Quality Assurance Data Analysis as a Leading Indicator for Infrastructure Condition Performance Management

PUBLICATION NO. FHWA-HRT-22-027

APRIL 2022

U.S. Department of Transportation
Federal Highway Administration

Research, Development, and Technology
Turner-Fairbank Highway Research Center
6300 Georgetown Pike
McLean, VA 22101-2296

FOREWORD

This report documents research undertaken to assess the impact of using quality assurance (QA) and other construction data to potentially serve as leading indicators of pavement performance. There is a desire by agencies to improve performance forecasts within their pavement management system (PMS) by using construction data. The project evaluated approaches to integrate QA and other construction data into an agency's PMS to improve performance forecasting. Data from four State agencies show the feasibility to project future performance based on QA and construction data. The results provide information and a framework for agencies to integrate QA and construction data into their PMS as leading indicators of performance. Leveraging QA and construction data in PMS can result in improved management of an agency's pavement network.

Cheryl Allen Richter, Ph.D., P.E.
Director, Office of Infrastructure
Research and Development

Recommended citation: Federal Highway Administration, *Quality Assurance Data Analysis as a Leading Indicator for Infrastructure Condition Performance Management* (Washington, DC: 2022) https://doi.org/10.21949/1521712.

TECHNICAL REPORT DOCUMENTATION PAGE

<table>
<tr><td>1. Report No.
FHWA-HRT-22-027</td><td>2. Government Accession No.</td><td colspan="2">3. Recipient’s Catalog No.</td></tr>
<tr><td colspan="2" rowspan="2">4. Title and Subtitle
Quality Assurance Data Analysis as a Leading Indicator for Infrastructure Condition Performance Management</td><td colspan="2">5. Report Date
April 2022</td></tr>
<tr><td colspan="2">6. Performing Organization Code:</td></tr>
<tr><td colspan="2">7. Author(s)
Chetana Rao (ORCID: 0000-0003-4202-9189), Leslie Titus-Glover, Ramon Bonaquist, Francesca Maier, and Alexa Mitchell</td><td colspan="2">8. Performing Organization Report No.</td></tr>
<tr><td colspan="2" rowspan="2">9. Performing Organization Name and Address
Rao Research and Consulting, LLC
1775 Tysons Blvd., 5th Fl.
Tysons, VA 22102</td><td colspan="2">10. Work Unit No.</td></tr>
<tr><td colspan="2">11. Contract or Grant No.
DTFH6115C00041</td></tr>
<tr><td colspan="2" rowspan="2">12. Sponsoring Agency Name and Address
Office of Infrastructure Research and Development
6300 Georgetown Pike
Mclean, Virginia 22101</td><td colspan="2">13. Type of Report and Period Covered
Final Report; August 2015–May 2018</td></tr>
<tr><td colspan="2">14. Sponsoring Agency Code
HRDI-20</td></tr>
<tr><td colspan="4">15. Supplementary Notes
The Contracting Officer’s Representative was Matthew R. Corrigan (HRDI-20; ORCID: 0000-0002-1230-8462).</td></tr>
<tr><td colspan="4">16. Abstract
Quality assurance (QA) and other construction data contain information about quality of materials and construction that can potentially serve as leading indicators of pavement performance. This project evaluated approaches to integrate QA and construction data into an agency’s pavement management system (PMS) for improving performance forecasting models. It also evaluated the ability to further combine site-specific soil, climate, and traffic information to enhance forecasting. Phase I of this study reviewed State department of transportation practices in collecting, storing, and accessing construction data, as well as their interest in relating these data to performance. Data from select agencies, along with other national databases, were then used for analyses and modeling in phase I and phase II. Data were obtained from traditional QA tests, innovative QA methods, and construction process control technologies. The performance metrics align with the Moving Ahead for Progress in the 21st Century performance targets—cracking, rutting, and smoothness for asphalt pavements, and cracking, faulting, and smoothness for concrete pavements. Results of this study suggest that traditional QA data elements are statistically correlated to performance and show promise for use in PMS forecasting. Data from innovative QA test methods and construction technologies demonstrate direct or indirect correlation to performance. However, for use in PMS, agencies need to establish systematic procedures for data collection, storage, and access. Further, considerable effort will be required to develop procedures for data conversion, processing, and integration at a project or network level. These efforts may be unique to each agency because QA and PMS databases generate different formats and use different referencing systems. This report provides a framework and broad guidelines for agencies to integrate QA and construction data as leading indicators of performance into their PMS.</td></tr>
<tr><td colspan="2">17. Key Words
MAP-21, quality assurance, construction data, leading indicator, pavement management system, performance prediction, geospatial referencing</td><td colspan="2">18. Distribution Statement
No restrictions. This document is available to the public through the National Technical Information Service, Springfield, VA 22161.
http://www.ntis.gov</td></tr>
<tr><td>19. Security Classif. (of this report)
Unclassified</td><td>20. Security Classif. (of this page)
Unclassified</td><td>21. No. of Pages
313</td><td>22. Price
N/A</td></tr>
</table>

Form DOT F 1700.7 (8-72) Reproduction of completed pages authorized

SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1,000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2,000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2,000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	2.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

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LIST OF ABBREVIATIONS

3D	three-dimensional
AADT	average annual daily traffic
AASHTO	American Association of State Highway and Transportation Officials
AC	asphalt concrete
ACI	American Concrete Institute
AMG	automated machine guidance
AMPT	asphalt mixture performance tester
ANOVA	analysis of variance
AQC	acceptance quality characteristics
ASR	alkali-silica reaction
BIM	building information modeling
CADD	computer-aided design and drafting
CBR	California bearing ratio
CFR	Code of Federal Regulations
CIM	Civil Integrated Management
CMS	construction management system
CMV	compaction meter value
COV	coefficient of variation
CRCP	continuously reinforced concrete pavement
CTE	coefficient of thermal expansion
DD	decimal degree
DL	drivability life
DOT	Department of Transportation
DSR	dynamic shear rheometer
ESAL	equivalent single-axle loads
FAA	fine aggregate angularity
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
FMIS	Financial Management Information System
FWD	falling weight deflectometer
GIS	geographic information system
GNSS	global navigation satellite systems
GPR	ground penetrating radar
GPS	global positioning system
HMA	hot mix asphalt
HPMS	Highway Performance Monitoring System
IA	independent assurance
IC	intelligent compaction
ICMV	intelligent compaction measurement value
ICST	intelligent construction systems and technologies
IR	infrared
IRI	International Roughness Index
JPCP	jointed plain concrete pavement
LiDAR	light detection and ranging

LIMS	laboratory information management system
LRS	linear referencing system
LTPP	Long-Term Pavement Performance
M&R	maintenance and rehabilitation
MAP-21	*Moving Ahead for Progress in the 21st Century Act*
MDSHA	Maryland State Highway Administration
MDT	Montana Department of Transportation
M-E	mechanistic-empirical
MMS	materials management system
MnDOT	Minnesota Department of Transportation
MP	milepost
NCHRP	National Council of Highway Research Program
NDT	nondestructive testing
NHS	National Highway System
NPRM	notice of draft proposed rulemaking
PAV	pressure aging vessel
PCC	portland cement concrete
PMS	pavement management system
PRESS	predicted residual error sum of squares
PRS	performance-related specifications
QA	quality assurance
QC	quality control
RAP	reclaimed asphalt pavement
RAS	recycled asphalt shingles
RFID	radio-frequency identification device
RMSE	root mean square error
RTFOT	rolling thin film oven test
RWD	rolling weight deflectometer
SHA	State Highway Agency
SHRP	Strategic Highway Research Program
sUAS	small unmanned aircraft systems
TSD	traffic speed deflectometer
TSDD	traffic speed deflection device
U.S.	United States
UAS	unmanned aircraft systems
UTM	universal transverse mercator
VFA	voids filled with asphalt
VIF	variance inflation factor
VMA	voids in mineral aggregate
w/c ratio	water-to-cementitious materials ratio
WGS	world geodetic system

CHAPTER 1. INTRODUCTION

BACKGROUND

Improving the performance and extending the life of transportation infrastructure is a long-standing goal of the Federal Highway Administration (FHWA) and the transportation community. The *Moving Ahead for Progress in the 21st Century (MAP-21) Act* further underscored the need for continued efforts in these areas.(1) The Act emphasizes risk-based and performance-based planning and programming for maintaining the National Highway System (NHS) and transportation investment decisionmaking. In keeping with the *MAP-21* requirements, in January 2015, the FHWA issued a notice of draft proposed rulemaking (NPRM) for the establishment of pavement performance measures, targets, and reporting.(2) The final ruling released in Code of Federal Regulations (CFR) Title 23, Part 490 in 2017 retained most of the provisions of the NPRM but made a few changes.(2) It established measures for State departments of transportation (DOTs) to use to carry out the National Highway Performance Program and to assess the condition of pavements on NHS excluding the interstate system, bridges carrying NHS including on- and off-ramps connected to the NHS, and pavements on the interstate system.

As agencies establish performance targets and measure progress to assess if they are meeting those targets, it is also recognized that condition assessment data can only serve as a lagging indicator to predict future performance. In other words, a prediction of the future rate of distress development after the onset of initial distress does not provide the opportunity to optimize maintenance needs. Likewise, generalizing the rate of deterioration for a family of pavement sections—typically grouped by surface type, functional class, and climate—fails to consider the impact of materials and construction quality, resulting in a less than optimal level of planning for maintenance and investment needs.

However, large volumes of data collected during construction, including quality assurance (QA) and other construction data, have shown potential to serve as leading indicators of pavement performance. This practice is the fundamental basis for the development of performance-related specifications (PRS) for QA, which tend to evaluate the relative impact of material and construction deviations on performance. Hence a tremendous opportunity exists to integrate these data into an agency's pavement management system (PMS) for improved performance forecasting models. Additionally, QA and construction data can be repurposed for performance modeling so that an agency might meet performance targets. These data align well with the hypothesis that pavement infrastructure delivered using the best construction technology and accepted using performance-based metrics has the best chance to meet these highly desirable construction and operational goals ushered in by *MAP-21*.

In general, highway agencies have made few advancements to formally link a construction phase with performance; however, this step is an essential undertaking. The goal of this study was to fill that gap and attempt to better associate construction QA and other as-built data as being leading indicators for performance prediction. If this association is validated, an opportunity will exist to integrate construction data into an agency's PMS models to support its pavement management and investment decisions. As digital data collection is increasingly becoming the norm in construction, it also supports data sharing and cross-functional activities within a highway agency. Moreover, repurposing these data into new procedures will increase the value gained from investments made in improved construction and QA technologies and practices. At a minimum, it is expected that a recurrent effort to correlate construction and QA data to performance would be a decisive method to monitor the effectiveness of specifications and to streamline future QA activities to maximize performance goals.

Pavement Management Data

The PMS model is a key planning tool used by a State Highway Agency (SHA) to support its pavement management program and investment decisions. PMS software programs store pavement condition data collected periodically from the agency's highway network. They also include pavement deterioration models used by agencies to plan their maintenance and rehabilitation (M&R) activities. These models are based on field distress data and highway classification information, and thus these models do not necessarily reflect the as-built pavement performance.

There are several challenges when considering statistical model development for performance prediction. The fundamental attribute of pavement management data is that it is never perfect; instead, it encompasses material or construction variability, impact of actual traffic levels, and unanticipated component variations. Essentially, pavement management data are actual and more realistic than data generated from controlled field experiments or test sections. Ultimately, PMS data cannot be refuted, as it is the best record of the performance of the entire network and the basis for performance forecasting.

Network-level field performance data cannot be used to determine the cause of, or circumstances leading to, failures. As a result, network-level analyses or performance forecasting models are not suitable to determine the age for the onset of failures and rate of deterioration, unless the factors that directly affect performance can be incorporated. Coincidentally, the most useful feature, cause-and effect-analyses, is possible with the integration of construction and QA data. This project evaluates the scope for improving performance forecasting by integrating the as-built construction and QA data. By doing so, distress development patterns can be less generalized and can more closely reflect field conditions for each project.

QA in Pavement Construction

QA comprises various planned and systematic activities performed to ensure that the best design practices, materials, and construction procedures are used to prevent premature performance failures. QA might adequately provide the public with a satisfactory level of service throughout the intended pavement design life. A QA program involves the evaluation of every activity that contributes to performance, including design, development of plans and specifications, construction, and maintenance. Processes in the QA program produce information that can be used to forecast performance, including materials certification, contractor quality control (QC), agency acceptance, inspection, and independent assurance (IA) testing.

Highway agencies in the United States have adopted different procedures to establish compliance requirements, which include materials and construction specifications, and to identify appropriate quality characteristics to calculate pay factors. Over the past two decades, agencies at the national level have attempted to synthesize State construction QA practices and develop optimal procedures for QA specifications. (See references 3, 4, 5, 6, and 7.) These studies show that a variety of attributes are used for QC and acceptance of hot mix asphalt (HMA) and portland cement concrete (PCC) materials and pavements (table 1). When calculating pay factors, SHAs generally use gradation, asphalt content, air voids, in-place density, and smoothness or international roughness index (IRI) as the acceptance quality characteristics (AQC) for HMA; PCC AQC include thickness, air content, smoothness, and flexural or compressive strength.(3,4)

Table 1. Pavement material and structural attributes used for QC and acceptance.

Pavement Type	Commonly Used Pavement Quality Characteristic	Less Commonly Used Pavement Quality Characteristic
HMA	• Asphalt content • Gradation • Density/composition • VFA • Voids total mix • VMA • Aggregate fractured faces • Thickness	• Modulus/stability • Indirect tensile strength and retained tensile strength (moisture sensitivity) • Aggregate shape, size, angularity, hardness • Wheel tracking test • Sand equivalence • Asphalt temperature at placement • Plant mix temperature • Binder properties
PCC	• Air content • Density • Thickness • Slump • Core/cylinder/beam strength • w/c ratio • Aggregate fractured faces	• Gradation • Sand equivalence • Permeability • Hardened air properties
Unbound materials	• Resilient modulus • CBR • Cohesion and angle of internal friction • Density	• Frost resistance • Durability index • Resistance to moisture damage
All	• Permeability • Ride quality • Friction	• Texture • Noise

VMA = voids in mineral aggregate; VFA = voids filled with asphalt; CBR = California bearing ratio; w/c ratio = water-to-cementitious materials ratio.

The QC and acceptance attributes summarized in table 1 provide a measure of the quality of materials and workmanship.

Previous attempts aimed to establish a correlation between material properties and field performance based on the key distresses modeled, especially those in the mechanistic-empirical (M-E) pavement design procedures. (See references 8, 9, 10, 11, 12, 13, and 14.) These studies are described in chapter 2. QA processes provide an opportunity to examine, at the time of construction, specific material characteristics that can directly affect performance.

Further studies, such as the National Council of Highway Research Program (NCHRP) project 10-65, which evaluated nondestructive testing (NDT) technologies used for flexible pavement QC/QA, recommended test methods and protocols that are effective in identifying anomalies in construction, material properties (stiffness of unbound or modulus of HMA), and layer thicknesses that can be related to performance.[15] A key element of these recommendations, giving agencies the opportunity to track as-built performance, was the focus on larger sample size and full coverage rather than localized testing. This focus would, however, require the use of performance prediction tools such as the American Association of State Highway and Transportation Officials (AASHTO) product, AASHTOWare Pavement ME Design procedure, for new and rehabilitated pavements developed over a series of national efforts. (See references 16, 17, 18, 19, 20, and 21.) The FHWA PRS tools are PaveSpec 4.0 for jointed plain concrete pavement (JPCP), FlexPAVE™ for flexible pavements, and High Performance Paving for analyzing early age behavior of PCC in rigid pavements.[22,23]

During the past two decades, some agencies have been proactively managing material durability through QA. This practice has resulted in additional tests being adopted, such as permeability and air void tests, to mitigate durability-related problems. Other recent, proven technologies that have been evaluated include infrared (IR) imaging for uniformity in placement temperature and evaluation of segregation potential in HMA paving, ground-penetrating radar (GPR) for layer thickness and material property measurements, magnetic tomography for dowel bar alignment in JPCP and layer thickness measurements, nonnuclear density gauge for in-place density, and various other ultrasound, seismic, and acoustic devices. However, these technologies see limited use by agencies during routine QC and acceptance.

Data from Automation in Highway Construction

Automation in highway construction data is relatively new, yet it constitutes an exponentially growing dataset related to the collection of construction data because it provides 100 percent coverage. Automation in highway construction refers to intelligent construction systems and technologies (ICST) that are rapidly evolving as construction moves away from paper-based document management to digital processes. Current and emerging ICST include remote sensing with various types of light detection and ranging (LiDAR) and unmanned aircraft systems (UAS), automated machine guidance (AMG), intelligent compaction (IC), GPR, and several digital methods of real-time verification for construction inspection and QA. ICST require and produce a vast amount of digital data, much of which is three-dimensional (3D). There is the potential to use some or all these data in executing, measuring, and accepting construction. This use is an emerging area that is the subject of FHWA research activities and technology deployment. There is an opportunity to use the data, when captured and stored during construction, in the management and maintenance of the assets. This data use fits in the wider initiative for building information modeling (BIM) (also referred to as civil integrated management [CIM] in some cases) that is being supported by NCHRP, AASHTO, and other organizations.

Another growing area is the use of 3D as-found survey data for asset inventory and condition. Currently, mobile LiDAR data are the 3D data source that is emerging as being most beneficial. Some States have begun to capture and consolidate mobile LiDAR data for large areas of their highway network to monitor the inventory and assess the condition of various assets. Although current asset management systems for pavements, bridges, and highways are databases, or geographic information system (GIS)-based geospatial databases, a looming convergence of 3D data of various types, formats, and spatial accuracies is available to support asset management decisions. The time is ripe—before these systems and processes mature based on parameters optimized for data collection, data storage, QA, or other functions—to include performance management as an important factor in establishing the cost benefit of different systems, data types, or spatial resolutions. With robust planning, 3D data-based construction processes can collect data in a format that supports use in performance management, such as collecting as-built pavement data at a spatial resolution that is compatible with the mobile LiDAR data being collected. This function might enable early detection of physical characteristics, like layer thicknesses, before pavement distress is apparent at the surface. At a more basic level, data from other QA testing with location referencing can be mapped to segments of a construction project.

Potential for Integration of QA and Construction Data for PMS

The preceding discussions alluded to the availability of large datasets and information from the field that can serve as more realistic leading indicators of in situ performance and can better guide agency pavement management and investment decisions. Additionally, agencies will be better equipped to meet performance targets in the *MAP-21* ruling. However, using data for these purposes requires assimilation and integration of various data and information sources. Also, no single dataset is likely to have great value standing alone, but, when aggregated, combined, and integrated, data become valuable resources for innovations in performance forecasting. This tenet is fundamental to this effort.

