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INDIANA DEPARTMENT OF TRANSPORTATION
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Lessening Density Requirement and Adjusting Density Pay Factors for Asphalt Pavements in Poor Sublayer Conditions



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16. Abstract <p>Current quality control and quality assurance practices for asphalt pavements rely heavily on density (%Gmm) measurements, which are directly linked to pay adjustments. However, these practices can inadvertently encourage over-compaction, leading to issues such as aggregate segregation, crushing, and reduced pavement quality, especially under poor subgrade conditions. This study examines the relationship between the density of newly laid asphalt layers and the conditions of underlying sublayers in Hot Mix Asphalt pavements. This study analyzed INDOT's historical compaction data and conducted gyratory compaction testing. The analysis result revealed a weak negative correlation between subgrade conditions and surface density. Similarly, the gyratory compaction testing demonstrated that poor sublayer conditions resulted in lower surface density values, while stable subgrades lead to higher densities. Based on these findings, this study proposes a probabilistic approach for pay factor adjustments using subgrade deflection as a key parameter. These findings offer a pathway to refine pay factor criteria, enhancing pavement consistency and durability while promoting equitable pay adjustments for both INDOT and contractors.</p>			
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EXECUTIVE SUMMARY

Introduction

Compaction is critical in asphalt pavement construction, and it determines the overall quality, durability, and performance of the pavement. Proper compaction ensures the adequate interlocking of aggregates and minimizes air void content, thus enhancing the structural integrity and resistance to traffic loads. Conversely, poorly compacted Hot Mix Asphalt (HMA) pavements are prone to premature deterioration, which leads to costly repairs. Over-compaction can also reduce flexibility, causing surface issues like aggregate crushing and segregation, which increase the likelihood of cracking and structural failure. To ensure quality standards, state transportation agencies implement comprehensive quality control and assurance systems to measure key performance indicators such as density. These measurements guide pay factor adjustments, where contractors are incentivized to achieve specific density targets. For example, the Indiana Department of Transportation (INDOT) uses higher pay factors for higher densities, promoting optimal compaction.

However, achieving target densities is challenging when working with unstable sublayers, such as weak subgrades, or with softer binders, such as cutback and coal tar. These sublayers can absorb compaction energy, which makes it difficult to attain the desired surface density and potentially leads to over-compaction and defects. Contractors often have limited control over pre-existing sublayer conditions, making it difficult to achieve consistent compaction. Therefore, the current density requirements and pay factors may not always be appropriate for pavements built on poor sublayers.

Given these challenges, it is crucial to establish a clear understanding of how variations in sublayer conditions impact surface density outcomes, so that density requirements and pay factors can be more accurately tailored to real-world conditions. Hence, this study investigated correlations between the density of newly laid asphalt surface layers and the condition of underlying sublayers. This study also develops data-driven recommendations for adjusting density pay factors in INDOT's standard specifications based on these correlations. To achieve these research goals, the research approach consisted of three main tasks: (1) historical data analysis, (2) laboratory testing and analysis, and (3) specification review and probabilistic approach for pay factor adjustment.

The historical data analysis involved using INDOT's databases, such as the falling weight deflectometer (FWD) and Pay Wizard databases, to identify patterns between sublayer conditions and compaction outcomes (%Gmm). Laboratory tests, including gyratory compactor and light weight deflectometer (LWD) tests, were conducted to simulate compaction under varying sublayer conditions and observe how factors like subgrade stiffness impact surface density. SmartKli sensors provided real-time data on pressure, rotations, and accelerations during compaction, which offered a nuanced understanding of how sublayer conditions affect the process. Lastly, this study reviewed existing pay factors on standard specifications and proposed a probabilistic approach to pay factor adjustments. The probabilistic scenarios account for sublayer variability and real-world field conditions, making pay factors more reflective of actual construction challenges.

Overall, this study provides INDOT with data-driven insights and evidence-based recommendations for refining density specifications, which ensures adaptability to sublayer conditions and better pavement performance.

Findings

This study explored the correlation between the density of newly laid asphalt layers and the conditions of underlying sublayers in HMA pavements to optimize density pay factors in the INDOT standard specifications. The findings indicate that sublayer conditions, particularly weak or unstable sublayers, significantly influence surface density outcomes, which are crucial for pavement durability and performance.

The historical data analysis revealed a weak negative correlation between subgrade deflection and surface density, with 12.5-mm mixtures displaying a slightly stronger correlation compared to 9.5-mm mixtures. Variations in sublayer conditions, such as those found in state roads and U.S. highways, were found to contribute to lower surface densities compared to interstates where conditions were more stable.

Lab testing and analysis further supported these findings, demonstrating that poor sublayer conditions (e.g., soft or loose subgrades) led to reduced density values on newly generated surface layer, while more stable sublayers or subgrades resulted in higher compaction quality. Real-time monitoring using SmartKli sensors captured dynamic interactions during compaction, revealing how sublayer stiffness affected the distribution of compaction forces on different sublayer or subgrade conditions.

The specification review recommended a probabilistic approach to pay factor adjustments based on subgrade deflections, and divided scenarios into favorable, moderate, and poor sublayer conditions. The analysis suggested that the current pay factors for state roads and U.S. highways may be overestimated, while interstates' pay factors could potentially be adjusted downward.

Implementation

The implementation strategy for this study is centered around a phased approach to effectively incorporate the proposed pay factor adjustments into INDOT's standard specifications. The first step involves revisiting existing and ongoing INDOT projects where current pay factor formulas were applied. By evaluating these projects using the probabilistic scenarios outlined in the study, which include subgrade deflection values for different road types, INDOT can assess how well the proposed adjustments align with observed field conditions.

Following this review, pilot projects are recommended for different road types—state roads, U.S. highways, and interstates. These pilot projects will enable the evaluation of the proposed pay factor adjustments under real-world conditions and will provide valuable insights into their effectiveness and applicability. Feedback from contractors and stakeholders during these pilot phases will be crucial to refine and validate the adjustments before broader implementation.

Roundtable discussions or feedback sessions with contractors are suggested during the pilot phase to address any practical concerns and ensure that the proposed pay factors are reasonable and applicable. These engagements will help gather feedback on whether the adjustments fairly represent compaction challenges faced in the field and whether they support achieving better compaction quality.

Successful pilot testing and feedback collection would pave the way for full-scale adoption of the revised pay factor system across various INDOT projects. This approach will ensure that the pay factor adjustments are not only theoretically sound but also practically effective, enhancing overall pavement performance and durability while ensuring a fair and consistent application of pay factors across different road types.

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1. INTRODUCTION

1.1 Background

Compaction is one of the most crucial steps in asphalt pavement construction, as it plays a pivotal role in determining the overall quality, durability, and performance of the pavement (Yiqiu et al., 2014). Proper compaction increases the interlocking between aggregates thereby enhancing the structural integrity of the asphalt and minimizing the air void content between particles, a metric often represented by the density (%Gmm) (Wang et al., 2022). Achieving the correct density during compaction ensures that the pavement is robust enough to withstand the pressures of traffic and environmental factors (Yao & Song, 2023). Poorly compacted Hot Mix Asphalt (HMA) pavements are unlikely to reach their intended design life, resulting in premature deterioration (Beainy et al., 2012; Horan et al., 2012). Such early failures in pavement performance necessitate costly maintenance and resurfacing interventions, placing a financial burden on agencies responsible for roadway infrastructure (Horan et al., 2012).

However, the other extreme—over-compaction—can also be detrimental. When HMA pavements are over-compacted, it can lead to a reduction in the mixture's plasticity, which in turn compromises the pavement's ability to flex under traffic loads (Wang et al., 2022). This rigidity may cause surface-level issues such as aggregate crushing and pavement segregation, eventually leading to more serious problems like premature cracking and structural failure (Miller et al., 2011). Both under-compaction and over-compaction highlight the importance of achieving optimal compaction levels to ensure the longevity and performance of asphalt pavements.

To ensure that contractors meet the desired quality standards for asphalt pavements, state transportation agencies rely on a comprehensive system of quality control (QC) and quality assurance (QA) testing. These tests measure key performance indicators of the HMA mixture, allowing agencies to assess compliance with project specifications and determine appropriate payment. The payment is often adjusted based on “pay factors,” which are assigned according to the degree to which the HMA properties meet the established criteria (Al-Khayat et al., 2020). Different state agencies apply various pay factors for HMA standards, reflecting regional performance expectations and design philosophies. In Indiana, for instance, the Indiana Department of Transportation (INDOT) specifies that higher pavement densities, up to 98%Gmm, correspond to higher pay factors, creating an incentive for contractors to aim for maximum density during compaction (INDOT, 2022).

1.2 Problem Statement and Objective

Asphalt mixtures placed on unstable sublayers or subgrades, such as weak sublayers or subgrades in poor

condition, are challenging to compact effectively (Jin et al., 2021). These sublayers tend to absorb much of the compaction energy, making it difficult to achieve the desired density in the surface layer. In severe cases, the struggle to meet density targets can result in excessive breakdown passes, as operators attempt to attain higher pay factors tied to density requirements. This over-compaction can lead to unintended consequences, such as density segregation within the asphalt lift and aggregate crushing on its surface, which compromise pavement performance and durability.

Compounding the issue is the fact that contractors often have little or no control over the existing sublayer conditions in many asphalt rehabilitation projects. These pre-existing conditions can vary significantly, adding further complexity to achieving consistent compaction. Given these challenges, the current density requirements and associated pay factors, especially in cases where sublayers are in poor condition, may not be appropriate. A study is necessary to evaluate potential adjustments to the density requirements or pay factors, enabling more realistic expectations and improving outcomes for pavements built on suboptimal sublayers.

The primary *objectives* of this study are twofold: (1) to identify a clear correlation between the density of newly laid asphalt surface layers and the condition of underlying sublayers in HMA pavements, and (2) to develop evidence-based recommendations for adjusting the density pay factors in INDOT's standard specifications based on the identified correlations. By achieving these objectives, this study provides INDOT with the necessary data-driven insights to refine and optimize their density specifications, ensuring that they are more adaptable to varying sublayer conditions and promote better pay adjustments across diverse project scenarios in QA practices.

1.3 Research Approach

The research approach for the study consists of three tasks (shown in Figure 1.1) which are (1) historical data analysis, (2) lab testing and analysis, and (3) specification review and probabilistic approach. The details of the sections are described below.

1.3.1 Task 1: Historical Data Analysis

This study conducts historical data analysis to establish a data-driven foundation for understanding the correlation between asphalt surface density and sublayer conditions. By analyzing historical data, such as falling weight deflectometer (FWD) values and previous asphalt density results from projects in Indiana, the research team identifies correlations between compaction qualities and varying sublayer conditions (depending on deflection values). The data mining and analyzing historical data reveals correlation patterns and linear regression models.

TASK 1 - Historical Data Analysis

- Collecting Historical FWD and Density Data in Indiana
- Mining Collected Historical Data
- Conducting Correlation Analysis

TASK 2 - Lab Testing and Analysis

- Conducting Gyratory Compactor Test
- Conducting LWD Test
- Conducting SmartKli Sensor

TASK 3 – Specification Review and Probabilistic Approach

- Reviewing State Agencies' Pay Factor
- Synthesizing Findings from Historical Data and Lab Testing
- Recommending Adjustment of the Current Pay Factor Implementation

Figure 1.1 Research approach.

1.3.2 Task 2: Lab Testing and Analysis

Using the gyratory compactor, the research team replicates the compaction of HMA under uniform conditions, ensuring consistency across all test specimens. This controlled environment allows the isolation of sublayer condition effects on compaction quality and asphalt density. The primary objective of this task is to examine how variations in sublayer conditions, such as soft versus rigid sublayers, impact the density and structural integrity of the surface layer. Along with gyratory compaction testing, the light weight deflectometer (LWD) is used to measure sublayer deflection, providing key insights into stiffness and how sublayers absorb compaction energy. Simulating different sublayer conditions—from dense crushed stone to loose, unbound layers—enabled the team to observe how subgrade stiffness influences surface density. SmartKli sensors are also employed, offering real-time measurements of pressure, rotations, and accelerations, to provide a detailed view of how compaction forces are distributed on different sublayer or subgrade conditions during compaction process. This advanced monitoring allowed for a more nuanced understanding of the interactions between sublayers and compacted asphalt.

1.3.3 Task 3: Specification Review and Probabilistic Approach

The research team takes a comprehensive look at the asphalt density pay factors utilized by various state transportation agencies. The team begins by reviewing pay factor standards, focusing on INDOT standard specifications and gathering information from other Midwest state agencies for comparison. Synthesizing findings from both historical data analysis and lab testing phases provides a clearer understanding of the relationship between sublayer conditions and surface layer density, allowing the team to predict density outcomes based on specific subgrade conditions (e.g., deflections). The task incorporates a probabilistic

approach to create data-driven recommendations for adjusting pay factors, ensuring a flexible system that reflects real-world sublayer variability and field conditions. The ultimate goal of these recommendations is to make pay factors more reflective of actual construction challenges, particularly in scenarios with unstable sublayers, thereby improving pavement durability, longevity, and fairness in pay factor assessments.

1.4 Research Scope

This study focuses primarily on HMA overlay and preventive maintenance projects on state roads, U.S. highways, and interstates. The research examines subgrades of asphalt pavement structures to conduct a comprehensive correlation analysis between these layers and surface density outcomes. In addition, the study emphasizes Superpave5, an advanced mixture design with a target air void content of 5%, as opposed to the current Superpave specification of 4%. Superpave5 is considered more effective in enhancing the durability and performance of the pavement structure (Rahbar-Rastegar et al., 2022). Superpave, as a system, offers a performance-driven approach to mixture design, taking into account the specific characteristics and demands of the pavement.

2. HISTORICAL DATA COLLECTION

This chapter outlines the process undertaken to gather and consolidate relevant data necessary for this study. The research team acquired historical datasets, including FWD results, asphalt compaction data, and QA records from various past projects in Indiana. This study's acquired data from different data sources were originally collected at different times and across various locations. Specifically, the FWD test data, which evaluates sublayer conditions, and the density testing data, which is performed after the new construction, were not originally collected in a way that allowed for direct comparison. INDOT selects density testing spots

randomly for QA purposes, meaning that the locations of FWD testing and density testing often did not coincide. The research team had to collect these datasets separately, sourcing FWD data and density testing data from different databases. To overcome this challenge, a significant amount of effort was devoted to manually matching the testing spots for each project. This involved reviewing and cross-referencing construction documents, including construction drawings, to align the FWD test locations with the randomly selected density test locations.

2.1 Data Sources

The research team investigated and retrieved data from four key sources: (1) contract letting information, (2) INDOT FWD database, (3) HMA Pay Wizard, and (4) AASHTO SiteManager.

2.1.1 Contract Letting Information

This web-database (Figure 2.1) provides a range of construction-related information, including contract information books, plan/drawing sets, permits, geotechnical reports, and more. For this research, the contract information books were used to collect details such as contract number, designation no, project description (project type), letting date, district, county, route, and reference points (RP). Plan/drawing sets were also used to identify the location of core samples. Corresponding contract information was collected based on HMA data from the HMA Pay Wizard using the contract number. Since the contract information is generated prior to construction, the data collected spans from 2019 to 2022.

