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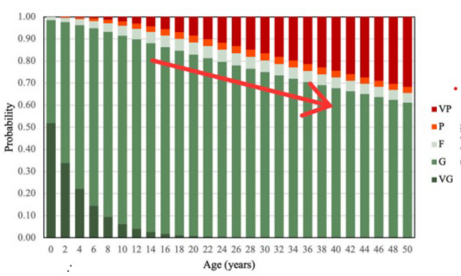
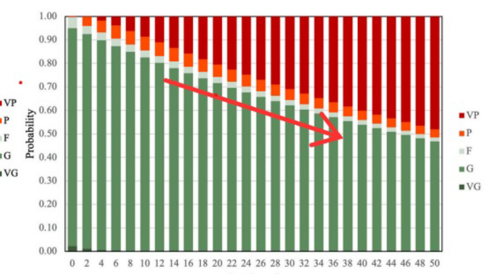
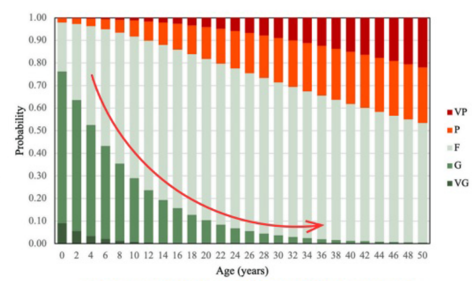
Performance Acceptance and Performance Monitoring of Pavement Using Falling Weight Deflectometer (FWD) and International Roughness Index (IRI)



Deterioration Predictions - Interstate Roads



Deterioration Predictions - U.S. Highways



Deterioration Predictions - State Roads

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SPR-3902 • Report Number: FHWA/IN/JTRP-2025/13 • DOI: 10.5703/1288284317877

RECOMMENDED CITATION

Khajehvand, M., Al Mamun, A., Nantung, T., & Cho, S. (2025). *Performance acceptance and performance monitoring of pavement using Falling Weight Deflectometer (FWD) and International Roughness Index (IRI)* (Joint Transportation Research Program Publication No. FHWA/IN/JTRP-2025/13). West Lafayette, IN: Purdue University. https://doi.org/10.5703/1288284317877

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Published reports of the Joint Transportation Research Program are available at http://docs.lib.purdue.edu/jtrp/.

NOTICE

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
FHWA/IN/JTRP-2025/13		

4. Title and Subtitle Performance Acceptance and Performance Monitoring of Pavement Using Falling Weight Deflectometer (FWD) and International Roughness Index (IRI)	**5. Report Date** April 2025 **6. Performing Organization Code**
7. Author(s) Maya Khajehvand, Abdullah Al Mamun, Tommy Nantung, Seong-Hwan Cho, and John E. Haddock	**8. Performing Organization Report No.** FHWA/IN/JTRP-2025/13
9. Performing Organization Name and Address Joint Transportation Research Program Hall for Discovery and Learning Research (DLR), Suite 204 207 S. Martin Jischke Drive West Lafayette, IN 47907	**10. Work Unit No.** **11. Contract or Grant No.** SPR-3902
12. Sponsoring Agency Name and Address Indiana Department of Transportation (SPR) State Office Building 100 North Senate Avenue Indianapolis, IN 46204	**13. Type of Report and Period Covered** Final Report **14. Sponsoring Agency Code**

15. Supplementary Notes

Conducted in cooperation with the U.S. Department of Transportation, Federal Highway Administration.

16. Abstract

The Indiana Department of Transportation (INDOT) utilizes the International Roughness Index (IRI) and Falling Weight Deflectometer (FWD) data to prioritize pavement maintenance across interstates, state roads, and U.S. highways. While IRI measures ride quality and FWD assesses structural integrity, their threshold values vary by road type, reflecting differing service expectations. Effective pavement maintenance requires a holistic approach, combining surface condition data from IRI with structural insights from FWD through predictive modeling. Additionally, these metrics should not only estimate service life but also provide indications of potential distress types, ensuring a comprehensive understanding of pavement performance and maintenance needs. The study employed a dual methodological approach that combined probabilistic and deterministic modeling techniques to evaluate pavement deterioration and predict performance across various road classifications. A Markov chain probabilistic model is utilized to analyze deterioration rates and assess the likelihood of pavements transitioning between condition states (e.g., Very Good to Poor) for each road category. In parallel, an empirical deterministic approach was applied to develop IRI-based prediction models, enabling cross-comparison of degradation trends and steady-state conditions derived from both methodologies. The deterministic approach further investigated the influence of initial IRI on pavement performance, emphasizing its critical role in maintaining functional performance within acceptable limits. Additionally, the remaining service life and life expectancy of pavements was estimated to establish terminal failure thresholds for different road categories. Finally, the study analyzed FWD data from various roads to predict maintenance priorities by establishing a correlation with IRI. The outcome of the study was the expected use of IRI and FWD data to support INDOT's commitment to proactive pavement maintenance.

17. Key Words	18. Distribution Statement
Falling Weight Deflectometer (FWD), International Roughness Index (IRI), Markov chain modeling, pavement service life	No restrictions. This document is available through the National Technical Information Service, Springfield, VA 22161.

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	25	

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EXECUTIVE SUMMARY

Introduction

The Indiana Department of Transportation (INDOT) primarily evaluates pavement layer properties individually, which limits their ability to predict long-term pavement performance. This layer-by-layer approach does not account for the integrated system behavior required for effective load distribution. To bridge this gap, different performance-based indicators, such as the International Roughness Index (IRI) and Falling Weight Deflectometer (FWD), offer the potential for holistic performance evaluation. These surrogate test methods capture both structural and functional pavement responses, which aid in system-level monitoring. This study developed practical predictive models for pavement deterioration and remaining service life (RSL) estimation using historical IRI and FWD data. The study also developed a performance-based acceptance framework for better pavement management by defining acceptable structural and functional performance limits, thus enhancing decision-making in scope, design, and preservation.

Findings

- Higher initial IRI values lead to accelerated deterioration, underscoring the importance of achieving low initial roughness levels during construction.
- Interstate highways exhibited the slowest rate of IRI increase, reflecting robust structural designs and quality maintenance practices. U.S. highways showed a moderate IRI rate increase, and state roads experienced a slightly faster rate of IRI increase.
- The IRI value ranges for U.S. highways and state roads were similar, indicating comparable levels of smoothness across both classifications, though both were noticeably rougher than interstate highways.
- Interstate highways consistently demonstrated the highest life expectancy across various IRI ranges. U.S. highways and state roads exhibit similar life expectancies and maintenance requirements.
- The relationship between surface curvature index (SCI) and IRI values varied across road types, with U.S. highways and state roads showing a comparable increase in IRI as SCI increased. Interstate highways exhibited a significantly smaller increase.
- Factors such as higher traffic volumes, heavier loads, and frequent maintenance strategies can influence the relationship between SCI and IRI, particularly for interstate highways, where different structural distress may impact IRI but are not well captured by SCI.

Implementation

These report findings can be implemented to enhance pavement longevity and performance in several ways. First, INDOT can incorporate pavement preservation treatments at both the network and project levels to ensure that construction practices prioritize achieving lower initial IRI values, as higher initial roughness accelerates pavement deterioration. Additionally, adopting pavement preservation treatment performance models within the pavement management system will enable maintenance strategies to be tailored based on highway classification, even when IRI values appear similar. Since the SCI-IRI relationship varies by road classification, the use of the remaining service life concept in strategy evaluation and project selection will help ensure that maintenance decisions account for both structural integrity and surface condition. Finally, integrating the pavement preservation framework into the network-level pavement management system will enable the inclusion of structural evaluations alongside surface condition monitoring, which leads to more accurate and data-driven maintenance decisions.

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1. INTRODUCTION

1.1 Introduction and Literature Review

Effective management and maintenance of pavements are essential for ensuring user safety, ride comfort, and cost-efficiency (Sarsam, 2016). A pavement management system (PMS) serves as a critical tool for achieving these objectives by integrating data-driven decision-making with predictive models to guide maintenance and rehabilitation (M&R) activities (Peraka & Biligiri, 2020). Central to PMS is the understanding of pavement deterioration, which is driven by traffic loads, environmental conditions, and material fatigue (Barriera et al., 2020; Chan et al., 2010; Sarsam, 2016). By forecasting the progression of pavement degradation, PMS enables transportation agencies to plan timely maintenance interventions, thereby minimizing life-cycle costs and mitigating the impacts of limited funding (Barriera et al., 2020; Chan et al., 2010; Peraka & Biligiri, 2020). However, balancing performance maximization and cost minimization remains a complex challenge in PMS decision-making. This complexity underscores the need for robust predictive tools that address both functional and structural performance, which is a key focus of this study.

Asset management frameworks further support this goal by providing a structured, systematic approach for maintaining, enhancing, and optimizing physical infrastructure assets (Laue et al., 2014). By integrating engineering principles with economic analysis, asset management extends the planning horizon of infrastructure projects, promoting sustainability and cost-effectiveness (Gavrikova et al., 2020; Hanski & Ojanen, 2020; Laue et al., 2014). The lifecycle of pavement performance, illustrated in Figure 1.1, highlights the progressive nature of pavement deterioration and the critical role of well-timed M&R interventions in preserving pavement functionality and extending service life (Babashamsi et al., 2016; Harvey et al., 2016; Zulu et al., 2020). Despite advances in design practices, including the adoption of the *Mechanistic-Empirical Pavement Design Guide* (MEPDG) in 2009, existing construction acceptance procedures remain centered on surrogate material properties, such as strength and density, rather than holistic system-level performance (Ahmed et al., 2023; Dehghani et al., 2013). This misalignment between design, construction, and performance assessment necessitates a shift toward integrated acceptance frameworks that emphasize in-service functional and structural performance criteria (Li et al., 2011).