The primary challenge faced when data results are integrated is not from a technical perspective, but from processes and organizational constraints; for instance, construction and pavement management are generally two separate groups within an SHA and may result in silos, from both a process and system perspective. That being stated, SHAs are pushing the pace of asset management advancement, including a holistic review of data and breaking traditional silos. This project explores the viability of integrating data collected by different functions of a highway agency and then demonstrates its value for pavement management.

OBJECTIVES

The main objective of this project was to examine QA data and other as-built construction data and then develop processes to utilize these data as leading indicators for performance predictions within an agency's PMS to support pavement management and investment decisions. The goal was to demonstrate that these developed processes improve performance prediction reliability because of the incorporation of construction and QA data. The ultimate objective was to develop practical recommendations and best practices for the inclusion of these data within the pavement management decisionmaking framework. This framework is expected to provide a foundation that may evolve, grow, and, in the future, incorporate improved pavement testing and data processing techniques. Importantly, the framework also will facilitate and encourage the development of pavement testing and data processing methodologies within each agency.

To achieve these objectives, the project involved the following procedures:

- Systematic evaluation of all data collected by agencies during construction, and review of best practices for using these data beyond acceptance needs, i.e., for potential future performance predictions, particularly in relation to the final National Performance Management Measures in 23 CFR Part 490. Data of interest included the following:
    - QA data that are most readily available, such as the AQC used in pay factors, and that can be directly correlated to performance.
    - QA data that are not used as AQC but serve as good indicators of future performance. These data may be available in mix-design-approval databases, material certifications, inspection reports, or checklists.
    - Other as-built data that are generated during construction but are not always used as performance indicators. These data may include the use of innovative technologies or other nontraditional QA test procedures that provide material and structural parameters that are highly correlated with performance, as well as knowledge about the use of 3D construction records from both the design and construction stages. Contractors are often not required to provide such as-built records to agencies.
- Identification of agencies that are proactive in using as-built data to track pavement performance and that willingly made data and information available for the project.
- Assessment of data storage, accessibility, and potential for integration across datasets, which are essential for performance prediction models.
- Evaluation of the viability of using QA and construction data to establish correlations and to develop performance models, so QA and construction data can be used as leading indicators of performance in an agency’s PMS.
- Development of methodologies and case studies to integrate these data and prediction models into PMS for enhanced performance predictions and improved management of their network and investment decisions.
- Recommendations for improved QA testing practices that could support and leverage their use in PMS and help characterize variability and reliability in performance prediction.

The project was divided into two phases. Phase I involved information gathering from State agencies and evaluation of the viability of integrating agency datasets for establishing correlations between QA parameters and performance. Phase II developed statistical models, generated use cases to examine improvements in forecasting, and developed guidelines for QA practices to support use of data for PMS.

ORGANIZATION OF REPORT

The report is divided into the following chapters:

- Chapter 1: introduces the research project and discusses project objectives.
- Chapter 2: provides a summary of QA practices, discusses construction parameter use that is significant for performance, and highlights the critical material properties that impact performance.
- Chapter 3: discusses the findings from the survey of State practices and the selection of State agencies to use their data for analyses and case studies.
- Chapter 4: describes the QA and PMS data collection and data assembly, provides a detailed description of the datasets used, and includes specifics necessary to integrate with other datasets. Note: This chapter does not identify QA parameters that impact performance and does not present performance prediction models.
- Chapter 5: describes the data integration methodologies adopted in the project. Note: This chapter does not identify QA parameters that impact performance and does not present performance prediction models.
- Chapter 6: describes the statistical analyses performed to correlate QA data with performance and presents use cases to demonstrate methodologies to integrate QA and construction data with performance.
- Chapter 7: provides the summary and conclusions from the study.
- Chapter 8: describes a general framework envisioned by the research team for integrating QA data into an agency's PMS and provides recommendations.

The report includes a list of cited references.

CHAPTER 2. REVIEW OF INFORMATION RELATED TO QA PROGRAMS AND PAVEMENT CONDITION

This chapter presents an overview of QA programs, evolving technologies, and methods to predict performance for use in pavement management. First, this chapter focuses on traditional QA practices and material testing involved at different stages of construction and describes the potential to establish correlation with performance. Next, this chapter discusses innovative technologies increasingly in use for QA and then advancements in construction technologies that permit real-time construction data storage along with spatial location referencing. Last, this chapter provides an overview of pavement management data collection. Published literature and State specifications provide a vast amount of information on these topics, but the project team has addressed these topics in the context of the project scope and project objectives discussed in chapter 1.

TRADITIONAL QA PRACTICES

A QA program aims to ensure that the quality of the final product after construction meets contract requirements. QA comprises several elements, including material certifications and mix design approvals, sampling and testing procedures for contractor QC, agency acceptance testing, verification testing, agency inspection, IA, and the agency's dispute resolution system. 23 CFR Part 637 provides policies and guidance for State DOTs to develop QA procedures that ensure the quality of materials and workmanship of a Federal-aid highway construction project on the NHS.[(24)] In addition to requiring qualified staff within the agency and maintaining a centralized laboratory testing capability, it also provides detailed requirements for the acceptance, IA, and material certification programs.

For the acceptance program, CFR Part 637 identifies the frequency of testing, test locations during production and construction, the specific attributes to be inspected, procedures and conditions for use of contractor QC test results for acceptance, dispute resolution system if IA deviates from QC results, and procedures for design build. For the IA program, it provides means and methods to evaluate the qualified sampling and testing personnel and the testing equipment, including test equipment calibration, laboratory certifications, use of split samples and proficiency samples, and submission of annual reports to FHWA.

Therefore, QA programs in SHAs are generally well developed and normally involve statistically based specifications for QC and acceptance. The QA programs are generally managed for each material type, HMA, PCC, aggregates, and earthwork. The primary difference between the various agency programs is whether contractor data are used in the acceptance decision.[(4)] This difference has no practical effect on what QA data are available or how the available data can potentially be used. However, the data that are available and accessible, which will vary from one agency to another, will determine whether the data can potentially be used for integration with PMS. QA practices for HMA and PCC are discussed in the following sections.

QA of HMA Materials

A typical HMA QA program includes the following three major components:

- Performance graded (PG) asphalt binder QA.
- Aggregate QA.
- HMA production and construction QA.

The following sections provide brief descriptions of these components and the data that are typically available for analysis.

PG Asphalt Binder QA

The performance grading system is used by all U.S. States for specifying asphalt binders, and highway agencies typically have QA programs for PG binders that require binder suppliers to have a QC program meeting the requirements of AASHTO R 26, *Standard Practice for Certifying Suppliers of Performance-Graded Asphalt Binders*.(25,26) This standard addresses the testing to be performed on the binder, the frequency of testing and reporting of results, the qualifications of the laboratory and personnel performing the tests, and steps the supplier will take to ensure the binder is supplied in compliance with AASHTO M 320, *Standard Specification for Performance-Graded Asphalt Binder* for the grade specified.(27) Under the typical SHA PG asphalt binder QA program, the binder supplier certifies the performance grade of the binder on a production lot basis, and the agency performs acceptance tests on independent samples of selected lots. The data available from typical PG asphalt binder QA programs are summarized in table 2, along with their relationship to pavement performance. It is important to note that the lot defined by the binder QA program is different than the lot defined in the HMA production and construction QA program for a given project. Therefore, typical PG binder QA programs can provide average properties at the specification temperatures for the various grades of binder used on projects in the State.

Table 2. Summary of data available for a typical agency performance grading QA program.

Property	Relationship to Performance
Original $G^*/\sin\delta$ at specified high pavement temperature.	Indicator of permanent deformation potential.
RTFOT residue $G^*/\sin\delta$ at specified high pavement temperature.	
PAV residue $G^*/\sin\delta$ at specified intermediate pavement temperature.	Indicator of load-associated cracking potential.
PAV residue creep stiffness at 10°C above the specified low pavement temperature.	Indicator of thermal cracking potential.
PAV residue *m*-value at 10°C above the specified low pavement temperature.	

G^* = shear modulus; δ = phase angle; RTFOT = rolling thin film oven test; PAV = pressure aging vessel.

Aggregate QA

The aggregates used in HMA, PCC, bases, and subbases are generally produced under an aggregate QA program. Because a standard practice similar to AASHTO R 26 is not available for aggregate production, the aggregate QA program is usually more detailed compared with the PG asphalt binder QA program.[26] The typical aggregate QA program describes the testing and control that the aggregate supplier must provide to ensure the aggregates:

- Are resistant to degradation during production and under traffic loading.
- Are resistant to disintegration due to weathering.
- Contain minimal amounts of clay particles and other deleterious materials.
- Are produced with specified gradations.

The data available from a typical aggregate QA program are listed in table 3. Although relationships between these aggregate properties and HMA mixture performance are not available, it is generally accepted that current specification limits provide suitable aggregates for HMA mixtures.[8,28]

Table 3. Summary of data available for a typical agency aggregate QA program.

Property	AASHTO Test Method
Toughness and abrasion resistance	AASHTO T 96[29]
Aggregate angularity and morphology	AASHTO T 335[30]
Durability and soundness	AASHTO T 104[31]
Clay content	AASHTO T 90[32] or AASHTO T 176[33]
Gradation	AASHTO T 27[34] and AASHTO T 11[35]
Specific gravity	AASHTO T 84[36] and AASHTO T 85[37]

HMA Production and Construction QA

HMA production and construction QA programs have detailed specifications that assign responsibilities for the contractor and the agency during:

- Mixture design.
- QC.
- Acceptance.

Most HMA production and construction QA programs also include pay factors based on statistical analysis of specific quality indicators. The data available from HMA production and construction QA are discussed in the following sections.

Mixture Design

Every HMA mixture used in flexible pavement construction has an associated mixture design. Most HMA mixtures in the United States are designed in accordance with AASHTO M 323, *Standard Specification for Superpave Volumetric Design*, or AASHTO M 325, *Standard Specification for Stone Matrix Asphalt*, with minor modifications to meet local conditions.[38,39] The mixture design identifies the grade of binder used in the mixture and establishes the target gradation of the aggregates, the amount of asphalt binder in the mixture, and the volumetric properties of the mixture. Table 4 summarizes the data available from a typical HMA mixture design. During production, many properties of the mixture might vary and, as shown in table 4, are included in the QC and acceptance testing records. Note that the performance grading properties of the binder, the type and percentage of recycled binder, and the bulk specific gravity of the aggregates and the binder are not usually tested as part of QC and acceptance. These properties are usually only available from the mixture design. These important properties are used to derive the inputs to some of the models that use QA data to estimate key engineering and performance properties of HMA that are discussed in the following sections.

Table 4. Summary of data available from a typical HMA mixture design.

Property	Reported During QC and Acceptance
Design traffic level	N/A
Nominal maximum aggregate size and gradation	Yes
Performance grade of the binder	No
Type and percentage of recycled asphalt binder	No
Bulk specific gravity of the combined aggregate	No
Effective specific gravity of the aggregate	Yes
Bulk specific gravity of the binder	No
Design compaction level	N/A
Design binder content	Yes
Design air void content	Yes
Design VMA	Sometimes
Design VFA	Sometimes
FAA	No
Coarse aggregate crushed faces	No
Fine aggregate sand equivalent	No
Coarse aggregate flat and elongated particles	No
Filler-to-effective asphalt ratio	Sometimes
Moisture sensitivity	No

FAA = fine aggregate angularity; N/A = not applicable.

In addition to the data in table 4, some agencies require specific performance tests to be conducted and reported during mixture design. The most common required performance testing is a test of rutting resistance usually measured with a wheel tracking device. A few agencies are beginning to require fracture tests for low- or intermediate-temperature cracking, and at least one agency requires mixture permeability to be measured and reported during mixture design.

QC and Acceptance

In a typical highway agency QA program for HMA, similar testing is performed for QC and acceptance; however, the frequency of testing is much greater for QC compared with acceptance. Table 5 summarizes the data available from QC and acceptance testing performed during HMA mixture production and pavement construction. Many agencies do not use volumetric properties such as voids in mineral aggregate (VMA), voids filled with asphalt (VFA), or filler-to-effective asphalt ratio for QC or acceptance; however, these properties can be calculated from the QC and acceptance data using aggregate and binder specific gravity data from the mixture design.

Table 5. Summary of data available from typical HMA production and construction QC and acceptance testing.

Property	Method
Asphalt content	AASHTO T 308[40]
Gradation	AASHTO T 27[34] and AASHTO T 11[35]
In-place compaction	Cores using AASHTO T 166[41] or nuclear gauge calibrated to cores
Laboratory air voids	AASHTO T 312[42]
Thickness	Cores or yield
Ride quality	AASHTO R 54[43]

Except for ride quality, the production and construction QC and acceptance data are collected on a lot and sublot basis. A lot is typically defined as 1 day's production, which is divided into four or more sublots for sampling and testing. When QC data are used for acceptance, the highway agency will typically perform verification testing on 10 percent of the QC samples.

QA of PCC Materials

QA for PCC materials is moving toward performance PRS from materials and methods provisions. Within the confines of the PRS, the contractor has scope for mix design adjustments to meet certain performance criteria specified by the agency. Again, just as with HMA, the QA program may vary from one agency to another in terms of whether the contractor's QC test data are used for agency acceptance.

The PCC QA program consists of the following components:

- QA for the individual components of a PCC mix design (e.g., cement, fly ash, coarse and fine aggregates, air-entraining admixtures [AEA], chemical admixtures, curing compounds).
- Mix design approval.
- PCC production and construction QA.

QA for Individual Components of PCC Mix Design

QA for individual components of PCC mix design is the process by which the agency ensures that each individual component of the PCC mix design meets the agency specifications. These specifications are intended for the selection of quality materials and identification of durability potential, especially specifications related to alkali-silica reaction (ASR) potential. The contractor is expected to provide material test data and/or material certification from the manufacturer or supplier. In some ways, these data are analogous to the binder certification provided by the binder supplier or contractor in QA for HMA materials. Some key test results and material certifications submitted to the agency are reported in table 6. Please note QA for admixtures and curing compounds are not discussed in this publication.

Table 6. Summary of data available from PCC materials QA program.

Material	Test Method	Information Provided
Cement type	ASTM C 150(44)	Cement type, the chemical/mineralogical composition, and the alkalinity, which is key to controlling durability/ASR problems.
Fly ash class	ASTM C 618(45)	Fly ash class (C or F), calcium oxide content (to decide use in ASR potential mixes), loss of ignition.
Fine aggregates (gradation, sand equivalency, fineness modulus, specific gravity, potential for ASR)	AASHTO M 6(46) AASHTO T 11(32) AASHTO T 176(33) AASHTO T 27(34) AASHTO T 84(36) ASTM C 1260(47)	Gradation, sand equivalency, fineness modulus, specific gravity, potential for ASR.
Coarse aggregates (gradation, nominal aggregate size, abrasion, specific gravity)	AASHTO M 80(48) AASHTO T 27(34) AASHTO T 96(29) AASHTO T 85(37)	Gradation, nominal aggregate size, abrasion, specific gravity.

Mix Design QA

Before construction, the agency obtains test results for the approved mix design. Often contractors may work with independent and private testing laboratories to develop mix designs that meet the performance-based specifications. In such cases, mix designs are optimized after a series of iterative trial batching. Depending on the owner agency and the governing specifications for PCC mix designs, several of the following test data are available for fresh concrete properties and hardened concrete properties. Table 7 provides a summary.

Table 7. Summary of data available from mix design approval stage.

Test Properties	Test Method	Information Provided
Fresh concrete properties	AASHTO T 121(49)	Unit weight air content
	AASHTO T 196(50)	Unit weight air content
	AASHTO T 119(51)	Slump
	ASTM C 232(52)	Bleeding
	ASTM C 403(53)	Initial and final set time
Hardened concrete properties	AASHTO T 22(54)	Compressive strength
	AASHTO T 97*(55)	Flexural strength,
	ASTM C 469*(56)	Modulus of elasticity
	AASHTO T 198*(57)	Splitting tensile strength
	AASHTO T 336*(58)	CTE
	AASHTO T 160*(59)	Length change due to concrete shrinkage
Durability properties	ASTM C 457(60)	Parameters of air void system in hardened concrete
	ASTM C 666(61)	Rapid freeze-thaw resistance
	ASTM C 672(62)	Scaling resistance

*Less commonly tested by agencies and contractors and increasing adoption because of AASHTOWare Pavement ME Design input requirement. The common practice currently is to determine these properties using laboratory testing and develop materials libraries for AASHTOWare Pavement ME inputs, particularly for PCC coefficient of thermal expansion (CTE) and length change due to shrinkage.

PCC Production and Construction QA

During production and construction, contractor QC and agency acceptance procedures require nearly the same battery of tests. The tests performed in QC and acceptance are presented in table 8. These data are often easily accessible through agency QA databases.

The main goal of presenting details of the traditional QA programs in this section is to highlight the fact that several material properties and index properties are collected as part of agency QA procedures. The availability and accessibility of these data might vary from one agency to another, as would the sophistication of their data storage methods. However, for the current study, the fact that such data are collected and should be available if systematic data management practices are followed is valuable for formulating performance prediction methods.

Table 8. Summary of test data collected in contractor QC and agency acceptance procedures.

Test Properties	Information Provided
Coarse and fine aggregate properties	Gradation Sand equivalence
Fresh concrete properties	Air content Slump w/c ratio
Hardened concrete properties	Compressive strength Flexural strength Permeability (AASHTO T 277)[63]
Pavement	Thickness IRI/ride quality (AASHTO R 54)[43] Texture Dowel bar alignment

Note: Gradation, air content, slump, compressive strength, thickness, and IRI are the most commonly tested. Dowel bar alignment is included among QA parameters listed in the section, Evolving QA and Pavement Evaluation Practices.

DERIVED ENGINEERING AND PERFORMANCE PARAMETERS AS INDICATORS OF PERFORMANCE

Each QA data item collected in traditional QA practices discussed in the previous section might not necessarily form a strong indicator of performance individually. In other words, each parameter on its own is not a standalone engineering property directly correlated to performance. However, several statistical models have been derived for estimating key engineering and performance properties of HMA and PCC materials based on mixture composition and/or index properties. Most of the input data needed to use these derived models are collected as part of a typical QA program for HMA and PCC.

This fact is especially relevant for this study because these engineering properties are considered strong indicators of performance and often are key inputs to M-E design procedures. The effort involved in measuring the mechanical and engineering properties might be far greater than would be practical for routine QA. It is worth noting that the AASHTOWare Pavement ME procedure recommends the use of some of these correlations to estimate level 2 and level 3 inputs to the design. In some ways, the use of these models would be aligned and in agreement with modern design methods. Some of these models are presented in the following sections, along with a discussion of the data needed to use the model.

