter describe the main components of the tool.

Example Utility Curves

Two example utility curves were selected based on those found in literature, and they are shown in equations below:

$$U = 1 - a \times e^{-\left(\frac{b}{x}\right)^{c}} \qquad [13]$$

$$U = 1 - e^{a - b \times c^{\log\frac{1}{x}}} \qquad [14]$$

where *U* is the utility value, which ranges from zero to one, the coefficients *a, b* and *c* are modified to fit the curve and *x* is the input, which changes for each GCR. For example, *x* is defined as IRI minus IRIref (IRIref = a reference IRI for roughness), and percent cracking plus one for cracking. Adding small values to cracking, rutting and faulting in the equations ensures that a utility value can be calculated when any of those values are zero. The value for IRIref was selected as an approximate lower bound for the IRI, and allows for the curvature for low values of IRI to be more sensitive to the model coefficients.

Next, a series of example utility curves was developed for each GCR using both equations, and these are presented in a series of tabs within the Excel tool. The goal of the example curves was to demonstrate a range of potential curves along with the coefficients corresponding to each. Figure 35 illustrates an example utility curve derived from equation [13]. The results in Figure 35 can be interpreted as:

- There is practically no difference between a PDS equal to zero and a PDS equal to 25 – values in that range are assigned a utility of zero.

- A PDS value of 70 is assigned a utility of 0.9, whereas a PDS value 60 is assigned a utility of 0.8. This implies that a change in PDS from 100 to 70 has an equal effect on utility as a change in PDS from 70 to 60.

Figure 36 shows an example utility curve using equation [14]. The results can be interpreted as:

- There is practically no difference between a PDS equal to zero and a PDS equal to 40 – values in that range are assigned a utility of zero.
- A PDS of 90 is assigned a utility of 0.75, and a PDS of 80 is assigned a utility of 0.5, which means that changes from 100 to 90 has an equal effect on utility as a change from 70 to 60.

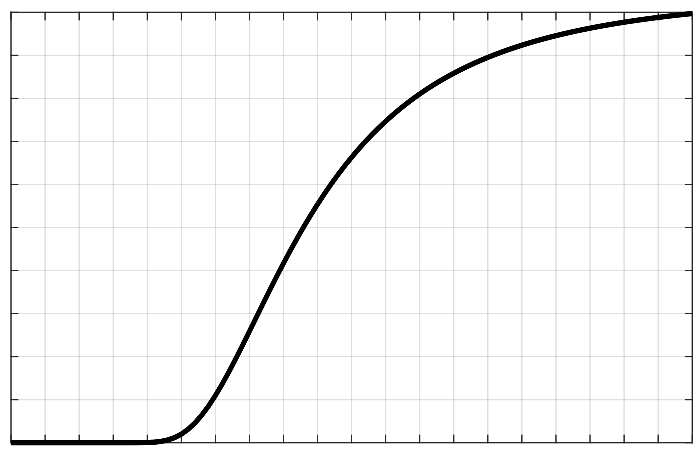


Figure 35. Example utility curve for PDS using equation [13]

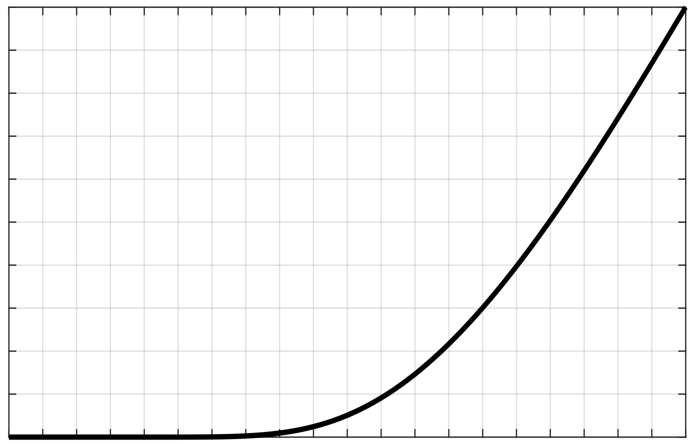
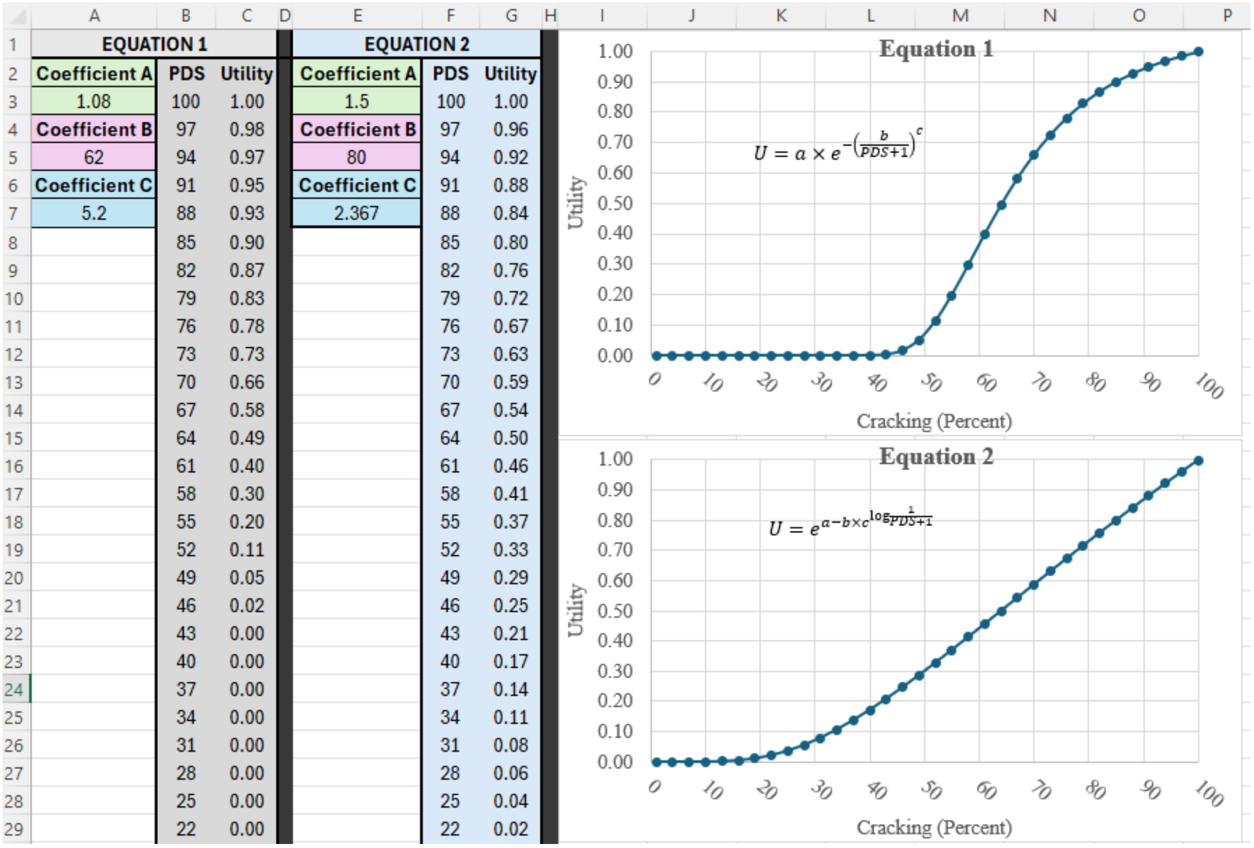