2.1.2 HMA Pay Wizard

This database contains information on HMA samples collected from construction sites to determine the pay factor. It includes details such as lot, subplot, acceptance type (percentage within limit (PWL) or volumetric), sample date, sample ID, material quantity, mixture type, layer, and density test results of cores A and B (INDOT takes two cores for QA purposes), as shown in Figure 2.2. For this study, the contract number, sample date, and sample ID were utilized to match the locations of the FWD data. Additionally, the mixture type, layer, and density cores A and B were collected for data analysis later. The research team

collected data from 2020 to 2023 projects in these years used Surpave5.

2.1.3 FWD Historical Data

This dataset includes essential information such as test ID (request number), reference points (RP), DMI, FWD Station, and drop data, which contains surface deflection and subgrade deflection (D1 through D9), in-situ CBR, structural number, resilient modulus, and more. For this study, the test ID and RP were collected to locate FWD test points for comparing with the sampled core locations. Also, the research team collected deflection data for further data analysis. As FWD testing is typically conducted prior to contract letting, data from 2017 to 2021 was used. To align the HMA core sample data with the FWD data—given the discrepancy between the station numbers for FWD and construction—additional location information was obtained using AASHTO SiteManager.

2.1.4 AASHTO SiteManager

This tool provides location data for core samples taken on-site during construction, represented by station numbers (Figure 2.3). Using this information, the locations of core samples were mapped with the aid of plan/drawing sets and displayed through Google Maps to cross-reference core sample density data with FWD data.

2.2 Data Mining and Screening

The data mining process for this study involved a multi-step approach, focusing on key criteria such as timeline consistency, geographical location accuracy, project scope alignment (e.g., resurfacing versus partial replacing), material type checks (e.g., Superpave5, 9.5-mm, 12.5-mm mixtures), and ensuring the exclusion of irrelevant data (e.g., outdated or incomplete records).

The study's scope only focuses on resurfacing projects using Superpave5 mixtures. The research team began by sourcing relevant data from several key databases, including HMA Pay Wizard for density-related data, contract letting information for construction-related data, and the FWD database for deflection values. Sample location data from AASHTO SiteManager was also integrated into the process. By cross-referencing these multiple datasets, the research team could align them to common entities such as

Posted Documents for View and Download							Contract Letting Information	180007
							Indiana Department of Transportation	
Search Criteria: • Document Type: All • Content Number: 29426 • District: Not Selected • Letting Date Month: Not Selected • Letting Date Year: Not Selected							Results Found: Begin a New Search	
Contract Information Books							Number of Records: 1	
Select File	Contract Number	Title	Content ID	District	Letting Date	Document Type	File Size in MB's	
Select File	R-29426-A	R-29426-A CIR	UCM11GDOT1955742	Seymour	1/13/21	Contract Information Book	3422	
Plan/Drawing Sets							Number of Records: 1	
Select File	Contract Number	Title	Content ID	Final Tracing Type	Document Type	District	Letting Date	Primary Designation Number
Select File	R-29426	FT Plans/Kcact 050875 For Contract Services	UCM11GDOT1871785	Final Tracings	Seymour	1/13/21		37645

Figure 2.1 Example of a data point in contract letting information.

QA/QC

QC

QAC

Appel Results

Pay Adjustments

Return to Summary

Previous List

Next List

Contract #: 29426CLIN: 9028DMP: 2231005Lot: 1Acceptance: VolumetricFinal

QA Results	Sample Date	Related Sample ID	Req. Qty (Tons)	Mix % Binder	Mix Gravel	PIB 1 Gravel	PIB 2 Gravel	PIB Avg. Gravel	Core A Gravel	Core B Gravel
Sublot 1	07/29/2022	R025440329001	400.00	7.11	2.433	2.291	2.298	2.295	2.193	2.220
Sublot 2	07/28/2022	R025440329002	734.36	7.39	2.429	2.353	2.358	2.356	2.362	2.345

INDOT T20 Detail

QA/QC A	Mix % Binder	Mix Gravel	PIB Avg. Gravel	Core A Gravel	Core B Gravel	Appel	Accept Results	Status
Sublot 1	0.06	0.005	0.001	0.007	0.003	Appel	Accepted	
Sublot 2	0.01	0.009	0.009	0.009	0.007	Appel	Accepted	

Mix Properties for Acceptance

	PIB	PIB1 / PIB	Gravel	Gravel for Calc	Gravel Mass %	PIB	Adjust	% Binder	% Air Inside	% VMA	% Density Core A	% Density Core B	% VMA	% Flow	% VMA over req
DMP	4.42	1.10	2.722	2.593	0.000	1.88	0.025	6.90	4.99	16.60	-	-	11.61	5.09	-
Sublot 1	4.50	1.21	2.716	2.593	1.80	-0.006	7.11	5.87	17.79	90.14	91.25	12.11	5.44	1.11	
Sublot 2	4.42	1.26	2.724	2.593	2.593	1.91	0.002	7.39	3.01	15.85	97.24	96.54	12.85	5.62	1.85

Figure 2.2 Example of a data point in HMA Pay Wizard.

AASHTO SiteManager

File Edit Services Window Help

Maintain Sample Information

Basic Sample Data Addtl Sample Data Contract Other Tests

Sample ID: R066165546041 Buy American: ☐ Spaces

Requested By:

Sample Size: None

Dist from Grade: Spaces

Station: 414+55 Offset: 8RT.EP Reference:

Sampled From: IN PLACE

Sample At: JOB SITE

Control Type: 73 Beginning Number: Ending Number:

Design Type: Spaces Mix ID:

Plant ID: 3373 Rieth-Riley Constr Plant Type: HMA Drum Plant

Sample Created from DWR: ☐ Creator User ID: d60crook Include Standard Remarks: ☐

DWR Date: 00/00/00 Last Modified User ID: mesumma

DWR Inspector: Last Modified Date: 05/29/20

INDOT

Figure 2.3 Example of a data point in AASHTO SiteManager.

contract number, station number, sample ID, and RP, ensuring the integrity of the compiled dataset.

One of the most challenging aspects of this phase was the alignment of FWD test locations with core sample locations. Core sample locations were identified through construction plans and drawing sets, and their corresponding physical locations were plotted using Google Maps. The construction drawings detailed the stations where the core samples were extracted, helping the research team pinpoint the specific project locations. For example, Core Sample A was located at station 427+00, while Core Sample B was found at station 450+75 (as shown in Figure 2.4). These station markers were vital in linking the core samples to their corresponding positions on the project map.

After identifying core sample points, the research team proceeded to locate where the FWD tests had been conducted along the same roadway sections. Using the FWD data and RP information from

contract letting information, the team mapped the FWD test locations and cross-referenced them with the core sample points. For instance, in Figure 2.5, FWD Station 12178 was associated with RP 49, which was located at station 443+11. This FWD test location provided crucial sublayer condition data, which was then mapped alongside the core sample locations for further analysis.

After determining the association between construction station 443+11 and FWD station 12178 with RP 49, we can calculate the distances between the core samples and RP 49, which are 1,611 feet and 764 feet, respectively (Figure 2.6). Using these distances, the FWD station for Core Sample A is calculated as 12178 minus 1,611, resulting in 10,567. Similarly, the FWD location for Core Sample B is 12,942, calculated by adding 764 to 12,178. Using these FWD station numbers, the core sample's density data and FWD deflection values are merged.

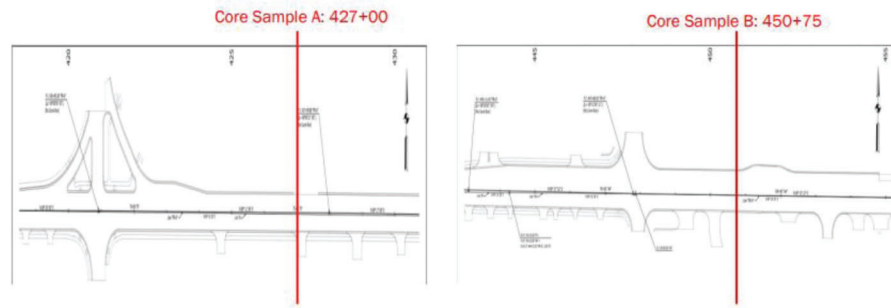


Figure 2.4 Example of core sample location in construction drawings.

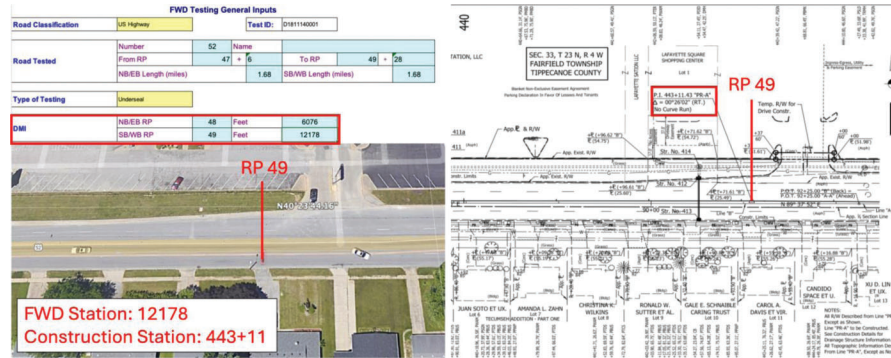


Figure 2.5 Identification of FWD testing location that corresponds to core sample location using FWD station and construction station number (#1).

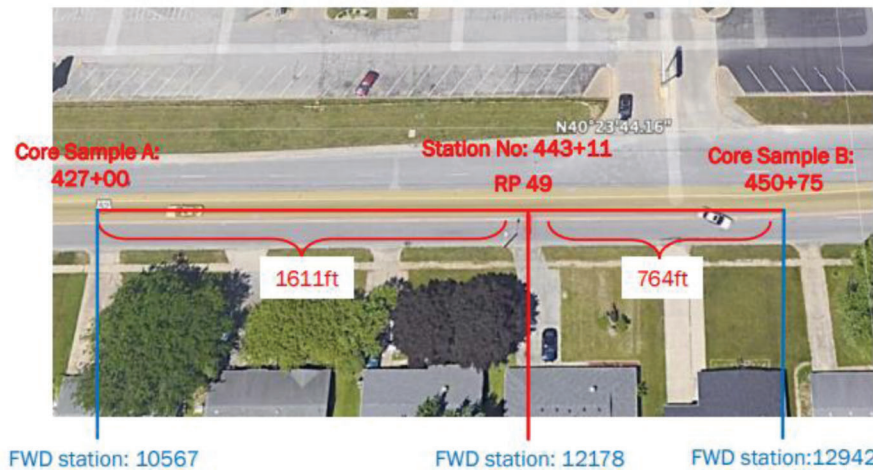
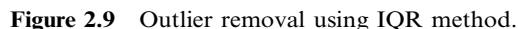
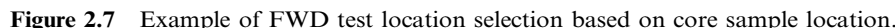


Figure 2.6 Identification of FWD testing location that corresponds to core sample location using FWD station and construction station number (#2).

However, due to the historical nature of the data and discrepancies in the geographic alignment, only data points where the core sample and FWD test locations were within 300 feet of one another were considered for analysis. In cases where multiple FWD test locations existed, the closest location to the core sample was selected. For instance, as shown in Figure 2.7, FWD test location A was used instead of B for a core sample because it is located within 300 feet from location A.

Finally, the research team merged and stored the datapoints based on geographical coordinates and station numbers, as shown in Figure 2.8. The core sample data was aligned with the FWD test data using shared identifiers such as station numbers, RP, and proximity. This merging process integrated information from all three data sources, allowing for a cohesive dataset ready for analysis. The final merged dataset included details from each source and was organized by



The study collected 985 data points from historical records, encompassing 43 contracts, all of which were focused on asphalt resurfacing projects. Of these, 566 data points related to 9.5-mm mixtures, 245- to 12.5-mm mixtures, 170- to 19.0-mm mixtures, and 3- to 25.0-mm mixtures. Since 19.0-mm and 25.0-mm mixtures are typically used for base and intermediate layers, these were excluded from the data pool as the focus of this study is on surface layer density. Therefore, only data

To refine the dataset further, the interquartile range (IQR) method was employed to remove outliers. This statistical method calculates the upper and lower bounds based on the first and third quartiles of the data, flagging any values outside this range as outliers. As shown in Figure 2.9, the IQR analysis identified and removed five data points related to HMA density and 24 data points associated with subgrade deflection (D8). Consequently, a total of 681 data points were deemed suitable for the final analysis.

3. CORRELATION ANALYSIS

3.1 Statistical Analysis of Historical Data

The research team conducted a statistical analysis of the historical data collected and merged from various sources (Table 3.1–3.3). The dataset consisted of 681 total entries, comprising two different asphalt mixture types: 9.5 mm and 12.5 mm. Among these, 545 samples were identified as 9.5-mm mixtures, and 136 samples were categorized as 12.5-mm mixtures.

The primary variables of interest for this analysis were surface layer density and subgrade deflection, both critical indicators of pavement quality and performance. For the entire dataset, the density values ranged from a minimum of 89.98% to a maximum of 97.78%, with a mean value of 94.36% and a standard deviation of 1.57%. The subgrade deflection, which represents the stiffness of the underlying layers, ranged from 0.34 mil to 4.34 mil, with a mean value of 2.10 mil and a standard deviation of 0.77 mil.

Breaking down the data further by mixture types, the 9.5-mm mixture exhibited a similar range of density values, from 89.98% to 97.78%, with a mean density of 94.44% and a slightly lower standard deviation of 1.53%. The subgrade deflection for the 9.5-mm mixture ranged from 0.34 mil to 4.29 mil, with a mean of 2.01 mil and a standard deviation of 0.73 mil.

In contrast, the 12.5-mm mixture had a slightly higher minimum density value of 90.16%, reaching a maximum of 97.18%. The mean density for the 12.5-mm mixture was 94.04%, with a standard deviation of 1.67%. Subgrade deflection values for the 12.5-mm mixture ranged from 0.51 mil to 4.34 mil, with a mean of 2.49 mil and a standard deviation of 0.78 mil, indicating slightly more variability in subgrade conditions compared to the 9.5-mm mixture.

3.2 Correlation Result per Mixture Types

The correlation between asphalt density (%Gmm) and subgrade deflection (D8) was examined across different mixture types. Scatter plots were generated for all mixtures, 9.5-mm mixtures, and 12.5-mm mixtures, providing a visual representation of the relationship between these two variables (Figure 3.1). The overall trend, as indicated by the red dashed lines in the plots, suggests a negative correlation between density and subgrade deflection. This observation implies that higher subgrade deflections are associated with lower densities in asphalt surface layers, though the strength of this correlation varies between mixture types.