Empirical Models for Estimating HMA Properties and Performance

HMA Dynamic Modulus

The dynamic modulus of HMA layers is a key input in the AASHTOWare Pavement ME Design software. Several models for estimating the dynamic modulus from binder properties and mixture composition have been developed.[9,16,64] However, most of these models require binder stiffness data from a binder master curve as an input, and databases of typical binder master curve parameters are not readily available. Therefore, the most useful model for estimating dynamic modulus for use as a potential leading indicator of pavement performance is the level 3 model used in NCHRP Project 1-37A and expressed as equations in figure 1 through figure 8.[16]

$$\log|E^*| = \delta + \frac{\alpha}{1 + e^{\beta + \gamma \log(t_r)}}$$

Figure 1. Equation. Estimation of HMA dynamic modulus.[16]

Where:

$|E^*|$ = dynamic modulus, 10^5 psi.

δ, α = mix-specific fitting parameters. δ represents the minimum value of E^*, and $\delta + \alpha$ represents the maximum value of E^*

β, γ = mix-specific parameters representing shape of the sigmoidal function in figure 1.

t_r = time of loading at the reference temperature, defined in figure 8.

$$\delta = 3.750063 + 0.02932\rho_{200} - 0.001767(\rho_{200})^2 - 0.002841\rho_4 - 0.058097V_a - 0.0802208(VFA)$$

Figure 2. Equation. Calculation of δ parameter.

Where:

ρ_{200} = percent passing No. 200 sieve.

ρ_4 = percent retained on No. 4 sieve.

V_a = percent air voids.

VFA = percent voids filled with asphalt, which is the difference between percent VMA and the percent V_a.

$$V_a = \left(1 - \frac{G_{mb}}{G_{mm}}\right) * 100$$

Figure 3. Equation. Calculation of air voids parameter.

Where:

G_{mb} = bulk specific gravity of compacted HMA.

G_{mm} = maximum specific gravity of HMA.

Figure 3 provides the expression for V_a, to calculate VFA shown in figure 2.

$$VMA = 100 - \left(\frac{G_{mb}(100 - P_b)}{G_{sb}}\right)$$

Figure 4. Equation. Calculation of voids parameter.

Where:

G_{mb} = bulk specific gravity of compacted HMA.
G_{sb} = bulk specific gravity of combined aggregate in HMA.
P_b = asphalt content of HMA.

Figure 4 provides the expression for *VMA*, used to calculate *VFA* shown in figure 2.

$$\alpha = 3.871997 - 0.0021\rho_4 + 0.003958\rho_{38} - 0.000017(\rho_{38})^2 + 0.005470\rho_{34}$$

Figure 5. Equation. Calculation of *α* parameter.

Where:

ρ_{38} = percent retained on 3/8 in sieve.
ρ_{34} = percent retained on 3/4 in sieve.

Figure 5 provides the expression for α, shown in figure 1.

$$\beta = -0.603313 - 0.393532 * log(\eta_{T_r})$$

Figure 6. Equation. Calculation of *β* parameter.

Where η_{T_r} = viscosity in 10^6 Poise at the reference temperature.

Figure 6 provides the expression for β, shown in figure 1.

$$log\ (\eta_t) = A + VTS\ log(\mathrm{t})$$

Figure 7. Equation. Calculation of viscosity temperature parameter.

Where:

η_t = viscosity at temperature of interest.
A = intercept of viscosity temperature susceptibility relationship.
VTS = slope of viscosity temperature susceptibility relationship.
t = temperature in degrees Rankine = °F + 459.67.
γ = 0.313351.

Figure 7 provides the expression for the viscosity parameter shown in figure 6.

$$log\ (t_r) = log(t) - c[log(\eta_t) - log(\eta_{T_r})]$$

Figure 8. Equation. Calculation of the temperature parameter.

Where c = 1.255882.

Figure 8 provides the expression for log (t_r) parameter shown in figure 1.

Typical values of the viscosity temperature susceptibility parameters *A* and *VTS* are tabulated in table 9 and table 10, respectively, for different PG asphalt binders.[16] Recycled binder from reclaimed asphalt pavement (RAP) or recycled asphalt shingles (RAS) can be accounted for by modifying the high- and low-temperature performance grade of the virgin binder in the mixture. Table 11 presents typical changes in the high- and low-temperature performance grade per percentage of recycled binder in the mixture.[65] Knowing the performance grade of the virgin binder and the amount and type of recycled binder in the mixture, the performance grade of the combined binder in the mixture can be estimated using the grade changes tabulated in table 11.

Table 9. Typical viscosity temperature susceptibility parameter *A* values for PG asphalt binders at the given high- and low-temperature grade.[16]

High-Temp. Grade	Low-Temp. Grade						
	−10	−16	−22	−28	−34	−40	−46
46	—	—	—	—	11.504	10.101	8.755
52	13.386	13.305	12.755	11.840	10.707	9.496	8.310
58	12.316	12.248	11.787	11.010	10.035	8.976	—
64	11.432	11.375	10.980	10.312	9.461	8.524	—
70	10.690	10.641	10.299	9.715	8.965	8.129	—
76	10.059	10.015	9.715	9.200	8.532	—	—
82	9.514	9.475	9.209	8.750	8.151	—	—

—No data.

Table 10. Typical viscosity temperature susceptibility parameter VTS values for PG asphalt binders at the given high and low temperature grade.[16]

High-Temp. Grade	Low-Temp. Grade						
	−10	−16	−22	−28	−34	−40	−46
46	—	—	—	—	−3.901	−3.393	−2.905
52	−4.570	−4.541	−4.342	−4.012	−3.602	−3.164	−2.736
58	−4.172	−4.147	−3.981	−3.701	−3.350	−2.968	—
64	−3.842	−3.822	−3.680	−3.440	−3.134	−2.798	—
70	−3.566	−3.548	−3.426	−3.217	−2.948	−2.648	—
76	−3.331	−3.315	−3.208	−3.024	−2.785	—	—
82	−3.128	−3.114	−3.019	−2.856	−2.642	—	—

—No data.

Table 11. Typical changes in performance grade when using recycled binders.[65]

Grade	Increase of Performance Grade per Percent Recycled Binder Added (°C), RAP	Increase of Performance Grade per Percent Recycled Binder Added (°C), RAS
High	0.23	0.58
Low	0.08	0.23

Although the equation in figure 1 appears complicated because it requires a number of inputs, all the inputs are available from a typical agency QA program for HMA. Table 12 maps the required input parameters to data available from a typical agency QA program.

Table 12. Location of input data for AASHTOWare Pavement ME level 3 equations.

Parameter	Data Location in Typical Agency QA Program
Binder viscosity temperature parameter *A*	Mix design binder grade modified for recycled binder content.
Binder viscosity temperature parameter *B*	
ρ_{200}	Production and construction QC and acceptance test data.
ρ_4	
ρ_{38}	
ρ_{34}	
V_a	Production and construction QC and acceptance test data: • G_{mb} and G_{mm} from in-place compaction. • P_b from mix testing. • Mix design for G_{sb}.
VMA	
VFA	

Low-Temperature Creep Compliance and Strength

Other key inputs in the AASHTOWare Pavement ME Design software for HMA layers are the low-temperature creep compliance and strength of the HMA mixtures. Data from a typical agency HMA QA program can be used with the level 3 models developed in NCHRP Project 1-37A to estimate the creep compliance and tensile strength using equations in figure 9 through figure 13.[16] All the inputs for figure 9 and figure 13 are available from a typical agency QA program for HMA.

$$D(t) = D_1 * t^m$$

Figure 9. Equation. Expression to determine creep compliance.[16]

Where:

$$\log D_1 = 8.524 + 0.01306 \times Temp + 0.7957 \times \log(Va) + 2.0103 \times \log(VFA) \\ - 1.923 \times \log(A)$$

Figure 10. Equation. Calculation of *D* parameter.

Where:

$$m = 1.1628 - 0.00185 \times Temp - 0.04596 \times Va - 0.01126 \times VFA + 0.00247 \times Pen77 \\ + 0.001683 \times Temp \times (Pen77)^{0.4605}$$

Figure 11. Equation. Calculation of *m* parameter.

Where:

$Temp$ = temperature at which creep compliance is measured, °F.

V_a = as-constructed air voids, percent.

VFA = as-constructed VFA, percent.

$Pen77$ = binder penetration at 77°F, mm/10.

$$Pen77 = 10^{\left[290.5013-\left(81{,}177.288+257.0694\times10^{(A+2.72973\times VTS)}\right)^{0.5}\right]}$$

Figure 12. Equation. Calculation of *Pen77* parameter.

Where A = viscosity-temperature susceptibility intercept.

$$TS = 7{,}416.712 - 114.016 * Va - 0.304Va^2 - 122.592VFA + 0.704VFA^2$$

Figure 13. Equation. Expression to determine indirect tensile strength.[16]

Where TS = indirect tensile strength at 14°F, psi.

Rutting Resistance Predictive Model

One strategy for using QA data as a leading indicator is to use predicted performance from the AASHTOWare Pavement ME Design software. This type of analysis will be computationally intensive. A second approach is to use an index derived from models relating properties in a typical QA program for HMA to measure resistance to rutting and cracking. In NCHRP Project 9-25, a model was developed to estimate HMA rutting resistance from mixture volumetric composition.[10] This model was subsequently improved through additional research in NCHRP Project 9-33 and Airfield Asphalt Pavement Technology Program Project 04-02.[10,11] Figure 14 and figure 15 present the model, which can be used to estimate the rutting resistance of a mixture from volumetric composition, in-place compaction, and binder properties.[11]

$$TR = 9.85 \times 10^{-5}(PN_dK_s)^{1.373}V_d^{1.5185}V_{IP}^{-1.4727}M$$

Figure 14. Equation. Allowable traffic for rutting criterion of 7.2 mm.[11]

Where:

TR = allowable traffic in million equivalent single-axle loads (ESALs) to an average rut depth of 7.2 mm.

N_d = design gyrations.

K_s = speed correction.

$K_s = (v/70)^{0.8}$, where v is the average traffic speed in km/h.

V_d = design air void content, volume percent.

V_{IP} = in-place air void content, volume percent.

M = 7.13 for mixtures containing typical polymer-modified binders, 1.00 otherwise.

$$P = resistivity, \frac{s}{nm} = \frac{(|G^*|/\sin\delta) * {S_a}^2 * {G_{sb}}^2}{49 * VMA^3}$$

Figure 15. Equation. Calculation of *P* parameter.

Where:

$|G^*|/\sin\delta$ = estimated aged PG grading parameter at high temperatures, determined at 10 rad/s and at the yearly 7-d average maximum pavement temperature at 20 mm below the pavement surface, as determined using LTPPBind, version 3.1 (units of Pa/s); aged value can be estimated by multiplying the rolling thin film oven test (RTFOT) value by 4.0 for long-term projects (10- to 20-yr design life), and by 2.5 for short-term projects of 1–2 yr.

S_a = specific surface of aggregate in mixture, m^2/kg.

S_a ≅ sum of the percent passing the 75-, 150-, and 300-µm sieves, divided by 5.0.

VMA = design VMA for the mixture, volume.

The primary difficulty in applying this model using data available from a typical agency QA program for HMA is estimating $|G^*|/\sin\delta$ at the pavement temperature for the location of the project. A typical agency PG binder QA program will provide average values of $|G^*|/\sin\delta$ for RTFOT condition at the grade temperatures (e.g., 58, 64, 70). Because most agencies specify binder grades using 98 percent reliability, the pavement temperature for the project location will generally be lower than the specified grade temperature. An approximation used in binder grading is that $|G^*|/\sin\delta$ doubles for each 6°C decrease in temperature. Figure 16 expresses this approximation, allowing the RTFOT value of $|G^*|/\sin\delta$ to be estimated at the pavement temperature from the RTFOT value of $|G^*|/\sin\delta$ at the binder grade temperature that is collected as part of the PG binder QA program. Table 13 maps the required input parameters to data available from a typical agency QA program.

$$(|G*|/\sin\delta)_{PT} = (|G*|/\sin\delta)_{SPEC}(e)^{[0.1155(T_{GRADE} - T_P)]}$$

Figure 16. Equation. Adjustment to estimate RTFOT result for pavement temperature.

Where:

$(|G^*|/\sin\delta)_{PT}$ = estimated RTFOT $|G^*|/\sin\delta$ at the pavement temperature, kPa.

$(|G^*|/\sin\delta)_{SPEC}$ = estimated RTFOT $|G^*|/\sin\delta$ at the specification temperature, kPa.

T_{GRADE} = binder grading temperature, °C.

T_P = LTPPBind 50 percent reliability pavement temperature, °C

Table 13. Location of input data for resistivity rutting model.

Parameter	Data Location in Typical Agency QA Program
$\lvert G^*\rvert/\sin\delta$	Average value from PG binder QA program for the grade specified in the mix design adjusted for recycled binder (table 6), pavement temperature (figure 16), and aging (4.0 times for normal design life).
S_a	Production and construction QC and acceptance gradation data.
G_{sb}	Mix design.
VMA	
N_d	
V_d	
V_{IP}	Production and construction QC and acceptance test data, G_{mb} and G_{mm} from in-place compaction.
K_s	Estimate based on roadway type.
M	PG binder QA program. Polymer modified binders are usually identified.

Asphalt Institute Fatigue Equation

The Asphalt Institute fatigue equation in figure 17 through figure 19 can be used in lieu of a structural analysis with AASHTOWare Pavement ME Design to develop an index related to the fatigue cracking potential of an HMA pavement section.(66) The tensile strain in figure 19 can be evaluated using the ILLI-PAVE algorithm for strain at the bottom of asphalt layer, which is reproduced as figure 19.(67) The HMA modulus required for both equations in figure 17 and figure 19 can be estimated at an appropriate intermediate pavement temperature using figure 1 and a loading time of 0.1 s. A reasonable intermediate pavement temperature is the mean annual air temperature at the project location, which is available from local weather stations. Table 14 maps the required input parameters for the equations in figure 17 through figure 19 to data available from a typical agency QA program.

$$N_f = 18.4 \ * \ 0.00432 \ C\varepsilon_t{}^{-3.291} \lvert E *\rvert^{-0.854}$$

Figure 17. Equation. Asphalt Institute fatigue equation.(66)

Where:

- N_f = number of cycles to failure.
- $\lvert E^*\rvert$ = mixture dynamic modulus, psi.
- ε_t = applied tensile strain, inches/inches.
- 18.4 = field adjustment factor.

$$C = 10^{(VFA - 0.69)}$$

Figure 18. Equation. Calculation of *C* parameter.

$$\log\left(\varepsilon_t\right) = 2.9496 + 1.1289\left(T_{ac}\right) - 0.5195\left[\frac{\log\left(T_b\right)}{T_{ac}}\right] - 0.0807\log\left(\left|E^*\right|\right)\left(T_{ac}\right) - 0.408\log\left(E_{ri}\right)$$

Figure 19. Equation. Estimation of tensile strain at the bottom of the asphalt layer.(67)

Where:

ε_t = tensile strain, μ inches/inches.
T_{ac} = thickness of asphalt concrete (AC), inches.
T_b = thickness of aggregate base/subbase, inches.
$|E^*|$ = mixture dynamic modulus, ksi.
E_{ri} = subgrade breakpoint resilient modulus; ksi suggested values are 12 for stiff, 8 for medium, 3 for soft, and 1 for very soft subgrade.

Table 14. Location of input data for cracking analysis using the Asphalt Institute fatigue equation.

Parameter	Data Location in Typical Agency QA Program
$\|E^*\|$	See figure 1 and table 7.
V_a	Production and construction QC and acceptance test data: • G_{mb} and G_{mm} from in-place compaction. • P_b from mix testing. • Mix design for G_{sb}.
VMA	
VFA	
T_{ac}	Production and construction QC and acceptance test data.
T_b	Construction QC and acceptance test data for granular layers.
E_{ri}	Estimated based on description of subgrade soil.

Critical Cracking Temperature

An alternative to performing a thermal cracking analysis using the AASHTOWare Pavement ME Design software is to use low-temperature creep compliance and strength data estimated with the equations in figure 9 and figure 13 to calculate a critical cracking temperature for the HMA and then use the critical cracking temperature as an index of low-temperature cracking potential. LTSTRESS.xls is an example of a Microsoft® Excel® application that can be used to perform this analysis. LTSTRESS was developed at the Northeast Center of Excellence for Pavement Technology to reduce data from AASHTO T 322 and to perform a simplified thermo-viscoelastic analysis.(68) This analysis is like the thermal fracture model in the AASHTOWare Pavement ME Design software. It provides an estimate of the expected thermal cracking temperature for the material tested. It does not consider thermal fatigue or crack propagation, and it is strictly accurate only for single-event thermal cracking, as occurs during extreme low-temperature events. Through the equations in figure 9 and figure 13, the inputs needed for a critical cracking temperature analysis using LTSTRESS can be obtained from data collected as part of a typical agency QA program for HMA.

Permeability

Permeability is an important factor affecting the durability of asphalt concrete (AC) pavements that is not directly addressed in AASHTOWare Pavement ME. In NCHRP Project 9-25, an equation to estimate permeability based on the volumetric properties of HMA was developed[10]; figure 20 presents this permeability equation. Table 15 maps the input parameters for the permeability equation to data available from a typical agency QA program.

$$\kappa = 108\left(VTM_{Eff}\right)$$

Figure 20. Equation. Estimation of permeability based on mix gradation and volumetrics.[10]

Where:

κ = coefficient of permeability, 10^{-5} cm/s.
VTM_{Eff} = effective air void content.
$VTM_{Eff} = V_{IP} + 1.87 - 1.53 \times S_a$ for $V_{IP} \geq 1.53 \times S_a + 1.87$.
$VTM_{Eff} = 0$ for $V_{IP} < 1.53 \times S_a + 1.87$.
S_a = specific surface of aggregate in mixture, m^2/kg.
$S_a \cong$ sum of the percent passing the 75-, 150-, and 300-μm sieves, divided by 5.0.

Table 15. Location of input data for permeability model.

Parameter	Data Location in Typical Agency QA Program
V_{IP}	Production and construction QC and acceptance test data, G_{mb} and G_{mm} from in-place compaction.
S_a	Production and construction QC and acceptance gradation data.

Models for Estimating PCC Properties and Performance

Correlations Adopted in the AASHTOWare Pavement ME

The AASHTOWare Pavement ME design procedure, now adopted by several agencies, includes several level 2 and level 3 correlations based on material property prediction models developed in the past. These correlations were used during the global calibration of the distress models and are default inputs integrated into the software program.[16,17] Parameters that are estimated using these correlations include PCC flexural strength, elastic modulus, coefficient of thermal expansion (CTE), and ultimate shrinkage, all of which are key inputs for damage calculation and performance predictions models. These models are:

- PCC flexural strength model, shown in figure 21, based on Portland Cement Association and Long-Term Pavement Performance (LTPP) studies.[69,70]

- PCC elastic modulus model as a function of density and compressive strength and shown in figure 22. This equation was borrowed from American Concrete Institute (ACI).[71] For unit weight of 145 lb/ft^3, this equation reduces to the expression shown in figure 23.