Figure 36. Example utility curve for PDS using equation [14]

Utility Curve Development

The example utility curves are provided as a starting point, and the tool also allows users to modify the coefficients in equations [8] and [14]. Figure 37 shows a screenshot of the Excel sheet used for developing a PDS utility curve. The values for coefficients A, B, and C can be changed, and the updated curves are plotted for the analyst to select the utility curve that best represents the user's preferences.



	A	B	C	E	F	G
1	EQUATION 1			EQUATION 2		
2	Coefficient A	PDS	Utility	Coefficient A	PDS	Utility
3	1.08	100	1.00	1.5	100	1.00
4	Coefficient B	97	0.98	Coefficient B	97	0.96
5	62	94	0.97	80	94	0.92
6	Coefficient C	91	0.95	Coefficient C	91	0.88
7	5.2	88	0.93	2.367	88	0.84
8		85	0.90		85	0.80
9		82	0.87		82	0.76
10		79	0.83		79	0.72
11		76	0.78		76	0.67
12		73	0.73		73	0.63
13		70	0.66		70	0.59
14		67	0.58		67	0.54
15		64	0.49		64	0.50
16		61	0.40		61	0.46
17		58	0.30		58	0.41
18		55	0.20		55	0.37
19		52	0.11		52	0.33
20		49	0.05		49	0.29
21		46	0.02		46	0.25
22		43	0.00		43	0.21
23		40	0.00		40	0.17
24		37	0.00		37	0.14
25		34	0.00		34	0.11
26		31	0.00		31	0.08
27		28	0.00		28	0.06
28		25	0.00		25	0.04
29		22	0.00		22	0.02

Figure 37. Screenshot of Utility Curve Development Sheet for PDS (PDS_Util)

The main utility curve development sheets (e.g., *PDS_Util*, *IRI_Util*, etc.) in the tool are linked directly to the utility calculation sheet (*Util_Calculation AC* or *Util_Calculation PCC*). Analysts can also choose to change the form of equation 1 or equation 2 by modifying the calculations in columns C or G (respectively). The equations are not coded into the main utility calculations in sheets *Util_Calculation* AC and *Util_Calculation* PCC, so updates to the utility curve development sheets will be reflected in the utility calculation sheets.

Utility Calculations

The sheets on the Excel® tool labeled *Util_Calculation AC* and *Util_Calculation PCC* are where GCR data are input and resulting utility values are calculated. Figure 38 is a screenshot of the *Util_Calculation AC* sheet, and contains the following information:

- A section to define weights (cells A2 through B5). These weights represent the relative importance of each GCR for the combined calculation (column M). These weights are used to calculate a weighted average of each GCR utility – i.e., the combined utility.
- A section to select the equation for each GCR (cells A8 through B11). These are dropdown menus to select either equation [13] or equation [14], which are directly linked to the utility curve sheets, such as *PDS_Util.*

- A section for inputting the GCR values (columns D through G). A series of example data are shown in Figure 38.
- A set of output utility values (columns I through M). These cells should not be modified and are linked directly to the utility curve sheets (PDS_Util) to assign utility values using either equation [8] or equation [9], depending on the selection made. The combined utility is a weighted average calculation based on the weights assigned.

	A	B	D	E	F	G	I	J	K	L	M
1	Asphalt Weights (0 to 10)		Asphalt GCR Inputs				Utility Values (Outputs)				
2	IRI	1	IRI	Cracking	Rutting	PDS	IRI	Cracking	Rutting	PDS	Combined
3	Cracking	1	90	5	0	82	0.73	0.94	1.00	0.76	0.86
4	Rutting	1	120	5	0	82	0.50	0.94	1.00	0.76	0.80
5	PDS	1	160	5	0	82	0.25	0.94	1.00	0.76	0.74
6			200	5	0	82	0.05	0.94	1.00	0.76	0.69
7	Select Equation		90	5	0	82	0.73	0.94	1.00	0.76	0.86
8	IRI	Equation 2	90	10	0	82	0.73	0.68	1.00	0.76	0.79
9	Cracking	Equation 1	90	15	0	82	0.73	0.48	1.00	0.76	0.74
10	Rutting	Equation 2	90	20	0	82	0.73	0.35	1.00	0.76	0.71
11	PDS	Equation 2	90	5	0.1	82	0.73	0.94	0.78	0.76	0.80
12			90	5	0.2	82	0.73	0.94	0.49	0.76	0.73
13			90	5	0.3	82	0.73	0.94	0.27	0.76	0.67
14			90	5	0.4	82	0.73	0.94	0.11	0.76	0.63
15			90	5	0	100	0.73	0.94	1.00	1.00	0.92
16			90	5	0	80	0.73	0.94	1.00	0.73	0.85
17			90	5	0	60	0.73	0.94	1.00	0.44	0.78
18			90	5	0	40	0.73	0.94	1.00	0.17	0.71

Figure 38. Screenshot of Util_Calculation AC sheet

EXAMPLE CALCULATIONS

A set of example calculations was developed to demonstrate the approach in the tool. The following GCRs for asphalt pavements were used: IRI, cracking, rutting, PDS. First, the utility curves for each GCR must be assigned. It was decided to use equation [13] and the following values were used as coefficients (a, b, and c, respectively):

- IRI: ($a = 1.1$, $b = 80$ and $c = 1.9$). See Figure 39 for the utility curve.
- Rutting: ($a = 1.1$, $b = 0.15$ and $c = 1.9$). See Figure 40 for the utility curve.
- Cracking: ($a = 1$, $b = 12$ and $c = 1.5$). See Figure 41 for the utility curve.
- PDS: ($a = 1.08$, $b = 62$ and $c = 5.2$). See Figure 42 for the utility curve.