The current Indiana Department of Transportation (INDOT) construction acceptance procedures primarily evaluate individual pavement layer properties, which are insufficient for predicting long-term pavement performance (Guerre & Evans, 2009). This layer-by-layer approach, while useful for quality control, does not account for the integrated system behavior of pavement layers, which must work cohesively to distribute traffic-induced loads to the subgrade (Dehghani et al., 2013; Guerre & Evans, 2009). The MEPDG marked a paradigm shift in pavement design toward system-level performance criteria, but acceptance procedures have not fully adapted to this perspective (Manik et al., 2012; Wu et al., 2013). To bridge this gap, advanced performance-based indicators, such as the International Roughness Index (IRI) and Falling Weight Deflectometer (FWD) data, offer potential for holistic performance evaluation. These surrogate testing methods capture the combined structural and functional response of pavements, making them well-suited for system-level performance monitoring (Wu et al., 2013). This study builds on this premise by using IRI as a functional performance indicator to develop predictive models for pavement deterioration and remaining service life (RSL) estimation.

The IRI is widely recognized as a key functional performance indicator in PMS, measuring pavement smoothness and its impact on vehicle efficiency, ride quality, and safety (Dela Cruz et al., 2021). Smoothness is a fundamental aspect of user experience, and its degradation directly influences user costs, vehicle wear, and travel time (Islam & Buttlar, 2012; Wang et al., 2014). Consequently, the IRI has been adopted as a design criterion in the American Association of State Highway and Transportation Officials (AASHTO) Pavement ME for both flexible and rigid pavements, further highlighting its importance in performance-based planning and design (Dela Cruz et al., 2021; Kravcovas et al., 2020; Tamagusko & Ferreira, 2023).

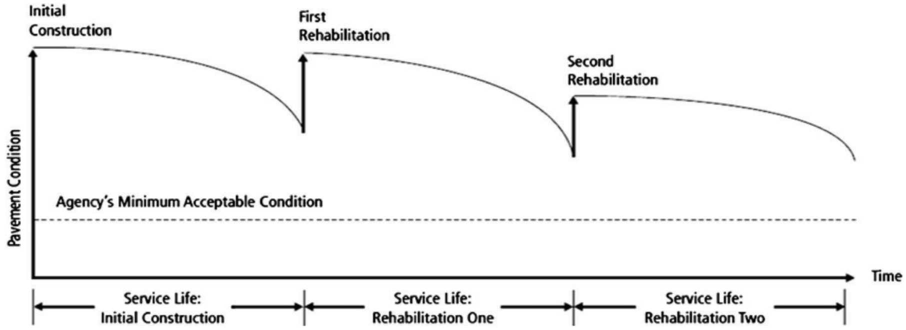


Figure 1.1 Scheduling rehabilitation in the pavement life cycle (FHWA, 2002).

Accurate prediction of IRI over time is essential for constructing performance deterioration curves, estimating RSL, and guiding M&R strategies (Kravcovas et al., 2020; Tamagusko & Ferreira, 2023). Despite its significance, IRI prediction models face challenges related to model complexity, data requirements, and transferability. Previous models have demonstrated varying degrees of accuracy and ease of use. For instance, models developed by Khattak et al. (2014) utilized overlay thickness, traffic, and climate indices but reported low predictive accuracy (R^2 = 0.47). Simpler empirical models, such as those by Lee et al. (2020) and Al-Suleiman and Shiyab (2003), have shown higher usability but are often constrained by initial IRI values and local data availability. This study addresses these limitations by employing probabilistic (Markov chain) and deterministic (empirical) approaches to develop IRI-based prediction models.

Beyond IRI, pavement deterioration models have been extensively studied using various methodologies, including empirical, mechanistic-empirical, and probabilistic approaches. The accuracy and reliability of these models heavily depend on the quality and comprehensiveness of input data, including traffic dynamics, material properties, and maintenance histories. Empirical models rely on observed trends in performance data, while mechanistic-empirical models combine material behavior with field data to predict performance under real-world conditions. Probabilistic models, notably Markov chains, offer distinct advantages for modeling pavement deterioration due to their ability to account for variability and uncertainty (Amador-Jiménez & Mrawira, 2011; Hu et al., 2022; Justo-Silva et al., 2021; Li et al., 1996; Morcous & Lounis, 2007). On the other hand, the lack of standardized and detailed datasets, particularly for local road pavements, remains a critical challenge in the pavement performance prediction curve. Within this context, Markov chains have emerged as an adaptable framework for modeling pavement deterioration over time (Li et al., 1996). The probabilistic foundation of Markov chains enables them to account for the uncertainty and variability inherent in pavement performance, making them especially effective in data-limited scenarios (Moreira et al., 2018). Furthermore, their flexibility in incorporating new data and their capacity to forecast degradation rates and trends offer actionable insights for M&R planning (Li et al., 1996; Moreira et al., 2018; Salman & Gursoy, 2022). These attributes underscore the utility of Markov chains in pavement management systems, facilitating a deeper understanding of how quickly pavements deteriorate.

1.2 Problem Statement

Pavement performance, both structural and functional, is influenced by a range of interdependent factors, including foundation support, material properties, construction quality, traffic loading, and environmental conditions. While these factors have been acknowledged since the AASHO Road Test, contemporary assessment practices continue to rely heavily on surrogate testing parameters, such as strength and density (Kennedy et al., 1994). Although these parameters provide insight into construction quality, they fail to capture the holistic, system-level responses of pavement layers under in-service conditions (Guerre & Evans, 2009). Consequently, these assessment methods offer limited predictive capability regarding long-term pavement performance or the extent to which constructed pavements meet their intended design expectations (Ong, 2010; Wang & Wang, 2017). This limitation underscores critical concerns about the efficacy of current quality assurance practices in ensuring that pavement performance objectives are achieved.

As pavements remain in service, they undergo progressive deterioration driven by traffic-induced stresses, environmental fluctuations, and material fatigue. Existing predictive models often emphasize individual material properties rather than accounting for the complex interactions between pavement layers that collectively determine system performance. This approach has limited the accuracy of predictive models, particularly in estimating key performance indicators such as functional condition (measured by IRI) and structural capacity (assessed using FWD data) (Gurjar et al., 2013; Madeh Piryonesi & El-Diraby, 2021; Wang et al., 2021; Xiao et al., 2023). Addressing these gaps requires the development of advanced, data-driven methodologies that account for system-level interactions, thereby enabling more accurate prediction of functional and structural performance curves, as well as RSL. Such predictive tools are essential for supporting effective decision-making in scoping, design, and preservation planning, where the ability to forecast performance outcomes directly influences maintenance strategies and investment prioritization.

To address these challenges, this study focuses on developing practical predictive models for both functional and structural performance, leveraging the IRI and FWD as key performance indicators. In the first part of the study, probabilistic (Markov chain) and deterministic (empirical) modeling approaches are employed to evaluate pavement deterioration, predict RSL, and assess the influence of initial IRI on long-term pavement performance. In the second phase, a correlation between FWD and IRI is developed to evaluate pavement deterioration and predict the RSL of pavement. By leveraging historical IRI data, this study aims to provide INDOT with actionable decision-support tools for scoping, design, and preservation, ensuring alignment between construction practices and long-term performance objectives. These contributions support INDOT's transition toward a performance-based acceptance framework that prioritizes system-level performance and optimizes long-term pavement management strategies.

1.3 Study Objectives

The primary objective of this study is to establish practical solutions for defining INDOT's acceptable structural and functional performance limits for pavements and to develop predictive performance models to support scoping, design, and preservation decisions. To achieve this objective, the study is structured into two key phases. The first phase focuses on reviewing and analyzing IRI data from newly constructed and in-service pavements to generate actionable tools for pavement engineers during various project phases. The second phase centers on assessing structural performance using FWD data. These efforts aim to provide INDOT with tools to support performance-based decision-making.

1.4 Scope of Work

The study scope is confined to the first phase of a broader research effort aimed at enhancing pavement performance prediction and management. This initial phase specifically addresses the functional performance of pavements, with a focus on IRI as the primary performance indicator. The study investigates pavement deterioration processes across various road classifications, including interstate highways, U.S. highways, and state roads, employing both probabilistic (Markov chain) and deterministic (empirical) modeling approaches. By leveraging historical IRI data, the research develops practical prediction models, estimates RSL, and evaluates the influence of initial IRI on long-term pavement performance. The study also develops structural and functional performance curves for pavement sections across different road classifications by utilizing time-history FWD testing and IRI data. In this process, the FWD data collected for these roads were paired with the corresponding IRI data. The FWD measurements were then numerically analyzed to establish a correlation between the FWD results and the IRI values.

2. STUDY METHODOLOGY AND DATA COLLECTION

2.1 Methodology

The methodological approach in the study is designed to achieve two primary objectives: first, to predict the rate of pavement condition deterioration in different functional classes using a probabilistic framework based on Markov chains, and second, to utilize a deterministic approach to estimate pavement ages, predict the functional performance change of pavements per year, and assess the accuracy and applicability of the probabilistic approach in comparison with a deterministic empirical methodology. The deterministic approach is further employed to calculate the RSL and estimate the life expectancy of the pavement in different functional classes. Finally, a relationship between FWD and IRI is developed for different functional classes, to tie pavement structural condition to pavement functional condition. Collectively, these methodologies address the critical need for predictive tools that support performance-based decision-making and align construction practices.