To quantify this relationship, Pearson correlation coefficients were calculated for the entire dataset and for each mixture type individually. The Pearson correlation coefficient, often denoted as r , is a statistical measure that calculates the strength and direction of the linear relationship between two continuous variables. It ranges from -1 to 1, where: +1 indicates a perfect positive linear relationship (as one variable increases, the other also increases), -1 indicates a perfect negative linear relationship (as one variable increases, the other decreases), and 0 indicates no linear relationship (the variables are uncorrelated).

The overall correlation between subgrade deflection and asphalt density for all mixture types was -0.145, a statistically significant negative correlation at the 0.01 level (p -value < 0.001). For the 9.5-mm mixtures, a weaker but still statistically significant correlation was observed, with a coefficient of -0.089 (p -value = 0.038). The strongest correlation was found in the 12.5-mm mixtures, with a Pearson coefficient of -0.246 (p -value = 0.004), indicating that subgrade deflection has a more pronounced impact on density in this mixture type (Table 3.4).

TABLE 3.1
Descriptive statistics for entire dataset

Variables	N	Minimum	Maximum	Mean	Std. Deviation
Density	681	89.98	97.78	94.36	1.57
Subgrade Deflection	681	0.34	4.34	2.10	0.77

TABLE 3.2
Descriptive statistics for 9.5-mm mix group

Variables	N	Minimum	Maximum	Mean	Std. Deviation
Density	545	89.98	97.78	94.44	1.53
Subgrade Deflection	545	0.34	4.29	2.01	0.73

TABLE 3.3
Descriptive statistics for 12.5-mm mix group

Variables	N	Minimum	Maximum	Mean	Std. Deviation
Density	136	90.16	97.18	94.04	1.67
Subgrade Deflection	136	0.51	4.34	2.49	0.78

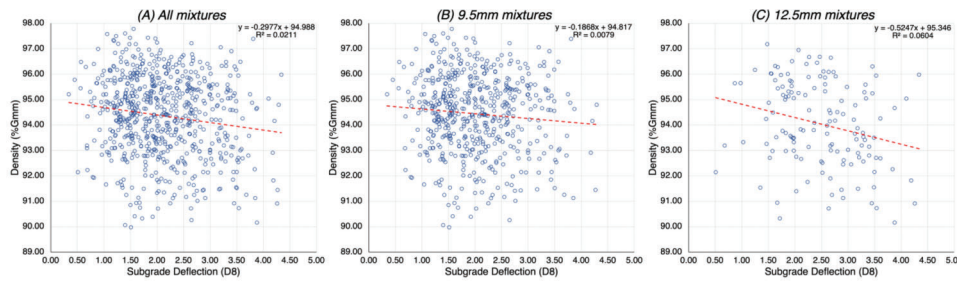


Figure 3.1 Scatterplots for (a) entire dataset, (b) 9.5-mm mix group, and (c) 12.5-mm mix group.

TABLE 3.4
Correlation analysis results for entire data: 9.5-mm mix group, and 12.5-mm mix group

Pearson Correlation		Density	Density (9.5 mm)	Density (12.5 mm)
Subgrade Deflection	Coef.	-0.145**	-0.089*	-0.246**
	Sig.	<0.001	0.038	0.004

*Correlation is significant at the 0.05 level (2-tailed).

**Correlation is significant at the 0.01 level (2-tailed).

These results suggest that subgrade conditions play a significant role in influencing the compaction outcomes of HMA pavements, with stronger correlations for 12.5-mm mixtures. These findings reinforce the need to consider subgrade stiffness in the assessment and adjustment of density pay factors, particularly in projects where subgrade deflection values are elevated.

3.3 Correlation Result per Road Types

This study evaluated the correlation between asphalt density (%Gmm) and subgrade deflection (D8) within the 9.5-mm mix group, which includes a total of 545 samples. These samples are distributed across three road types: state roads (358 samples), U.S. highways (163 samples), and interstate highways (24 samples). Scatter plots were generated to visually depict the relationship between density and subgrade deflection for each road type, with the red dashed lines representing the trendlines (Figure 3.2). These plots suggest variability in the correlation strength depending on the road type.

In Table 3.5 for state roads, the correlation between density and subgrade deflection showed a statistically significant negative relationship, with a Pearson correlation coefficient of -0.146 (p-value = 0.006). This indicates that, for state roads in the 9.5-mm mix group, higher subgrade deflections are associated with lower asphalt densities, implying that weaker or more unstable sublayers can negatively affect compaction quality.

In contrast, for U.S. highways and interstate highways in the 9.5-mm mix group, no statistically significant correlations were observed. The Pearson correlation coefficient for U.S. highways was -0.054 (p-value = 0.495), and for interstate highways, it was 0.065 (p-value = 0.763), both of which were not statistically significant. This suggests that subgrade deflection has a

lesser impact on asphalt compaction density for these road types compared to state roads.

These findings indicate that subgrade conditions play a more critical role in compaction quality for state roads, where poor sublayers can significantly reduce asphalt density. For U.S. highways and interstate highways, the correlation is much weaker, possibly due to better construction standards and more stable sublayers typically found in these road types. Consequently, these results emphasize the importance of adjusting compaction requirements and pay factors for state roads, where the condition of the subgrade has a more pronounced effect on the overall pavement performance.

This research also analyzed the correlation between asphalt density (%Gmm) and subgrade deflection (D8) within the 12.5-mm mix group, which consists of 136 total samples. These samples are divided between two road types: state roads (72 samples) and U.S. highways (64 samples). There were no interstate highway samples in the 12.5-mm mix group.

The scatterplots for state roads and U.S. highways (Figure 3.3) illustrate the relationship between density and subgrade deflection for the 12.5-mm mix group, with red dashed trendlines indicating the general direction of the correlation. The Pearson correlation results are presented in the Table 3.6.

In Table 3.6 for state roads, the Pearson correlation coefficient is -0.147, indicating a negative relationship between subgrade deflection and density. However, with a p-value of 0.217, this correlation is not statistically significant. This suggests that, for the 12.5-mm mix group on state roads, subgrade deflection does not have a strong or significant effect on asphalt density.

For U.S. highways, the correlation coefficient is more negative at -0.205, suggesting a stronger inverse

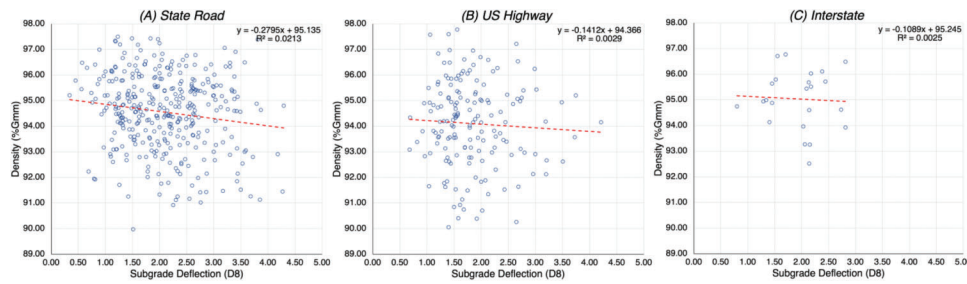


Figure 3.2 Scatterplots for (a) state road, (b) U.S. highway, and (c) interstate in 9.5-mm mix group.

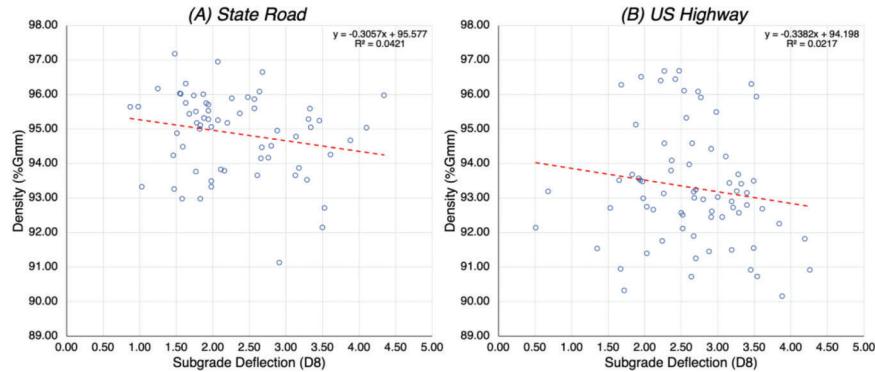


Figure 3.3 Scatterplots for (a) state road, and (b) U.S. highway in 12.5-mm mix group.

TABLE 3.5
Correlation analysis results for 9.5-mm mix group with different road types

Pearson Correlation		Density (state road)	Density (U.S. highway)	Density (interstate)
Subgrade Deflection	Coef.	-0.146**	-0.054	0.065
	Sig.	0.006	0.495	0.763

**Correlation is significant at the 0.01 level (2-tailed).

TABLE 3.6
Correlation analysis results for 12.5-mm mix group with different road types

Pearson Correlation		Density (state road)	Density (U.S. highway)
Subgrade Deflection	Coef.	-0.147	-0.205
	Sig.	0.217	0.104

relationship between subgrade deflection and density. However, the p-value of 0.104 indicates that this correlation is also not statistically significant. Similar to state roads, subgrade deflection in the 12.5-mm mix group for U.S. highways does not show a significant impact on compaction density.

Overall, while the correlations indicate a trend where higher subgrade deflections might correspond to lower asphalt densities, the lack of statistical significance suggests that the subgrade deflection's effect on asphalt density is not as prominent for the 12.5-mm mix group in both state roads and U.S. highways.

4. GYRATORY COMPACTION TESTING

By using the gyratory compactor, the research team was able to replicate the compaction of HMA under uniform conditions, thereby ensuring consistency across all test specimens. This provided a controlled environment to isolate the effects of different sublayer conditions on the compaction quality and resulting asphalt density. The primary objective of this task was to examine how variations in sublayer conditions, such as the difference between soft and rigid layers, impact the density and structural integrity of the surface layer.

In addition to gyratory compaction testing, the research incorporated the LWD to measure the deflection of sublayers, a key indicator of their stiffness and load-bearing capacity. These deflection values were used to further understand the degree to which sublayers absorb compaction energy, which has a direct impact on the effectiveness of surface compaction. By simulating different sublayer conditions—ranging from dense crushed stone to loose, unbound layers—the team was able to observe how variations in subgrade stiffness influence the resulting surface density.

To provide even more granular insights, the study employed SmartKli sensors during the compaction process. These advanced sensors measured the pressures, rotations, and accelerations exerted on the specimens in real time. The data from SmartKli sensors offered a detailed perspective on how compaction forces were distributed across the layers, and how different sublayer conditions affected the dynamics of the compaction process. For instance, SmartKli allowed the team to monitor variations in pressure distribution between the X, Y, and Z axes and relative rotation with height, offering a more nuanced understanding of the interactions between sublayers and the compacted asphalt mix.

Lab testing was vital for validating the correlation patterns identified in the historical data analysis phase. By replicating various sublayer conditions in a controlled environment, the research team was able to verify if the correlations observed in real-world projects held true in a laboratory setting. Moreover, these tests allowed the team to measure the impact of specific variables, such as sublayer stiffness and surface density, under repeatable conditions.

4.1 Experiments for Exploration of Various Sublayer Conditions

The exploratory phase of the experiments was designed to simulate and investigate how various low-

layer conditions impact the compaction quality and surface density of asphalt mixtures (Figure 4.1). During this phase, a range of sublayer scenarios were created to reflect common field conditions, including comparisons between 1st trial; soft versus rigid layers, 2nd trial; bound versus unbound sublayers, and 3rd trial dense versus loose unbound materials. By recreating these conditions in a controlled laboratory environment, the research team aimed to better understand how each sublayer scenario influences the effectiveness of compaction, as measured by the maximum theoretical density (%Gmm).

In the first trial of the exploratory experiments, the research team compared the density (%Gmm) of HMA disks compacted on top of two distinct sublayer conditions: soft and rigid. Four samples were prepared to observe the preliminary results and assess the influence of sublayer conditions on compaction outcomes (Figure 4.2). This study utilized a 2,019.7-g mixture for 2-inch targeted samples (Samples A and C) and a 4,039.3-g mixture for 4-inch targeted samples (Samples B and D). Following the placement of the mixture in the mold, the heights for Samples A and B measured 2.61 inches and 5.19 inches, respectively. In contrast, for Samples C and D, where a rubber pad was placed at the bottom of the mold, the heights were measured at 3.23 inches and 5.85 inches, respectively.

Post gyratory compaction, the heights of all samples underwent changes to 53.4 mm, 102.3 mm, 60.2 mm, and 108.4 mm, respectively. The height depending on the number of gyrations for each sample are depicted in Figure 4.3 (left). The heights of all samples exhibited a significant decrease during the initial gyration, as illustrated in Figure 4.3 (right). Specifically, the height variations between zero gyration and the first gyration were 2.9 mm for Sample A, 5.6 mm for Sample B, 2.3 mm for Sample C, and 4.9 mm for Sample D. This outcome indicates that samples with a relatively higher target thickness exhibited greater changes. In other words, it is easier to compact a larger amount of



Figure 4.1 Superpave gyratory compactor test in the INDOT research facility.

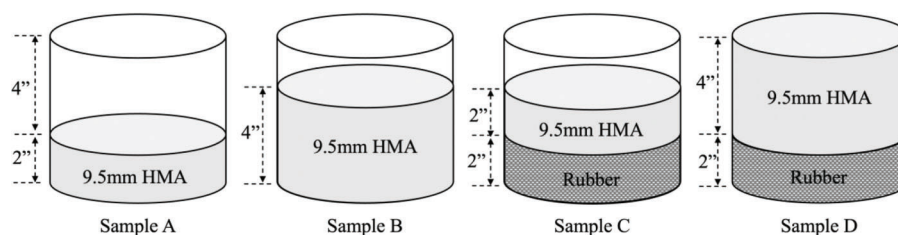


Figure 4.2 First trial of the exploratory experiment method.