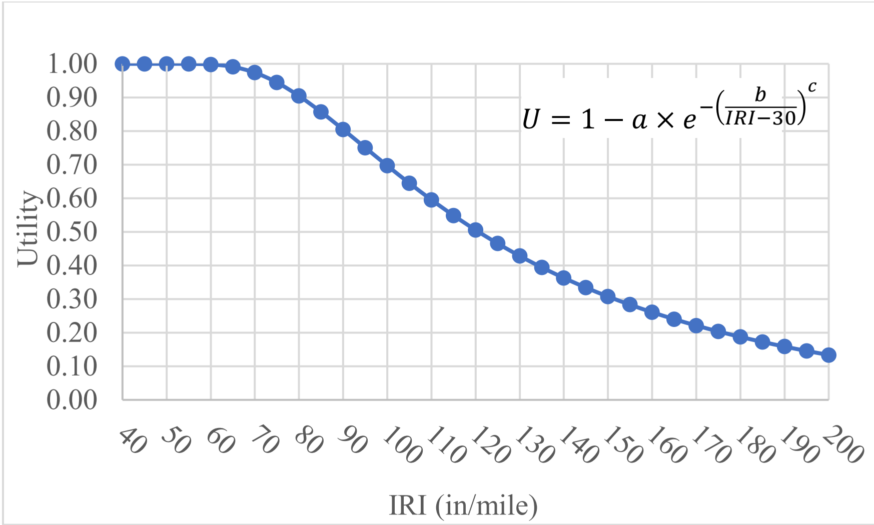


Figure 39. IRI utility curve using equation [13] with *a* = 1.1, *b* = 80 and *c* = 1.9.

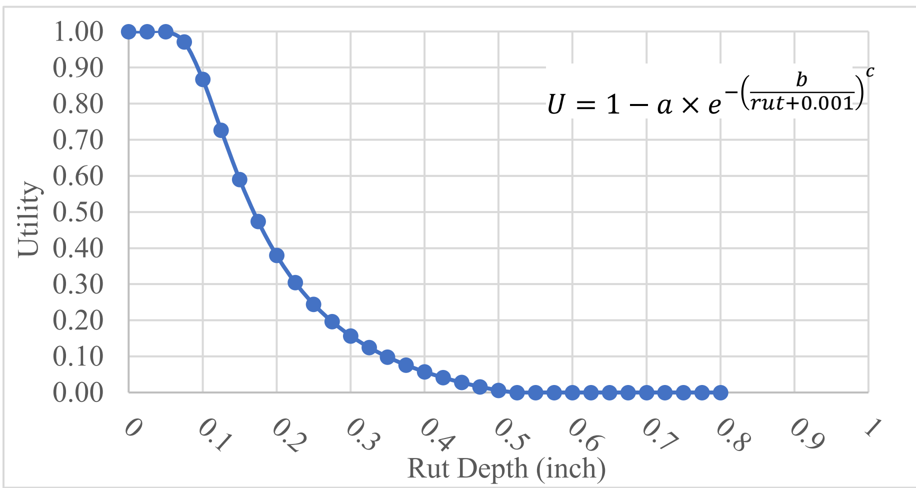


Figure 40. Rutting utility curve using equation [13] with *a* = 1.1, *b* = 0.15 and *c* = 1.9

Next, the input data were developed, and those are shown in Table 6. The inputs were designed to demonstrate a simple sensitivity analysis, beginning with a pavement in very good condition and then changing each GCR one at a time to poor values, with the last row representing a pavement in very poor condition. All weights were set to one, and the utility values were calculated for each GCR and then combined into a single weighted utility value for each segment. The resulting utility values are shown in Table 7. The pavement in very good condition has an overall (combined) utility value of 0.96, whereas the very poor pavement has an overall utility of 0.12.

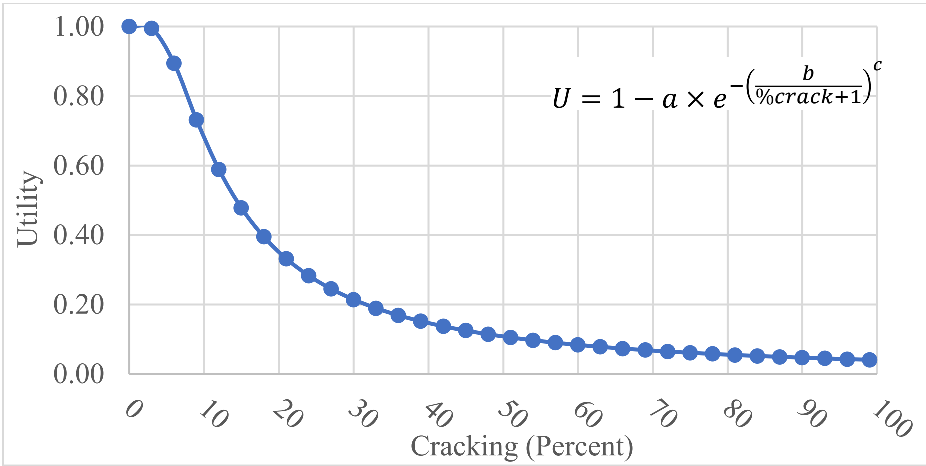


Figure 41. Cracking utility curve using equation [13] with *a* = 1, *b* = 12 and *c* = 1.5

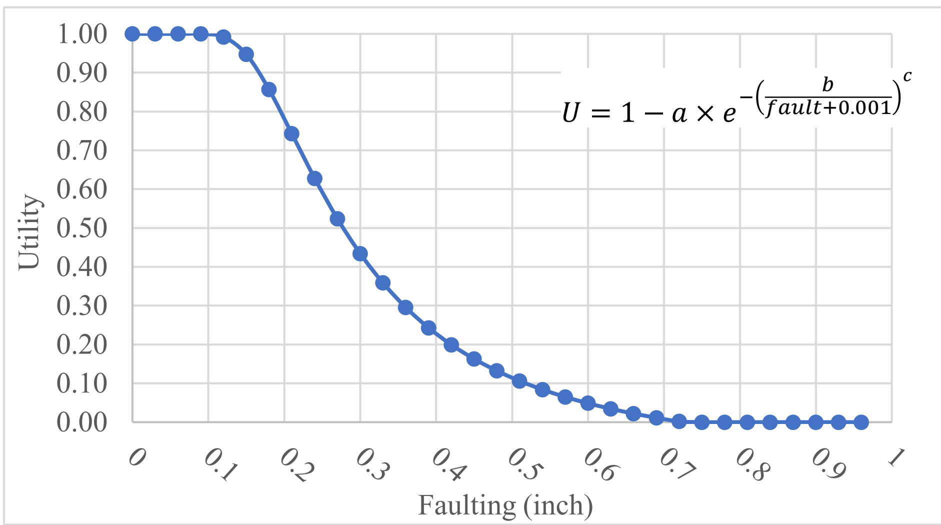


Figure 42. Faulting utility curve using equation [13] with *a* = 1.08, *b* = 62 and *c* = 5.2