2.2 Data Description

The study incorporates two different sets of data. In the first phase, Indiana's flexible pavement data from 2014 to 2021 are used to identify factors that affect pavement conditions and their deterioration over time. The dataset includes details such as road sections, project locations, dates of construction, traffic volumes, structural characteristics, and performance metrics. Due to limitations in data availability, the IRI was selected as the sole indicator of functional pavement performance. This analysis incorporates the mean IRI per 0.1 mile for each roadway segment, utilizing these data points as a basis for a statistical examination of annual pavement conditions. The analysis does not apply a uniform strategy across Indiana's entire road network pavements. Instead, the network is divided into subnetworks based on the functional classifications of interstate highways, U.S. highways, and state roads. This categorization facilitates a more nuanced understanding of the pavements by incorporating traffic level and levels of service (LOS) into evaluation.

The second phase of the study utilizes data from 75 road sections, with 25 sections representing each of the three functional road classes, all featuring full-depth pavement. FWD data collected between 2016 and 2021 for these roads are paired with corresponding IRI data from the same years. The FWD data are then numerically analyzed to develop a correlation between FWD measurements and IRI.

2.2.1 Markov Chain Modeling

Markov chain theory offers a probabilistic framework for constructing models that predict pavement deterioration over time. This approach has been extensively explored and validated by numerous researchers. At its core, Markov chain models work well for pavement deterioration because they focus on two main principles: the analysis of pavement conditions at discrete time intervals (e.g., annually) and the categorization of pavement conditions into a finite set of distinct states or condition bands (Hassan et al., 2015). These principles align closely with standard practices for monitoring road conditions, which include periodic evaluations to categorize pavement quality into defined groups. One of the fundamental assumptions of Markov chain theory, critical for modeling pavement deterioration, is the Markov property, indicating that the future condition of a pavement segment depends solely on its current state, irrespective of its historical conditions (Hassan et al., 2015; Salman & Gursoy, 2022). This assumption simplifies the modeling process where data may be sparse, subjective, and collected at irregular intervals (Li et al., 1996; Moreira et al., 2018; Pérez-Acebo et al., 2019). A functional Markov chain model can be established with at least 2 years of pavement condition data (Ansarilari & Golroo, 2020; Hassan et al., 2015).

2.2.1.1 Number of states. The modeling categorizes pavement conditions into five states based on IRI measurements (Table 2.1). This classification enables a finite state for modeling, which agrees with Markov chain theory principles and facilitates the detailed analysis of pavement performance across varying condition levels. Figure 2.1 shows the temporal progression of roadway conditions from 2014 to 2021, as inferred from the available IRI datasets.

In the context of Markov chain modeling, two essential vectors are utilized: the initial state vector and the start condition vector. The initial state vector represents the hypothetical distribution of pavement section conditions immediately following construction. Specifically, at the inception point, or time zero, it is assumed that all pavement sections are categorized under the Very Good condition (Hassan et al., 2015). This assumption is mathematically represented by the initial state vector $X(0) = [1, 0, 0, 0, 0]$, indicating a 100% probability of being in the Very Good state at the start. Conversely, the start condition vector is derived from actual data reflecting the current condition in a specific year, here taken as 2021. This vector captures the present distribution of pavement conditions across the network by assessing each pavement section's IRI value, assigning it to one of five condition states, and calculating the proportion of the network's total length that each state encompasses.

TABLE 2.1
Classification of pavement condition states

Pavement Condition	IRI (in./mile)
Very Good (VG)	<70
Good (G)	71–100
Fair (F)	101–130
Poor (P)	131–70
Very Poor (VP)	>170

2.2.1.2 Duty cycle adaptation. Considering the data collection frequency and sample size limitations, a 2-year duty cycle is adopted for this study. This period aligns with the common interval for INDOT condition data collection, thus optimizing the predictive capabilities of the Markov chain model for practical pavement management applications.

2.2.1.3 Transition probability matrix. Central to the methodology is the transition probability matrix (TPM) utilized in Markov chain modeling to predict future pavement conditions (Park & Kim, 2003). This matrix models the life of a pavement segment from its inception in near-perfect condition, as indicated by current state vectors, through successive duty cycles to capture its deterioration. Each element within the TPM, denoted as P_{ij}, represents the probability of a pavement transitioning from its present state i to a future state j within one duty cycle (Pérez-Acebo et al., 2018). A standard 5×5 TPM is presented in Equation 2.1. The matrix uses specific probabilities, such as P_{12}, P_{23}, and so on, to show how likely it is to move from one state to another. It also uses probabilities like P_{11}, P_{22}, etc., to represent how likely it is for a condition to stay the same. In constructing a TPM for pavement deterioration simulation, several key conditions are observed (Pérez-Acebo et al., 2018).

- Improvements in roadway conditions without intervention are considered impossible, hence $P_{ij} = 0$ for $i > j$.
- The final state ($P_{nn} = 1$) acts as an absorbing state, indicating the pavement has reached its lowest condition

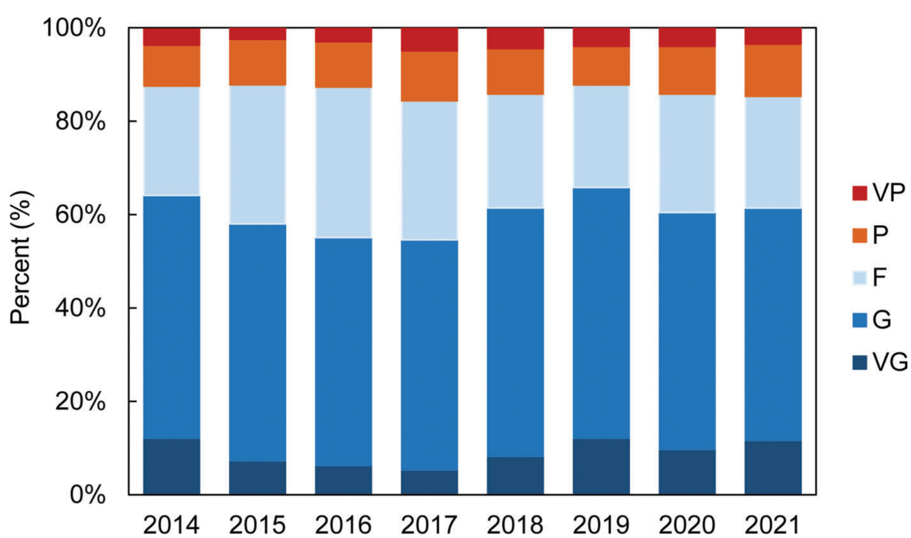


Figure 2.1 Temporal progression of roadway roughness conditions from 2014 to 2021.

and cannot deteriorate further without first being reconstructed.

$$Deterioration\ TPM_{ij}(No\ Maintenance) = \begin{bmatrix} P_{11} & P_{12} & 0 & 0 & 0 \\ 0 & P_{22} & P_{23} & 0 & 0 \\ 0 & 0 & P_{33} & P_{34} & 0 \\ 0 & 0 & 0 & P_{44} & P_{45} \\ 0 & 0 & 0 & 0 & P_{55}=1 \end{bmatrix} \quad \text{(Eq. 2.1)}$$

In the development of TPMs for this study, the decision to model the pavement deterioration process as stationary was implemented on the system's homogeneity. Consequently, the count proportions method was selected for constructing stationary TPMs to track network deterioration over time (Pérez-Acebo et al., 2019). This method determines the transition probability (Equation 2.2).

$$P_{ij} = \frac{n_{ij}}{n_i} \quad \text{(Eq. 2.2)}$$

where n_{ij} is the number (i.e., total length) of road sections transitioning from state i to state j within a duty cycle, and n_i is the total number of sections in state i before the transition.

2.2.2 Empirical IRI Model Application

The primary assumption in this study is that the IRI values would exhibit a consistent increase over time in the absence of maintenance interventions. Consequently, any IRI data points smaller than those recorded in the preceding collection year were identified as outliers and excluded from the dataset. Additionally, the potential impact of surface treatments or repairs, which could reduce IRI values, was not accounted for due to the unavailability of maintenance history records. These assumptions ensure that the filtered historical IRI data reliably represent the temporal changes in IRI, unaffected by external factors or anomalies.

For each dataset, representing historical data from a specific testing location, the pavement age at the first data point collected in 2014 was estimated using the structure of an existing IRI prediction model. This approach converted the time index from the data collection year to the corresponding pavement age. The empirical IRI model developed by Lee et al. (2020) was utilized for the data adjustment process due to its simplicity, requiring only the initial IRI and pavement age, as outlined in Equation 2.3. It is important to emphasize that the model's form was specifically employed for data alignment purposes (Lee et al., 2020).

$$IRI_n = IRI_{ini} \times e^{an} \quad \text{(Eq. 2.3)}$$

where n symbolizes the pavement age in years, IRI_n represents the IRI value at the corresponding pavement age n, IRI_{ini} is the initial IRI value recorded immediately after construction, and a denotes a regression constant.

The empirical model's reliance on the initial IRI (IRI_{ini}) and pavement age (n) as its core independent variables allows for a focused analysis of how the initial pavement condition influences pavement deterioration trajectory over time (Lee et al., 2020). First, a coefficient was estimated by considering two adjacent IRI data points for each test location. Equation 2.4 shows how this coefficient was derived after solving for the two adjacent IRI data points at each location.

$$\begin{aligned} IRI_n &= IRI_{ini} \times e^{an} \\ IRI_{n+1} &= IRI_{ini} \times e^{a(n+1)} \\ \frac{IRI_n}{IRI_{n+1}} &= \frac{e^{an}}{e^{an+a}} \\ \ln\left(\frac{IRI_n}{IRI_{n+1}}\right) &= an-(an+a) \end{aligned} \quad \text{(Eq. 2.4)}$$

The methodology's implementation involves identifying the initial IRI values for each flexible pavement. The initial IRI was set to 70 in./mile, representing the maximum permissible IRI value for flexible pavements following construction, as specified in the INDOT standards. Obtained coefficients were used to calculate the pavement age of IRI data measured in 2014 (Equation 2.5).

$$n = \frac{1}{a} \times \left(\frac{IRI_n}{IRI_{ini}}\right) \quad \text{(Eq. 2.5)}$$

After estimating the age of flexible pavements, the IRI prediction models were developed. A non-linear regression analysis was performed on the adjusted IRI data to develop an IRI prediction model for each road classification. As shown in Equation 2.6, an exponential function was chosen for the model. The exponential function is commonly applied in IRI prediction due to its effectiveness and simplicity, requiring fewer input parameters, which helps minimize potential noise from other variables (Al-Suleiman & Shiyab, 2003; Lee et al., 2020). This approach not only simplifies the prediction process but also enables the estimation of functional pavement age based on current IRI measurements.

$$IRI_n = a \cdot e^{b \cdot n} + c \quad \text{(Eq. 2.6)}$$

where n represents pavement age in years, IRI_n is IRI value at pavement age n (in./mile), and a, b, and c are coefficients.