- PCC ultimate shrinkage strain model, which is a function of compressive strength, cement type, curing type, cement content, and water-to-cementitious materials ratio (w/c) ratio. This model was generated using historical shrinkage data and was subsequently adopted by the ACI.[72] The model is shown in figure 24.

$$MR = 9.5 * f_c'^{0.5}$$

Figure 21. Equation. PCC flexural strength model.(69,70)

Where:

MR = flexural strength in psi.

f_c' = compressive strength in psi.

$$E_c = \rho^{1.5} * 33 * f_c'^{0.5}$$

Figure 22. Equation. PCC elastic modulus model.(71)

Where:

E_c = modulus of elasticity in psi.

ρ = the density in lb/ft^3.

$$E_c = 57{,}000 f_c'^{0.5}$$

Figure 23. Equation. Modulus prediction based on compressive strength alone.(71)

$$\varepsilon_{su} = C_1 \cdot C_2 \cdot \left\{ 26w^{2.1} \left(f_c' \right)^{-0.28} + 270 \right\}$$

Figure 24. Equation. Ultimate shrinkage strain.(72)

Where:

ε_{su} = the ultimate shrinkage strain, $\times 10^{-6}$.

C_1 = the cement type factor = 1.0, 0.8, and 1.1 for type I, II, III cements, respectively.

C_2 = the curing factor = 0.75, 1.0, and 1.2 for steam curing, wet curing, and curing compound, respectively.

w = water content, lb/ft^3 for the PCC mix.

f_c' =28-d PCC compressive strength, psi.

CTE defaults by coarse aggregate type, which was established based on testing and petrography performed under the LTPP program. The recommended CTE values for all aggregate types are summarized in table 16.[18] Note that these values represent materials nationwide.

Table 16. National PCC CTE averages based on LTPP data.[18]

Primary Aggregate Origin	Primary Aggregate Class	Average PCC CTE (10^{-6}/°F)	Standard Deviation PCC CTE (10^{-6}/°F)	Number of LTPP Test Sections
Igneous (extrusive)	Andesite	N/A	N/A	N/A
Igneous (extrusive)	Basalt	4.4	0.5	18
Igneous (plutonic)	Diabase	5.2	0.5	21
Igneous (plutonic)	Granite	4.8	0.6	69
Metamorphic	Schist	4.4	0.4	17
Sedimentary	Chert	6.1	0.6	25
Sedimentary	Dolomite	5.0	0.7	30
Sedimentary	Limestone	4.4	0.7	160
Sedimentary	Quartzite	5.2	0.5	9
Sedimentary	Sandstone	5.8	0.5	7

The level 2 correlations listed in the equations in figure 21 through figure 24 and the level 3 default values in table 16 have been modified by agencies as they adopted locally calibrated distress prediction models for the AASHTOWare Pavement M-E. However, note that these material properties are estimated as a function of the compressive strength of the PCC and/or other mix design parameters that are available from QA data collection (summarized in table 7 and table 8). Therefore, these engineering properties can be calculated from the derived models and can be used as potential indicators of performance in statistical analyses.

Correlations Developed from Long-Term Pavement Testing Data to Estimate PCC Properties

Several previous research studies have attempted to develop correlations to predict PCC material properties based on index properties and mix proportioning factors. A very detailed review of existing literature and the models developed historically have been discussed in an LTPP research study.[14] However, the LTPP Data Analysis program conducted a study to utilize data collected from LTPP test sections to derive correlations to estimate PCC material properties. A key benefit recognized from this effort was that the correlations developed represented paving mixes (rather than a larger dataset from ACI and PCA studies that included structural concrete) and that they also represented the sections used in the calibration. Several correlations were developed for compressive strength, flexural strength, elastic modulus, indirect tensile strength, CTE, and rigid pavement design features. The correlations developed are presented, and their applications summarized, in the following figures and tables:

- Compressive strength models are presented in figure 25 through figure 29, and their applications are summarized in table 17.

- Flexural strength models are presented in figure 30 through figure 32, and their applications are summarized in table 18.

- Elastic modulus models are presented in figure 33 through figure 35, and their applications are summarized in table 19.

- Tensile strength model is presented in figure 36. This model is applicable in design and PMS for continuously reinforced concrete pavement (CRCP) projects when compressive strength is available.

- Permanent built-in curl or warp effective temperature gradient (*deltaT*) model is presented in figure 37. This model is applicable in PMS when mix design and construction weather information are available, which typically is not known at the time of design.

Note that all these correlations show how the engineering properties, directly considered as inputs to predict performance, can be derived as a function of QA data reported in table 6 through table 8.

$$f_{c,28d} = 4{,}028.41841 - 3{,}486.3501 * w/c + 4.02511 * CMC$$

Figure 25. Equation. 28-d cylinder strength model.[(14)]

$$f_{c,t} = 6{,}358.60655 + 3.53012 * CMC - 34.24312 * w/c * uw + 633.3489 * ln(t)$$

Figure 26. Equation. Short-term cylinder strength model.[(14)]

$$f_{c,t} = 98.92962 + 5.70412 * CMC + 28.48527 * uw + 2{,}570.13151 * MAS * \frac{w}{c} - 199.84664 * FM + 611.30879 * ln(t)$$

Figure 27. Equation. Short-term core strength model.[(14)]

$$f_{c,t} = -6{,}022.44 - 854.46 * w/c + 4.8656 * CMC + 68.5337 * uw + 533.15 * ln(t)$$

Figure 28. Equation. All-ages core strength model.[(14)]

$$f_{c,LT} = -3{,}467.3508 + 3.63452 * CMC + 0.42362 * uw^2$$

Figure 29. Equation. Long-term core strength model.[(14)]

Where, in equations presented in figure 25 through figure 29:

CMC = cementitious material content, lb/ft^3.
uw = unit weight, lb/ft^3.
t = age, yr: $t < 1.0$ in figure 26 and figure 27; $t > 5.0$ in figure 29.
MAS = maximum nominal aggregate size, inches.
FM = fineness modulus of fine aggregate.

Table 17. Applications of the PCC compressive strength models in design, QA, and PMS.[14]

Model	Application
Figure 25. Equation. 28-d cylinder strength model.	28-d strength for design, QA.
Figure 26. Equation. Short-term cylinder strength model.	Design, QA, PMS, opening strength for ages < 1 yr.
Figure 27. Equation. Short-term core strength model.	Design, QA, PMS, opening/in situ strength, for ages < 1 yr.
Figure 28. Equation. All-ages core strength model.	Design, QA, PMS, in situ strength, at any age.
Figure 29. Equation. Long-term core strength model.	Rehabilitation design and in situ strength for ages > 5 yr.

$$MR = 22.7741 * f_c^{'0.4082}$$

Figure 30. Equation. Flexural strength based on compressive strength.[14]

$$MR_t = 676.0159 - 1120.31 * w/c + 4.1304 * uw + 35.74627 * ln(t)$$

Figure 31. Equation. Flexural strength based on age, unit weight, and w/c ratio.[14]

$$MR_t = 24.15 + 0.55579 * CMC + 2.96376 * uw + 35.54463 * ln(t)$$

Figure 32. Equation. Flexural strength based on age, unit weight, and cementitious material content.[14]

Where, in equations presented in figure 30 through figure 32:

MR = flexural strength, psi.

MR_t = flexural strength at age t yr, psi.

$f_c^{'}$ = compressive strength determined at the same age, psi.

t = pavement age, yr.

Table 18. Applications of the PCC flexural strength models in design, QA, and PMS.[14]

Model	Application
Figure 30. Equation. Flexural strength based on compressive strength.	Design and PMS when compressive strength at given age is available.
Figure 31. Equation. Flexural strength based on age, unit weight, and w/c ratio.	Design and PMS when index properties are available; predicts for any age.
Figure 32. Equation. Flexural strength based on age, unit weight, and cementitious material content.	Design and PMS when index properties are available; predicts for any age.

$$E_c = (4.499 * (uw)^{2.3481} * (f'_c)^{0.2429}) * D_{agg}$$

Figure 33. Equation. Elastic modulus based on aggregate type.(14)

$$E_{c,t} = 59.0287 * (f'_{ct})^{1.3} * \left(\ln\left(\frac{t}{0.03}\right)\right)^{-0.2118}$$

Figure 34. Equation. Elastic modulus based on age and compressive strength.(14)

$$E_{(c,t)} = 375.6 * (f'_{c(28-day)})^{1.1} * \left(\ln\left(\frac{t}{0.03}\right)\right) 0.00524$$

Figure 35. Equation. Elastic modulus based on age and 28-d compressive strength.(14)

Where, in equations represented in figure 33 through figure 35:

E_c = PCC elastic modulus, psi.
E_t = elastic modulus at age t yr.
uw = unit weight, pcf.
f'_c = compressive strength at same age, psi.
$f'_{c_{28-day}}$ = 28-d compressive strength.
t = age at which modulus is determined, yr.
D_{agg} = regressed constant depending on aggregate type: andesite (1), basalt (0.9286), chert (1.0079), diabase (0.9215), dolomite (1.0254), granite (0.8333), limestone (1), quartzite (0.9511), sandstone (1).

Table 19. Applications of the PCC elastic modulus models in design, QA, and PMS.(14)

Model	Application
Figure 33. Equation. Elastic modulus based on aggregate type.	Design and PMS when compressive strength at given age and aggregate type are available.
Figure 34. Equation. Elastic modulus based on age and compressive strength.	Design and PMS when compressive strength at given age is available; predicts for any age.
Figure 35. Equation. Elastic modulus based on age and 28-d compressive strength.	Design and PMS when 28-d compressive strength is available; predicts for any age.

$$f_t = 8.9068 * (f'_c)^{0.4785}$$

Figure 36. Equation. Indirect tensile strength model based on compressive strength.(14)

Where:

f_t = indirect tensile strength of the PCC material.
f'_c = compressive strength of the mix determined at the same age.

$$deltaT / inch = -5.27805 - 0.00794*TR - 0.0826*\mathrm{SW}+0.18632*PCCTHK$$
$$+0.01677*uw+1.14008*w / c+0.01784*latitude$$

Figure 37. Equation. *DeltaT* for JPCP design.(14)

Where:

deltaT/inch = predicted gradient in JPCP slab, °F/inch.
TR = difference between maximum and minimum temperature in construction month, °F.
SW = slab width, ft.
PCCTHK = JPCP slab thickness, inches.
uw = unit weight of PCC used in JPCP slab, lb/ft^3.
latitude = latitude of the project location, degrees.

Fatigue Life of PCC from AASHTOWare Pavement ME or PRS Models

The nationally calibrated PCC fatigue model, used for calculating damage accumulation for JPCP and CRCP fatigue models, presented in figure 38, can be used to develop an index related to the fatigue cracking potential of PCC pavement sections.(16)

$$Log\left(N_{i,j,k,l,m,n}\right) = C_1 * \left(\frac{M_R}{\sigma_{i,j,k,l,m,n}}\right)^{C_2}$$

Figure 38. Equation. PCC fatigue model.(16)

Where:

N = number of allowable load repetitions under conditions *i*, *j*, *k*, *l*, *m*, and *n*.
M_R = PCC modulus of rupture or flexural strength, psi.
σ =applied stress at condition *i*, *j*, *k*, *l*, *m*, and *n*.
C_1 and C_2 = PCC fatigue calibration constants 2.0 and 1.22.

The adoption of such an equation will require certain approximations about traffic and other conditions. The applied stress can be determined through *ISLAB 2000* analyses. However, combined with a good estimate for flexural strength using models presented in figure 30 through figure 32, the feasibility of using the fatigue model can be evaluated for use in PMS. Likewise, models developed under PRS can also be adopted.

EXISTING STRATEGIES FOR USING HMA/PCC QA DATA AS LEADING PERFORMANCE INDICATORS FOR PAVEMENT MANAGEMENT

The preceding sections described the data that are available from a typical agency QA program for HMA and PCC materials and models that use these data to estimate key engineering and performance properties for HMA/PCC. With these models, available QA data can be used to estimate the following properties of HMA and PCC materials summarized in table 20.

Table 20. Properties of HMA and PCC materials.

HMA Properties	PCC Properties
• Dynamic modulus. • Low-temperature creep compliance. • Low-temperature tensile strength. • Critical thermal cracking temperature. • Rutting resistance as measured by the allowable traffic to an average rut depth of 7.2 mm in the HMA layer. • Fatigue resistance as measured by the number of cycles to failure. • Permeability.	• Compressive strength. • Flexural strength. • Elastic modulus. • CTE. • *deltaT*. • Fatigue resistance measured by number of cycles to failure.

The following sections discuss two strategies already existing that can use properties derived from QA data as leading indicators of pavement performance in the agency PMS.

AASHTOWare Pavement Design ME Software

The primary HMA material inputs for the performance models in the AASHTOWare Pavement Design ME software can be estimated using the level 2 and level 3 relationships and QA data for HMA and PCC. This process will permit estimates of performance to be made directly with the AASHTOWare Pavement Design ME software. This approach has the advantage that the leading indicators are tied directly to the design methodology, should an agency adopt AASHTOWare Pavement Design ME for design. This approach, however, is computationally intensive, and for it to be reasonably accurate, local calibration of the AASHTOWare Pavement Design ME models will be necessary. The AASHTOWare Pavement Design ME performance models could be implemented in a less rigorous manner (such as national calibration using an 18,000 single-axle load); however, such an implementation would be similar to the index approach discussed in the following section. It was not the intent of the project team to evaluate this strategy under the current project. However, it is appropriate to say that States may consider this option and conduct the specific analyses necessary. This approach also does not provide a method to integrate QA data into an agency's PMS, but a very basic form of performance prediction from construction data already exists.

Performance Indexes

The preceding sections present several models that use data collected in a typical agency QA program for HMA and PCC to estimate performance-related properties. These can serve as indexes to improve pavement life models currently used in pavement management, such as the following:

- Rutting resistance from the NCHRP 9-25 resistivity model.
- Fatigue life from the Asphalt Institute fatigue equation combined with ILLI-PAVE algorithms.
- Permeability from the NCHRP 9-25 permeability equation.
- Critical cracking temperature from a thermal viscoelastic analysis using creep compliance and tensile strength estimated using the AASHTOWare Pavement Design ME level 3 models.
- Fatigue life of PCC pavements from AASHTOWare Pavement ME.

The primary advantage of these indexes is that they are easy to calculate and likely capture many of the important factors affecting the performance of HMA or PCC mixtures. Additionally, calibration of an approach using these properties as indexes will require significantly less effort and use performance data currently available in agency PMS.

EVOLVING QA AND PAVEMENT EVALUATION PRACTICES

Several innovative technologies, particularly those that nondestructively test materials, have been developed, evaluated, and adopted in the evaluation of highway structures. The most comprehensive evaluations were under the NCHRP 10-65 project and a series of Strategic Highway Research Program 2 (SHRP 2) research and implementation projects that advanced the state of practice for specific NDT technologies. (See references 15, 73, 74, 75, 76, and 77.) The main benefits of using NDT procedures are that a larger coverage can be achieved, and tests can be completed within short test times, even if the tests are performed at point locations.

NCHRP 10-65 recommends technologies most effective for use in QC/QA, i.e., technologies capable of identifying construction anomalies, showing repeatability, and measuring material properties directly related to performance.[15] For example, the parameters considered performance indicators are key material inputs to the ME Design procedure, such as HMA modulus (rather than density) and unbound material stiffness (rather than density and moisture content). The SHRP 2 effort further evaluated specific NDT procedures under independent studies and made specific recommendations for appropriate technologies for construction evaluation. In addition, a few States (such as Washington, Texas, Wisconsin, Minnesota, Iowa, Utah, and Colorado) have been champions of, and have made significant advancements with the adoption of, these technologies, including the development of specifications. The project team observed that these evolving technologies have not seen wider adoption and implementation at a significant pace. Table 21 provides a summary of recommended and accepted practices for use in evaluating materials and construction quality.

Table 21. Summary of evolving technologies for use in QA.

Material Property and Construction Issue	Innovative and Evolving QA Technologies
Modulus and stiffness	Seismic methods, PSPA for HMA PSPA or impact echo for PCC. GeoGauge, a steady state vibratory device for unbound materials. FWD for rehabilitation design and evaluation.
Density	Nonnuclear density gauges for HMA.
HMA layer delaminations	GPR and impact echo/SASW.
Thermal segregation and uniformity	IR and GPR.
VMA	GPR.
Layer thickness	GPR, impact echo (especially for PCC).
Dowel bar location and alignment in JPCP	Magnetic tomography.
Chemical composition and detection of additives	Spectroscopy.
Structural condition	Continuous deflection measuring devices (also for PMS).
Smoothness and IRI	Profilers (also for PMS).

FWD = falling weight deflectometer; PSPA = Portable Seismic Pavement Analyzer; SASW = spectral analysis of surface waves.

Location Reference and Materials Data Tracking

One of the main challenges with linking QA and construction data with pavement condition data is the difficulty in integrating the data because of the absence of common location referencing. The construction stage of the project identifies locations based on stationing in the plans. However, the performance data are referenced by the physical roadway mile referencing or mileposts (MPs). Construction QA, which is performed typically by lots, cannot be directly mapped to the physical location on the roadway, which could make performance tracking easier and enable a closer correlation to construction issues, should early failures occur. A recent FHWA study considered the application of radio-frequency identification (RFID) technology, a widely used system for inventory tracking in the commercial and consumer goods industries, for pavement applications.[78] RFID-based tracking of HMA material placement on roadways was identified as a successful application. The technology was not as effective for tracking PCC placements or for tracking temperature during the compaction of various lifts during paving operations. Although this technology has not gained traction in implementation, it is significant for the current study, as it enables RFID-assisted geolocation, which can be linked to pavement management data. All QA data collected at the time of construction can be tagged to the specific location on the project.

The recent advancements in geospatial referencing, which is discussed in the next section, has also made the collection of QA data with location referencing a priority for many agencies. For example, Utah and Iowa DOTs have made significant efforts to enable density measurements and other field QA test data collection with global positioning system (GPS) coordinates. This practice is expected to become the norm.

Continuous Record of Pavement Data and Coverage

Innovative technologies used for pavement evaluation, either in service or for QA, offer full coverage of the pavement layer surface, in contrast to test data collected only at point locations in traditional QA tests. This practice can offer a significant advantage for assessing material or construction variability and can be very useful for performance prediction in a finer mesh. Establishing correlations at the project level (unless for a forensic-type investigation) might not be practical, but the variability in results can be incorporated into performance prediction at the network level, as required for the current project. Data from full coverage can be incorporated into the framework to be developed under this project, especially if construction-related data with full coverage is foreseen to be the practice for the future of pavement construction.

IC

IC technology uses vibratory rollers with an integrated control system that can automatically adjust compactive effort in response to real-time feedback on changes in material stiffness during the compaction process. The rollers include accelerometers on the axle of drums that provide a continuous feedback to the machine. IC rollers also include survey-grade GPS tracking for location referencing, IR temperature sensors to measure mat temperature, and on-board computers that can display IC measurements as color-coded maps in real time.