Table 6. GCR data in example analysis

Scenario	IRI (inch/mile)	Percent Cracking	Rutting (inches)	PDS
1	80	3	0	90
2	200	3	0	90
3	80	20	0	90
4	80	3	0.5	90
5	80	3	0	40
6	200	20	0.5	40

Table 7. Calculated utility values for each GCR and a combined weighted utility

Scenario	IRI	Cracking	Rutting	PDS	Combined
1	0.90	0.99	1.00	0.94	0.96
2	0.13	0.99	1.00	0.94	0.77
3	0.90	0.35	1.00	0.94	0.80
4	0.90	0.99	0.01	0.94	0.71
5	0.90	0.99	1.00	0.00	0.72
6	0.13	0.35	0.01	0.00	0.12

DISCUSSION

Utility theory has proven to be a valuable tool for investigating problems with multiple criteria that cannot be easily compared (e.g., combining GCR values). A strength of utility theory is that a non-linear function can easily describe preferences. For example, utility theory allows for the same change in input value (e.g., a 20-inch increase per mile for IRI) to have different levels of significance depending on the starting value. A change in IRI from 60 to 80 inches per mile is not required to have the same impact as a change in IRI from 120 to 140 inches per mile. Those non-linear preferences are described using the utility curve.

While many sources of literature in pavement and transportation engineering detailed the use of utility theory, most did not provide details on how the utility curves were formed. Some sources of literature described the use of expert input or survey data to develop the utility curves, but detailed examples were not provided. However, the broader literature on utility theory, particularly the field of decision analysis, provided more guidance and insight into the development of the utility curves. That guidance was distilled into five steps and discussed in this chapter. Example utility curves were developed and provided in the simple Excel-based tool developed in the task described in this chapter.

While this chapter presents one framework for the application of utility theory, numerous modifications can be made and implemented within the framework. For example, different equations for utility functions can be introduced, and the simple Excel-based tool can be modified to include these equations. Another change is how the utility values are combined. The method in this chapter assumes linear additive combinations of utility values, but some sources use multiplicative combinations to account for interactions between the variables. The additive utility functions in this chapter are based on the assumption that the utility curves for one criterion are independent of the values of other criteria (e.g., the utility curve developed for IRI does not depend on the distribution of rutting values). Multiplicative utility functions are used when that assumption of independence is expected to be violated. Consider the case of two measures that each have a utility value of 0.5: the additive score is 1.0 and the multiplicative score is 0.25. A direct comparison of the utility scores has no meaning, so a comparison of the sensitivity of the combined scores to changes in the individual scores must be evaluated. Changing one score to 0.9 while leaving the other at 0.5, the additive score is 1.4 (40 percent change from the original 1.0 stated above) and the multiplicative score is 0.45 (80 percent change from the original 0.25 stated above). In this case, the relative change in the multiplicative score is much higher than the relative change in the additive score.

Multiplicative combinations are considerably different because small variations in individual utility values dominate the overall combined utility. For example, the PDS utility value for the last two rows in Table 6 and Table 7 is zero. The combined utility values are 0.72 and 0.12 with additive utility functions, whereas they are both zero with multiplicative utility. Both additive and multiplicative forms of utility theory are used in utility theory, with the multiplicative being used when mutual utility independence is not held. For the problem described in this chapter, either form can be used. Weighting each GCR is not valid when using a multiplicative function to combine the utility values.

TASK 12. NETWORK POLICY

This task is closely related and essentially contained in a previous task (*Task 10. Action benefits*). The spreadsheet that was built for the previous task ("Before-and-after" situation, see Figure 20) already contains the condition metrics measured immediately before the fix events.

ANALYSIS BASED ON FIX CATEGORIES: RCN, RHB AND CPM

To analyze values of GCRs before each of the different improvement categories (RCN, RHB, or CPM), histograms were generated using the histogram Excel template developed in Task 9. The process involved the following steps, which are very similar to the tasks explained in Task 11:

1. **Filter by pavement surface type** – Use the `FLX_RIG` column in `bef_aft.xlsx` excel sheet to select either FLX or RIG (see Figure 21).
2. **Filter by fix category** – Use the `FIX_CAT` column (see Figure 22).
3. **Exclude blank values** – For the selected GCR (e.g., IRI0, representing the value of IRI before each improvement; see Figure 43), remove rows with blank cells.
4. **Generate histogram** – Copy the filtered GCR data (e.g., IRI0) into the histogram template sheet (Figure 44) to create the histogram and calculate percentile values. Enter the desired percentile (as a fraction) in cell E19; the corresponding percentile value will appear in cell D19.

These steps were repeated for each GCR within each fix category. The resulting histogram Excel files are listed in Figure 25 and provided in the digital appendix. For each histogram, the 25th, 50th, and 75th percentiles were calculated and compiled in the file `FIX_CAT_Histograms_summary.xlsx`, under the sheet "`Distress0`", whose contents are shown in Table 8.

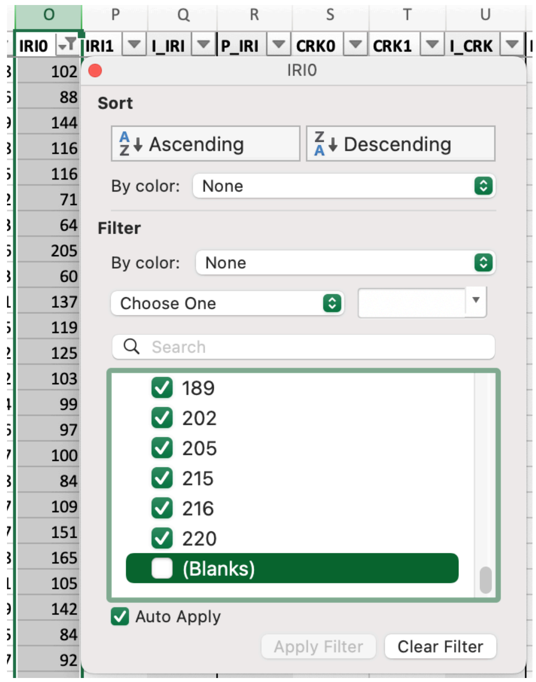


Figure 43. Filtering "bef_aft.xlsx" sheet based on "IRI0" column to exclude the blank cells