After developing the pavement performance prediction models for each road classification, the RSL of each road classification was calculated (Equation 2.7) for an IRI_{limit} of 150 (in./mile) (Al-Suleiman & Shiyab, 2003).

$$RSL = \frac{1}{b} \times \ln\left(\frac{IRI_{limit} - c}{IRI_n - c}\right) \quad \text{(Eq. 2.7)}$$

3. RESULTS AND DISCUSSIONS

3.1 Performance Monitoring of Pavement Using IRI

3.1.1 Probabilistic Approach: Markov Chain

Stationary transition probability matrices. Time series data spanning the years 2014 to 2021 were analyzed to construct TPMs for each of the three identified subnetworks. The process unfolded several key steps to ensure the accuracy and relevance of the TPMs.

1. Initially, any sections undergoing maintenance activities that resulted in an IRI value decrease during this period, were excluded.
2. Subsequently, each selected section was evaluated to determine its condition state based on the IRI values for each year.
3. Sections experiencing a change greater than one condition state were excluded from the dataset. This step ensured the focus remained on sections with more stable condition trajectories.
4. The analysis then focused on quantifying transitions between condition states. For sections progressing to a progressively worse state (e.g., Very Good to Good) within a duty cycle, the lengths of such sections were aggregated.
5. The proportion of these lengths relative to the total network length calculated previously was then determined, represented as P_{ij}. Consequently, the proportion of sections remaining within the same condition state P_{ii} was identified by subtracting P_{ij} from 1.
6. All other elements of the TPM not directly calculated in the previous steps were set to zero, except P_{nn}. This element was assigned a value of 1 to signify it as a holding state, indicating sections that have reached their lowest condition state and would not deteriorate further without intervention.

The development of 5×5 TPMs for interstate highways, state roads, and U.S. highways, as detailed in Table 3.1 to Table 3.3, provides a framework for analyzing flexible pavement condition transitions over a 2-year duty cycle. These matrices quantify the probabilities of shifting among five condition states—Very Good, Good, Fair, Poor, and Very Poor—offering essential insights into infrastructure resilience and management.

For interstate highways (Table 3.1), the TPM illustrates a 65% probability for flexible pavements in the Very Good condition to remain unchanged. Conversely, there exists a 35% chance for these pavements to transition to Good condition, indicating potential for slight deterioration. The matrix further reveals that flexible pavements in Good condition have a 98% likelihood of maintaining their state, with only a marginal 2% probability of declining to Fair. Fair condition flexible pavements exhibit a 70% probability of remaining stable, while facing a 30% risk of declining to Poor, marking a critical point for potential intervention.

For U.S. highways, the analysis reveals flexible pavements in Good condition are primarily stable, with a 97% chance of maintaining their status, and a small 3% risk of declining to Fair. However, Fair condition flexible pavements are notably vulnerable, with a 79% probability of deteriorating to Poor. Poor flexible pavements face a substantial likelihood (58%) of maintaining their condition, while 42% might further degrade to Very Poor, indicating critical maintenance needs (see Table 3.3).

The state roads, TPM, present a 61% probability for Very Good flexible pavements to retain their condition, with a 39% chance of downgrading to Good. This indicates a slightly higher vulnerability to deterioration compared to interstate highways. Good condition flexible pavements on state roads have an 81% probability of remaining so, while 19% may slip to Fair. Notably, Fair condition flexible pavements are particularly stable, with a 97% likelihood of not deteriorating further. Poor flexible pavements have a very high probability (94%) of not deterioration (see Table 3.2).

Markov chain-based modeling of functional performance deterioration. In the Markov chain models for the three subnetworks, the pavement deterioration process is modeled through iterative multiplication of the initial state vector with TPM. This iterative process is structured as follows.

1. The state vector for each subsequent stage is derived by multiplying the preceding stage's state vector by the TPM. For instance, the state vector at Stage 1 is obtained from the initial state vector (Stage 0) multiplied by the TPM.
2. The state distribution for the deterioration process at any given time t is represented as $X(t) = X(0) \times TPM^t$, where $X(0)$ is the initial condition distribution, and TPM^t is the TPM elevated to the power of t, indicating the years elapsed.

TABLE 3.1
Cumulative TPM calculations for interstate highways across five conditions

Cumulative TPM Interstate Highways	Very Good SV (.518)	Good SV (.467)	Fair SV (.015)	Poor SV (.000)	Very Poor SV (.000)
Very Good	0.65	0.35	0	0	0
Good	0	0.98	0.02	0	0
Fair	0	0	0.70	0.30	0
Poor	0	0	0	0.50	0.50
Very Poor	0	0	0	0	1.00

Note: SV = start vector. Start vectors are for 2021.

TABLE 3.2
Cumulative TPM calculations for U.S. highways across five conditions

Cumulative TPM U.S. Highways	Very Good SV (.023)	Good SV (.927)	Fair SV (.047)	Poor SV (.003)	Very Poor SV (.000)
Very Good	0.50	0.50	0	0	0
Good	0	0.97	0.03	0	0
Fair	0	0	0.21	0.79	0
Poor	0	0	0	0.58	0.42
Very Poor	0	0	0	0	1.00

Note: SV = start vector. Start vectors are for 2021.

TABLE 3.3
Cumulative TPM calculations for state roads across five conditions

Cumulative TPM State Roads	Very Good SV (.091)	Good SV (.671)	Fair SV (.217)	Poor SV (.020)	Very Poor SV (.001)
Very Good	0.61	0.39	0	0	0
Good	0	0.81	0.19	0	0
Fair	0	0	0.97	0.03	0
Poor	0	0	0	0.94	0.06
Very Poor	0	0	0	0	1.00

Note: SV = start vector. Start vectors are for 2021.

The Markov chain analysis, as presented in Table 3.4 through Table 3.7, systematically projects the evolution of pavement conditions across interstate highways, state roads, and U.S. highways over a 50-year period, accounting for a total of 25 stages based on a 2-year duty cycle. This projection is rooted in the initial condition vectors of 2021 and employs TPMs presented in Table 3.1 through Table 3.3 to offer a forward-looking perspective on infrastructure degradation.

For interstate highways (Table 3.4), the analysis anticipates a gradual decline in the proportion of pavements in Very Good condition, with a corresponding increase in Good, Fair, Poor, and Very Poor conditions over time. By 2071, a notable reallocation of pavement conditions is expected.

While the initial quality of U.S. highways may mitigate the onset of significant deterioration, the eventual progression into Fair, Poor, and Very Poor conditions becomes unavoidable in the absence of proactive management strategies (see Table 3.5).

In contrast, state roads, as illustrated in Table 3.6, exhibit a more pronounced and accelerated transition from higher to lower condition states when compared to interstate highways. This pattern is characterized by a notably rapid decline in Very Good and Good condition states, accompanied by a corresponding increase in Fair and Poor states. These trends underscore the importance of implementing a comprehensive, long-term maintenance strategy. Early intervention and consistent upkeep are critical to mitigating the accelerated degradation and ensuring sustainable pavement performance over time.

Figure 3.1 through Figure 3.3 display Markov model results for each condition state for the three road classification subnetworks: interstate highways, U.S. highways, and state roads. These plots represent the probability distributions of condition states within each subnetwork as they evolve over time. The figures facilitate a quantitative analysis of the expected evolution in flexible pavement conditions over discrete time periods, effectively illustrating the dynamic shifts in pavement quality anticipated through the Markov chain analysis.

3.1.2 Deterministic Approach: Empirical Analysis

Coefficient determination and pavement age estimation analysis. The empirical analysis initial step involved determining the coefficient based on adjacent IRI data for each test location and then calculating the average for each classification category. This analysis yielded distinct coefficients "a" for time-series IRI data across different road classifications (Table 3.7).

Utilizing these newly derived coefficients, the ages of flexible pavements were estimated using the 2014 data, projecting up to 2021. This longitudinal analysis revealed the IRI evolution over time across the three functional classes. Figure 3.4 illustrates that IRI for all three functional classes generally increases as pavement age increases. As shown in Figure 3.5, the predicted IRI values demonstrate strong agreement with the measured data across the three functional classes.