IC has been evaluated under national- and State-level projects that assessed the reliability of the technology in different soil types.(79,80,81) The early projects, which were mostly conducted by States interested in the technology, performed field demonstrations and evaluations on select construction jobs that favored the use of IC for controlling the compaction of unbound layers. The stiffness of the soil and unbound area can be mapped before surface layers/HMA materials are placed, so areas with weak supporting layers can be identified before compaction. It is also possible to develop stiffness-growth relationships to optimize the rolling pattern required during construction. Some of these studies also provided guidelines for specification development.(79,81) IC is widely used for both unbound and asphalt material compaction. Typical IC measurements include compaction meter value (CMV), number of roller passes, asphalt surface temperatures, and roller settings (vibration frequencies, amplitudes, and speeds).

However, because the IC output is a composite value that is a response to the combined layer structure, there are concerns about the validity of the apparent stiffness reported by the IC roller for the layer being compacted. Several studies have been performed to authenticate the validity of IC measurements and to determine their use for pavement construction QA. This issue has yet to be resolved, as outcomes of such studies to date have, at best, been mixed. For example, an FHWA study reported that the final IC measurement value (ICMV) does not correlate well with core densities and stated that the ICMV is not recommended to replace cores for acceptance.(82) Several agencies use IC in construction, but none use it for QA. It is instead used to verify coverage and number of passes. From a pavement management or asset management standpoint, the ability to backtrack performance data to a compaction issue (number of passes or coverage) should be extremely valuable to an agency. Given the upsurge in its implementation, and the coordinate tracking for each location in the project, IC becomes a valuable construction practice for potentially storing and using data in pavement management performance modeling.

Continuous Deflection Monitoring Devices

Continuous deflection monitoring devices (sometimes referred to as continuous deflection measuring devices or traffic speed deflection devices [TSDDs]) were identified by SHRP 2 as a promising technology for indepth evaluation.(73,76) Technologies for continuous deflection measurements are still evolving. The two devices that have been most commonly used for testing in the United States at the time of this study are the traffic speed deflectometer (TSD) and the rolling weight deflectometer (RWD). The Rapid Pavement Tester, or RAPTOR, has recently been introduced in the United States. While the specific device is not relevant to this study, it is noted that data collected using any given continuous deflection monitoring device can provide an indication of structural condition of the highway at a network level. Continuous deflection monitoring is considered an improvement over the falling weight deflectometer (FWD) device for the following main reasons:

- Ability to measure pavement surface deflections at highway travel speeds rather than requiring traffic control and lane closures for testing.
- Ability to provide data with spatial coverage rather than at specific points.
- Practical for network-level testing.
- Potential to integrate with PMS within an agency and provide the structural indication of the roadway.

A recent FHWA study evaluated existing devices to establish reliable structural condition metrics.(83) Two devices were selected, the TSD and the RWD, for the evaluation at Minnesota DOT MnROAD facility. First, it was found that the RWD-based deflections were well correlated to the TSD-based deflections, validating the fact that measurements from both TSDDs related to the structural condition. The measurements were statistically repeatable. Indexes derived from the TSDD data were indicative of the structural condition at the network level. Data were averaged at different rates across the two devices: 0.1 mi for the RWD and 0.006 mi for the TSD. It was recommended that, for wider implementation, the highway agency should have the necessary data to assess the variability in deflection responses.

The research produced several recommendations that essentially would validate the magnitude of response and its applicability to testing PCC pavements. However, one additional recommendation that is most relevant to this study is to utilize TSDD-derived structural indexes for the development of methodologies to predict the future condition of the highway.

GEOSPATIAL CONSIDERATIONS IN CONSTRUCTION

The state of the practice for construction data collection and management is in flux, thanks to a convergence of disruptive technologies. LiDAR technology, in both static and mobile forms, is maturing, as is global navigation satellite systems (GNSS) and AMG technology, while mobile computer applications (such as tablets and smartphones) and small unmanned aircraft systems (sUAS) are creating an opportunity for capturing more information digitally than ever before. These technologies also change how information is collected. Past methods relied heavily on completing paper forms and providing narrative accounts of construction. These emergent technologies are beginning to add to narrative records with photographs, videos, and 3D data to provide a record of construction.

Time savings of mobile technologies in particular offer opportunities for an increased volume of documented observations. Mobile technologies have also been found to change the makeup of observations. With traditional processes, text and equipment observations dominate inspection daily reports. When mobile technologies are used, photo and video observations become a significant part of the record, and more weather observations are collected. Mobile technologies offer the opportunity to read and write directly into databases, which has resulted in increases in both the volume of data and the consistency of those data.(84)

This digital revolution that is sweeping through the construction industry also involves an increase in digital design information entering construction. Currently, much of this digital information is in the form of PDF documents, some with searchable text. Increasingly, agencies are providing 3D digital design data.(85,86) Contractors are using AMG technology in increasingly sophisticated practices, such as trench excavation, milling, and paving, and they are supplementing or creating new 3D data to load into this AMG equipment. However, there is still a lack of consistency in how, when, and indeed if these 3D data created by the contractor are provided to the agency.(87)

The processes and policies that govern this emergent data are slow to change. Thus, the digital workflows developed with mobile technology often replicate the same manual processes. In some cases, there is reluctance to embrace the digital data, and it is secondary to the traditional paper-based process. For instance, 3D engineered model data are provided for reference information, subject to disclaimers, whereas the contract documents are the plans.(85) The design intent is more complete and more visually accessible in the 3D model than in the plans, which require interpolation, but resident engineers may lack the software and skill to interact with 3D models.

During design, engineers focus a great deal of effort on precise geometric properties with little regard for the uncertainty associated with the depiction of the original ground conditions. In construction, however, the quantities and specifications take precedence, and design modifications are common when there are issues with mass balance or with the actual in situ conditions being significantly different from those anticipated in design.(87) These changes are increasingly being documented digitally, such as raster red lines in a PDF document, but not in a way that updates the 3D data from the design. These practices make for a systemic reliability problem with 3D design data for postconstruction applications. There is a trade-off between available digital data that could be ingested by, for example, GIS asset registries, and information that reflects the as-built conditions that must be manually transcribed from paper or digital records that are not consumable, such as red-lined PDF or paper plans.

While the volume of data being delivered or collected in construction is increasing, the efforts to organize, streamline, and align that data lag. There is a significant gap in creating process efficiencies to modify inspection practices to take advantage of modern technology. Use of

GNSS rovers, for instance, in construction inspection offers many advantages. It is safer, as it is used more quickly in a more upright body position with a wider range of peripheral vision, than traditional methods. It affords the opportunity to collect more data, documenting measurements and constructed conditions that are repeatable and transparent. Contractors and resident engineers feel that the measurements using this technology are more accurate.(87)

However, this technology is severely underused by inspectors, in part because of the cost of the GNSS rover technology, in part because of the reluctance by designers to provide reliable 3D design data, and in part because of the initial and ongoing training needs for implementing the technology. By contrast, contractors have embraced this technology widely, in particular for layout and QC, and do not report the same barriers to implementation.

Contractor adoption of data-driven processes and mobile technology far exceeds that of owner agencies. Some emergent technologies are fleet management by means of on-board sensors (such as GPS) and materials tracking using RFID sensors.(88) These technologies provide increased documentation accuracy, as well as opportunities for real-time fleet and materials management. This approach is of interest because it provides more opportunities to increase efficiency and automation in fulfilling inspectors' obligations to monitor construction equipment usage.

Contractor adoption of AMG and processes to use AMG data and survey networks for QC are more mature and have much higher adoption rates, in particular for earthwork construction, which is typically performed with GNSS guidance. AMG applications that require more precise grade control, either with robotic total stations or laser-augmentation systems for elevation control, have less market penetration; however, the number is growing. These applications include fine grading of pavement stone base, asphalt paving (which has very low penetration in the highway market), and concrete paving. Asphalt milling is an emerging area that should grow as survey technologies evolve to make it more affordable to collect the data necessary to design milling profiles.

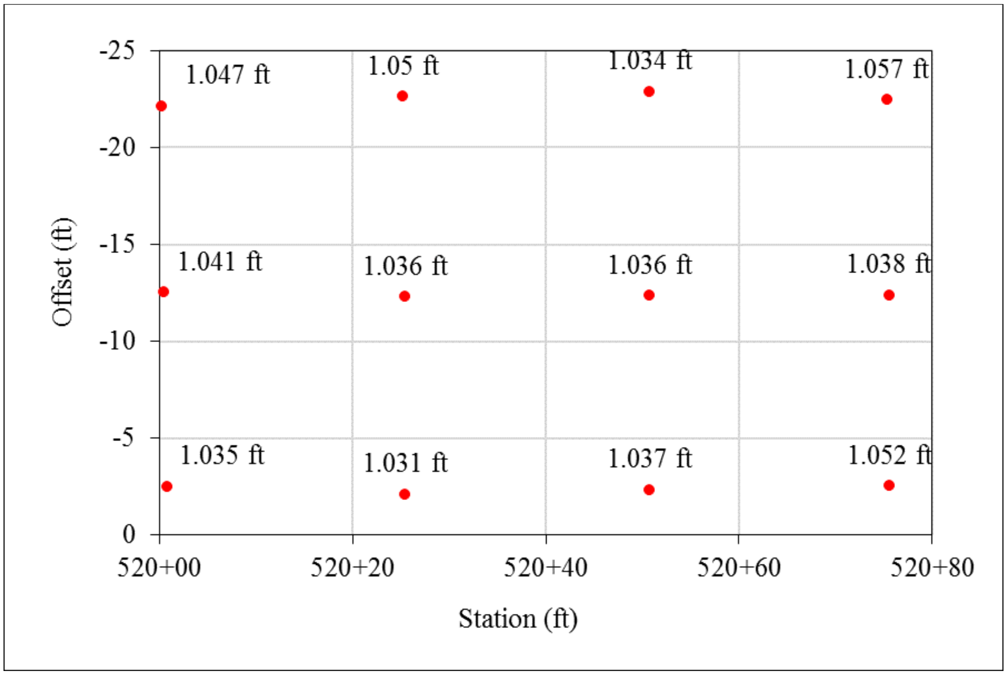
AMG is of particular interest for two reasons. First, it requires a 3D model of the proposed roadway. Second, it can capture an as-built 3D surface model of each successive pavement operation. In practice, rather than discrete 3D models for each activity, the 3D model of the proposed final grade can be offset up or down in the cab of the equipment for each stage in pavement construction. The challenge with the AMG as-built data is reliability. The AMG operators are primarily building the road and usually have little training in the AMG systems. The as-built records would require careful checking. For this and other reasons, other methods of acquiring the interim surfaces might be more practical. Technology from sUAS is one option for subgrade and fine grade, although the current photogrammetry technology is less precise with paved surfaces.

The interim surfaces may be compared to compute the depth of each pavement layer across the entire roadway. The depth can be presented visually in a highly detailed and accessible manner, such as heat maps and contours. However, it is important to recognize that there is a large degree of interpolation in the surfaces. For the sake of accuracy, data points are needed in a dense grid for microscale pavement analyses. Also, a very precise survey method needs to be correctly used. The types of surveying tools that can capture repeatable measurements at the necessary precision are sophisticated. The learning curve for robotic total stations is steeper than for GNSS rovers, but it is surmountable. However, the precision of the instrument is usually reported at ¼ inch, which means that depth measurements within payment bands (as little as 1/8-inch increments) are not repeatable to the degree necessary. Static LiDAR has better precision but a much steeper learning curve to operate and extract data.

The contractor's QC observations might be more accessible and would require less manipulation than surfaces. For concrete paving, contractors use a robotic total station behind the paver to check depth relative to a 3D surface. Depending on whether the surface represents the as-built base or design final grade, the QC will report either the depth (as a positive or negative number; the absolute difference represents the depth) or the tolerance relative to the final grade. The depth is more meaningful because it correlates with the acceptance criteria and payment bands.(89) In table 22, the contractor's QC process is recorded in a spreadsheet of depths by station and offset, at 25-ft intervals. This QC process can be plotted, as shown in figure 39, to create depth contours for the entire slab. The challenge is to reconcile these station-based data to the lots for smoothness acceptance data and to the linear referencing system (LRS) to make it usable in asset management.

Table 22. QC process at various stations and depths.

Station	Offset (ft)	Depth (ft)
520+00.789	−2.483	−1.035
520+00.547	−12.505	−1.041
520+00.312	−22.144	−1.047
520+25.502	−2.111	−1.031
520+25.459	−12.283	−1.036
520+25.242	−22.606	−1.050
520+50.727	−2.340	−1.037
520+50.776	−12.341	−1.036
520+50.798	−22.853	−1.034
520+75.570	−2.521	−1.052
520+75.545	−12.372	−1.038
520+75.307	−22.440	−1.057



Source: FHWA.

Figure 39. Graph. Plot of slab depths from contractor's QC.

The 3D data are easy to use and can be directly consumed, which are significant factors for a process to be accepted by resident engineers and inspectors. However, 3D equipment and data are incidental to the core functions of inspection. Usability is also a factor in the acceptability of the postconstruction data for asset managers. In the preceding example, the software converted the 3D data into a format that the contractor's grade checkers could use. It provided immediately relevant data to the paving crew who could adapt in real time to ensure continuous QC. This direct link between 3D data and pavement payment factors leads to the technology being easily accepted by contractors and paving crews. This outcome creates an opportunity to collect additional information that is currently not required, such as the locations of saw cuts, dowel bars, existing or new repairs in the base or subgrade, and locations at which materials tests were collected.

Contractors are now heavily engaged in collection of profile data to meet agencies' smoothness specifications. These 3D raw data files are available from the contractor, and some agencies request this information in addition to the final report of the smoothness analysis for acceptance. However, requesting 3D raw profile data is not a consistent practice. The use of these 3D profile data as a deliverable for as-built records is a missed opportunity. Smoothness profile data could be used for future performance-based analysis because there is a correlation between initial pavement smoothness and LTPP.[90]

The 3D engineered models used for design and AMG construction (and occasionally inspection) are not composed of data that are directly imported into a database for the purposes of reduction or analysis. The data collected in construction are survey points, which can be tagged with field codes that provide information about the feature that each point represents (such as subgrade, final grade, flow line, edge of pavement). Computer-aided design and drafting (CADD) software then converts the survey points into two-dimensional or 3D lines, polygons, and surfaces. These data need to be processed to extract meaningful information such as payment quantities or pavement depths.

Inspectors who use 3D data and GNSS rovers or robotic total stations check construction tolerances in real time, but they usually do not store observations unless there is a difference to the plans that needs to be captured.(87) In practice, as-built record requirements are not robust. Thus, most survey data collected for inspection are used only to measure pay quantities. No formal policies for inspection data organization are known; informally, data are sorted by item number and collection date for project-level storage and by construction project number on a network or document management system.(87)

Even if the data could be located, the organization and the granularity of the data entering construction, from design or collected in construction, are not directly consumable by asset management systems. Data are spatially organized by geospatial coordinates and local station references during design and construction. Data are also organized by the LRS, which is tied to geospatial coordinates during asset management and planning. Information is organized by pay item during design and construction, but by asset for maintenance and preservation planning. Table 23 summarizes the data characteristics and organization strategies for asset information in different phases of the lifecycle.(91)

Table 23. Data characteristics and organization by asset lifecycle phase.(91)

Asset Information	Design	Construction	Planning
Spatial resolution	3D	3D	1D
Network accuracy	Subinch	Subinch	Feet
Spatial datum	Geospatial coordinates	Station, offset, elevation	Linear reference
Data type	CADD	Paper/PDF documents	Database fields
Primary organization	Project number	Contract number	Asset class
Secondary organization	Plan sheet	Specification reference or pay item number	Asset ID

1D = one-dimensional.

PAVEMENT MANAGEMENT SYSTEMS

As per a recent synthesis of pavement management practices and quality management of pavement condition data, network-level pavement distress and smoothness data were collected by almost all agencies in the United States, with only one agency not collecting pavement distress data and three not collecting smoothness data at the network level.(92) Agencies in general defined distress (extent and severity) using methodologies similar to the LTPP program's *Distress Identification Manual for the Long-Term Pavement Performance Program*.(93) A summary of the extent of distress data collection by the various agencies is given in table 24. This table also shows almost 100 percent coverage for IRI and rutting, while only 64 percent of DOTs collected faulting data. It must be noted that some DOTs do not collect faulting data because they have not constructed jointed concrete pavements historically.

Table 24. Summary of extent of distress data collection by the various agencies.

Distress/IRI	All Respondents Collecting Distress Type/IRI (Percent)
IRI	100
Cracking (fatigue)	89
Cracking (transverse)	93
Rutting	100
Faulting	64

The quality and accuracy of the pavement condition data reported in the PMS are pertinent to this study as the project explores the feasibility of correlating QA data to performance. States are increasingly invested in improving the quality of the pavement condition data. The 2009 review also determined that two-thirds of the agencies either maintain a QC plan for condition data collection or require the service producer to maintain one.[93] Further, about half of the States have a formal quality acceptance plan. The plans typically include calibration and verification of equipment and methods before the data collection; testing of known control segments before data collection; testing of known control or verification segments during data collection; checking of the reasonableness, completeness, and consistency of the data using software routines; and comparing the production data with existing time-series data. A small number of States are also using GIS-based tools to enhance the acceptance process.

Review of FHWA Ruling

Distress data maintained in the PMS form the metrics to meet *MAP-21* performance targets. *MAP-21* section 1203 proposed establishment of national goals to maintain the highway infrastructure asset system in a state of good repair. *MAP-21*, therefore, required the establishment of performance measures, in consultation with State DOTs, Metropolitan Planning Organizations, and other stakeholders, for assessment of pavement conditions on the interstate system and the NHS.

In the ruling, FHWA determined performance ratings of Good, Fair, or Poor condition using a combination of pavement condition metrics. These data elements are routinely collected by SHAs and reported to Highway Performance Monitoring System (HPMS). As stated before, the ruling rates pavement condition in terms of roughness and cracking for all pavement types, rutting for asphalt pavement surfaces, and faulting for JPCP. The NPRM offered proposed performance targets in 80 FR 326 in January 2015, but provided revised threshold values in 23 CFR Part 490 for the final ruling, which are presented in table 25.[2]

Table 25. Proposed national performance management measures, targets, and reporting.