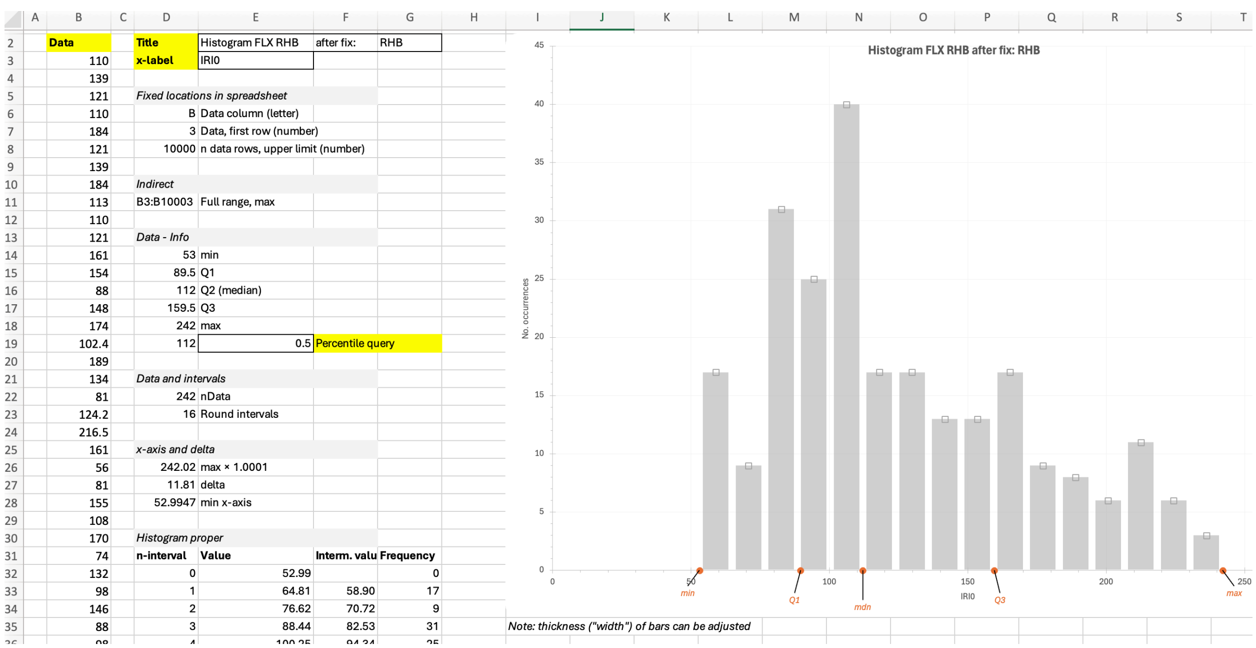


Figure 44. Pasting data into the histogram excel sheet template to compute the histogram and the desired percentile: for IRI0.

Table 8. Contents of the "Distress0" sheet of "FIX_CAT_Histograms_summary.xlsx" excel file, showing the GCR values before each improvement.

Surface	FIX_CAT	GCR value before the improvement	25th Percentile	50th Percentile	75th Percentile	Units
FLX	1_CPM	CRK0	0	1	6	%
FLX	2_RHB	CRK0	3	12	22	%
FLX	3_RCN	CRK0	2	4.5	13	%
RIG	1_CPM	CRK0	1	22	64	%
RIG	2_RHB	CRK0	19	79.5	93.25	%
RIG	3_RCN	CRK0	8	37	80	%
RIG	1_CPM	FLT0	0.05	0.09	0.12	in
RIG	2_RHB	FLT0	0.12	0.15	0.23	in
RIG	3_RCN	FLT0	0.045	0.125	0.14	in
FLX	1_CPM	IRI0	56.0	70.0	93.0	in/mile
FLX	2_RHB	IRI0	90.1	112.0	159.0	in/mile
FLX	3_RCN	IRI0	99.8	121.0	190.0	in/mile
RIG	1_CPM	IRI0	87.0	104.0	130.5	in/mile
RIG	2_RHB	IRI0	129.0	163.0	208.0	in/mile
RIG	3_RCN	IRI0	108.0	141.0	200.5	in/mile
FLX	1_CPM	PDS0	80.1	94.3	98.7	-
FLX	2_RHB	PDS0	40.3	61.5	87.0	-
FLX	3_RCN	PDS0	45.4	70.6	96.2	-
RIG	1_CPM	PDS0	82.3	93.4	98.7	-
RIG	2_RHB	PDS0	71.3	85.6	89.1	-
RIG	3_RCN	PDS0	61.3	79.8	92.0	-
FLX	1_CPM	RUT0	0.08	0.11	0.15	in
FLX	2_RHB	RUT0	0.12	0.16	0.2	in
FLX	3_RCN	RUT0	0.11	0.14	0.2	in

Figure 45 shows the median IRI value prior to the application of each fix category, separated by pavement type. For flexible pavements, CPM treatments have the lowest starting IRI at 70 in/mi, while rehabilitation (RHB) and reconstruction (RCN) begin at much higher median values of 112 in/mi and 121 in/mi, respectively. This pattern suggests that CPM is generally applied to smoother pavements, while RHB and RCN are triggered when ride quality has already deteriorated substantially. For rigid pavements, the same trend is evident—CPM starts at 104 in/mi, compared to 163 in/mi for RHB and 141 in/mi for RCN—indicating that major fixes are typically reserved for segments in significantly worse condition.