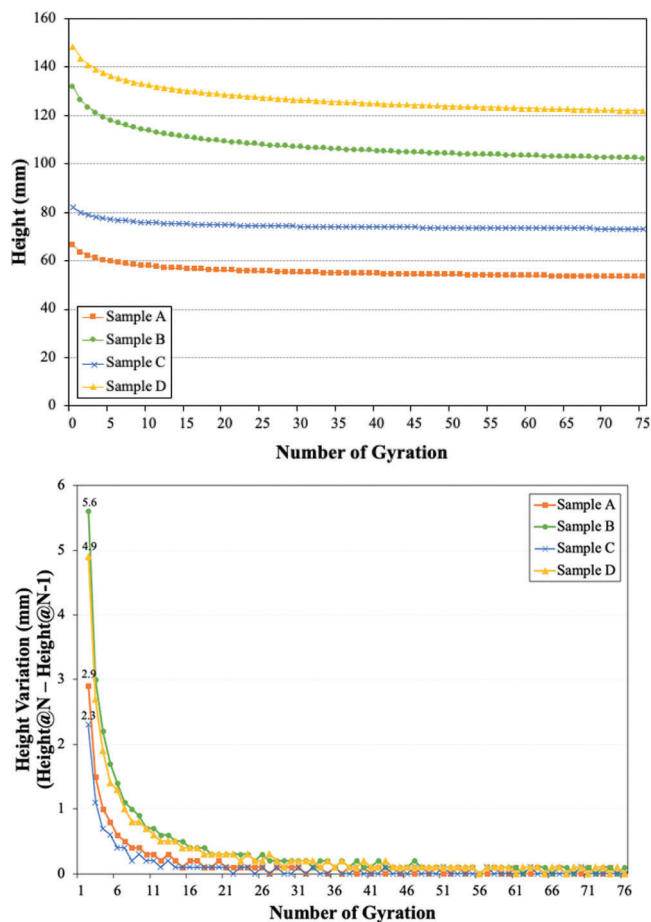


Figure 4.3 Height (top) and height variation (bottom) per number of gyrations.

mixture for a 4-inch sample (e.g., Samples B or D) compared to a 2-inch sample (e.g., Samples A or C). Conversely, when comparing samples with the same target thickness (e.g., A and C or B and D), those with a rubber pad (Samples C and D) demonstrated relatively higher height variations than samples without a rubber pad (Samples A and B). This implies that samples without a rubber pad were more effectively compacted. These findings suggest that compaction may face challenges in actual sites with poor subgrade conditions.

After compaction, the bulk specific gravity values for the individual samples were as follows: 2.22 for Sample A, 2.28 for Sample B, 2.11 for Sample C, and 2.20 for Sample D. Revealing that Sample A exhibited the highest density at 93.61%, while Sample C had the lowest density at 86.48%. Upon comparing samples compacted without a rubber pad (i.e., Samples A and B), the 4-inch target sample displayed a higher density than its 2-inch counterpart. Similarly, within the group featuring a rubber pad, the 4-inch target sample surpassed the 2-inch target sample in terms of density. Furthermore, when comparing samples with the same target thickness, Sample A demonstrated higher density

than Sample C, and Sample B had a higher density than Sample D. Notably, samples compacted without a rubber pad exhibited higher density than those with a rubber pad. This implies that the surface layer compacted on a subgrade with poor conditions may exhibit relatively lower density compared to a subgrade in good condition.

Notably, the height variations (Figure 4.3) are correlated with the density results (Figure 4.4). The samples with and without a rubber pad revealed that the absence of a rubber pad led to more effective compaction, resulting in higher density. This interconnected relationship between height variation and density underscores the importance of considering compaction conditions such as subgrade qualities in achieving optimal density for asphalt surface.

In the second trial of the exploratory experiments, the research team compared the density (%Gmm) of HMA disks compacted on two different sublayer conditions: old HMA cores (bound layers) and crushed stones (unbound layers). The research team conducted tests by using five different setups to evaluate the compaction quality of HMA. As shown in 2.1 on Figure 4.5, two samples were created by placing 2-inch HMA directly on a steel plate with no sublayers. In 2-2, the new HMA was compacted on top of an old HMA disk, while in 2-3, a steel plate was placed between the new HMA and the old HMA disk. For 24, two samples were made with HMA directly on the crushed stone, while in 25, a steel plate was added between the HMA and crushed stone. This trial aimed to further investigate how sublayer types of impact surface layer compaction and the resulting density of the HMA.

Figure 4.6 illustrates the density result for the second trial experiment. The results showed that the %Gmm values of the HMA were slightly higher when compacted on the crushed stone sublayer. In contrast, the presence of steel plates, used as part of the testing setup, tended to result in lower %Gmm values for the HMA. This suggests that the interaction between the surface and sublayer material plays a significant role in determining compaction quality, with unbound layers (crushed stones) providing slightly better compaction outcomes in this trial. These findings indicate that sublayer material types directly influence the compaction process and surface density outcomes. Additionally, it was found that the bottom layer material—whether old HMA core or crushed stone—affects the surface layer's density. Therefore, further trials were necessary to more thoroughly investigate the influence of bottom layer conditions.

In the third trial of the exploratory experiments, the research team simulated real-world construction conditions to compare the effects of dense and loose crushed stone as sublayers on the compaction and density (%Gmm) of HMA disks. This study utilized 2,038.1 g of HMA mixtures for the 2-inch targeted new surface layer, and 2-inch of old HMA sample on the middle, then utilized the 1,950 g of loose

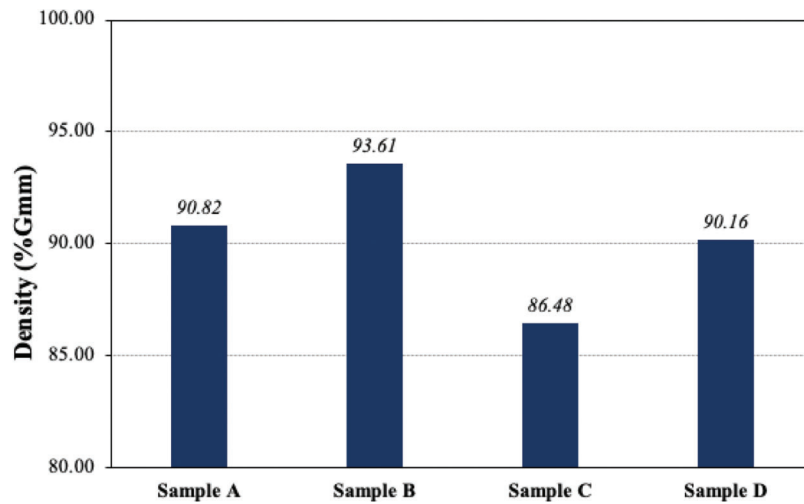


Figure 4.4 Density results for the first trial experiment.

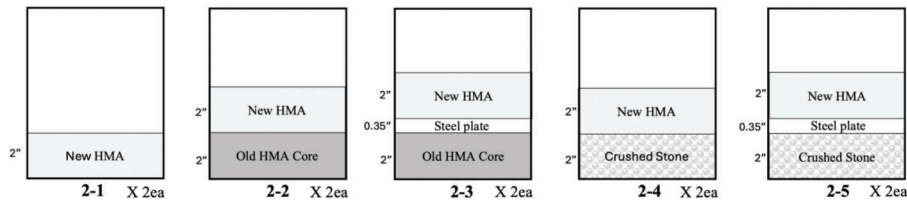


Figure 4.5 Second trial of the exploratory experiment method.

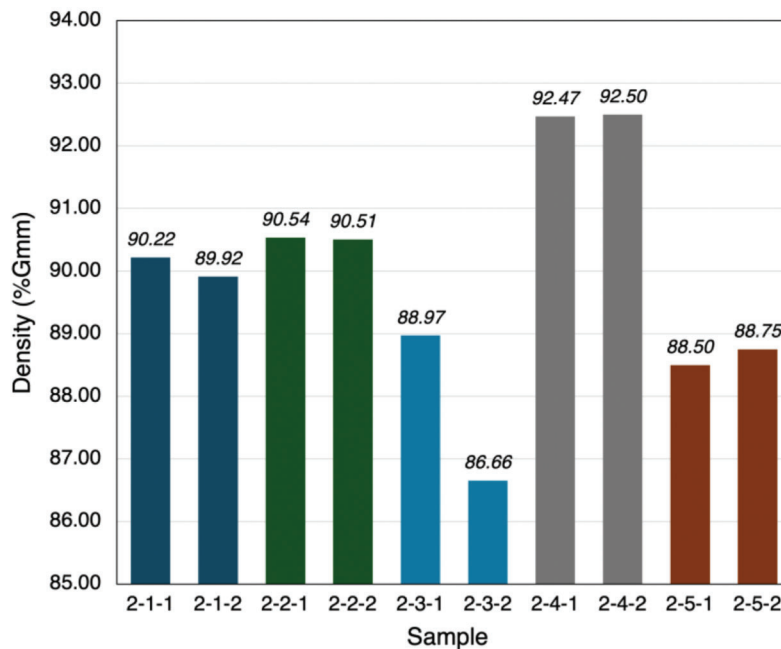


Figure 4.6 Density results for the second trial experiment.

crushed stone for the 3-inch targeted bottom layer to simulate a poor bottom layer condition, as illustrated in Figure 4.7.

To produce the dense crushed stone, the research team performed gyratory compaction (50 gyrations) by placing the crushed stone directly into the mold. Table 4.1 presents the height measurements of the dense

crushed stone after compaction. Following the preparation of both loose and dense crushed stone layers, an old HMA sublayer was applied. Finally, a new HMA mixture was added and compacted using 75 gyrations. In total, 10 samples were created, with 5 samples using loose crushed stone sublayers and 5 samples using dense crushed stone sublayers.

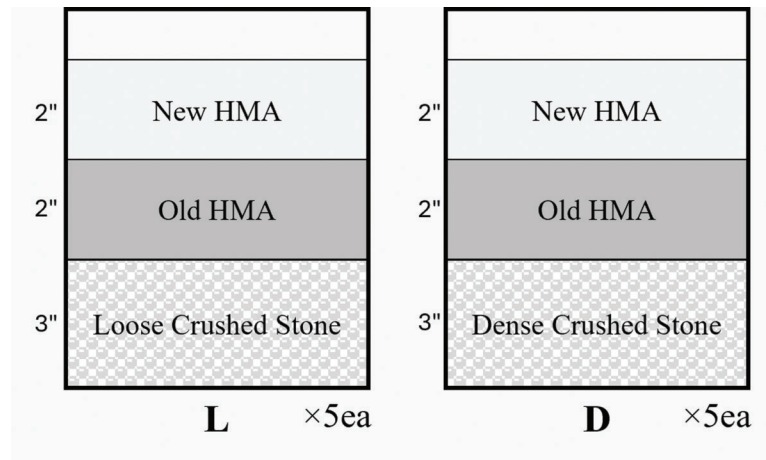


Figure 4.7 Third trial of the exploratory experiment method.

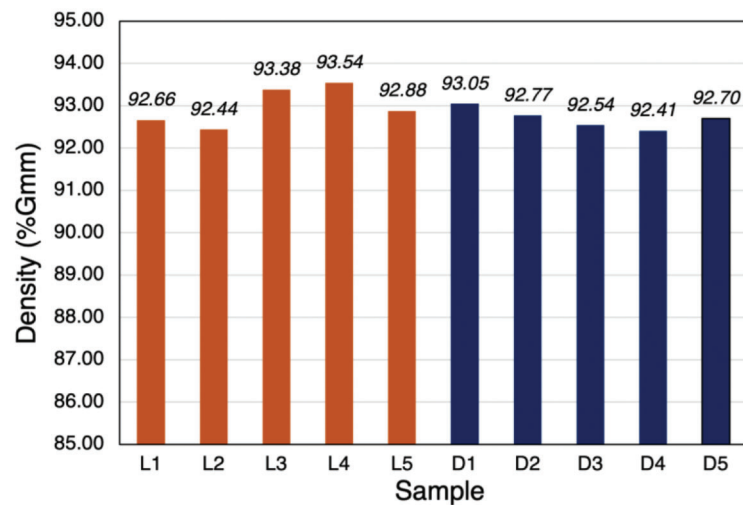


Figure 4.8 Density results for the third trial experiment.

TABLE 4.1
Thickness variance after gyratory compaction by samples

Thickness (inch)	L1	L2	L3	L4	L5	D1	D2	D3	D4	D5
Thickness (Before)	3.11	2.99	2.91	3.03	3.03	3.06	3.02	3.10	3.12	3.09
Thickness (After)	—	—	—	—	—	2.61	2.61	2.62	2.66	2.65
Variance (B-A)	—	—	—	—	—	0.45	0.41	0.48	0.48	0.44

Figure 4.8 shows the density values recorded for each condition. As shown in the results, there was no significant difference between the %Gmm results for HMA compacted over dense versus loose crushed stone sublayers. This suggests that the compaction of the crushed stone sublayer, whether dense or loose, may not have a considerable impact on the resulting surface layer density in this specific scenario. These findings contribute to the overall understanding of how sublayer conditions influence asphalt compaction, though further research may be needed to explore other factors that could play a role in different real-world conditions.

4.2 Experiments for Deflection and %Gmm Comparison

In this phase of the study, a comparison experiment was conducted to explore the correlation between sublayer stiffness, measured using the LWD, and the density of the asphalt surface layer. The LWD is a non-destructive tool used to assess the stiffness of unbound pavement surfaces, providing key data about how the subgrade influences the effectiveness of surface compaction.

The experiment involved several carefully structured steps, as illustrated in Figure 4.9. First, deflection

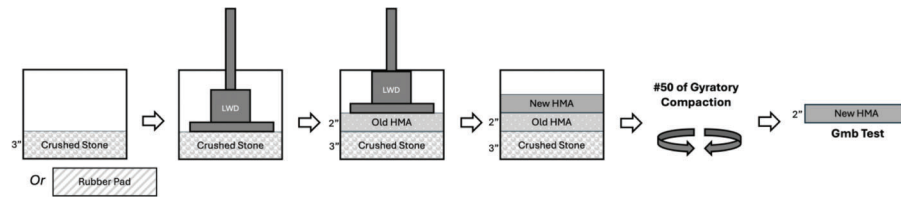


Figure 4.9 Deflection and density comparison experiment method.

TABLE 4.2
Descriptive statistics for crushed stone group and rubber pad group

Group (Unit)	N	Min	Max	Mean	Std. Deviation
Crushed Stone Density (%Gmm)	29	94.49	96.00	95.25	0.37
Crushed Stone Deflection (mil)	29	51.64	132.43	94.11	17.48
Rubber Pad Density (%Gmm)	29	94.08	95.38	94.61	0.32
Rubber Pad Deflection (mil)	29	522.27	707.93	603.60	53.95

measurements were taken at the bottom layer of the sample, which could either consist of crushed stone or a rubber pad. These materials were chosen to represent different subgrade conditions, from typical dense and supportive sublayers to softer, more flexible materials like the rubber pad, which could mimic weak subgrades.

Next, the deflection was measured again at the middle layer of the sample, which was comprised of old HMA. These measurements helped capture how the intermediate layer responded to the applied loads and how this could impact the overall compaction process. By taking measurements at multiple layers, the team could assess how variations in subgrade stiffness propagated through the pavement system and affected the compaction process.

Following the LWD testing, the samples underwent gyratory compaction to simulate real-world compaction scenarios. The gyratory compactor applied pressure to the asphalt sample in a controlled manner, allowing the team to replicate the forces experienced during field compaction. After compaction, the %Gmm test was performed on the newly compacted asphalt surface to determine its density.

This experimental design provided a comprehensive view of how sublayer stiffness influences the compaction and ultimate density of the asphalt surface. By correlating the LWD deflection values with the %Gmm results, the team was able to evaluate the extent to which subgrade conditions affected the overall quality of compaction. This information is crucial for making data-driven recommendations about density pay factors, particularly when working with varying subgrade conditions that may pose challenges to achieving optimal compaction quality.