As expected, the predictive models confirm that IRI increases with pavement age, following an exponential growth pattern. However, the rate of deterioration differs across road classifications. interstate highways exhibit the slowest rate of IRI progression, with IRI values mostly 150 in./mile or less. This may be attributable to two main factors: first, the possibility of pavement overdesign, where pavements are designed

TABLE 3.4
Pavement condition projections for interstate highways over a 50-year period

Year	Time	Stage	Very Good	Good	Fair	Poor	Very Poor
2021	0	0	0.518	0.467	0.015	0.000	0.000
2023	2	1	0.338	0.638	0.020	0.004	0.000
2025	4	2	0.220	0.742	0.027	0.008	0.002
2027	6	3	0.144	0.804	0.034	0.012	0.006
2029	8	4	0.094	0.838	0.040	0.016	0.012
2031	10	5	0.061	0.854	0.045	0.020	0.020
2033	12	6	0.040	0.858	0.048	0.023	0.030
2035	14	7	0.026	0.854	0.051	0.026	0.042
2037	16	8	0.017	0.846	0.053	0.028	0.055
2039	18	9	0.011	0.835	0.054	0.030	0.069
2041	20	10	0.007	0.822	0.055	0.031	0.085
2043	22	11	0.005	0.808	0.055	0.032	0.100
2045	24	12	0.003	0.793	0.055	0.033	0.116
2047	26	13	0.002	0.779	0.054	0.033	0.133
2049	28	14	0.001	0.764	0.054	0.033	0.149
2051	30	15	0.001	0.749	0.053	0.032	0.165
2053	32	16	0.001	0.734	0.052	0.032	0.181
2055	34	17	0.000	0.719	0.051	0.032	0.197
2057	36	18	0.000	0.705	0.050	0.031	0.213
2059	38	19	0.000	0.691	0.049	0.031	0.229
2061	40	20	0.000	0.677	0.049	0.030	0.244
2063	42	21	0.000	0.663	0.048	0.030	0.259
2065	44	22	0.000	0.650	0.047	0.029	0.274
2067	46	23	0.000	0.637	0.046	0.029	0.289
2069	48	24	0.000	0.624	0.045	0.028	0.303
2071	50	25	0.000	0.612	0.044	0.027	0.317

TABLE 3.5
Pavement condition projections for U.S. highways over a 50-year period

Year	Time	Stage	Very Good	Good	Fair	Poor	Very Poor
2021	0	0	0.023	0.927	0.047	0.003	0.000
2023	2	1	0.011	0.913	0.036	0.039	0.001
2025	4	2	0.006	0.893	0.033	0.051	0.018
2027	6	3	0.003	0.871	0.032	0.056	0.039
2029	8	4	0.001	0.848	0.031	0.058	0.062
2031	10	5	0.001	0.825	0.030	0.058	0.086
2033	12	6	0.000	0.802	0.029	0.058	0.110
2035	14	7	0.000	0.780	0.028	0.057	0.135
2037	16	8	0.000	0.758	0.028	0.056	0.158
2039	18	9	0.000	0.737	0.027	0.055	0.182
2041	20	10	0.000	0.716	0.026	0.053	0.204
2043	22	11	0.000	0.696	0.025	0.052	0.227
2045	24	12	0.000	0.677	0.025	0.051	0.248
2047	26	13	0.000	0.658	0.024	0.049	0.269
2049	28	14	0.000	0.639	0.023	0.048	0.290
2051	30	15	0.000	0.621	0.023	0.047	0.309
2053	32	16	0.000	0.604	0.022	0.045	0.329
2055	34	17	0.000	0.587	0.021	0.044	0.348
2057	36	18	0.000	0.571	0.021	0.043	0.366
2059	38	19	0.000	0.555	0.020	0.042	0.384
2061	40	20	0.000	0.539	0.020	0.040	0.401
2063	42	21	0.000	0.524	0.019	0.039	0.418
2065	44	22	0.000	0.509	0.019	0.038	0.434
2067	46	23	0.000	0.495	0.018	0.037	0.450
2069	48	24	0.000	0.481	0.018	0.036	0.465
2071	50	25	0.000	0.468	0.017	0.035	0.480

TABLE 3.6
Pavement condition projections for state roads over a 50-year period

Year	Time	Stage	Very Good	Good	Fair	Poor	Very Poor
2021	0	0	0.091	0.671	0.217	0.020	0.001
2023	2	1	0.055	0.580	0.337	0.025	0.002
2025	4	2	0.034	0.492	0.437	0.034	0.004
2027	6	3	0.021	0.412	0.517	0.045	0.006
2029	8	4	0.012	0.342	0.580	0.057	0.008
2031	10	5	0.008	0.282	0.627	0.071	0.012
2033	12	6	0.005	0.232	0.662	0.085	0.016
2035	14	7	0.003	0.190	0.687	0.100	0.021
2037	16	8	0.002	0.155	0.702	0.114	0.027
2039	18	9	0.001	0.126	0.711	0.128	0.033
2041	20	10	0.001	0.103	0.714	0.142	0.041
2043	22	11	0.000	0.084	0.712	0.155	0.049
2045	24	12	0.000	0.068	0.707	0.167	0.058
2047	26	13	0.000	0.055	0.699	0.178	0.067
2049	28	14	0.000	0.045	0.689	0.188	0.078
2051	30	15	0.000	0.036	0.677	0.197	0.089
2053	32	16	0.000	0.030	0.664	0.206	0.100
2055	34	17	0.000	0.024	0.650	0.214	0.112
2057	36	18	0.000	0.019	0.636	0.220	0.124
2059	38	19	0.000	0.016	0.621	0.226	0.137
2061	40	20	0.000	0.013	0.605	0.231	0.150
2063	42	21	0.000	0.010	0.590	0.236	0.164
2065	44	22	0.000	0.008	0.575	0.240	0.177
2067	46	23	0.000	0.007	0.559	0.243	0.191
2069	48	24	0.000	0.006	0.544	0.245	0.205
2071	50	25	0.000	0.004	0.529	0.247	0.219

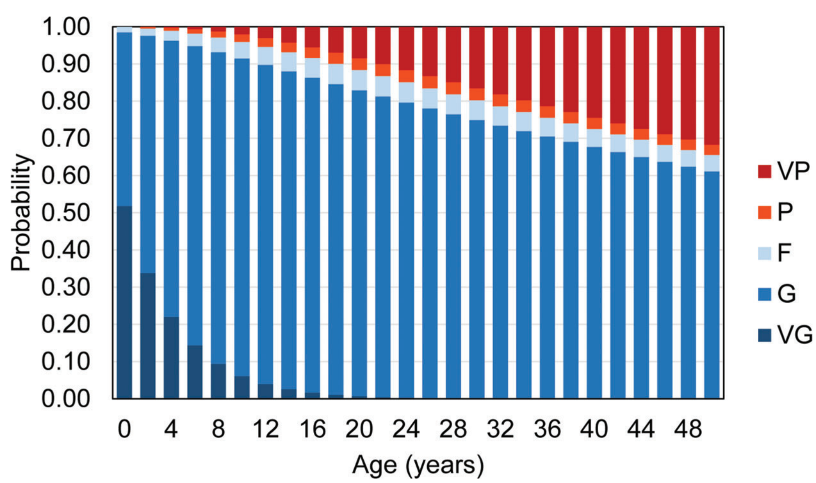


Figure 3.1 Probabilistic transition of interstate highway pavement conditions over time using Markov chain modeling.

and constructed with a higher structural capacity than required; and second, timely rehabilitation efforts that are implemented as soon as IRI values show signs of increasing. The latter may also be an indication that INDOT's maintenance strategies are highly effective in preserving smooth pavement conditions.

By comparison, U.S. highways display a moderate rate of IRI growth, signifying a more gradual deterioration of pavement smoothness, while state roads demonstrate the fastest IRI progression rate. Also, the roughness value ranges for U.S. highways and state roads are quite similar, suggesting that both classifications achieve comparable levels of smoothness, although they are both noticeably rougher than interstate highways. The accelerated deterioration observed for state roads through the deterministic approach is consistent with findings from the probabilistic Markov chain analysis, reinforcing the validity of these observations. Table 3.8 provides a summary of the functional pavement performance prediction models derived from empirical analyses for each road classification. Additionally, it outlines the average

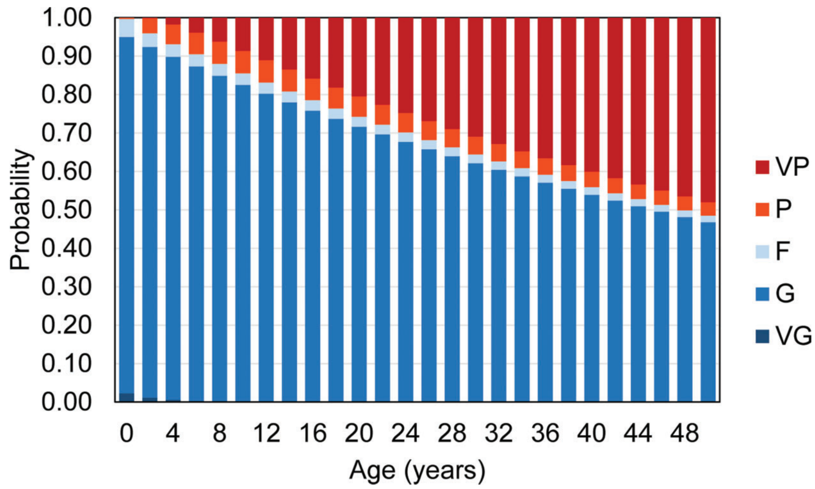


Figure 3.2 Probabilistic transition of U.S. highway pavement conditions over time using Markov chain modeling.