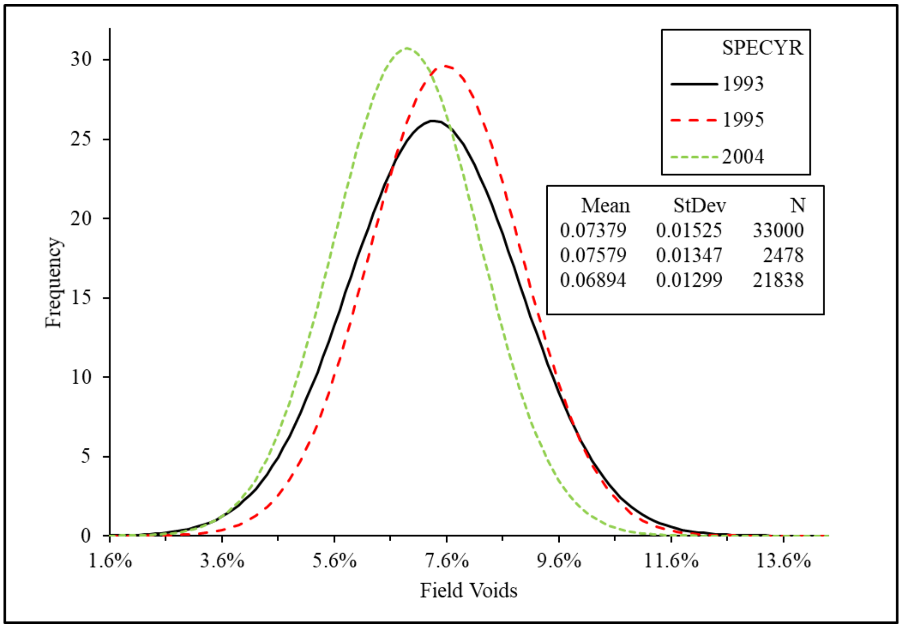
Surface Type	Metric	Good Rating Metric Range	Fair Rating Metric Range	Poor Rating Metric Range
All pavements	IRI, inches/mi	<95	95–170	>170
Asphalt pavement	Cracking, percent	<5	5–20	>20
Asphalt pavement	Rutting, inches	<0.20	0.20–0.40	>0.40
Jointed concrete pavement	Cracking, percent	<5	5–15	>15
Jointed concrete pavement	Faulting, inches	<0.1	0.1–0.15	>0.15
CRCP	Cracking, percent	<5	5–10	>10

To optimize infrastructure investments, a combined rating has been defined based on individual ratings for each pavement type. For a section in the HPMS to be rated in Good condition, the absolute values for all relevant metrics in table 25 need to remain below the threshold values reported. However, for a section to be rated in Poor condition, two or more of the relevant metrics must exceed the threshold values for Poor. Note that in specifying the thresholds, the ruling does not make a distinction between roadways in rural or urban areas or the population of the region.

RELATIONSHIP BETWEEN QA AND PERFORMANCE DATA

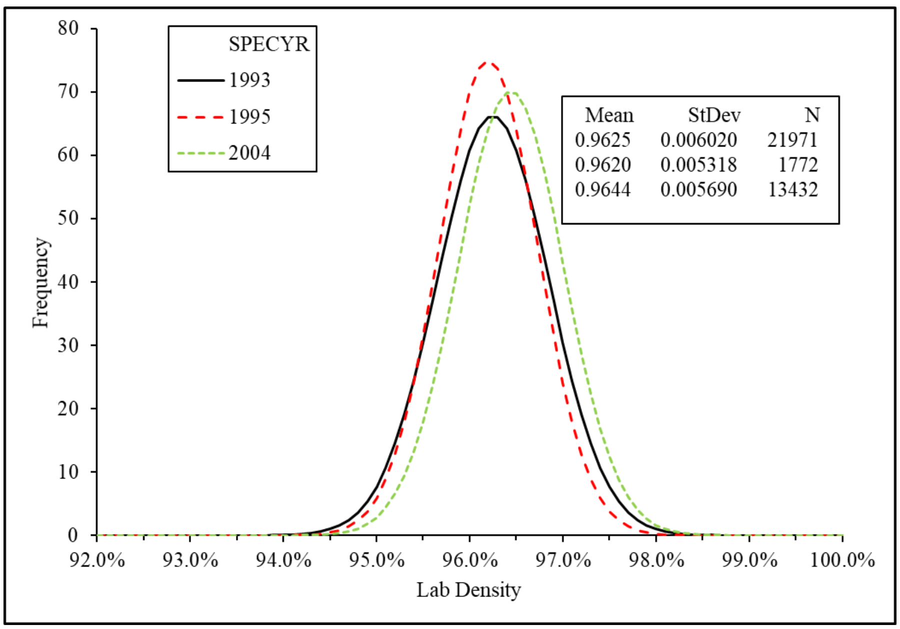
One of the first and very comprehensive efforts to link QA data to PMS was made by Hudson in 2003 with detailed reviews of five State databases.[94] This study focused on Superpave material data. The absence of a common location reference did not permit a smooth integration of QA and PMS wherein the performance of each lot and sublot could be compared with construction quality data. The study also noted that data were averaged for a specific project segment, and, therefore, the ability to track QA to performance at a project level was a challenge to overcome. Furthermore, it was noted that a single QA material property was inadequate to draw a correlation to performance because failures are caused by the combination of material and construction factors, rather than due to a single factor at times. Future efforts examined variability in construction or attempted to relate construction and performance data. (See references 6, 7, 95, 96, and 97.) These studies noted the importance of considering the impact of variability on performance.

Under the FHWA Advanced Quality Systems program, the value of well-managed databases was demonstrated through the correlation of QA and PMS data.[7] The project analyzed data from two State databases, one for HMA and the other for PCC pavements. The study performed a variety of analyses using QC data, acceptance data, and other State databases, including a comparison of contractor versus acceptance data. The analyses also focused on evaluating the effectiveness of specifications, and these showed how agencies could streamline QA and specification development process with regular review of their QA data. For example, as shown in figure 40 and figure 41 for one State, while there is no evidence of change in variability of mixture design, with the introduction of new specifications in 2004, the mean density of mixtures has slightly increased, and the air voids have decreased as anticipated.



Source: FHWA.

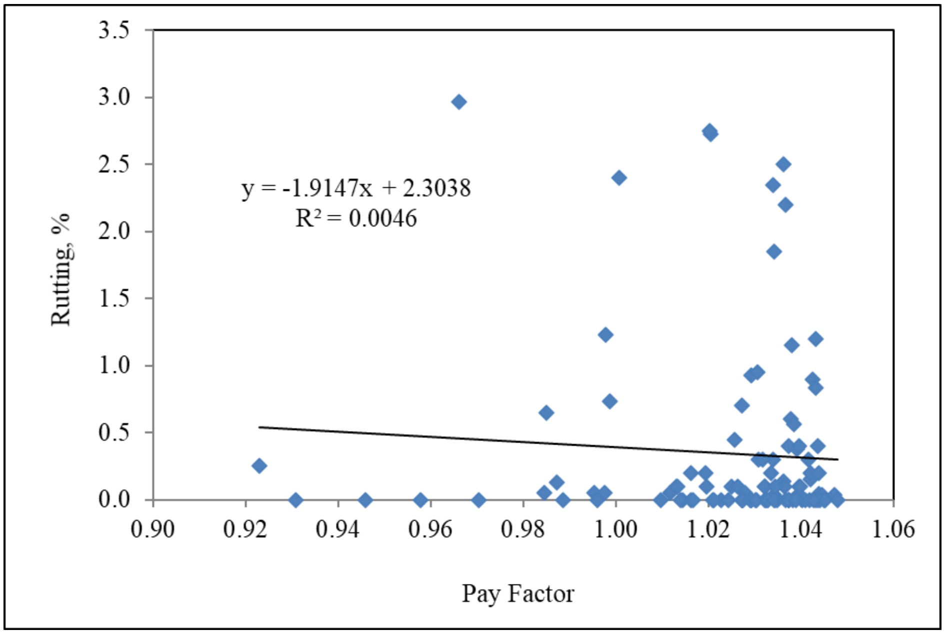
Figure 40. Graph. Variability in air voids with different specifications.(7)



Source: FHWA.

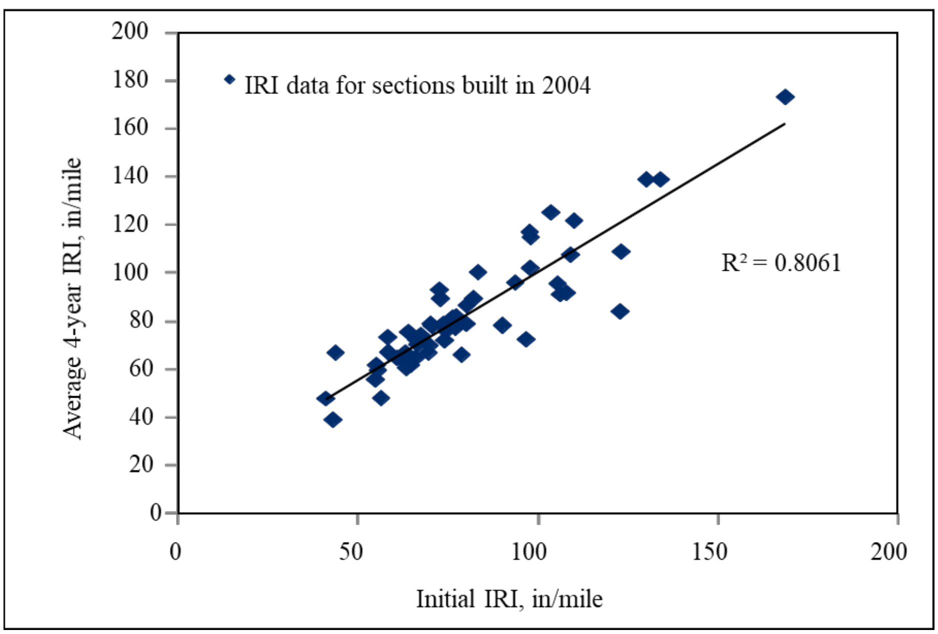
Figure 41. Graph. Variability in density with different specifications.(7)

This study also demonstrated that there was not necessarily a correlation between pay factors obtained with QA data and performance, but certain key QA parameters held a strong correlation.(7) Figure 42 and figure 43 show that higher pay factors did not necessarily lead to reduced rutting, but IRI at the time of construction showed a strong correlation to future performance. However, the scope of this study did include developing statistical models to predict performance using combinations of construction parameters. Most studies up until this stage have concluded that, regardless of the data collection methodology, QA data can be related to performance when an empirical or mechanistic relationship exists or can be developed.



Source: FHWA.

Figure 42. Graph. Pay factors and performance.



Source: FHWA.

Figure 43. Graph. Initial IRI and final IRI.

Relationship Between QA Data Elements and Pavement Performance

Research to enhance pavement condition forecasting models since the AASHTO Road Test in the late 1950s has established several empirical/mechanistic relationships that related QA and construction data, among others, to pavement performance measures. Examples of QA and construction-type data variables that impact the 23 CFR Part 490 national performance management measures or closely related performance measures are presented in table 26 and table 27 for flexible and rigid pavements, respectively. It is worth noting that, while all critical material properties that relate to performance are not directly measured, there are several correlations or models to predict the parameter based on material index properties or properties measured in QA. For example, PCC flexural strength and modulus can be predicted from compressive strength, while AC gradation, voids, and binder content can be used to predict AC modulus using Witczak's model, similar to the methodology used in the AASHTOWare Pavement ME procedures, and as discussed in detail earlier in this chapter.(16)

Table 26. Relationship between commonly occurring AC pavement distress and QA test quality characteristics.

Distress Types	Cause and Failure Mechanism	QA Test Properties													
		Thickness	Modulus/Stability	Indirect Tensile Strength	HMA Asphalt Content	HMA Air Void Content	HMA VMA/VFA	HMA Gradation	Aggregate Shape, Angularity, and Hardness	Mix Permeability and Aggregate Porosity	HMA Density and Compaction	Base/Subgrade Density and Compaction	Base Modulus/CBR	AC Mix Temperature at Time of Construction	Ride Quality at Construction
Alligator cracking	Fatigue in AC layer from repeated horizontal tensile strain at the bottom of AC layer due to heavy axle loads.	✓	✓	—	✓	✓	✓	✓	—	—	✓	✓	✓	—	—
Rutting	Permanent deformation in the AC, unbound base, and subgrade layers due to traffic loads, low strength, high voids in mix.	✓	✓	—	✓	✓	✓	✓	✓	—	✓	✓	✓	✓	—
Block and shrinkage cracking	Permanent shrinking and hardening of the asphalt, low asphalt content (dry mix), excessive fines in AC mix, use of absorptive aggregates.	—	—	—	✓	—	—	✓	—	✓	—	—	—	—	—
Longitudinal cracking, wheel path	Top-down fatigue associated with the state of bending stress near a wheel load.	✓	✓	—	✓	✓	✓	✓	—	—	—	—	—	—	—
Longitudinal cracking, non-wheel path	Poor joint constructing, AC surface temperature-related shrinkage, hardening of AC.	—	—	✓	—	—	—	—	—	—	✓	—	—	✓	—

Distress Types	Cause and Failure Mechanism	QA Test Properties													
		Thickness	Modulus/Stability	Indirect Tensile Strength	HMA Asphalt Content	HMA Air Void Content	HMA VMA/VFA	HMA Gradation	Aggregate Shape, Angularity, and Hardness	Mix Permeability and Aggregate Porosity	HMA Density and Compaction	Base/Subgrade Density and Compaction	Base Modulus/CBR	AC Mix Temperature at Time of Construction	Ride Quality at Construction
Transverse cracking	Contraction of AC due to low temperatures, hardening of asphalt cement, permanent shrinkage of AC due to absorption of asphalt into aggregates.	—	✓	✓	—	✓	—	✓	—	✓	✓	—	—	—	—
Ride quality	High initial roughness, excessive distress, swelling, and heaving.	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

—No data.

Table 27. Relationship between commonly occurring PCC pavement distress and QA test quality characteristics.

Distress Types	Cause and Failure Mechanism	QA Test Properties													
		PCC Thickness	PCC Strength	PCC Permeability and Durability	PCC Composition and w/c Ratio	PCC Air Voids and Spacing Factor	PCC Consolidation	PCC Coefficient of Thermal Expansion	PCC Aggregate Texture, Mineralogy, Gradation, Size, and Hardness	Base/Subgrade Strength and Properties	Improper Construction	Dowel Misalignment	Corrosion of Dowels/Steel	Temperature at the Time of PCC Placement	Ride Quality at Construction
Transverse cracking	Combination of heavy load repetitions on pavement with weak foundation support, slab curling, and loss of foundation support.	✓	✓	—	✓	—	—	✓	—	✓	—	—	—	✓	—
Faulting at transverse joint	Poor joint transfer, slab curling due to PCC thermal/moisture gradients, free moisture in underlying layers, pumping of fines in the underlying base/subbase.	✓	✓	—	✓	—	—	✓	✓	✓	✓	✓	✓	✓	—

Distress Types	Cause and Failure Mechanism	QA Test Properties													
		PCC Thickness	PCC Strength	PCC Permeability and Durability	PCC Composition and w/c Ratio	PCC Air Voids and Spacing Factor	PCC Consolidation	PCC Coefficient of Thermal Expansion	PCC Aggregate Texture, Mineralogy, Gradation, Size, and Hardness	Base/Subgrade Strength and Properties	Improper Construction	Dowel Misalignment	Corrosion of Dowels/Steel	Temperature at the Time of PCC Placement	Ride Quality at Construction
Punch-out in CRCP (represented as percent cracking)*	Development of longitudinal crack 2–3 ft from pavement edge, loss of edge support, loss of load transfer across transverse cracks, increasing transverse crack widths, and development of high tensile stresses at the top of the slab, causing the slab to punch out from the CRCP.*	✓	✓	—	✓	—	✓	✓	✓	✓	✓	—	—	✓	—
Corner breaks	Combination of repeated loading, low joint load transfer, and thermal curling and moisture warping, leading to pumping and cracking.	✓	✓	—	—	—	—	✓	—	✓	—	✓	—	✓	—

Distress Types	Cause and Failure Mechanism	QA Test Properties													
		PCC Thickness	PCC Strength	PCC Permeability and Durability	PCC Composition and w/c Ratio	PCC Air Voids and Spacing Factor	PCC Consolidation	PCC Coefficient of Thermal Expansion	PCC Aggregate Texture, Mineralogy, Gradation, Size, and Hardness	Base/Subgrade Strength and Properties	Improper Construction	Dowel Misalignment	Corrosion of Dowels/Steel	Temperature at the Time of PCC Placement	Ride Quality at Construction
Longitudinal slab cracking	Repeated truck loads, loss of foundation support, and thermal/moisture gradient stresses resulting from upward slab curling, improper construction of joints, and/or opening the pavement to traffic before PCC has achieved adequate strength.	✓	✓	—	—	—	—	✓	—		✓	—	—	✓	—

Distress Types	Cause and Failure Mechanism	QA Test Properties													
		PCC Thickness	PCC Strength	PCC Permeability and Durability	PCC Composition and w/c Ratio	PCC Air Voids and Spacing Factor	PCC Consolidation	PCC Coefficient of Thermal Expansion	PCC Aggregate Texture, Mineralogy, Gradation, Size, and Hardness	Base/Subgrade Strength and Properties	Improper Construction	Dowel Misalignment	Corrosion of Dowels/Steel	Temperature at the Time of PCC Placement	Ride Quality at Construction
Spalling	Slab expansion/ contraction, allowing trapping of incompressible in the joint, weak concrete at the joint, joint sawing time, poorly functioning load transfer device (misalignment, corrosion), and disintegration of PCC from freeze-thaw action.	✓	✓	✓	✓	✓	—	✓	✓	—	✓	✓	✓	✓	—
Ride quality	High initial roughness, excessive distress, swelling, and heaving.	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

—No data.
*CRCP punch-out development is also affected by longitudinal steel content, depth of placement of longitudinal steel, friction characteristics with the base, and PCC shrinkage. In defining targets, the national pavement performance measure 23 CFR Part 490 expresses punch-outs in percent cracking.
Note: M-E design procedures, including the AASHTOWare, quantify punch-outs as the number of punch-outs per mile.

CHAPTER 3. SUMMARY OF CURRENT STATE AGENCY PRACTICES

STATES SELECTED FOR INTERVIEWS

The project team required QA, construction, and performance data for analyses under this study. Thus, it was necessary to collect information from States with advanced QA and pavement management programs to select the most suitable datasets. Therefore, it was also important to ascertain the agency's interest to utilize their construction and QA data for performance modeling and management of their highway network.

The project team developed a short list of about 15 agencies most suitable for this study based on inputs from the team members who had worked with State QA, materials, and pavement management databases on other research projects. Most of these States also have experience with the use of innovative technologies in construction and 3D construction. Preliminary information was obtained from online reviews of State specifications to further narrow down agencies for detailed interviews. Four States were ultimately selected to obtain data appropriate for this research. The agencies considered for indepth interviews are listed in table 28; however, in keeping with the requirements of FHWA's nonattribution policy, the project team does not identify the specific States that provided the data described (chapter 4), processed (chapter 5), and analyzed (chapter 6) under this study. Therefore, if the information provided in this chapter easily reveals the data source for the performance predictions presented in chapter 6, the project team chose not to identify the State agency in table 28 or elsewhere in this report.

Table 28. State agencies included in the interviews and the subject areas of discussion.