The primary goal of this experiment was to determine if there was a significant correlation between subgrade deflection, as measured by the LWD, and the resultant asphalt surface density. Initially, 64 samples were created, but after removing outliers caused by human error, 58 samples were used for analysis. The samples were evenly divided between two subgrade

conditions: 29 samples were prepared on a crushed stone base, and another 29 samples were compacted on a rubber pad, representing weaker subgrade conditions.

Using these 58 samples, we analyzed the density results and deflection results of samples compacted on two different subgrade conditions: crushed stone and rubber pad, as described in Table 4.2. The mean values for the density of samples compacted on the crushed stone subgrade were slightly higher than those compacted on the rubber pad subgrade, with a mean density of 95.25%Gmm for crushed stone and 94.61%Gmm for the rubber pad. In terms of LWD deflection, the mean deflection on the crushed stone was 94.11 mil, while the rubber pad had a substantially higher mean deflection of 603.60 mil, indicating a much weaker subgrade.

A T-test analysis was performed to assess whether the differences in asphalt density between the two subgrade conditions were statistically significant (Table 4.3). The results showed that the mean density difference between the two groups was statistically significant, with a p-value of 0.001 and a T-value of 6.977. This indicates that, although the two groups had relatively similar density levels, the differences were significant enough to confirm that the subgrade type had a meaningful impact on asphalt compaction results.

After completing the T-test analysis, we further examined the relationship between the surface layer density and subgrade deflection under different subgrade conditions using a scatterplot (Figure 4.10). The scatterplot accompanying the analysis visually demonstrates this relationship. Samples compacted on the rubber pad, which produced higher LWD deflection values, generally showed lower densities. Conversely, samples compacted on the crushed stone subgrade exhibited lower deflection values and correspondingly higher densities. This finding supports the hypothesis that subgrade stiffness plays a crucial role in achieving the desired surface density during compaction. The stronger and stiffer the subgrade (lower deflection), the

TABLE 4.3
T-test analysis result

Group	N	Mean	Std. Deviation	t	p
Crushed Stone Density (%Gmm)	29	95.25	0.37	6.977	0.001*
Rubber Pad Density (%Gmm)	29	94.61	0.32		

*p < 0.05

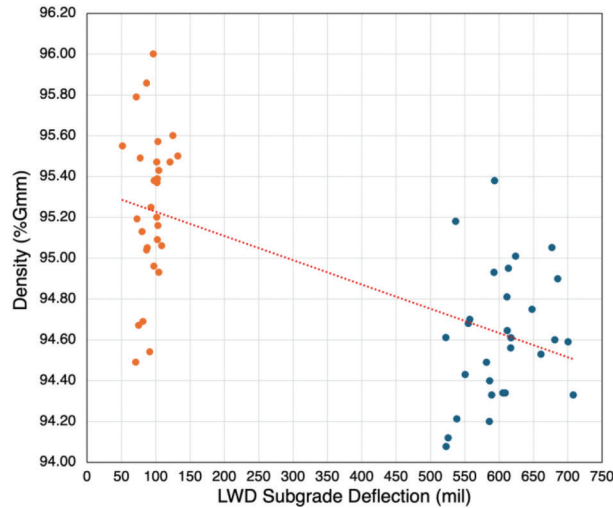


Figure 4.10 Scatterplot for compacted samples on crushed stone (orange) and rubber pad (blue).

more effective the compaction process, leading to higher %Gmm values. Conversely, when the subgrade is weaker (higher deflection), the compaction energy is less effectively transferred, resulting in lower surface densities. This correlation is critical for developing practical recommendations on density pay factors, especially for pavements built on suboptimal subgrade conditions, and for guiding adjustments to field compaction techniques.

After identifying a preliminary relationship between subgrade deflection and asphalt density, we conducted a more detailed analysis using the Pearson correlation method. In Table 4.4, the Pearson correlation coefficient for this analysis was calculated to be -0.652, indicating a strong negative correlation between subgrade deflection and asphalt density. In other words, as subgrade deflection increased, which suggests a weaker or less stiff sublayer, the asphalt density tended to decrease. The statistical significance of this correlation was confirmed with a p-value of less than 0.001, meaning the correlation is highly significant and unlikely to be due to random chance.

These findings emphasize the critical role of subgrade stiffness in achieving the desired surface density during compaction. Stronger subgrades, such as crushed stone, provide better support during compaction, resulting in higher densities, while weaker subgrades, like the rubber pad, lead to less effective compaction and lower surface densities. This significant difference reinforces the need to consider subgrade conditions when setting

TABLE 4.4
Correlation analysis result between density and LWD subgrade deflection

Pearson Correlation		Density
LWD Subgrade Deflection	Coef.	-0.652**
	Sig.	<0.001

**Correlation is significant at the 0.01 level (2-tailed).

density requirements and pay factors for asphalt pavement projects.

4.3 Experiments for Monitoring Physical Parameters Using Sensors

In the monitoring phase of the experiment, SmartKli sensors were employed to capture detailed real-time data during the compaction process. These advanced sensors, embedded within the asphalt specimens, allowed for the continuous monitoring of various physical parameters crucial to understanding the interaction between the subgrade and the surface layers during compaction (Figure 4.11). Specifically, the sensors recorded pressures, temperatures, quaternions (which describe orientation), and accelerations across different layers of the asphalt mix, providing a comprehensive dataset on the compaction dynamics.

The SmartKli sensors, small in size and designed to withstand the high-pressure environment of asphalt compaction, were placed within the HMA during the compaction process. Their ability to measure multiple parameters simultaneously allowed the research team to analyze how compaction forces were distributed across the layers and how variations in subgrade conditions affected the overall process.

For example, the sensors tracked changes in pressure distribution, giving insight into the amount of force transferred from the compactor to the subgrade and surface layers. This was particularly useful for understanding how softer subgrades might absorb more compaction energy, reducing the effectiveness of surface compaction. The accelerations measured by the sensors also revealed how the compaction vibrations propagated through the layers, offering additional information about the dynamic interactions between subgrade and surface.

The quaternion measurements, which provide a mathematical description of the sensor's orientation in space, helped monitor any rotational shifts during the

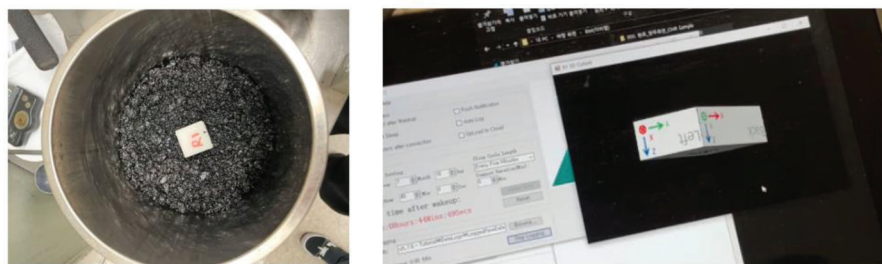


Figure 4.11 Example of SmartKli sensor movement while in compaction.

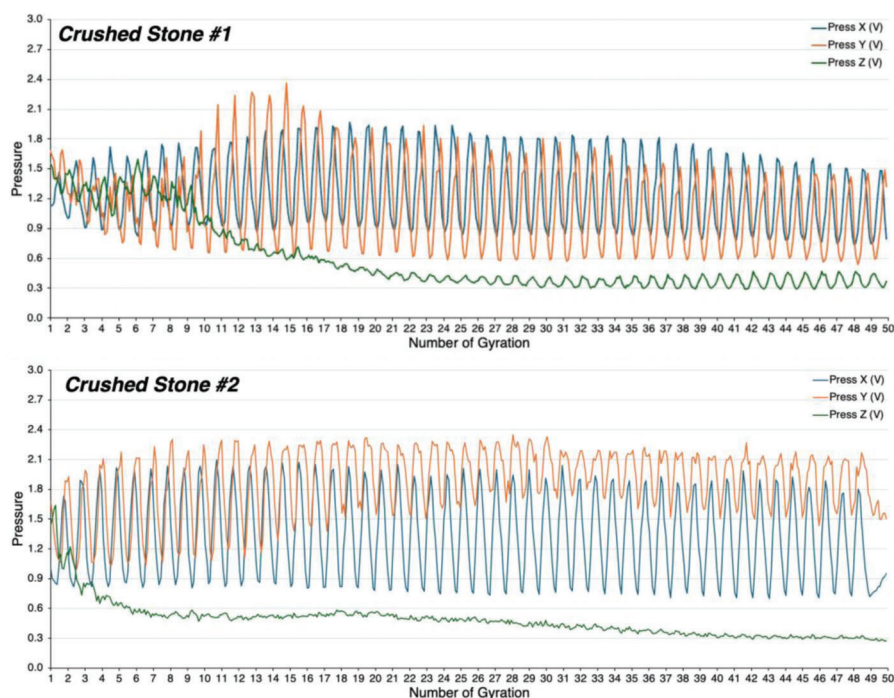


Figure 4.12 Measured pressure by the number of gyrations for samples on crushed stone.

compaction process. This data was useful in determining whether the surface or subgrade layers experienced any twisting or tilting, which could impact the quality of the compaction.

By integrating these sensor measurements, the research team could obtain a more granular understanding of how compaction mechanics vary depending on subgrade stiffness and surface characteristics. This detailed monitoring helped bridge the gap between lab-controlled conditions and real-world application, offering data-driven insights into improving compaction practices for future projects.

The pressure data collected from the SmartKli sensors during the compaction process revealed consistent trends across both the crushed stone and rubber pad setups. The sensors, which measured pressures in three dimensions (X, Y, Z), provided a detailed view of how the compactor applied force during the gyratory compaction.

In Figure 4.12 representing crushed stone samples, the consistent oscillation of the pressure lines in all three dimensions indicates that the compactor applied pressure evenly throughout the compaction process. The crushed stone layers displayed stable pressure patterns, which suggest that the compaction energy was evenly distributed and effectively transferred to the surface layer. This even distribution is critical for achieving optimal surface density.

On the other hand, the graphs representing rubber pad samples in Figure 4.13 also demonstrated consistent oscillations in the X and Y dimensions but showed lower pressure values in the Z dimension (green line). This lower pressure indicates that the rubber pad sublayer absorbed some of the compaction energy, preventing full transmission of force to the surface layer. The rubber pad results highlight the impact of a softer subgrade, which can lead to lower compaction efficiency.

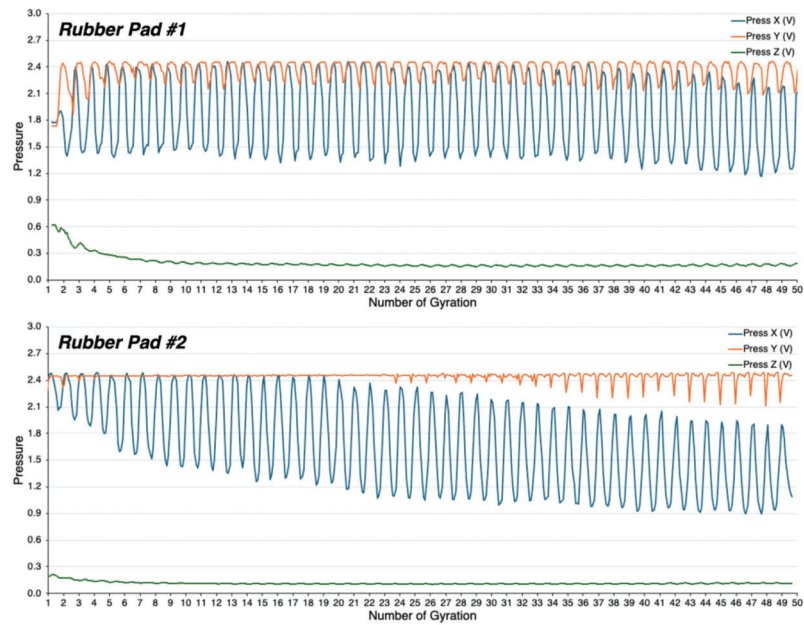


Figure 4.13 Measured pressure by the number of gyrations for samples on rubber pad.

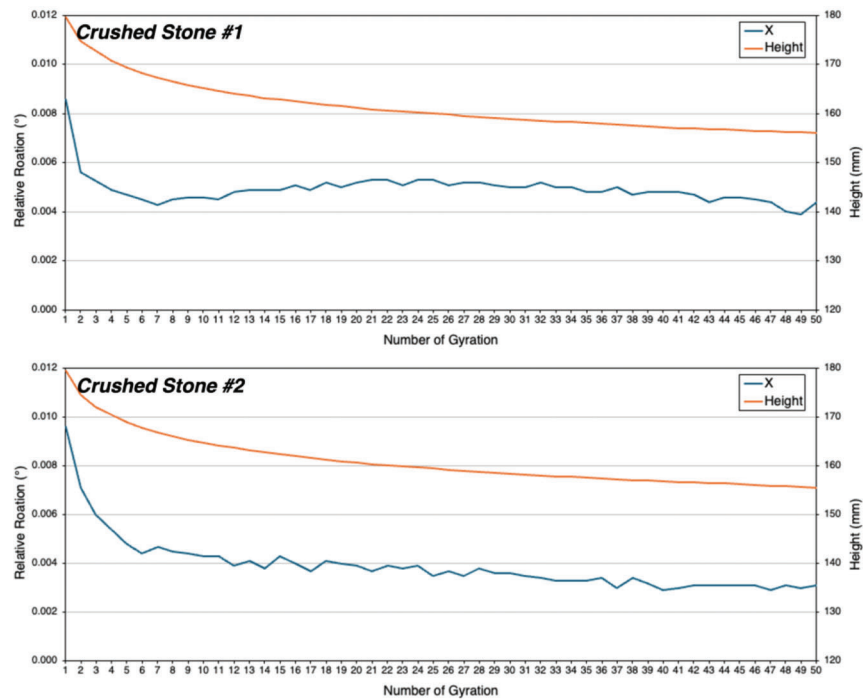


Figure 4.14 Relative rotation (X) and height by the number of gyrations for samples on crushed stone.

Overall, the consistent pressure trends in the crushed stone graphs suggest that this subgrade provided a more reliable foundation for compaction, whereas the rubber pad results show how a more flexible or absorptive sublayer can affect the effectiveness of surface compaction. This information is key to understanding how different subgrade materials influence the

compaction process and the final density of the asphalt surface.