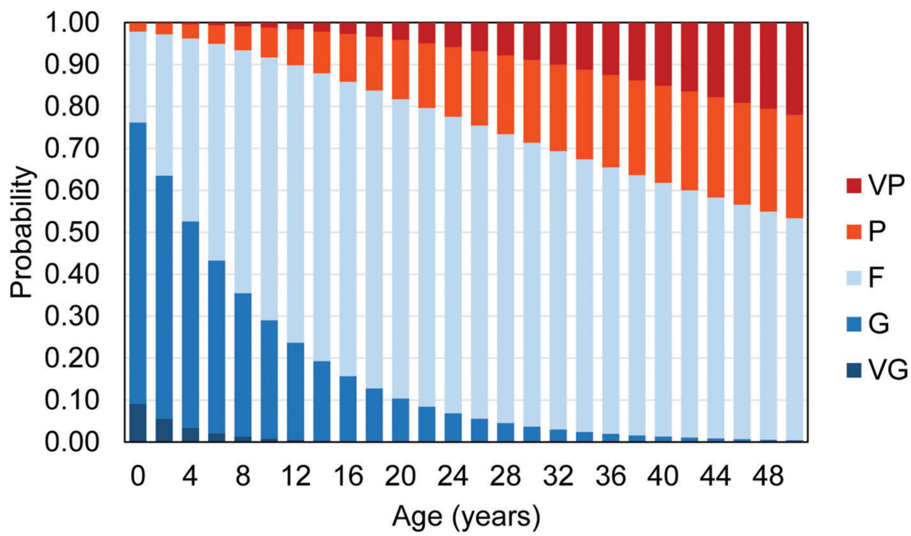


Figure 3.3 Probabilistic transition of state road pavement conditions over time using Markov chain modeling.

TABLE 3.7
Determined coefficient for full-depth flexible pavements in Indiana

Road Classification	Full-Depth Flexible Pavements
Interstate Highway	0.100239
U.S. Highway	0.118715
State Road	0.110825

remaining service life, assuming an IRI threshold of 150 in./mile as the terminal failure point for functional pavement performance.

3.1.3 Sensitivity Analysis of Initial IRI Impact on Flexible Pavement Performance

The results of the sensitivity analyses, depicted in Figure 3.6, provide an understanding of initial IRI value influencing flexible pavement performance roughness. According to previous studies, the initial IRI has been identified as a pivotal factor in predicting pavement performance and long-term roughness progression. Figure 3.6a, obtained from Alnaqbi et al. (2024), demonstrates that initial IRI exhibits a strong positive correlation with subsequent IRI values.

Their finding highlights the substantial influence of early-life pavement quality on the overall performance and deterioration rate of flexible pavements. In this study, sensitivity analysis was also performed to demonstrate how varying the initial IRI affects the predicted IRI at different ages. As seen in Figure 3.6b, the data provides a clear depiction of the relationship, with higher initial IRI values leading to significantly increased subsequent IRI values over time. It also reveals that pavements with higher initial roughness experience accelerated deterioration. From a construction and management perspective, this insight underscores the importance of integrating performance-based specifications into acceptance and quality assurance processes. Such measures could include incentivizing contractors to attain low initial IRI levels through

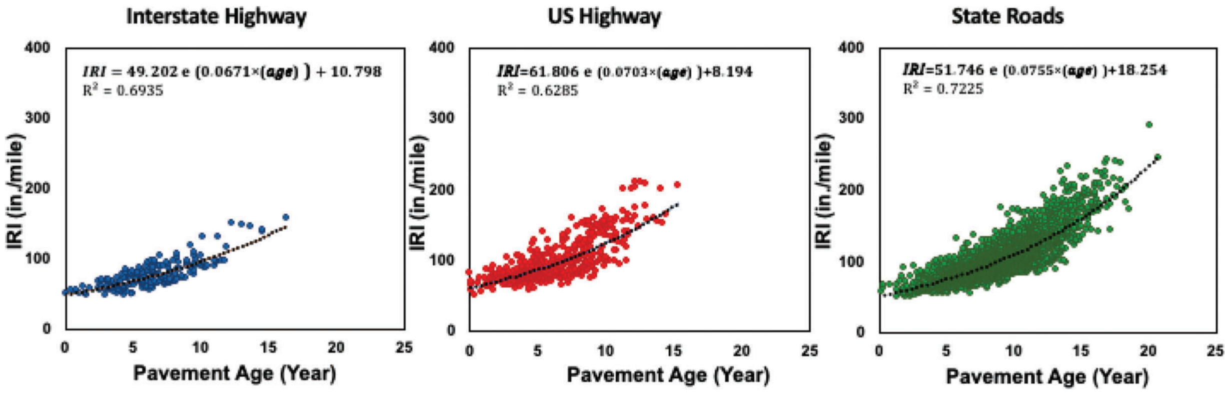


Figure 3.4 Longitudinal analysis of IRI progression with pavement age across different functional classifications.

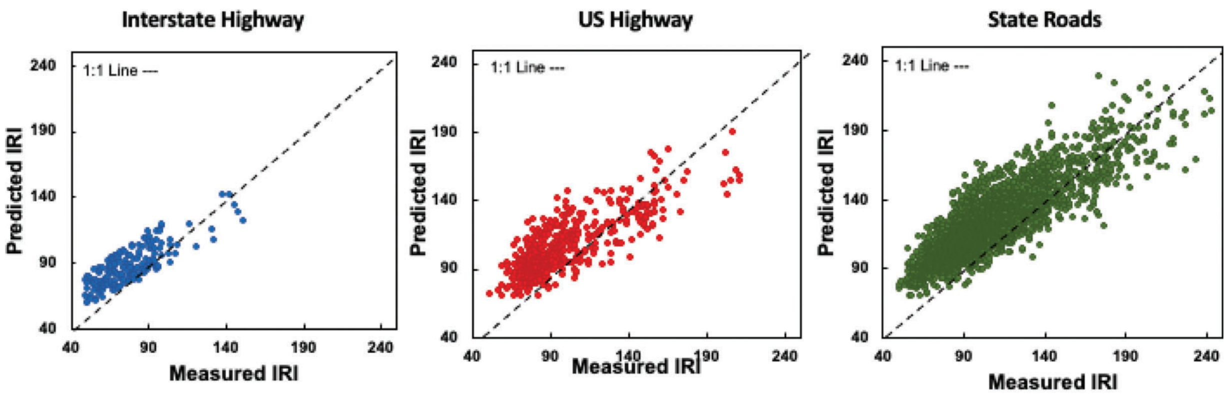


Figure 3.5 Model validation for predicted IRI values of the three functional classes.

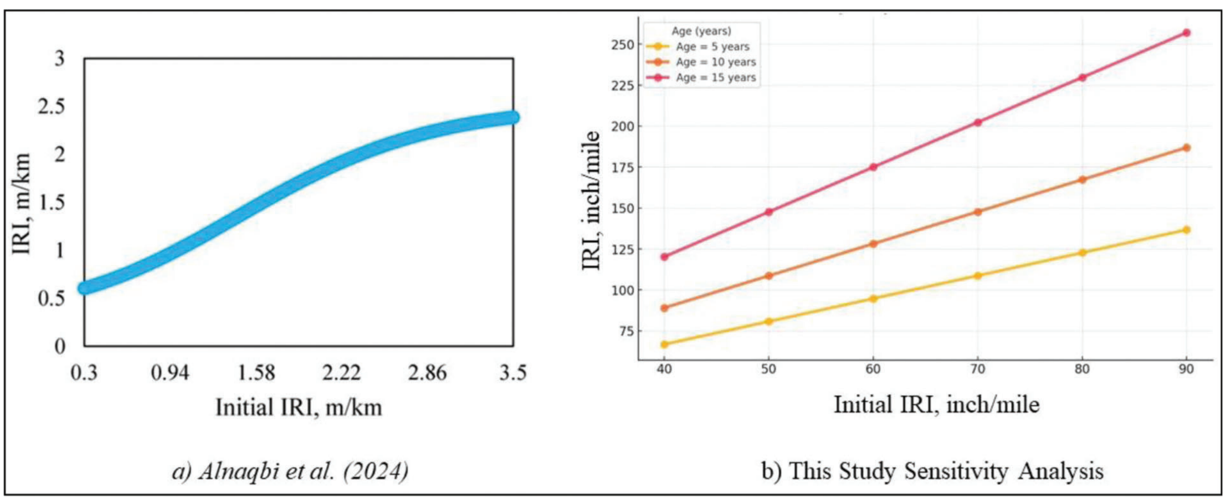


Figure 3.6 Impact of initial IRI on flexible pavement performance: (a) Alnaqbi et al. (2024), (b) sensitivity analysis across pavement ages from the current study.

incentives for compliance with stringent standards and disincentives for substandard outcomes.

3.1.4 Pavement Remaining Service Life Analysis

After predicting the IRI performance over time and developing models for each road classification, the RSL was calculated. Using the IRI values, the RSL for each road section was evaluated to determine whether the section had already surpassed the terminal failure threshold (150 in./mile), or the number of years remaining before reaching it since the last recorded measurement, which in this case was the year of 2021. Subsequently, the average RSL for

TABLE 3.8
IRI prediction models and average remaining service life for three road classifications

Road Classification	Predictive Models	Average Remaining Service Life
Interstate Highway	$IRI = 49.202\ e^{0.0671\ \times\ (age)} + 10.798$	12 years
U.S. Highway	$IRI = 61.806\ e^{0.0703\ \times\ (age)} + 8.194$	6 years
State Road	$IRI = 51.746\ e^{0.0755\ \times\ (age)} + 18.254$	4.5 years

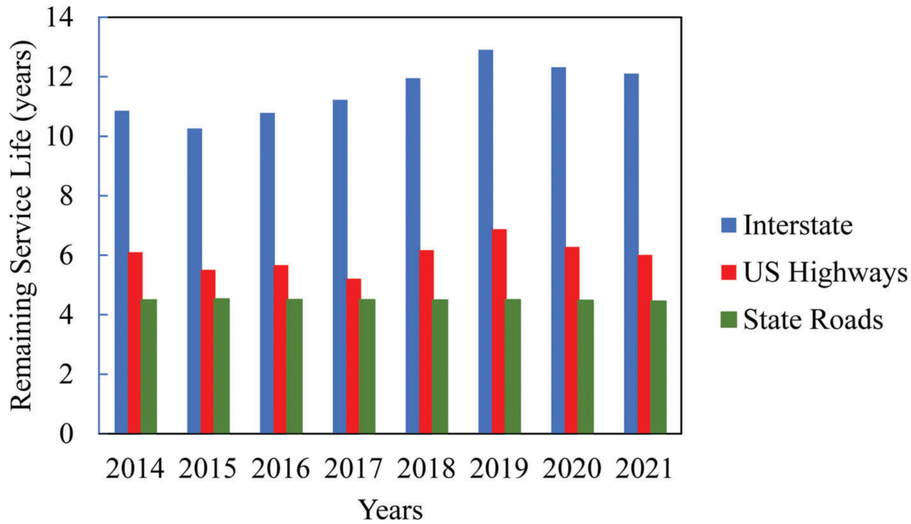


Figure 3.7 Remaining service life evolution for different road classifications over the years using an IRI failure threshold of 150 (in./mile).

each road classification was computed to provide an overall perspective.