State	PMS	Construction	QA HMA	QA PCC	QA UB	NDT and Innovations (IC, GPR, MIT-Scan)	3D and CIM
Colorado	●	●	●	●	●	●	●
Maryland	●	●	●	●	●	—	●
Florida	●	●	●	●	●	●	●
Minnesota	●	●	●	●	●	●	—
Michigan	●	●	●	—	●	●	●
Utah	●	●	●	●	●	●	●
Mississippi	●	—	●	—	—	—	—
State 1	●	—	●	—	●	—	—
Oregon	●	—	●	—	—	●	●

—No data.
UB = unbound.

During the interviews, the objective was to review specifications, the QA data collection practices (material approval, material certifications, QC, verification, and acceptance), data storage systems, PMS, condition data collection procedures, and performance forecasting models in the PMS. In addition, their adoption of nontraditional QA procedures and construction methods was specifically addressed. Information was gathered with the perspective of identifying if the agency had the needed data for use in this project and if the agencies were interested in exploring the value of using construction data for performance prediction. The data categories evaluated with each agency are summarized in table 28.

State Interview Details

The information gathered from these agencies, as noted in table 28, clearly covered various aspects of construction and QA practices, as well as PMS, but also included details about the databases from the standpoint of data integration for the purposes of this project. The specific information collected was grouped into three broad areas—QA procedures, innovative technologies, and PMS and forecasting models. Within each agency, the project team contacted multiple staff from various departments/divisions.

The project team submitted a summary of the objectives and the research approach for the current project and provided a formal list of questions and topics of discussion under each subject category. The participants were not expected to complete a formal survey, but the document was intended for highlighting discussion topics ahead of the interviews. While the document provided to the agencies is not included with this report, the specific topics discussed under each subject area in the questionnaire are listed as follows:

QA Procedures

The QA procedures are as follows:

1. Stages of data collection and data storage/management:
    - Material certification.
    - QC.
    - Acceptance.
    - Special cases (warranties, PRS, design-build, and so on).
2. Data being collected for each material type:
3. Data collection methods:
    - Nonelectronic format.
    - Database—stand-alone or integrated.
4. Location referencing system used by the different stages of data collection:
    - Grouped by project, lot, and MP.
    - Grouped by test number and day and time.
    - Time of sampling and testing.
    - Individual test results, replicates, and averages.
    - Test procedure identified.
    - Identification of test result source—contractor or agency.

5. Current status of data integration by department:

   - QA and PMS data.
   - PMS and cost data.
   - QA and M&R procedures.

Innovative Technologies

6. Use of nontraditional and innovative NDT technologies and sampling rate:

   - IC, GPR, IR, RWD—for full coverage.
   - Seismic, FWD, LWD, MIT-Scan, spectroscopy—point location tests.
   - Existing specifications or QA requirements in contracts.
   - Purpose of use—QC, QA, routine, forensics, rehabilitation, research and development, or pilot projects.

7. Use of data from these technologies in managing a pavement network:

   - Is it incorporated into QA databases?
   - Is the location referencing adequate/suitable for wider use of these data?
   - Is it consistent with other QA information for easy referencing and integration?
   - Is there 100 percent sampling/mesh size data for each pass of compaction or lift by lift?

8. Automation in highway construction:

   - Technologies (3D LiDAR, AMS, and so on).
   - Standard agency practice with specifications and on a project-by-project case.
   - Data collected.
   - Status of as-built records (whether submitted to agency).

PMS and Forecasting Models

9. Performance measures in the PMS and metrics used:

   - All pavements—IRI, inches/mi.
   - Asphalt pavement and jointed concrete pavement—fatigue cracking, percent.
   - Asphalt pavement—rutting, inches.
   - Jointed concrete pavement—faulting, inches.
   - CRCP—cracking, percent (percent area with longitudinal crack or punch-out).

10. Other distresses/functional characteristics.

11. Indexes such as pavement condition index (PCI), deduct values, safety index.

12. Types of models used for pavement performance forecasting:

- Polynomials for families of pavements.
- Empirical models.
- M-E models.

13. Data being used to drive the models:

- Distress—e.g., cracking, rutting, PCI, IRI at different ages.

- Design—e.g., pavement type, thickness, base type.

- Materials—e.g., PCC strength, HMA modulus, gradation, subgrade type.

- Traffic—e.g., average annual daily traffic (AADT), percentage of trucks.

- QA data—e.g., HMA density, PCC compressive strength, aggregate moisture content, subgrade density, IR in-place paving temperature, initial IRI.

- Construction data—e.g., IC, density, survey data, inspection reports data, QC data.

- Other data.

SUMMARY OF INTERVIEWS

This section presents a summary of the information collected from key States listed in table 28. The information was clearly more detailed and more comprehensive for some States than for others. Information is, therefore, presented by State. Information on State practices for CIM is presented under a separate section titled State Practices with Use of CIM in this chapter because it provides a general overview of the state of practice and covers additional State agencies beyond those listed in table 28.

Florida DOT

Florida DOT (FDOT) is known to have comprehensive QA and PMS programs. The agency has made modest advancements with the adoption of 3D construction and the evaluation of innovative technologies like GPR and IC. The project team recognized that FDOT has also pursued the implementation of the AASHTOWare Pavement ME program and, therefore, will be proactive about collecting material data that are indicators of performance. Finally, FDOT is one of the few States that includes both HMA and PCC pavements in its highway network and thorough material testing programs for both materials.

PMS

Pavement management condition data are collected and officially published on April 1 every year. The PMS incorporates data from the Roadway Characteristics Inventory database and combines the pavement condition data collected as part of the surveys. The reference IDs available in the database include the roadway ID, MP, deficiency, and IRI. Before the collection of the PMS data, various kinds of information about the roadway are collected, including county, section, subsection, construction limits, section length, surface type, significant changes in pavement condition, presence of structures longer than 0.25 mi, and presence of roadway segments longer than 0.25 mi with a different surface type.

Condition data are collected annually between April and December, and the data are provided by the State Materials Office. It includes four groups of surveyors with four vans to collect imagery for several distresses and laser data to estimate rutting.

The forecasting models use homegrown statistical models based on SAS® analyses. The models are grouped by location and materials, i.e., surface type. The PMS divides the statewide network into eight locations, which consists of seven districts and one turnpike.

Construction

All planning and design elements are incorporated into the construction plans. All surveying is done by the construction team and by the contractors. An estimated 80 percent of the design surveys are performed by consultants on behalf of the agency, and 100 percent of the construction surveys are performed by the contractors. FDOT has been moving toward 3D construction in recent years, and all data are acquired in 3D format for the development of construction plans. Virtually all survey is in 3D format. They are combining aerial data from helicopters and topographic data from traditional surveys and LiDAR to develop 3D construction models. LiDAR data are limited, but FDOT also collects asset data and pavement marking data. LiDAR data collection is not standardized at this time.

For large projects, planning and design are being performed in 3D. FDOT has 40 to 50 projects designed in 3D format to date. Furthermore, the focus of the 3D data collection is for planning and design, e.g., in determining the right-of-way acquisition and availability.

As-built data are collected by the contractors, and postconstruction surveys are not performed by the agency. Postconstruction information is not available with the State at this time. However, FDOT is exploring the option of collecting 3D postconstruction from the contractors. e-Construction has been initiated and is in place at FDOT. However, there are no tools to manage all the 3D data and use the data for other analyses, which FDOT is interested in doing.

Innovative Technologies

FDOT has evaluated and has used GPR on a limited scale. The main idea is in moving from manual to highway speeds. It is mainly used for predesign testing for rehabilitation projects and for forensic cases. The GPR technology used is different for the two applications, air-coupled antenna for high-speed surveys and ground-coupled antenna for forensic evaluations. GPR is also used to locate utilities. The DOT also planned to collect cross-slope data with smoothness.

QA

QA data are collected at different stages of the construction project, like the standard procedures discussed in chapter 2. The data are stored by project number, highway/State road number, district, and stations. With the current referencing system, it is not convenient to reference the physical location on a roadway.

QA data are available from embankment to the surface layer. Materials test data are stored from HMA/PCC mix preapproval stage, QC, and independent verification stages. Unbound materials data that can be accessed from the QA database include gradation, optimum moisture content, dry density, percent compaction, permeability, Atterberg limits, organic content, sulfates, and chloride contents. For AC, the process control data include gradation, bulk specific gravity, rice density, and gyratory air voids. Therefore, test data are collected from lose material samples as well as cores taken from the pavement. All data are stored in the laboratory information management system (LIMS). Currently, the contractor test data are input by the contractor into LIMS. In addition, Microsoft Excel spreadsheets are used for some field data such as straight-edge data and core information. Materials data can be obtained or summarized by project, but they are typically accessed only when a need arises, as in the event of a dispute resolution.

FDOT expected to replace LIMS with an in-house developed materials database system, MAC. The key difference is that the LIMS database can track material test location by construction station numbers, but the MAC system has spatial or GPS referencing. As of now, there are no plans to convert the legacy system to the MAC.

Maryland State Highway Administration

QA

The Maryland State Highway Administration (MDSHA) QA data include preapproval or material certification data as well as construction data. Construction data are stored in the construction management system (CMS). It includes typical QA data such as binder type, polished aggregates, and aggregate gradation, as discussed in chapter 2. MDSHA is also developing the materials management system (MMS), which has about 3 yr of materials data available. The information will be more suitable for linking with PMS.

The AC binder data are stored in a different Microsoft Access® database, MDWareTestData020216. These data include binder certification data from the supplier with M 320 results, as well as agency acceptance tests performed during construction. MDSHA uses *f*-test and *t*-test verifications to decide whether to include contractor test results for calculating pay factors.

With unbound materials, nuclear density testing is the only type of QA testing currently being performed. Maryland is familiar with new technologies such as LWD and IC. New technologies are routinely evaluated. The State is interested in adopting new technologies, but there are no immediate plans to do so.

Pavement Management

MDSHA manages 17,000 lane miles. PMS condition data are collected annually for highways on the NHS, whereas for State-maintained highways, condition data are collected in 3-yr cycles (one-fourth of the network is State Highways [SHs]). Data are collected for both HMA and PCC surface pavements, but most of the highways fall under the HMA pavement category (98.5 percent). To develop condition data, images and profiles are collected using ARAN, and all condition data are stored in an Oracle® database. Condition data include the following:

- IRI.
- Rutting.
- Structural cracking (longitudinal cracking in the wheel path).
- Functional cracking (transverse cracking, longitudinal cracking [non-wheel path]), also including sealed cracks.
- Friction.
- Faulting and cracking for JPCP.

PMS section is at least 1 mi long; some are longer. Images collected for the PMS condition data are available from 2001. However, the existing distress data represent only the last 3 yr. The algorithms to calculate distresses were updated in 2015, and the PMS was updated starting in 2016. MDSHA uses a combination of commercial software and in-house developed modules, which include unit cost, performance, and construction history. Commercial software is also used for postprocessing. MDSHA has a robust QA process for validating and verifying condition data.

The network is divided into multiple families for each distress type. For example, the network comprises 30 families of pavements for ride quality based on traffic level, surface type, climate, and highway class. Linear and exponential models that are a function of pavement age are used for performance forecasting. The model coefficients are updated periodically.

The forecasting horizon is 5–7 yr with a 6-yr optimization window. The PMS has target lane mile years, and, therefore, the performance measure is the extension of lane mile years possible with each treatment type. Local districts make the M&R decisions based on rate of return on investments.

Integration with QA and Other Data for Improving Forecasting Models

MDSHA has a keen interest to link data from other databases, including QA data with PMS. At this stage, the value of doing this is not perceived to be of significance for improving forecasting alone. They are not certain whether it may truly improve the precision of predictions. However, the interest also extends to the value for policymaking (specification developments) and future decision making, as well as for changing project cost and life cycle cost. Examples cited by MDSHA include the following:

- Example 1: service life of different HMA mixes:
  - Do gap-graded HMA mixes crack faster/earlier than other mix types?
  - Does RAP crack faster/earlier than other mix types?
  - Can dust content from RAP affect performance?
  - How can performance of these mix types be improved?

- Example 2: material specifications:
  - Is there a relationship between raveling potential and aggregate angularity for chip seals?
  - Is it more raveling for less angular aggregates?
  - Is it better to invest in more angular aggregates to reduce future raveling?

- Example 3: friction characteristics based on aggregate sources and traffic:
  - Can a relationship be developed between quarry source, mix percent, and crash rates or stopping distance?
  - Is congestion a better indicator of crash rates than aggregate quality?
  - Can aggregate hardness (mix blended hardness) be linked to field-measured friction?
  - Can current MDSHA model consider traffic level (functional class) only?
  - Is it possible to link eventually with safety data?

- Example 4: cracking and rutting prediction:
  - Do AC mix design properties, binder properties, and dust-to-binder ratio impact cracking and rutting?

- Example 5: establish rutting prediction:
  - Is rutting more significant in localized areas (e.g., 200 ft to stopping at an intersection; poor rutting at intersection, rut depth = 0.24 inches, very poor rutting = 0.5 inches for 100 ft).
  - Are point-by-point rutting properties more important?
  - Does rutting need all layer properties, thicknesses, and so on?

PMS can be linked with CMS for information such as construction date, quantities, bid items, cost, overall project cost broken by treatment cost, and so on. There are plans to merge a MMS to PMS. However, keeping up with evolving linear referencing methods in a CMS is challenging. The State is beginning to use Esri products for location referencing for highways, and the implementation is in the early stages. No plans exist as of now to reference materials data with GPS. MDSHA is working internally to link construction, QA, and PMS databases. They recognize that, because networks were built before establishing MMS, a great opportunity was missed to link construction and performance data.

There are also several challenges for a smooth integration of QA and PMS for reliable forecasting. Issues in using QA data may include the following:

- There may be difficulty in determining from where quarry materials will be coming for new projects. Maryland is a geologically diverse State with many quarries, bedrocks/faults, limestone pockets, and so on, and there is significant diversity even within quarries. The prediction may be done postconstruction after the quarry source is known.

- QA data alone are not adequate; instead project-specific construction quality must be considered in the models.

- There are some concerns with current QA data:
  - HMA can have the same volumetric properties but with very different coarse aggregate gradations.

  - HMA with varying binder amounts can achieve the same volumetric properties. Percent binder in HMA can influence cracking potential. MDSHA has not established a minimum binder content for mixes. Acceptance is mostly based on volumetrics.

- QA data will help with forecasting performance of existing pavements and future pavements with similar materials.

- At the planning stage, performance may be estimated based on design. Postconstruction, with known QA and construction properties, performance predictions can be revised.

Minnesota DOT

Pavement Management

Minnesota DOT (MnDOT) PMS system covers approximately 4,100 mi of pavement. Typical the PMS section is 1 mi long. PMS is based on collection of up to 10 distress types and is identified by route, MP, direction, and so on. Distress/condition data are collected using various standards. Transverse and longitudinal cracking is collected at low, medium, and high severities, while alligator cracking is collected with the yes/no rating. PMS uses a rating system to develop and report condition indexes. Individual distress is not reported or directly used.

Distress collection and reporting effort are not aligned to *MAP-21* or HPMS. PMS data are currently linked to a roadway history database, which can be integrated with PMS files. Roadway history database contains information on layer type, thickness, M&R type, construction number, and so on. Detailed information on materials properties (e.g., mix design, binder type) is not available in the construction history table. MnDOT updates M&R history data as new information is obtained from the districts or when there is a significant change in distress/smoothness. Pavement layer-type and thickness data are provided in a separate table. Thus, with the current setup, for each PMS section, reports containing construction and maintenance histories, layer type, and so on, can be generated.

PMS allows for forecasting future conditions and can project future conditions. Forecasting is done for up to 50 yr. Simple regression models are fitted to historical condition data (data collected since last significant M&R). PMS uses default forecasting models where historical condition data are not available, the data available are erroneous, or there is no change in condition. Currently, pavement layer types and thickness, although available, are not used in condition forecasting. PMS reports percentage of the network in Good/Fair/Poor condition. This report is compared with actual values obtained the following year. Comparisons have shown the predictions/forecasts are accurate within the short term. Forecasts in the 8- to 10-yr prediction horizons are much sketchier. For forecasting condition in the 10- to 15-yr prediction horizons, default models are used. Inputs for the forecasting models include:

- Location (rural/urban).
- Thin/thick.
- Mix type.
- Maintenance type (e.g., microsurfacing, seal coat).
- Minor/major rehabilitation (e.g., unbonded overlay, diamond grinding).

The default forecasting models are updated with major changes to pavement materials or design/construction practices (e.g., Marshall to Superpave HMA). Distress data are currently not collected using HPMS reporting standards. Thus, the MnDOT distress data are converted into HPMS formats for reporting purposes.

Work is underway to improve PMS and other related databases. Specific improvements include development of new location referencing system for MnDOT PMS and other related databases; redevelopment of roadway history database (new schema, revised inputs, and so on); and replacing the current mainframe data storage setup with an Oracle database. As currently set up, integrating QA and PMS data will be very cumbersome and challenging. MnDOT believes that including QA data in PMS will be beneficial in improving the accuracy of default forecasting models.

QA of HMA

For MnDOT, asphalt and HMA material test data are obtained from many sources. For AC, sampling is typically done at the plant, site, or behind the paver. Each sample is split by MnDOT and the contractor. MnDOT inspectors randomly test the MnDOT samples, while the contractor is required to perform lab air voids, maximum/rice specific gravity, AC binder content, gradation, asphalt film thickness, coarse/fine aggregate angularity (FAA), and fine-to-effective asphalt content-type tests on their samples. For AC binders, at least one test is performed per 1,000 T or one test per 50,000 gal for each test/sampling. Binder samples are taken just before it enters the drum at the plant. The MnDOT inspector observes/supervises contractor sampling. For typical production rates, contractor performs up to four tests, while MnDOT performs at least one companion test. MnDOT does not test virgin aggregates. In-place density and thickness are obtained from field cores. DOT's chemical lab performs asphalt binder acceptance tests, including dynamic shear rheometer (DSR), and other standard M 320 tests. Additional AC binder data are available from the combined State binder group (namely Minnesota, Iowa, Wisconsin, Nebraska, North Dakota, and South Dakota). These are supplier's certification test data. Testing is part of the supplier's internal QA program, which is done to allow the States to reduce testing frequency (making 1 per 50,000-gal testing frequency feasible). The MnDOT chemical lab works with binder suppliers and thus has the suppliers' test results.

MnDOT does not have an established QA database at the State level. All contractors track QA testing and results in Excel spreadsheets or PDF files (legacy data are paper hardcopies or PDFs, while more recent data are electronic Microsoft Excel spreadsheets). Contractors provide mix design and certification tests for approval. The test data provided by the districts are stored in the DOT's LIMS databases. Asphalt mix test from the MnDOT chemical lab is stored in LIMS and other databases. The LRS or coordinate system in place in LIMS contain project number, location (if available), station, and date.

MnDOT is currently considering the feasibility of setting up a QA database. Although road contractors are supposed to provide QA test data to MnDOT, this procedure mostly does not happen at the State level. For the most part, QA test-type information is kept at the district level.