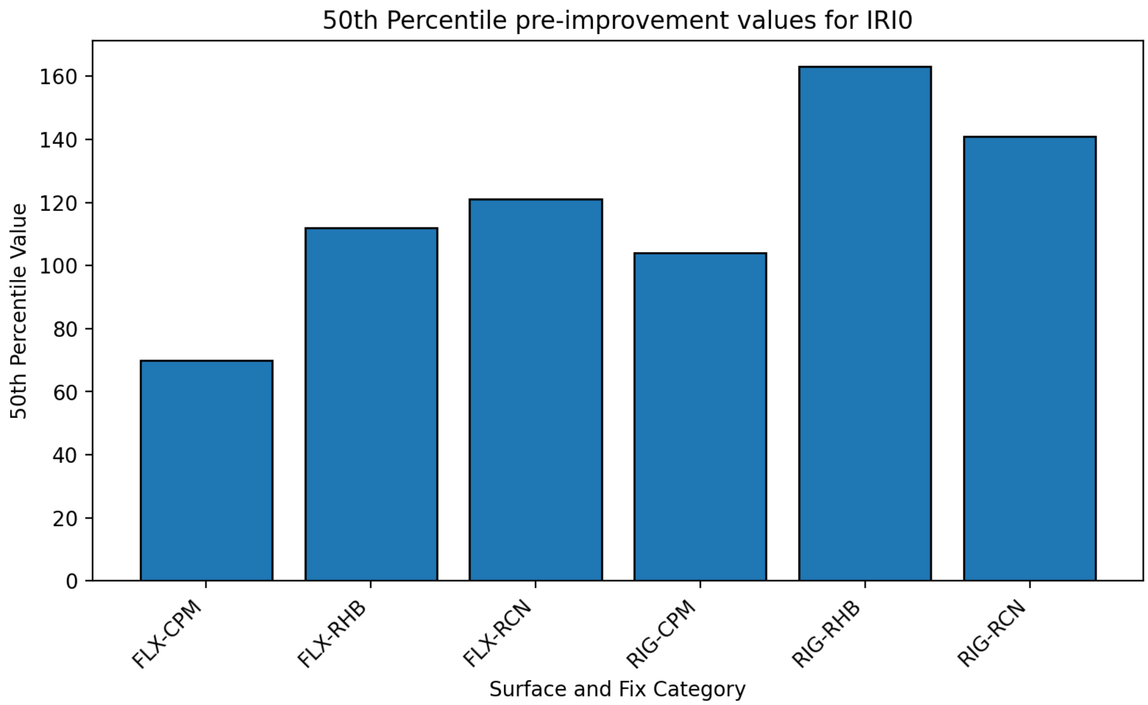


Figure 45. IRI values before for each fix category

Figure 46 illustrates the median Pavement Distress Score (PDS) before each fix category. For flexible pavements, CPM is applied to sections with the highest median PDS (94.3), indicating relatively good condition, while RHB and RCN are triggered at lower scores of 61.5 and 70.6, respectively. In rigid pavements, CPM also starts at a high PDS (93.4), with RHB and RCN at lower medians of 85.6 and 79.8.

Figure 47 presents the median cracking percentage prior to each fix category. For flexible pavements, CPM is applied to sections with very little cracking (1%), while RHB and RCN target pavements with higher cracking levels of 12% and 4.5%, respectively. In rigid pavements, CPM starts at a higher median cracking level (22%), while RHB and RCN are used on much more deteriorated sections, with median cracking of 79.5% and 37%, respectively.