The results from the SmartKli sensors also captured the relative rotation angle during the compaction process, which provides insight into how the horizontal axis was moving throughout compaction. These rotation angles were calculated by analyzing the differences

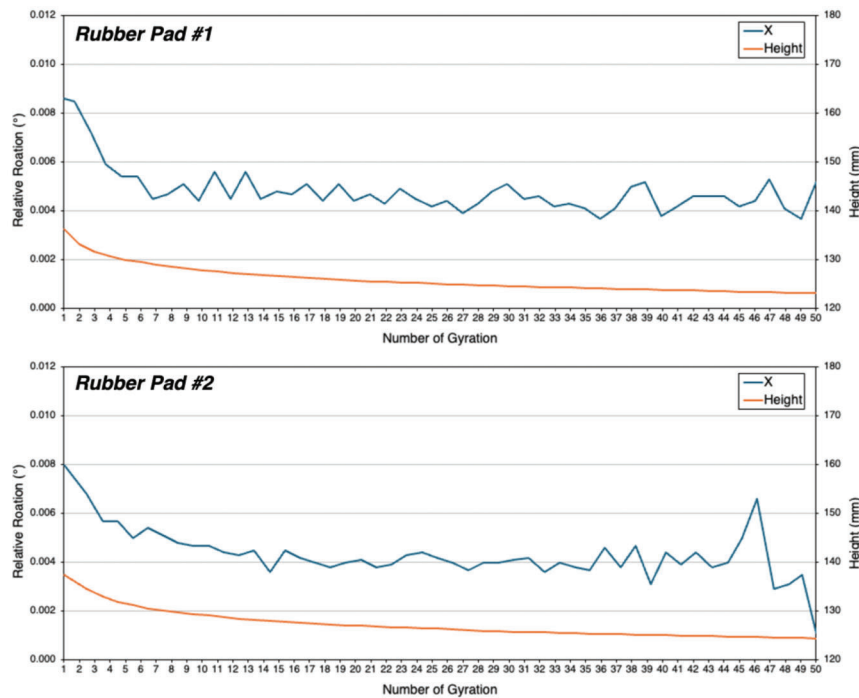


Figure 4.15 Relative rotation (X) and height by the number of gyrations for samples on rubber pad.

in the Euler angle's X-axis amplitude. Both the rotation curves (in blue) and the height curves (in orange) are displayed for the crushed stone and rubber pad samples, allowing us to observe how these parameters evolved during the compaction process.

For the crushed stone samples (#1 and #2) in Figure 4.14, the relative rotation and height curves show a clear convergence toward a single point by the end of the compaction process. This indicates a stable compaction process where the material consolidated uniformly over time. The consistency of the blue and orange curves reflects that the asphalt surface achieved a relatively uniform compaction level, resulting in optimal pavement density.

In contrast, the rubber pad samples (#1 and #2) in Figure 4.15 show less convergence between the relative rotation and height curves, with both the rotation angle and height remaining variable throughout the compaction process. This variability suggests that the softer, more flexible rubber pad absorbed compaction energy inconsistently, leading to irregular movements and less effective surface compaction.

The comparison between the crushed stone and rubber pad results highlights how different sublayer conditions affect the dynamics of compaction. While the samples generated on the crushed stone provided a firm foundation for uniform compaction, the samples created on rubber pads demonstrated the challenges of achieving consistent density when working with more absorptive sublayers. Understanding these differences is

crucial for making informed decisions about sublayer preparation and compaction strategies in future asphalt pavement projects.

5. SPECIFICATION REVIEW AND PROBABILISTIC APPROACH

The research team took a comprehensive look at the asphalt density pay factors utilized by various state transportation agencies. The team begins by reviewing the pay factor standards currently in use, particularly focusing on the INDOT specifications, which serve as the baseline for this study. Additionally, the task involves gathering information from other Midwest state agencies to compare how pay factor adjustments are made based on pavement conditions.

By synthesizing the findings from both historical data analysis and lab testing phases, the team can provide the recommendations produced in this task, which aim to ensure that asphalt density pay factors are more reflective of the actual challenges contractors face in the field, especially in cases where the sublayers are unstable or weak. By using probabilistic scenario modeling, the research team proposes a system where pay factors are adjusted based on realistic subgrade performance expectations, improving the durability and longevity of asphalt pavements. Ultimately, these adjustments seek to make the pay factor system fairer and more aligned with the true compaction challenges posed by varying sublayer conditions.

5.1.1 Indiana

$$Lot\ PF = 0.3PF_{Voids} + 0.35PF_{VEB} + 0.35PF_{Density} \quad (\text{Eq. 5.1})$$
$$PF_{Density} = \frac{(0.5 \times PWL) + 55.00}{100} \quad (\text{Eq. 5.2})$$
$$PF_{Density} = \frac{(0.4 \times PWL) + 64.00}{100} \quad (\text{Eq. 5.3})$$

Quality Index (QI) Values														Quality Index (QI) Values														Quality Index (QI) Values													
PWI: for a given sample size (n)														PWI: for a given sample size (n)														PWI: for a given sample size (n)													
QI	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10	n=11	n=12	n=13	n=14		QI	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10	n=11	n=12	n=13	n=14		QI	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10	n=11	n=12	n=13	n=14	
1.30	100	100	100	100	100	100	100	100	100	100	100	100	100	1.89	100	100	100	100	100	99	98	98	98	98	98	98	98	1.48	100	99	96	95	94	94	94	94	94	94	94	94	94
1.29	100	100	100	100	100	100	100	100	100	100	100	100	100	1.88	100	100	100	100	100	99	98	98	98	98	98	98	98	1.47	100	99	96	95	94	94	94	94	94	94	94	94	94
1.28	100	100	100	100	100	100	100	100	100	100	100	100	100	1.87	100	100	100	100	100	99	98	98	98	98	98	98	98	1.46	100	99	96	95	94	94	94	94	94	94	94	94	94
1.27	100	100	100	100	100	100	100	100	100	100	100	100	100	1.86	100	100	100	100	100	99	98	98	98	98	98	98	98	1.45	100	99	96	95	94	94	94	94	94	94	94	94	94
1.26	100	100	100	100	100	100	100	100	100	100	100	100	100	1.85	100	100	100	100	100	99	98	98	98	98	98	98	98	1.44	100	99	96	95	94	94	94	94	94	94	94	94	94
1.25	100	100	100	100	100	100	100	100	100	100	100	100	100	1.84	100	100	100	100	100	99	98	98	98	98	98	98	98	1.43	100	99	96	95	94	94	94	94	94	94	94	94	94
1.24	100	100	100	100	100	100	100	100	100	100	100	100	99	99	1.83	100	100	100	100	100	99	98	98	98	98	97	97	1.42	100	99	96	95	94	94	94	94	94	94	94	94	94
1.23	100	100	100	100	100	100	100	100	100	100	100	99	99	99	1.82	100	100	100	100	100	99	98	98	98	98	97	97	1.41	100	97	94	94	94	94	94	94	94	94	94	94	94
1.22	100	100	100	100	100	100	100	100	100	100	100	99	99	99	1.81	100	100	100	100	100	99	98	98	98	98	97	97	1.40	100	97	94	94	94	94	94	94	94	94	94	94	94
1.21	100	100	100	100	100	100	100	100	100	100	100	99	99	99	1.80	100	100	100	100	100	99	98	98	98	98	97	97	1.39	100	96	94	94	94	94	94	94	94	94	94	94	94
1.20	100	100	100	100	100	100	100	100	100	100	100	99	99	99	1.79	100	100	100	100	100	99	98	98	98	98	97	97	1.38	100	96	94	94	94	94	94	94	94	94	94	94	94
1.19	100	100	100	100	100	100	100	100	100	100	100	99	99	99	1.78	100																									

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PWL can be estimated from Figure 5.1, which shows the pre-defined estimated PWL based on the number of samples and Quality Index. Quality Index can be calculated using Equation 5.5.

Where, Q_L is lower Quality Index, LSL is Lower Specification Limit, \bar{x} is average of the lot density values, and s is standard deviation of the density of the lot. LSL is 93%Gmm, and it is specified in Figure 5.2.

$$SCPF = 0.3PF_{voids} + 0.35PF_{VEB} + 0.35PF_{density} \quad (\text{Eq. 5.6})$$

Ohio's pay factor specifications, unlike those of Indiana, directly apply the PF density to determining the pay factor. Ohio's pay factor specifications for asphalt pavements applied the acceptance criteria for asphalt surface and intermediate courses through the evaluation of mat and joint cores obtained from each day's production, with specific consideration given to the density for both joint cores and mat cores.

Specification Limits		
Mixture		
	LSL*	USL**
Air Voids at N_{des} , %	3.60	6.40
Volume of Effective Binder at N_{des} , %	Spec	Spec +2.50
Density		
	LSL*	USL**
Roadway Core Density (%Gmm), %	93.00	n/a
* LSL, Lower Specification Limit		
** USL, Upper Specification Limit		

Figure 5.2 Low and upper specification limits regarding air voids and V_{be} at N_{des} and density in Indiana specification.

For each construction project lot, ten cores that were randomly selected from specified locations are required. This includes three cores extracted from cold longitudinal joints and seven cores from the mat. Ohio Department of Transportation (ODOT) divides one lot into five equal sublots and calculates two random core locations in each sublots.

The pay factors for three joint cores are determined by the average density of the cores as a percentage of the maximum specific gravity (MSG) for the day's production by using Figure 5.4 and Figure 5.5 and Figure 5.6. Lots with less than 3 joint cores, which means not afford to reach out the 10 cores in total, should be determined the disposition of lot by following the OMM (Office of Material Management). Based on the mean density of the mat cores, pay factors for 7 mat cores are determined by using Figure 5.6. After collecting a mean of cores density values from both joint and mat cores, ODOT will determine the pay factor for each lot cored by the pay schedule in Figure 5.4 through Figure 5.6.

5.1.3 Illinois

Illinois pay factor specifications are under the PFP criteria (pay for performance) to set an acceptable limit for air voids, field VMA, density, dust/AB ratio. Illinois Department of Transportation (IDOT) did utilize the PWL which is similar to Indiana's pay factor specifications. Illinois considered not only the density and air voids but also the field VMA and dust/AB ratio to calculate the pay adjustment by using the test results of those pay parameters. (Figure 5.7)

To apply the air voids, field VMA, density as a pay parameter and unconfined edge density, dust/AB ratio as a payment deduction parameter, IDOT utilized the three different lot specifications, which are (1) a mixture lot, (2) a density lot, and (3) unconfined edge density.

- A mixture lot consists of 10 mixture sublots. Mixture sublots for air voids and field VMA will be a maximum of 1,000 tons. If the project quantity is less than 8,000 tons, the subplot size will be adjusted to achieve a minimum of 8 tests.
- A density lot consists of 30 density intervals. Density is measured every 0.2 miles for asphalt lifts of 3 inches or less, and every 0.1 miles for lifts greater than 3 inches. If multiple lanes are paved at once, and the total lane width

exceeds 20 feet, the intervals will be 0.1 miles for thin lifts and 0.05 miles for thick lifts.

- The unconfined edge density test location is selected randomly within each 0.5 miles sublots for mixtures with an unconfined edge. The last subplot may be less than 0.5 miles but must be at least 200 feet.

IDOT only gives acceptable limits for the density related pay factor and does not specify the density range in pay adjustment factor as Indiana does, but the IDOT additionally applied the monetary deduction in Dust/AB ratio, and unconfined edge as is shown in Figure 5.8 and Figure 5.9.

5.1.4 Kentucky

Kentucky's pay factor specifications, unlike those of Indiana, applied the lot pay adjustment equation below (Equation 5.7) to evaluate the pay factor. The Kentucky Transportation Cabinet (KYTC) specified that 1 lot should consist of 4 sublots to monitor and evaluate the asphalt binder contents (AC), air void (AV), voids in mineral aggregate (VMA), density, and gradation. The department also specified that 4 cores per subplot are needed for mainline, and 2 cores per subplot needed for the joint.

KYTC uses the lot pay adjustment method to assign a pay value for specific properties within each subplot. These subplot pay values are then averaged to determine the overall pay value for each property in the lot, as outlined in Figure 5.10. Additionally, to determine the pay factor for lane density and AV value, KYTC considered the AADTT (Annual Average Daily Truck Traffic) Class.

Lot Pay Adjustment

$$\begin{aligned}
 &= (50.00) \times (\text{Quantity}) \\
 &\times \{ [0.05 (\text{AC Pay Value}) + 0.25 (\text{AV Pay Value}) \\
 &+ 0.25 (\text{VMA Pay Value}) \quad (\text{Eq. 5.7}) \\
 &+ 0.30 (\text{Lane Density Pay Value}) \\
 &+ 0.15 (\text{Joint Density Pay Value}) - 1.00 \}
 \end{aligned}$$

5.1.5 Iowa

Iowa's pay factor specifications, similar to those of Indiana, applied the PWL to determine the pay factor. However, unlike Indiana's pay factor specifications, Iowa does consider the field voids, laboratory voids, and film thickness to determine the pay factor. Table 5.1 shows a field and laboratory voids payment when PWL is used for acceptance.

Iowa DOT specified that the length laid in each lot will be divided into approximately equal sublots and one sample at a random location in each subplot is needed. Each lot size should be no less than eight and no more than 15 sequential tests for the lab voids. For the lab void acceptance by using PWL, the limits are $\pm 1.0\%$ from the target air voids. And for the field voids, a lot is defined as a single layer of one asphalt

Density	
Percentages are based on %MSG	Pay Factors, %
Dense Graded	
≥ 98.0	Submitted to the Division of Materials and Tests*
97.0 - 97.9	1.00
96.6 - 96.9	1.05 - 0.01 for each 0.1% above 96.5
95.0 - 96.5	1.05
94.1 - 94.9	1.00 + 0.005 for each 0.1% above 94.0
93.0 - 94.0	1.00
92.0 - 92.9	1.00 - 0.005 for each 0.1% below 93.0
91.0 - 91.9	0.95 - 0.010 for each 0.1% below 92.0
90.0 - 90.9	0.85 - 0.030 for each 0.1% below 91.0
≤ 89.9	Submitted to the Division of Materials and Tests*
* Test results will be considered and adjudicated as a failed material in accordance with normal Department practice as listed in 105.03.	

Figure 5.3 Density pay factor table where dense graded mixture is lower than one lot and open graded mixture.

Mean of Cores ^[1]	Pay Factor	
	Surface Course	Intermediate Course
98.0% or greater	[2]	[2]
97.0 to 97.9%	0.94	[2]
96.0 to 96.9%	1.00	0.94
93.4 to 95.9%	1.04 ^[4]	1.00
92.4 to 93.3%	1.00	1.00
91.4 to 92.3%	0.98	1.00
90.4 to 91.3%	0.90	0.94
89.4 to 90.3%	0.80	0.88
88.4 to 89.3%	[3]	[3]
Less than 88.4%	[2]	[2]
<p>[1] Mean of cores as percent of average MSG for the production day.</p> <p>[2] For surface courses, remove and replace. For other courses, the District will determine whether the material may remain in place. If the material may not remain in place, remove and replace this course and all courses paved on this course. The pay factor for material allowed to remain in place is 0.60.</p> <p>[3] The District will determine whether the material may remain in place. If the material may not remain in place, remove and replace this course and all courses paved on this course. The pay factor for material allowed to remain in place is 0.70.</p> <p>[4] No incentive will be paid if any single cold joint core is less than 91.0%.</p>		

Figure 5.4 Ohio specification: pay factor for lots with three cold joint cores.

mixture placed in one day's operation but the sampling for field voids may be waived or modified when the area paved is not more than 2,500 square yards, and the quantity placed is not more than 500 tons. The PWL between 91.5% of the maximum specific gravity (%Gmm) and 100% of Gmm will be accepted for field air void.