The results indicate that interstate highways have the longest average RSL, higher than 10 years from 2021. U.S. highways exhibit a shorter average RSL of approximately 6 years, while state roads display the average RSL, at around 4.5 years (see Table 3.8). These findings are consistent with expectations based on the Markov chain analysis, which demonstrated that state roads and U.S. highways deteriorate at a faster rate than interstate highways.

Figure 3.7 illustrates the RSL trends for the three functional classes from 2014 to 2021. As expected, interstate highways demonstrate the highest RSL values compared to U.S. highways and state roads, reflecting their superior structural design and more frequent maintenance. U.S. highways exhibit moderate RSL values, with a notable increase to 6.87 years in 2019 which may suggest the implementation of targeted maintenance or rehabilitation activities during this period. Interestingly, U.S. highways and state roads have comparable RSL values overall, highlighting similar levels of remaining service life despite differences in construction standards.

3.1.5 Evaluation of Pavement Life Expectancy

Figure 3.8 compares the life expectancy and average IRI across three road functional classifications, over various IRI ranges. The findings indicate that interstate highways with IRI values between 70 and 100 exhibit a life expectancy of approximately 16 to 19 years. Overall, they consistently demonstrate higher life expectancy compared to U.S. highways and state roads, underscoring the effectiveness of INDOT's design, construction, and maintenance strategies.

Interestingly, U.S. highways show life expectancy values that are either similar to or slightly lower than those of state roads, while both categories remain notably below interstate highways. This trend may suggest that INDOT prioritizes surface smoothness over structural improvements for U.S. highways and state roads. One possible explanation for this observation is the potential presence of composite pavements on U.S. highways in Indiana, where concrete pavements may be surfaced with asphalt overlays. However, this remains a hypothesis rather than a confirmed fact. INDOT frequently employs milling and overlay treatments for these highways, which improve surface smoothness but may not address underlying structural issues.

Conversely, state roads are generally thinner and less structurally complex, which could make full reconstruction a feasible option. A possible explanation for this trend is that INDOT may consider reconstruction as an approach to enhance the structural integrity of state roads; however, this remains a hypothesis rather than a statement supported by specific data. Another potential factor could be the lower traffic volume, particularly truck traffic, on state roads compared to U.S. highways.

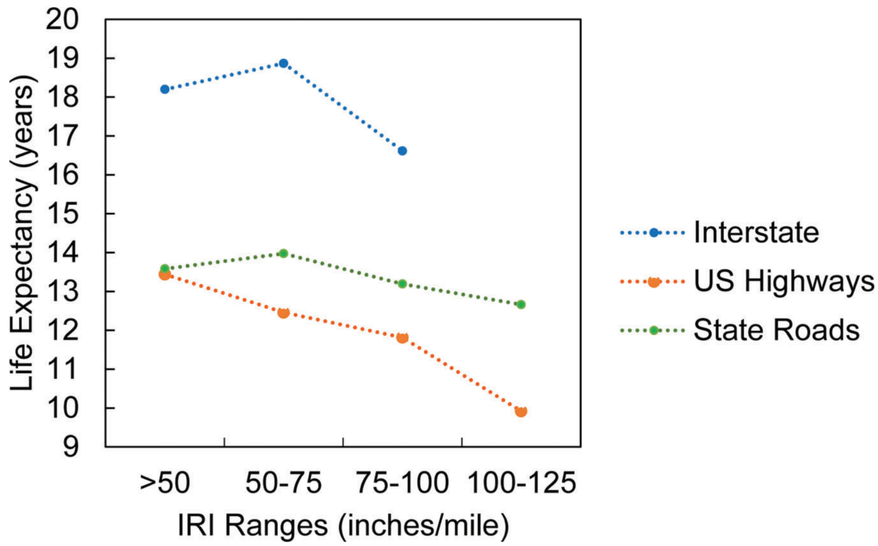


Figure 3.8 Flexible pavement life expectancy and average IRI values.

This reduced loading may contribute to preserving the structural condition of state roads over their service life.

3.2 Falling Weight Deflectometer Performance Monitoring of Pavements

The Falling Weight Deflectometer (FWD) is a nondestructive testing device commonly used to assess pavement structural capacity. By delivering a transient impulse load that mimics the effect of a moving vehicle, the FWD measures the pavement's response in terms of surface deflections. This data helps engineers evaluate the stiffness and load-bearing capacity of a pavement system, which is essential for maintenance planning, rehabilitation design, and performance monitoring.

The FWD is a trailer-mounted system, typically towed by a vehicle. Its main components include a circular loading plate, a weight-dropping mechanism, and an array of geophones or deflection sensors. The loading plate transmits the applied load uniformly onto the pavement surface, while the geophones, arranged radially from the plate, measure deflections at specific distances from the load center. The load is applied dynamically by dropping weight onto a buffer system positioned above the loading plate. This process generates an impulse force, typically ranging from 2,000 to 27,000 pounds, similar to the load exerted by a moving wheel. The applied force and the corresponding deflections are recorded for further analysis. The pavement's response to the load is captured as a series of deflections, which together form a deflection basin. This basin represents the total deformation of the pavement under the applied load. The shape and depth of the deflection basin provide insights into the stiffness of the pavement layers and the subgrade, helping to identify potential areas of weakness or distress.

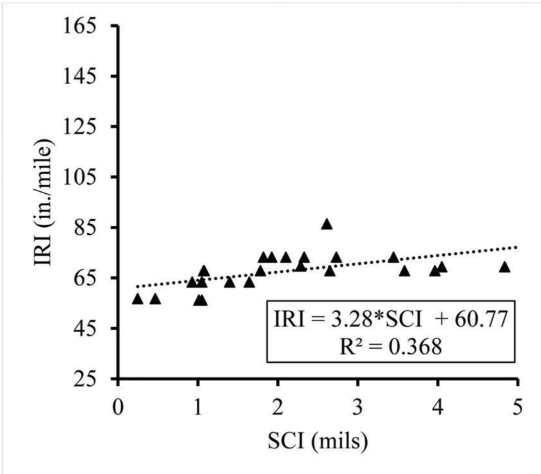
A key analytical process in FWD testing is back-calculation, which estimates the mechanical properties of the pavement layers. Using the measured deflections, back-calculation derives parameters such as the elastic moduli of the surface, base, and subgrade layers. This iterative process compares theoretical deflections computed from multi-layer elastic theory with the measured values to determine the best-fit parameters. While back-calculation is a widely used technique, it relies on assumptions about layer thicknesses, material homogeneity, and boundary conditions, which can introduce uncertainties. In some analyses, simpler metrics like the Surface Curvature Index (SCI) are used instead of back-calculated parameters.

The SCI is calculated using the deflection measurements recorded by sensors positioned at specific distances from the load and represents the difference in deflection between the load center and a point 10 in. away, providing insight into the stiffness and condition of the pavement surface. The SCI is determined using the following equation.

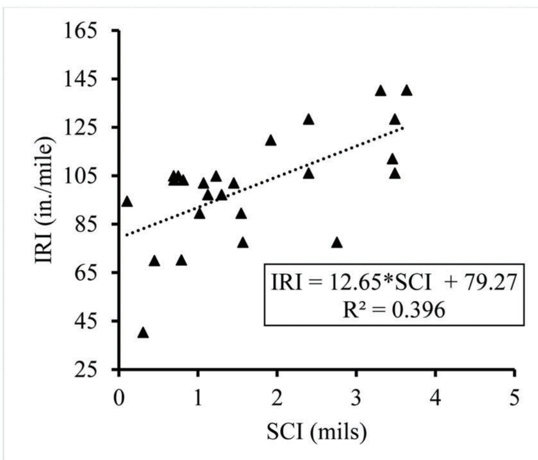
$$SCI = D_0 - D_{300} \qquad \text{(Eq. 3.1)}$$

where D_0 is the deflection (thousandths of an inch) at the load plate center, and D_{300} is the deflection (thousandths of an inch) at a sensor located 10 in. from the load plate center.

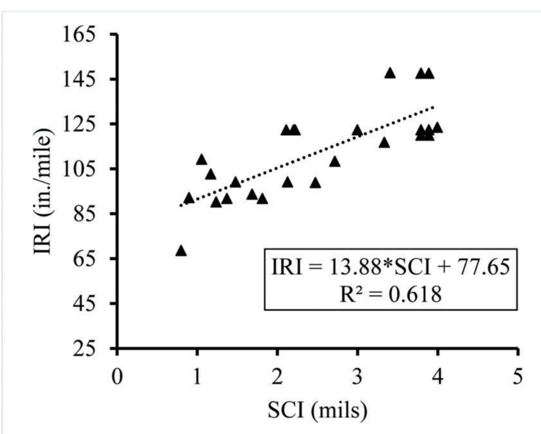
SCI provides a straightforward measure of the surface layer's curvature, reflecting its stiffness and condition. The choice of SCI over back-calculated parameters often stems from its simplicity and reliability. Unlike back-calculation, SCI does not depend on assumptions about underlying layer properties, making it less susceptible to errors. A high SCI value indicates a stiff and well-performing surface layer, while a low SCI suggests reduced stiffness and potential surface distress. By focusing on SCI, engineers can efficiently assess



(a)



(b)



(c)

Figure 3.9 Relationship between SCI and IRI for (a) interstate highways, (b) U.S. highways, and (c) state roads.

surface-layer performance without the complexities of full back-calculation.