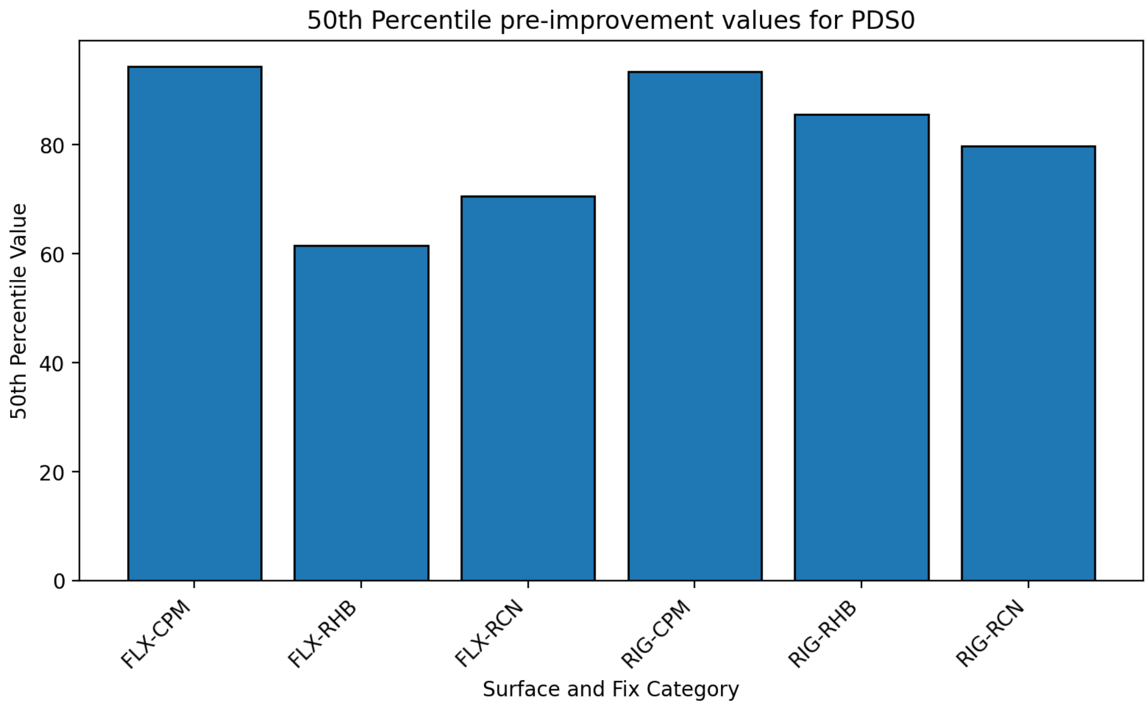


Figure 46. PDS values before for each fix category

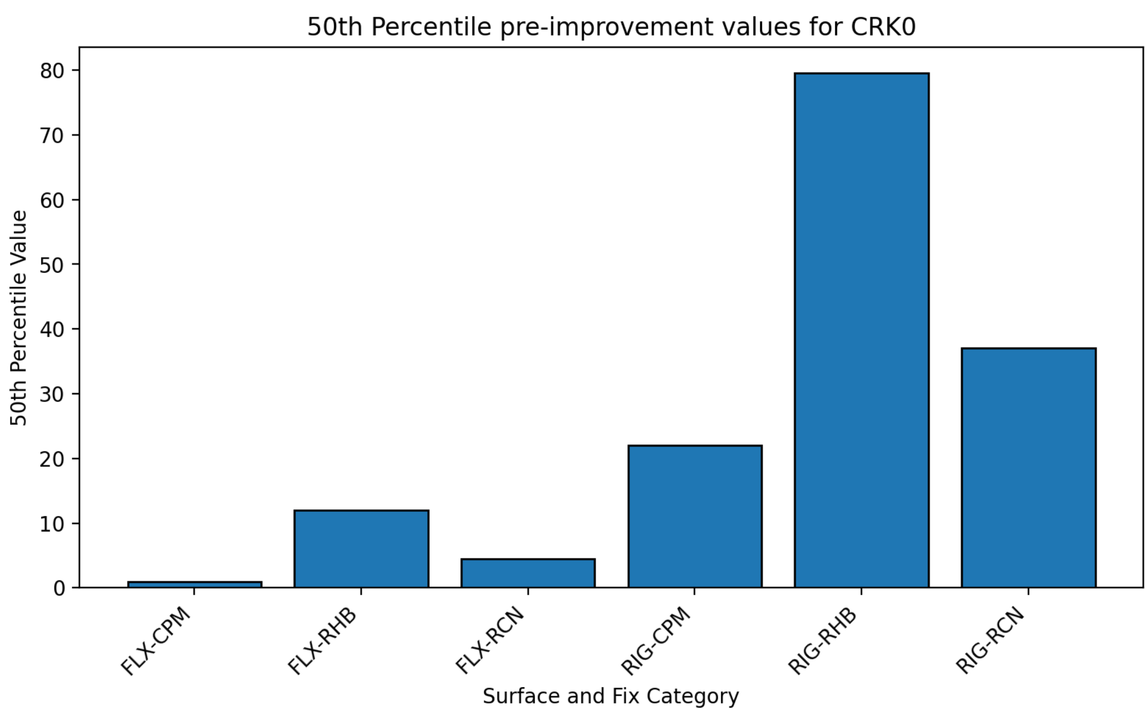


Figure 47. CRK values before for each fix category

Figure 48 presents the median rut depth (in inches) before each fix category for flexible pavements. CPM addresses segments with the smallest median rutting (0.11 inches), while RHB and RCN are performed on sections with greater rut depths of 0.16 inches and 0.14 inches, respectively.

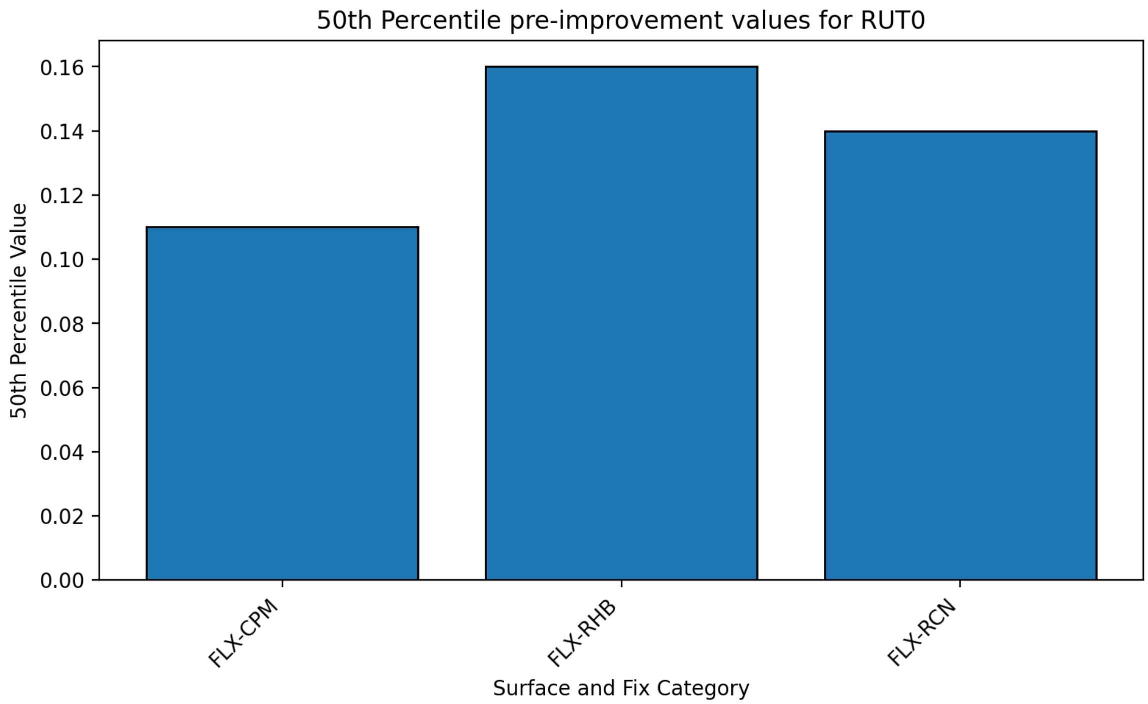


Figure 48. RUT values before for each fix category

Figure 49 shows the median faulting (in inches) before each fix category for rigid pavements. CPM is used on segments with relatively minor faulting (0.09 inches), while RHB and RCN address sections with greater faulting, at 0.15 inches and 0.125 inches, respectively. Although the absolute differences are small, this trend suggests that major fixes are directed toward segments with more pronounced faulting.