The research team conducted a comprehensive review of asphalt density pay factors from several states, including Indiana, Illinois, Kentucky, Ohio, and Iowa, to compare how pay adjustments are determined based on density ranges. Each state applies different criteria for calculating pay adjustments, making direct comparisons challenging. The analysis focused on density values between 90% and 96% to standardize comparisons across states. Indiana's pay factors are

based on a composite pay factor system, while other states like Ohio and Iowa utilize different acceptance criteria, including core sample evaluations and density range specifications. This review provided insights into varying regional specifications and highlighted opportunities for refining Indiana's pay factor formula based on subgrade conditions and density outcomes.

5.2 Probabilistic Approach for Pay Factor Adjustment per Road Types

The research team recommends a probabilistic approach for pay factor adjustment per road type based on historical data and regression models because it provides a nuanced and data-driven method for determining

Mean of Cores ^[1]	Pay Factor	
	Surface Course	Intermediate Course
98.0% or greater	[2]	[2]
97.0 to 97.9%	0.94	[2]
96.0 to 96.9%	1.00	0.94
94.0 to 95.9%	1.04 [4]	1.00
93.0 to 93.9%	1.00	1.00
92.0 to 92.9%	0.98	1.00
91.0 to 91.9%	0.90	0.94
90.0 to 90.9%	0.80	0.88
89.0 to 89.9%	[3]	[3]
Less than 89.0%	[2]	[2]

[1]Mean of cores as percent of average MSG for the production day.
[2]For surface courses, remove and replace. For other courses, the District will determine whether the material may remain in place. If the material may not remain in place, remove and replace this course and all courses paved on this course. The pay factor for material allowed to remain in place is 0.60.
[3]The District will determine whether the material may remain in place. If the material may not remain in place, remove and replace this course and all courses paved on this course. The pay factor for such material allowed to remain in place is 0.70.
[4]No incentive will be paid for lots where 3 joint cores are required to be taken but less than 3 cores are taken.

Figure 5.5 Ohio specification: pay factor for lots with less than three cold joint cores.

Mean of Cores [1]	Pay Factor
	Surface Course
98.0% or greater	[2]
97.0 to 97.9%	0.94
96.0 to 96.9%	1.00
94.0 to 95.9%	1.04
93.0 to 93.9%	1.00
92.0 to 92.9%	0.98
91.0 to 91.9%	0.90
90.0 to 90.9%	0.80
89.0 to 89.9%	[3]
Less than 89.0%	[2]

[1]Mean of cores as percent of average MSG for the production day.
[2]Remove and replace.
[3]The District will determine whether the material may remain in place. If the material may not remain in place, remove and replace this course. The pay factor for material allowed to remain in place is 0.70.

Figure 5.6 Ohio specification: pay factor for mat density lots.

Acceptable Limits		
Parameter		Acceptable Range
Air Voids		2.0 – 6.0 %
Field VMA		-1.0 – +3.0 % ^{1/}
Density	IL-19.0, IL-9.5, IL-9.5FG, IL-4.75	90.0 – 98.0 %
	SMA 12.5, SMA 9.5	92.0 – 98.0 %
Dust / AB Ratio		0.4 – 1.6 ^{2/}

Figure 5.7 Illinois specification: acceptable limits.

pay factors under diverse conditions. The probabilistic approach is a method used to incorporate uncertainty and variability into predictions and decision-making processes. Rather than relying on fixed values or deterministic out-

comes, it considers a range of possible outcomes and their associated probabilities. This allows for a more comprehensive understanding of the likelihood of achieving specific results under varying conditions.

Unconfined Edge Density Deduction Table	
Density	Deduction / Sublot
≥ 90 %	\$0
89.0 - 89.9 %	\$1,000
88.0 - 88.9 %	\$3,000
< 88.0 %	Outer 1.0 ft (300 mm) will require remedial action acceptable to the Engineer

Figure 5.8 Illinois specification: unconfined edge density monetary deduction.

Dust/AB Ratio Deduction Table ^{1/}	
Range	Deduct / Sublot
$0.6 \leq X \leq 1.2$	\$0
$0.5 \leq X < 0.6$ or $1.2 < X \leq 1.4$	\$1,000
$0.4 \leq X < 0.5$ or $1.4 < X \leq 1.6$	\$3,000
$X < 0.4$ or $X > 1.6$	Shall be removed and replaced

Figure 5.9 Illinois specification: dust/AB ratio deduction.

In the context of pay factor adjustments, the probabilistic approach enables agencies to predict expected pay factors based on historical data and subgrade conditions. By modeling different scenarios, such as the probability of achieving certain density levels given the variability in subgrade stiffness or road types, this approach can help establish more flexible and realistic pay factors.

The probabilistic approach for pay factor adjustment per road type uses historical data that the research team collected, regression models from the historical data, and probabilistic scenarios to refine the existing pay factor system. The research team started by analyzing historical data, which included Percent Within Limits (PWL) values and FWD data, specifically focusing on the D8 values. The D8 parameter indicates subgrade deflection, which is crucial for understanding sublayer conditions. Using this data, the research team developed regression models to predict density pay factors based on subgrade conditions.

5.2.1 Statistical Analysis and Regression Model of Historical Data (%Gmm and D8)

The statistical analysis of historical pay factor (PWL) and FWD data reveals varying characteristics across road types, indicating the influence of subgrade conditions on asphalt compaction quality. In Table 5.2, the PWL statistics show that interstate roads achieve the highest average density of 95.03%Gmm, with a relatively low standard deviation (SD) of 1.14, reflecting better compaction uniformity. State roads and U.S. highways follow with average densities of 94.55%Gmm and 94.11%Gmm, respectively, but exhibit higher variability in density outcomes (SD of 1.47 and 1.66). These findings correspond to distinct pay factor (PF) values for each road type: interstates have a PF of 1.04, state roads a PF of 0.98, and U.S. highways a PF of 0.94. This suggests that,

in general, state road and U.S. highway projects tend to incur penalties related to the density-based pay factor, while interstate projects are more likely to receive incentives due to achieving higher density performance.

In terms of descriptive statistics for historical FWD D8 values (Table 5.3), state roads show the highest mean subgrade deflection at 2.38 mil, suggesting weaker sublayers relative to U.S. highways (1.99 mil) and interstates (1.81 mil). The smaller standard deviation for interstates (0.62) compared to state roads (0.99) and U.S. highways (0.82) further supports the notion that interstate roads possess more consistent subgrade stiffness and strength. This variation in subgrade conditions likely contributes to the observed differences in compaction quality and pay factors, highlighting the need to consider subgrade conditions when assessing the effectiveness of asphalt pavement compaction.

The research team developed regression models of D8 and expected %Gmm per road types using the statistical analysis results, as shown in Equation 5.8–Equation 5.10. The regression models per road type are shown below and these models are developed using the scatter plots in Figure 3.2. These regression models are used for developing the probability approach-based pay factor adjustment.

Expected %Gmm (State Roads)

$$= -0.2795 \times D8(\text{mil}) + 95.135 \quad (\text{Eq. 5.8})$$

Expected %Gmm (U.S. Highways)

$$= -0.21412 \times D8(\text{mil}) + 94.366 \quad (\text{Eq. 5.9})$$

Expected %Gmm (Interstates)

$$= -0.1089 \times D8(\text{mil}) + 95.245 \quad (\text{Eq. 5.10})$$

WEIGHTED VALUES					
	AC	AV	VMA	Lane Density	Joint Density
Weight (%)	5	25	25	30	15

AC	
Pay Value	Deviation From JMF (%)
1.00	$\leq \pm 0.5$
0.95	± 0.6
0.90	± 0.7
(i)	$\geq \pm 0.8$

VMA	
Pay Value	Deviation From Minimum
1.00	$\geq \text{min. VMA}$
0.95	0.1-0.5 below min.
0.90	0.6-1.0 below min.
(i)	>1.0 below min

AV		
Pay Value	Test Result (%)	
	AADTT Class 2	AADTT Class 3 or 4
1.05	3.0-4.0	3.0-4.0
1.00 + 0.1 (AV-3.0)	1.5-2.9	2.0-2.9
1.00 + 0.1 (4.5-AV)	4.1-6.0	4.1-6.0
0.75	6.1-6.5	----
(i)	< 1.5 or > 6.5	< 2.0 or > 6.0

LANE DENSITY		
Pay Value	Test Result (%)	
	AADTT Class 2	AADTT Class 3 or 4
1.05	94.0-96.0	94.0-96.0
1.00	92.0-93.9 or 96.1-97.0	92.0-93.9 or 96.1-97.0
0.95	91.0-91.9	91.0-91.9
0.90	90.0-90.9 or 97.1-97.5	90.0-90.9 or 97.1-97.5
0.85	97.6-98.5	----
0.75	89.0-89.9	----
(i)	< 89.0 or > 98.5	< 90.0 or > 97.5

JOINT DENSITY	
Pay Value	Test Result (%)
1.05	92.0-96.0
1.00	90.0-91.9 or 96.1-96.5
0.95	89.0-89.9
0.90	88.0-88.9 or 96.6-97.0
0.75	< 88.0 or > 97.0

Figure 5.10 Kentucky specification: lot pay adjustment schedule for surface mixtures.

TABLE 5.1
Iowa specification: PWL and pay factor for field voids and laboratory voids

PWL	Pay Factor
100.0	1.060
90.1–99.9	$0.00600 \times \text{PWL} + 0.4600$
90.0	1.000
50.0–89.9	$0.00625 \times \text{PWL} + 0.4375$
Less than 50.0	0.750 maximum

5.2.2 Probability Distribution and Three Scenarios per Road Types

The next step involved constructing three probabilistic scenarios for each road type: state roads, U.S. highways, and interstates. The research team (1)

developed the normal distribution and cumulative distribution of FWD D8 values per road types, (2) constructed three probabilistic scenarios, and (3) estimated expected density pay factor ranges per each scenario of road types using the regression models of D8 and %Gmm.

Scenario 1, representing the most favorable subgrade conditions, assumes that D8 values of next projects fall below the mean value observed in the historical data. Scenario 2 considers D8 values between the mean and a defined threshold, indicating moderate subgrade conditions. Scenario 3 represents the worst-case scenario, where D8 values exceed the threshold, suggesting poor subgrade conditions. Figure 5.11 shows the normal distribution and cumulative distribution of FWD D8 values of the State Roads in Indiana. The graph included in the slide visually represents these scenarios by dividing the probability distribution of D8 values

TABLE 5.2
Pay factor determination by road type based on basic statistical analysis result

Road Type	Average (%Gmm)	SD (%Gmm)	Q _L	PWL	PF _{Density}
State Road	94.55	1.47	1.05	85	0.98
U.S. Highway	94.11	1.66	0.67	74	0.94
Interstate	95.03	1.14	1.79	97	1.04

TABLE 5.3
Descriptive statistics for historical FWD subgrade deflection (D8) data

Road Type	Min	Max	Mean	Std. Deviation
State Road	0.34	7.92	2.38	0.99
U.S. Highway	0.82	6.23	1.99	0.82
Interstate	0.84	4.55	1.81	0.62

into three distinct segments. Scenario 1, marked in green, shows that if a new D8 value falls within this range, it is likely to yield high pavement density. Scenario 2, shown in yellow, indicates a mid-range performance, while Scenario 3, marked in red, represents the highest risk for achieving low density. Similarly, the normal distributions and cumulative distributions of FWD D8 values of U.S. highways and interstate highways in Indiana are shown in Figure 5.12 and Figure 5.13, respectively, followed by the summary of each graph and expected density pay factor values per road types.

- *Scenario 1 (green zone):* $D8 < 2.38$ mil: Represents a 50% probability of achieving D8 values below 2.38 mil, the mean of the dataset (red line in Figure 5.11). In this scenario, the expected pay factor for density ($PF_{Density}$) is predicted to be greater than 0.98 using the Equation 5.8. This indicates that pavements constructed on sublayers with these characteristics are likely to meet or exceed the target density, resulting in higher pay factors for contractors.
- *Scenario 2 (yellow zone):* $2.38 \leq D8 < 3.12$ mil: Encompasses a 27.6% probability, where D8 values range between 2.38 mil and 3.12 mil (threshold). In this scenario, the expected $PF_{Density}$ falls between 0.96 and 0.98. The drop in expected pay factor indicates that the subgrade conditions in this range pose moderate challenges for achieving the desired surface density. Consequently, pavements built under these conditions may require more compaction passes or adjustments in construction practices to meet the density targets, leading to slightly lower pay factors.
- *Scenario 3 (red zone):* $D8 \geq 3.12$ mil: Accounts for the remaining 22.4% probability with D8 values exceeding 3.12 mil. Here, the expected $PF_{Density}$ is less than or equal to 0.96, highlighting the difficulty of achieving high density on weak or unstable subgrades. Pavements built on these subgrade conditions are at a greater risk of poor performance, potentially leading to lower pay factors for

contractors due to under-compaction or the need for excessive compaction that may damage the asphalt mix.

- *Scenario 1 (green zone):* $D8 < 1.99$ mil: Represents a 50% probability where the D8 values are less than the mean value. In this scenario, the expected pay factor for density ($PF_{Density}$) is greater than 0.94, suggesting optimal subgrade conditions that support achieving high surface density.
- *Scenario 2 (yellow zone):* $1.99 \leq D8 < 3.26$ mil: Covers a range between the mean and the threshold, indicating that there is a 43.9% probability of D8 values falling within this range. The expected $PF_{Density}$ lies between 0.92 and 0.94, reflecting intermediate compaction conditions where achieving the target density might be challenging but feasible.
- *Scenario 3 (red zone):* $D8 \geq 3.26$ mil: Represents the worst-case scenario, where there is only a 6.1% probability of D8 values being this high. In this case, the expected $PF_{Density}$ is less than or equal to 0.92, indicating suboptimal compaction conditions likely due to a weak or unstable subgrade layer.
- *Scenario 1 (green zone):* $D8 < 1.81$ mil: This scenario, representing a 50% probability, includes cases where D8 values are less than 1.81 mil. Under these conditions, the expected density pay factor ($PF_{Density}$) is higher than 1.04. This suggests optimal compaction outcomes for pavements with D8 values below this threshold. This zone is often characterized by subgrades that provide sufficient stability and resistance to compaction energy absorption, thus enabling better asphalt surface densities.
- *Scenario 2 (yellow zone):* $1.81 \leq D8 < 3.45$ mil: With a probability of 49.6%, this scenario includes cases where D8 values range between 1.81 and 3.45 mil, representing a transition zone for subgrade conditions. The expected $PF_{Density}$ falls between 1.02 and 1.04. This indicates that pavements within this range are likely to have moderately good compaction, though not as optimal as Scenario 1. The compaction quality may vary more significantly in this zone due to the subgrade's varying degrees of stiffness and load-bearing capacity, which can cause inconsistencies in the resulting density values.
- *Scenario 3 (red zone):* $D8 \geq 3.45$ mil: Representing the worst-case scenario, with only a 0.4% probability, this scenario encompasses cases where D8 values exceed 3.45 mil. Here, the expected $PF_{Density}$ is 1.02 or less, indicating suboptimal compaction outcomes. Subgrades in this range are likely to be too weak or too loose, absorbing much of the compaction energy and leading to insufficient surface densities. This could result in early pavement failures or increased maintenance requirements, as the asphalt surface layer would not achieve its desired density and strength.