Figure 3.9 illustrates the relationship between SCI and IRI values. As expected, the relationship between SCI and IRI varies among road functional classifications. As shown in the figure, the correlation between the two is poor for interstate (R^2 of 0.368) and U.S. highways (R^2 of 0.396), while it is fair to good for state roads (R^2 of 0.618). However, it is observed that the rate of change in IRI values for U.S. highways and state roads exhibit a similar pattern, whereas the increase in IRI values for interstates is significantly lower.

The observed relationships indicate an IRI threshold value of 150 in./mile corresponds to a significantly higher SCI for interstates compared to U.S. highways and state roads. However, based on traditional maintenance practices following FWD test data, it can be inferred that those interstates receive maintenance priority before reaching the IRI threshold, unlike U.S. highways and state roads, and eventually have a longer service life compared to other road types. It also indicates that the U.S. highways and state roads, with less intervention, exhibit a clearer relationship between surface deterioration and roughness. In addition to that, interstates are built with thicker, more resilient pavement structures that can develop surface distresses without significantly affecting roughness, whereas U.S. highways and state roads, with thinner pavement layers, experience a stronger link between distress and ride quality or IRI. Another potential reason could be higher traffic volumes and heavier loads on interstates, which can lead to structural fatigue and rutting, which may not be well captured by SCI but can still influence IRI.

Overall, the SCI-IRI relationship likely results from pavement characteristics and lower maintenance levels, allowing surface distress to impact ride quality more directly. The finding aligns with Markov chain modeling results, highlighting a longer service life for interstates. A previous study also concluded that state roads exhibited the highest FWD deflection parameter values, while interstate highways demonstrated the lowest values at an equivalent reliability level (Jha et al., 2023). Their finding suggested that a conservative threshold value should be adopted for roads with heavier and higher traffic speeds, such as interstate highways, to ensure superior conditions compared to U.S. highways and state roads, which experience lower traffic volumes, less heavy traffic, and slower traffic speeds. Therefore, the model demonstrated that prioritizing maintenance on interstate highways can delay deterioration and preserve their condition, while U.S. highways and state roads face shorter service lives due to less frequent maintenance interventions. The finding emphasizes the impact of maintenance prioritization on pavement longevity, supporting tailored strategies to optimize pavement performance across different road networks in Indiana.

4. FINDINGS

Effective management of pavement conditions requires predictive tools to address the functional and structural performance of pavements. While existing methods often focus on surrogate material properties, they fail to capture the system-level behavior critical for long-term performance evaluation. This study bridges this gap by developing practical models that define acceptable functional performance limits and predict pavement deterioration trends. The primary focus of the study was on functional performance, employing the IRI and SCI as key performance indicators. A dual methodological approach was implemented: the probabilistic Markov chain model analyzed pavement deterioration through condition state transitions, while the deterministic empirical model developed IRI-based prediction models and evaluated the RSL. The analysis was conducted across three road classifications, interstate highways, U.S. highways, and state roads, using historical IRI data to assess trends, predict RSL, and examine the influence of IRI and SCI on long-term performance. Additionally, sensitivity analyses emphasized the critical role of initial IRI values, showing that pavements with higher initial roughness deteriorate more rapidly over time.

4.1 Summary of Main Findings

The following conclusions are drawn from analyzing IRI and FWD data using various predictive models.

- The Markov chain (probabilistic) and deterministic models provide consistent insights, with both approaches highlighting similar trends in flexible pavement deterioration.
- Higher initial IRI values lead to accelerated deterioration, underscoring the importance of achieving low initial roughness levels during construction.
- Interstate highways exhibit the slowest rate of IRI increase, reflecting robust structural designs and superior maintenance practices aimed at preserving pavement smoothness.
- U.S. highways show a moderate IRI rate increase, while state roads experience a slightly faster rate of IRI increases.
- The IRI value ranges for U.S. highways and state roads are quite similar, suggesting that both functional classifications achieve comparable levels of smoothness, although they remain noticeably rougher than interstate highways.
- Interstate highways have the longest RSL, averaging over 10 years.
- U.S. highways and state roads demonstrate an RSL of approximately 6 years and 4.5 years, respectively, emphasizing their higher deterioration rates compared to interstate highways.
- Interstate highways consistently demonstrate the highest life expectancy across various IRI ranges.
- U.S. highways and state roads exhibit similar life expectancies and maintenance requirements, with U.S. highways life expectancy slightly lower than those of state roads.
- The relationship between SCI and IRI values varies across road types, with U.S. highways and state roads showing a comparable increase in IRI as SCI rises, while interstates exhibit a significantly smaller increase.
- Factors such as higher traffic volumes, heavier loads, and frequent maintenance strategies could influence the relationship between SCI and IRI, particularly for interstates, where different structural distress may impact IRI but are not well captured by SCI.

4.2 Implementation

To enhance pavement longevity and performance, it is recommended that construction practices prioritize achieving lower initial IRI values, as higher initial roughness has been shown to accelerate long-term deterioration. Maintenance strategies should be tailored to meet the specific needs of different highway classifications, even when IRI values appear similar. Since the relationship between SCI and IRI varies by road type, relying solely on one of these indicators may lead to incomplete assessments. Therefore, it is essential to integrate both functional (IRI) and structural (SCI) performance metrics to improve the accuracy of maintenance decision-making and support targeted interventions. While this study does not include a direct cost-benefit analysis, the findings provide a strong foundation for improving cost-effectiveness in pavement management. By leveraging the IRI-based RSL projections and structural insights from FWD testing, transportation agencies can better schedule treatments to prevent over-maintenance or costly reconstruction. Future research may incorporate formal life cycle cost analysis (LCCA) or cost-benefit modeling to quantify these benefits more precisely. The integration of FWD and IRI data enables early identification of both structural and functional pavement deficiencies, allowing engineers to take proactive measures before conditions worsen. By combining IRI progression models with SCI measurements, agencies can strategically target surface or structural treatments, particularly before pavements exceed critical IRI thresholds. This predictive approach ensures that maintenance is neither performed too early, which would waste resources, nor too late, which could necessitate costly reconstruction, thereby optimizing both treatment timing and overall maintenance costs. To translate the research findings into practical use, the following steps are recommended for integration into INDOT's pavement management strategies.

- *Adopt Initial IRI Thresholds:* Incorporate performance-based acceptance thresholds (e.g., IRI $\leq$ 70 in./mile) into construction quality assurance protocols to ensure smoother pavements at the outset and reduce long-term deterioration rates.
- *Develop Predictive Dashboards:* Integrate the probabilistic (Markov chain) and deterministic (empirical) models developed in this study into network-level decision support systems that can forecast IRI trends and estimate remaining service life (RSL).
- *Institutionalize Routine Monitoring:* Conduct regular (annual or biennial) evaluations using both IRI and SCI indicators to track functional and structural pave-

ment performance. This dual approach enables earlier detection of surface and subsurface issues.

- *Prioritize Preventive Maintenance:* Use IRI-based RSL estimates and SCI patterns to flag pavement sections nearing critical thresholds (e.g., IRI $\geq$ 150 in./mile) and prioritize them for timely intervention before severe degradation occurs.
- *Integrate Structural Insights from FWD:* Utilize SCI–IRI correlations to enhance surface evaluations with structural diagnostics. This is particularly important for U.S. highways and state roads, where surface distress more directly affects ride quality and structural performance.
- *Support Budgeting with Data:* Apply projected deterioration patterns and RSL outcomes to inform budgeting decisions, optimize resource allocation, and improve return on investment (ROI) across the pavement network.

4.3 Recommendations for Future Research

Based on the findings, some of the recommended scopes for future research to enhance understanding and practical application are as follows.

- Explore how environmental conditions, material properties, and traffic loading influence pavement deterioration to refine model accuracy.
- Investigate the feasibility of applying Pavement ME's critical strain-based indicators in practice, despite sensor-related challenges.
- Further analyze the SCI–IRI relationship across different pavement structures to better understand how surface and structural distress jointly influence performance.
- Expand on this study by incorporating cost-effectiveness analysis (e.g., LCCA) to translate predictive insights into financial impacts and long-term savings for agencies.

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On March 11, 1937, the Indiana Legislature passed an act which authorized the Indiana State Highway Commission to cooperate with and assist Purdue University in developing the best methods of improving and maintaining the highways of the state and the respective counties thereof. That collaborative effort was called the Joint Highway Research Project (JHRP). In 1997 the collaborative venture was renamed as the Joint Transportation Research Program (JTRP) to reflect the state and national efforts to integrate the management and operation of various transportation modes.

The first studies of JHRP were concerned with Test Road No. 1—evaluation of the weathering characteristics of stabilized materials. After World War II, the JHRP program grew substantially and was regularly producing technical reports. Over 1,600 technical reports are now available, published as part of the JHRP and subsequently JTRP collaborative venture between Purdue University and what is now the Indiana Department of Transportation.

Free online access to all reports is provided through a unique collaboration between JTRP and Purdue Libraries. These are available at http://docs.lib.purdue.edu/jtrp.

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Khajehvand, M., Al Mamun, A., Nantung, T., & Cho, S. (2025). *Performance acceptance and performance monitoring of pavement using Falling Weight Deflectometer (FWD) and International Roughness Index (IRI)* (Joint Transportation Research Program Publication No. FHWA/IN/JTRP-2025/13). West Lafayette, IN: Purdue University. https://doi.org/10.5703/1288284317877