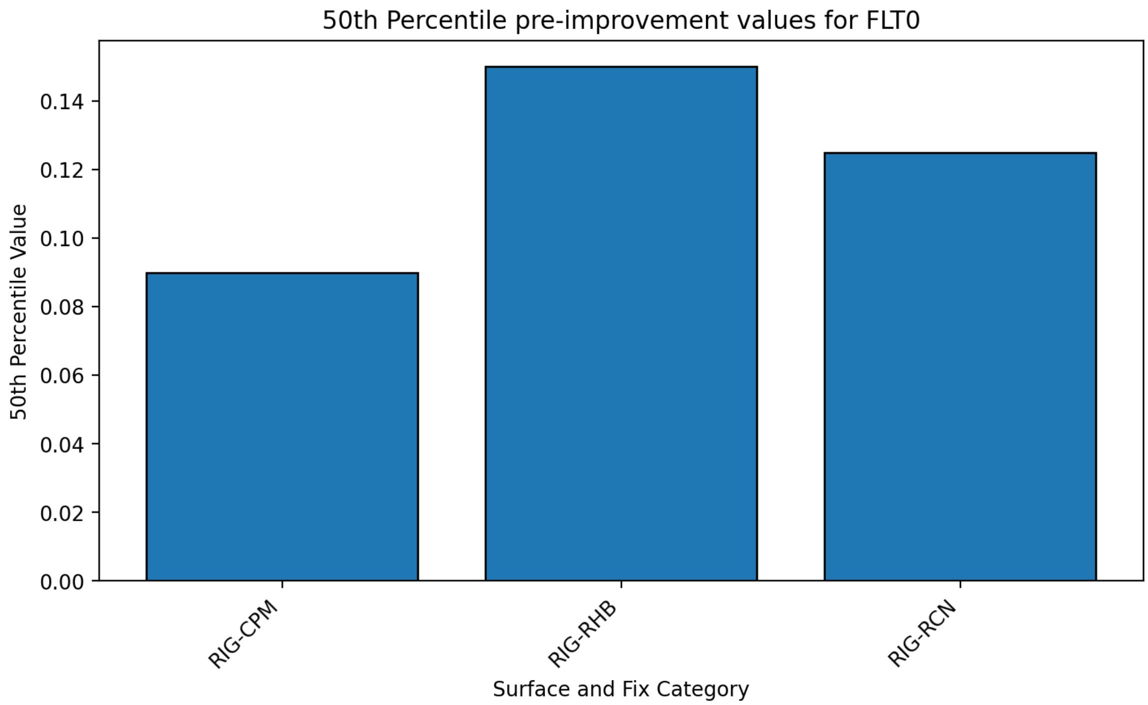


Figure 49. FLT values before for each fix category

ANALYSIS BASED ON EACH INDIVIDUAL FIX TYPE

The procedure described in the previous section was repeated for each specific fix type (as listed in the FIX_TYPE column) rather than for the broader fix categories (FIX_CAT). The resulting histogram Excel sheets are provided in the "FLX_Histograms" and "RIG_Histograms" folders in the digital appendix. As an example, Figure 50 present these histograms as boxplots for CRK FLX. The full set of before-and-after data and summary figures is included in the digital appendix.

The digital appendix also contains two summary files—*FLX_Histograms_summary.xlsx* and *RIG_Histograms_summary.xlsx*—which list the 25th, 50th, and 75th percentiles for each fix type (like Table 8 but for reach fix type). Due to the length of these lists, they are not reproduced in this report to maintain brevity.

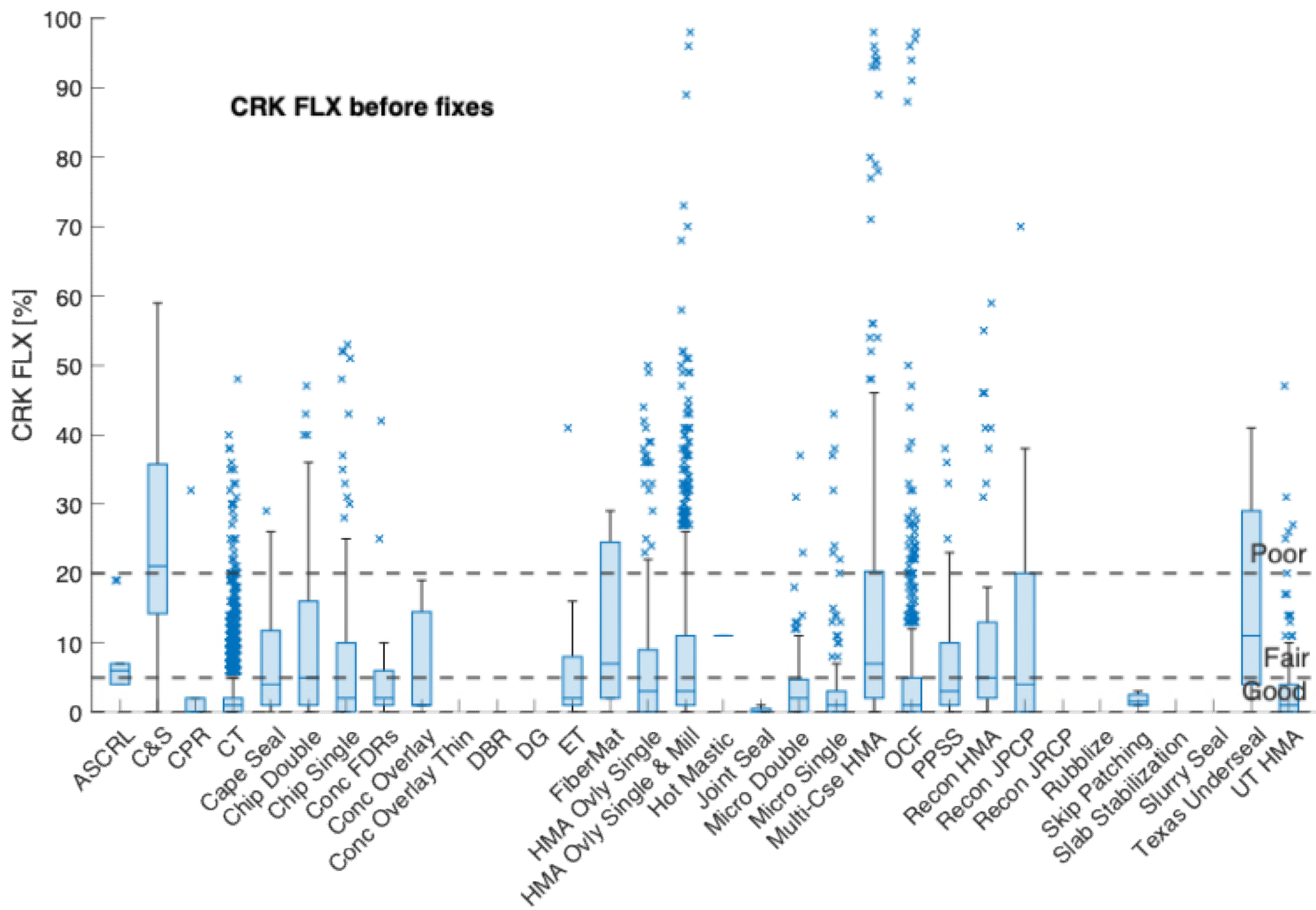


Figure 50. CRK FLX values before treatment, grouped by fix type.

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APPENDIX A: DIGITAL APPENDIX

The report is accompanied by a digital appendix containing supporting files developed throughout the project. These files represent processed data, modeling outputs, and analysis tools used in the completion of Tasks 9 through 12:

- All Tasks
    - Master "Stack" spreadsheet combining *GroupRecords* data, extended with PDS values
- Task 9 – GCR Modeling
    - Spreadsheet of model fitting parameters for all sections
    - Individual plots of GCR deterioration
    - Combined plots grouped by fix type and region
- Tasks 10 & 12 – Action Benefits and Network Policy
    - Summary spreadsheets of pre- and post-treatment GCR metrics
    - Plots comparing before/after conditions and treatment effectiveness
    - Excel spreadsheet for generating histograms from GCR data
- Task 11 – Utility Scoring
    - Spreadsheet summarizing utility scaling and weighting outputs