5.2.3 Summary of Expected Pay Factors per Scenarios and Road Types

This probabilistic approach leverages historical data to set realistic performance benchmarks and adjust expectations for surface density based on the inherent variability of subgrade conditions. In Table 5.4 for state roads, Scenario 1 with D8 values below 2.38 mil suggests an expected $PF_{Density}$ above 0.98, representing

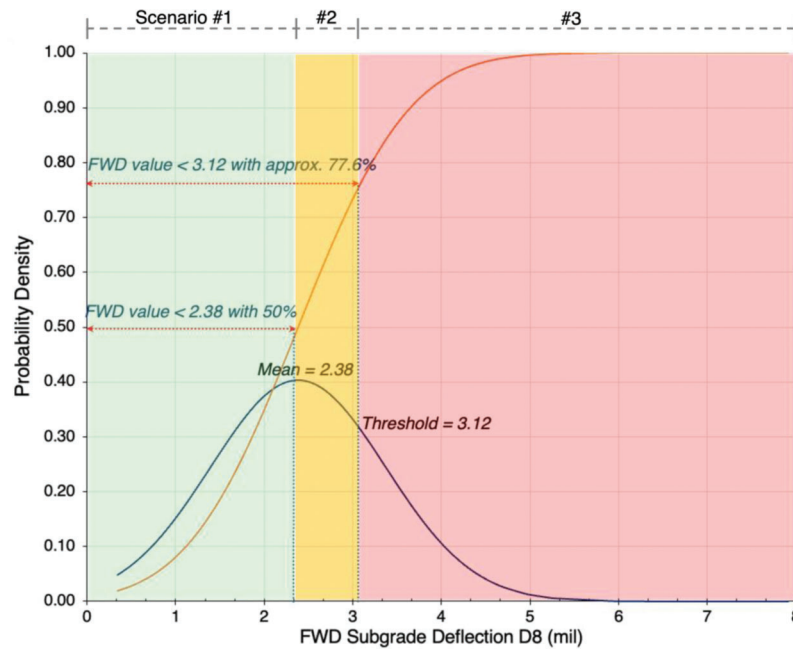


Figure 5.11 The normal distribution and cumulative distribution of FWD D8 values of the state roads in Indiana.

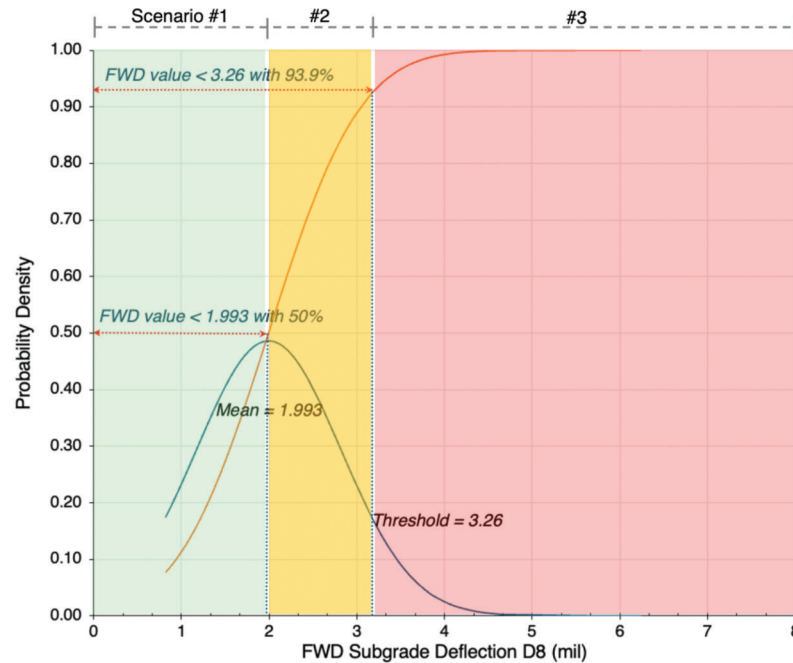


Figure 5.12 The normal distribution and cumulative distribution of FWD D8 values of the U.S. highways in Indiana.

the best compaction conditions. Scenario 2, covering D8 values between 2.38 and 3.12 mil, shows a reduced $PF_{Density}$ ranging between 0.96 and 0.98. Scenario 3, with D8 values greater than 3.12 mil, indicates the lowest $PF_{Density}$, which is equal to or below 0.96.

For U.S. highways, Scenario 1 has D8 values less than 1.99 mil, corresponding to an expected $PF_{Density}$ greater than 0.94. Scenario 2 (D8 values between 1.99 and 3.26 mil) results in a $PF_{Density}$ between 0.92 and

0.94, while Scenario 3 (D8 > 3.26 mil) is associated with a $PF_{Density}$ below 0.92.

Interstate highways, due to their superior subgrade conditions, show higher expected $PF_{Density}$ values. Scenario 1 (D8 < 1.81 mil) predicts a $PF_{Density}$ greater than 1.04, Scenario 2 (D8 between 1.81 and 3.45 mil) suggests values ranging from 1.02 to 1.04, and Scenario 3 (D8 > 3.45 mil) shows a lower limit of $PF_{Density}$, not exceeding 1.02.

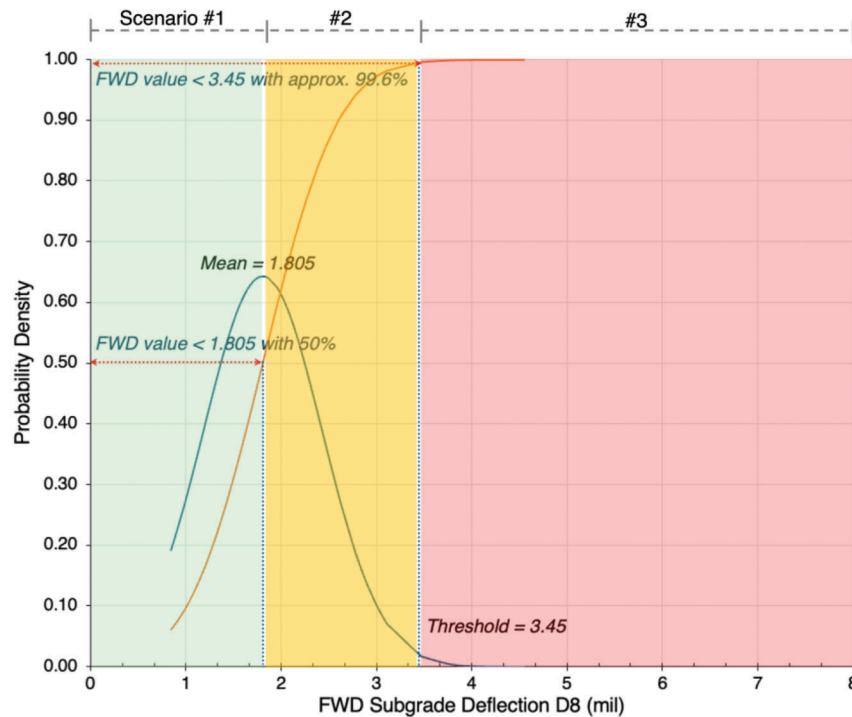


Figure 5.13 The normal distribution and cumulative distribution of FWD D8 values of the interstate highways in Indiana.

TABLE 5.4
Expected $PF_{Density}$ range per scenarios and road types

Road Type	Scenario No.	D8 Range (mil)	Probability (%)	Expected $PF_{Density}$ Range Using Eqs. 5.1–5.3
State Roads	1	$D8 < 2.38$	50	$0.98 < \text{Exp. } PF_{Density}$
State Roads	2	$2.38 \leq D8 < 3.12$	27.6	$0.96 < \text{Exp. } PF_{Density} \leq 0.98$
State Roads	3	$3.12 \leq D8$	22.4	$\text{Exp. } PF_{Density} \leq 0.96$
U.S. Highways	1	$D8 < 1.99$	50	$0.94 < \text{Exp. } PF_{Density}$
U.S. Highways	2	$1.99 \leq D8 < 3.26$	43.9	$0.92 < \text{Exp. } PF_{Density} \leq 0.94$
U.S. Highways	3	$3.26 \leq D8$	6.1	$\text{Exp. } PF_{Density} \leq 0.92$
Interstates	1	$D8 < 1.81$	50	$1.04 < \text{Exp. } PF_{Density}$
Interstates	2	$1.81 \leq D8 < 3.45$	49.6	$1.02 < \text{Exp. } PF_{Density} \leq 1.04$
Interstates	3	$3.45 \leq D8$	0.4	$\text{Exp. } PF_{Density} \leq 1.02$

These findings highlight that expected $PF_{Density}$ values for state roads and U.S. highways are generally lower compared to those of interstate highways due to the inferior subgrade conditions and other factors often found on state and U.S. highways. This analysis supports the need for differentiated pay factor adjustments per road type to more accurately reflect real-world conditions.

The recommendations derived from these scenarios help INDOT and other transportation agencies anticipate pay factors and compaction outcomes based on the initial subgrade conditions, providing a data-driven approach to pavement management and quality assurance. These recommendations can serve as a basis for adjusting density specifications and ensuring that the pay factors applied in contracts more accurately reflect the quality and durability of the constructed pavement.

6. CONCLUSION AND RECOMMENDATION

6.1 Conclusion

This research investigated the relationship between subgrade conditions and asphalt pavement density to develop data-driven recommendations for adjusting density pay factors in INDOT's specifications. The objectives of this study were to establish a clear correlation between the density of newly laid asphalt surface layers and the condition of underlying sublayers in HMA pavements.

To achieve these objectives, the study employed a comprehensive research approach. First, a detailed historical data analysis was conducted, examining various datasets including FWD test data and density records from multiple projects, focusing on subgrade deflection and density values from 29 state roads,

16 U.S. highways, and 3 interstate highways. This analysis revealed a weak but significant negative correlation between subgrade deflection (D8 values) and the resulting pavement density. Specifically, the correlation results varied depending on mixture types and road categories, with the 12.5-mm mixtures showing a slightly stronger correlation compared to the 9.5-mm mixtures. Additionally, the study found that state roads and U.S. highways exhibited lower expected density pay factors than interstate roads, suggesting that sublayer conditions play a significant role in influencing surface layer density.

Second, controlled laboratory testing using gyratory compactor simulations validated the field data findings by reproducing various sublayer conditions. The lab experiments confirmed that pavements compacted over poor sublayers (e.g., rubber pads) resulted in lower density values compared to those compacted over stable sublayers like crushed stone. This phase also demonstrated that compaction quality is significantly impacted by the stiffness and load-bearing capacity of the sublayers, as evidenced by the variations in pressure distribution and rotational movement captured through advanced sensor monitoring. Additionally, variations in pressure distribution and rotation angles, monitored using SmartKli sensors, highlighted the dynamic nature of the compaction process under different sublayer conditions.

Lastly, a probabilistic approach was adopted for pay factor recommendations, accounting for the variability in subgrade deflection values across different road types. The research team developed three scenarios—favorable, moderate, and worst-case—based on the distribution of D8 values. By applying these scenarios, the study provided a framework for adjusting the pay factor formula for density, ensuring that the specifications are more reflective of actual field conditions. This probabilistic approach was shown to be effective in making data-driven recommendations for specification adjustments, particularly for state and U.S. highways. This approach can offer a more nuanced and fair assessment of density pay factors, ensuring that contractors are evaluated based on realistic field conditions rather than a one-value-fits-all standard.

Overall, the study successfully achieved its objectives by demonstrating a correlation between sublayer conditions and surface layer density, and by formulating recommendations that can improve compaction quality and pavement longevity across various road types in Indiana.

6.2 Recommendation

Based on the findings of this study, a review of INDOT's current pay factor specifications for density is recommended, particularly for state roads, U.S. highways, and interstates. The data analysis showed that the density outcomes on state roads and U.S. highways were generally lower when placed over suboptimal sublayer conditions, suggesting that the current pay

factor formula may not be adequately capturing these variations. As a result, it is advisable to consider adjustments to the pay factor formula to better reflect these conditions and offer a more accurate evaluation of pavement quality. On the other hand, the analysis for interstates suggests that the existing pay factor criteria may be set too high, which could lead to unrealistic expectations for density outcomes, especially when sublayer conditions are not ideal. A revision to lower the density pay factor for interstates may be necessary to align the specifications more closely with the achievable results under current construction practices and sublayer conditions.

Adopting a probabilistic approach for determining pay factors can help incorporate different scenarios based on subgrade deflection values (D8). This methodology, as demonstrated in the study, enables a more comprehensive understanding of expected density outcomes under varying subgrade conditions, leading to a fairer pay factor criteria that acknowledges field variations. In scenarios where subgrade conditions are known to be weak or unstable, adjusted pay factors can mitigate issues related to over-compaction or density segregation. Additionally, more testing and data collection should be conducted to validate the proposed pay factor adjustments. Expanding the database with more diverse project types and sublayer conditions can improve the reliability of the recommendations and support broader implementation across different pavement projects and regions.

These recommendations aim to support INDOT in refining the pay factor specification system, ensuring it aligns more closely with the actual field conditions encountered and promotes the overall performance and durability of asphalt pavements in Indiana.

6.3 Implementation

To implement the proposed pay factor adjustments, a phased approach may be a strategic course of action. Initially, it could be beneficial for INDOT to revisit recently completed projects that have used the existing pay factor formulas. By comparing these projects to the probabilistic scenarios presented in this study, which incorporate subgrade deflection values for different road types, INDOT could assess how well the revised pay factors align with actual field conditions. Implementing these revisions could enhance the accuracy and fairness of pay factors across varying subgrade conditions.

Following this initial assessment, the next step might involve initiating pilot projects to test the effectiveness of these pay factor adjustments. Conducting pilot studies across a diverse range of road types (e.g., state roads, U.S. highways, and interstates) would provide valuable insights into how the revised pay factors perform in real-world scenarios. Throughout this pilot phase, it would be crucial to gather feedback from contractors and stakeholders to ensure that the

proposed adjustments are both reasonable and practical for field application.

Consideration should also be given to organizing roundtable discussions or feedback sessions during this phase. Such engagement would help identify potential areas for refinement, fostering collaboration and ensuring that the revised pay factor system is well-aligned with stakeholder expectations and project requirements. Ultimately, successful pilot testing and comprehensive stakeholder consultation could pave the way for a full-scale implementation of the revised pay factor system, promoting consistent pavement quality across INDOT projects.

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About the Joint Transportation Research Program (JTRP)

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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