QA of PCC

MnDOT has developed and adopted an advanced QA program for PCC materials that focuses on durability and long-lasting characteristics instead of strength alone. This program has created increased testing and process control for all materials, especially aggregates. The improved specifications and QA program, which in effect provide higher incentives for quality materials, have resulted in enhanced performance of concrete pavements. MnDOT has performed studies to validate field performance results for the revised specifications. Principal factors that guide the current specifications are:

- Mix durability.
- Curing practices.
- Incentives/disincentives based on w/c ratio, aggregate gradation, coarse aggregate quality, and smoothness.

Strength is achieved through the control of the w/c ratio. In fact, mix strength values have increased by 30 percent with the control on the w/c ratio. In the process, concrete is made more durable by reducing permeability and thus making it more freeze-thaw resistant and less susceptible to aggregate deteriorations. The specifications also ensure that w/c ratio is reduced by taking out water and not by increasing cementitious content.

MnDOT has incorporated a unique aggregate QC. The material tests on the aggregates depend on the aggregate type. Granites, gneiss, and quartzite provide an automatic incentive. Carbonates and dolostones have a control on absorption, and gravels have a control on carbonate content. The gradation specification promotes lower water demand, which leads to lower w/c ratios, thus reducing permeability. It also reduces segregation, promotes workability, and reduces paste content, thus reducing the risk of shrinkage cracks.

Currently, statewide field testing and acceptance data are entered in the State LIMS database. However, before the aggregates are used in a paving mix for a construction project, MnDOT ensures the aggregates and other materials meet specification requirements. Aggregate supply sources test aggregates every month, and MnDOT ensures that the plant meets specification requirements (or alternatively provides test data). Certified sources for cementitious arterials are also encouraged. Flexural strength of beams is used for acceptance. While the QA program is extremely effective, data are not formatted for integration with PMS. Validations may be performed on an individual project basis.

Innovative Technologies

MnDOT has piloted some innovative test technologies such as IC and thermal profiling using IR. In fact, MnDOT was one of the first agencies to hold IC demonstration projects and pilots more than a decade ago. Use of IC has been relatively limited. The criteria for using IC is that highways have four or more lanes, or the projects are for six-lane highway. MnDOT was scheduled for 100 percent deployment of IC in the 2017/2018 construction season. As of 2015, IC was used in approximately 18 out of the 135 projects. Developing a relationship between IC and cut cores (density) will reduce the need for coring.

MnDOT is also piloting IR technologies for thermal profiling. Starting in 2015, at least 20 percent of their projects use IR. Currently, IC and IR are not part of the regular pavement construction specifications. They can, however, be included via special provision. MnDOT encourages districts to use IC as IR as much as possible.

MnDOT does not use nuclear density testing, as the quality of density estimates is inadequate. Thus, nuclear density testing can be used for internal contractor QC but not DOT acceptance testing. MnDOT researchers have investigated feasibility of 3D GPR (including use of TTI scanning technologies for assessing HMA density along with the longitudinal joint). This assessment is currently being done at the research-level testing, with researchers evaluating the feasibility of using it on limited 1-mi sections of pavement.

DOT suggestions for data integration include the following:

- Software is needed for use in integration.
- Information must be entered once.
- Including location information (i.e., GPS) as part of overall QA testing/sampling will make integration much more straightforward.
- Target data must include vast contractor test data.

Advantages of integrated data include the following:

- Development of trends and relationships between QA-type data and performance (e.g., FAA relationship with density).

- Statistical analysis and development of type mean value and variance. Currently, the setup does not allow for such statistical analysis, correlations, and so on.

Colorado DOT

Pavement Management

The Colorado DOT (CDOT) collects distress data consistent with LTPP protocols. Data are averaged to every 1/10th mi. The data include all distress measures relevant to the 2017 ruling in 23 CFR Part 490. In addition, cracking distresses are categorized by severity levels. Distress types include fatigue cracking, longitudinal cracking, transverse cracking, corner breaks, rutting, and ride quality as IRI. Cracking distress severities used are low, moderate, and high. As of 2015, although CDOT had not made significant changes for meeting *MAP-21* requirements yet, changes to the performance indicators/metrics had been made, and a new manual and models were being developed. Data inputs had not been changed either.

A new index referred to as the drivability life (DL) has been introduced that replaces the serviceability index parameter. DL is an indication, in years, of how long a highway will have acceptable driving conditions:

- Acceptable driving condition implies that safe and effective travel is possible on a roadway. It is a function of smoothness, pavement distress, and safety.

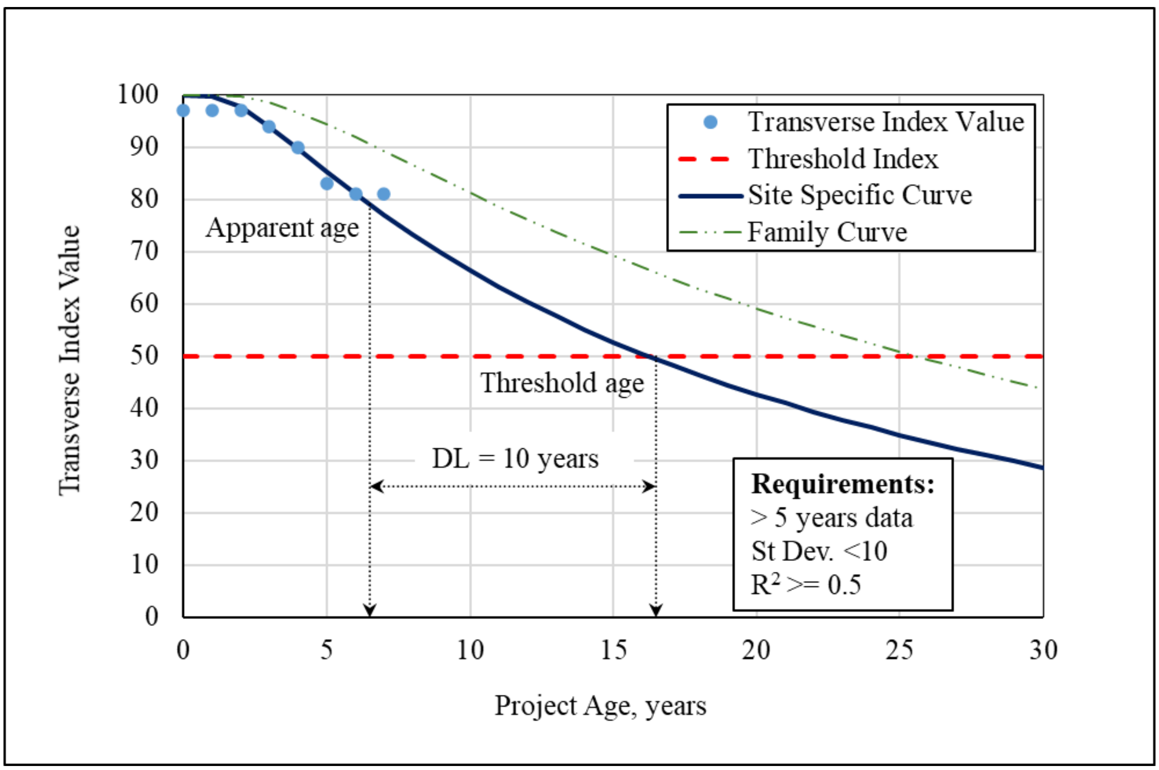
- Unacceptable driving condition does not mean “impassable.” It implies that drivers must reduce speeds to compensate for unsafe factors, navigate around damaged pavement, or endure rough rides.

DL scale for reporting condition is represented as follows:

- Over 10 yr DL (High).
- 4–10 yr DL (Moderate).
- 3 yr DL or less (Low).

The current forecasting models use S-shaped logarithmic curves to forecast future conditions. The performance curve is a pavement deterioration model based on a distress index collected over time. A performance curve is generated on a project segment basis and regressed using the historical index values for the road section. Figure 44 shows a sample PMS segment for which the last work was performed in 2006. To use the DL concept, there must be at least 5 consecutive yr of historical data, including the current year, available since the last treatment. The standard deviation cannot be greater than 10, and the R^2 value cannot be less than 0.5. If these criteria are satisfied, project-specific forecasting is done. If not, additional data from similar projects are used to develop predictions. If the use of additional data does not meet the criteria, default curves are used for prediction. The default family curve is also shown in figure 44 for this specific PMS segment.

DL is determined from the performance curve to estimate when the next major rehabilitation or reconstruction should be considered. This procedure entails defining the apparent age and the threshold age. The apparent age is the age at which the performance curve shows the current measured distress level. The threshold age is the age at which the performance curve indicates failure. DL is defined as the time needed from the apparent age to reach the threshold age starting from the apparent age, as shown in figure 44.



Source: FHWA.

Figure 44. Graph. DL regression curve for a CDOT PMS section.

CDOT uses an internal LRS and consists of MP, route, and direction. GPS referencing is available on a limited basis and may enable data integration. A cross reference through contracts data enables the integration with QA data. PMS and QA data cannot be mapped to a specific location. Rather, mapping is limited to a construction contract.

Performance projections are made for 20-yr analysis periods and provide inputs for strategic funding levels. However, their actual short-term budgeting is for 4 yr, and CDOT regions use it for 4 yr for project selection. The State Governor's office uses a 10-yr planning term, and goals and plans for highway investments are based on 10-yr forecasting. Changes to forecasting models may impact these activities. With their current forecasting models, their predictions are accurate some years and deviate from field outcomes in other years. Nevertheless, CDOT has found that, over time, the averages predictions are close to field data. Distress data directly measured by sensors, such as IRI, are generally more stable. Variability is mostly observed in distresses that involve a more subjective process.

Concerning interest in using QA data for PMS forecasting models, CDOT believed that such correlations might help identify causes for the failures noted in their network. They recognize that adequacy of construction impacts performance.

QA Program

CDOT QA program uses SiteManager, as well as multiple in-house database programs. HMA data are managed in a program called Quality Control Quality Assurance HMA Master, which consists of three modules for air voids, mix design, and gradation information. These data are purely field construction data. Preconstruction and mix design information are maintained in SiteManager and in-house databases. All PCC QA data, including mix design data and lab/field test data, are stored in a Microsoft Access database. Details of the QA database are provided in chapter 4 and chapter 5.

Utah DOT

The project team conducted a very short and brief meeting with Utah DOT (UDOT). The meeting attendees from UDOT comprised staff from various functions of the DOT, rather than individual discussions with staff from each function.

QA and Innovative Technologies

The existing QA program at Utah was standard, although UDOT is preparing to enhance the geospatial referencing for the QA data collection. Typical QA parameters discussed in chapter 2 were included in the QC and acceptance procedures. For HMA, criteria were established for binder content, gradation, voids, and density. For PCC, criteria were established for gradation, slump, strength, and density. All HMA and PCC test data, including mix design, QC, and verification results, are stored in a database. Unbound material data are not stored in the database. The database program is an Oracle Apex application with a web-based interface for statewide use. The referencing used is project stationing and offset. Other supplementary programs (using Microsoft Excel) are maintained to record project accounting, pay quantities, and other documentation. UDOT has evaluated IC for HMA under demonstration projects and mapped stiffness values for the construction projects. IC has not been used for acceptance.

PMS

Pavement condition data are collected every other year on the entire network, and the distresses included in the PMS are IRI, slab cracking, joint spalling, faulting for PCC pavements and IRI, cracking, fatigue cracking, and wheel-path rutting for HMA pavements. Pavement forecasting is performed for a 20-yr analysis period. Forecasting models used are polynomial models. Condition forecasting is performed to manage funding allocations and project selection.

Mississippi DOT

QA

The Mississippi DOT maintains its QA data in the SiteManager application. All test data generated at the district and central headquarters laboratories are stored in the database. The majority of paving projects in Mississippi constitute flexible pavements, and therefore detailed information on PCC test data were not available.

HMA QA procedures begin with the submission of mix design information from contractors and verifications from within the Mississippi DOT performed at the central laboratory. The contractor's mix design is used and is stored in the database. Binder testing includes the AASHTO M 320 test data, which are provided by the supplier. Binder test results are integrated into the QA database. The mix approval testing is maintained in Microsoft Excel files and in soft copies. Once the mix design is approved, the project test data entry is transferred to the districts. For acceptance, volumetrics testing is performed in the district laboratories, and binder testing is performed in the central laboratory. For acceptance, the district uses a sample size that is about 10 percent of that used for QC. Districts maintain all data in Microsoft Excel files. All construction QA data are referenced by project number, county, road, and station number. Test results from field cores are referenced by station and offset. All soil QA tests are performed in the district labs, and data are stored in SiteManager. No innovative technologies have been used for QA.

Pavement Management

The Mississippi DOT manages 27,000 lane miles, and PMS data are collected for over 13,500 lane miles. Pavement condition data have been collected annually since 2010. On divided highways, testing is conducted in both directions, and on undivided highways, tests are performed in either the northbound or eastbound lanes. Mississippi performs condition surveys on 100 percent of the roadways every year, and data are averaged over a 0.1-mi length. PMS data include alligator cracking, transverse cracking, longitudinal cracking, and rutting IRI, and these data may be available for several months of the year. The State is transitioning to probability matrices for performance prediction. Pavement condition ratings on a scale of 1–100 are used. M&R treatments are selected based on decision trees that are designed for each pavement-type number of lanes-traffic category.

Michigan DOT

Pavement Management

Michigan DOT has been collecting visual distress data since the early 1990s on approximately 12,000 lane miles of pavements. Sampling rate for distress surveys is 30 percent. Automated imaging technologies have been used since 1992/1993. Images are reviewed at workstations, and the extent and severity of distress is determined and recorded. Extent and severity of distress types—such as transverse, block, and longitudinal cracking, raveling, flushing, scaling, shattered slabs, joint deterioration, and so on—are determined from the images collected from the field. Note that load- and nonload-related distress are aggregated separately, and load-related cracking is not reported in Michigan DOT database. Distress surveys are conducted every 2 yr for 100 percent of the truck outer lane. For separated highways, distress data are collected in both directions. Longitudinal and transverse profile has been collected for highways since the late 1990s. For highways on the NHS, this profile collection is done annually. IRI, faulting, and rutting are reported every 1/10th mi using field distress data collected every 2 yr. Faulting data were collected in the last decade. Michigan DOT is currently in compliance with the provisions of *MAP-21* (although the national performance management measures ruling requires 100 percent sampling rate). Michigan DOT may adopt automated distress recognition systems to achieve 100 percent sampling rate. Michigan DOT has some concerns about use of such technology at this time, as new 3D technologies are currently being developed. There is no need at this stage for making significant changes.

Distress data are stored in an Oracle database. Images are stored on Michigan DOT servers and external hard drives. Michigan DOT uses two main LRS: route and MPs as well as construction control points. Longitudinal/transverse profile data and derived performance measures (IRI, faulting, rutting) are linked directly to GPS coordinates, which are easily integrated into the route/MP system. Condition forecasting consists of the following:

- Transform data on cracking and rutting (extent, severity, type, and so on) into an index for cracking, rutting, and so on.
- Plot historical distress index versus age/time.
- Fit logistic growth model to distress index and age data.
- Set the threshold distress index value to 50.
- Set the distress index below 50, which triggers preventive maintenance treatment.

Thus, historical distress index data are used to forecast future condition and performance. Time to distress index = 50 is a key measure for maintenance programming and planning. A list of pavement sections needing M&R is determined and published annually.

Default performance models are available for each pavement and M&R type (i.e., families of pavement). The default deterioration curves are used in PMS and for lifecycle cost analysis. Planning and programming are done separately for the seven Michigan DOT regions in 5-yr cycles.

QA

Testing for soils and subgrade characterization is not done. The same tests are conducted for all pavement types, and these are aggregate material density tests (for acceptance and certification). Testing conducted on geosynthetic materials is done only for certification.

Base/subbase aggregate tests are conducted by Michigan DOT full-service regional laboratory facilities or by suppliers as part of certification. A variety of tests are conducted to characterize frost susceptibility. Sampling and lab testing along with field nuclear density testing frequency are recommended as per material type. Regional test data are reported and stored in paper files to the central office/lab. Certification of regional labs is done by Michigan DOT's central lab.

Lab density tests are conducted on site. The tests are conducted basically for payments and not forensics or QA. Density testing has been incorporated into Michigan DOTs e-Construction system. The e-Construction system is currently in the process of digitizing paper documents.

Innovative Technologies

Michigan DOT has piloted some innovative test technologies such as IC. Michigan DOT is in the process of adopting this technology. Currently, IC is for contractor QC only. Michigan DOT uses the IC test maps (not data) obtained from contractors to identify "soft spots" for nuclear density testing. IC utilizes a combination of station and offset as LRS. There is no direct way to integrate with other LRS, such as route and MP. Michigan DOT is internally working on establishing uniform LRS across business units.

e-Construction

Currently most QA test data in Michigan DOT are stored on paper and reside as hardcopies of project files. With moves toward e-Construction, Michigan DOT is adopting the PDF format for storing records. No electronic database for storing QA test data is currently under development. Current e-Construction initiative comprises attempts to document all key construction activities using PDF. Michigan DOT has no plans for a database yet. Paper hardcopies will all be replaced by PDF electronic documents. Information from Michigan DOT inspectors (e.g., date, weather, progress, issues, work items, material placement) will all be tracked and documented electronically. FieldManager and SiteManager will be used by Michigan DOT as part of e-Construction. FieldManager is currently used to store field data from inspectors. All activities from construction to payments are being tracked electronically, including material sources.

State 1 DOT

This DOT is not being identified in this report to satisfy the nonattribution policy because data from State 1 were used in the statistical data analyses for this project. Certain features and practices are unique to State 1 in the list in table 28, making its identity obvious in the data analyses section. It is therefore being referred to as State 1 in this section and throughout this report.

The project team was aware from experience working with State 1 DOT data that the QA data contained multiple test results per lot and, therefore, provided an opportunity to consider the impact of variability on performance. The data used from State 1 are explained in detail in chapter 4 and chapter 5.

State 1 was not interviewed in detail; however, State 1 DOT has actively advanced its QA procedures, developed construction quality database systems, and engaged in enabling cross-linking its databases. The database systems were originally established in supporting the agency's intentions to ensure all materials and construction workmanship meet specification requirements. It continues to use most of the traditional QA test methods and is making ongoing efforts in the adoption of PRS. State 1 DOT maintains a database to store and track material approval tests performed in the central laboratory and includes test results for soils, aggregates, and asphalt materials. It also maintains a separate database to store data from construction and includes QC, acceptance, and IA test results that cover aggregates, soils, asphalt binders, HMA, and PCC materials. Data are stored by project, material type, layer, lot, and individual test results. These data are used to calculate project averages for quality acceptance and contractor pay factors. The QA database has no direct links to the PMS or traffic database.

Oregon DOT

A brief discussion with Oregon DOT was held, particularly about its long-term plans to digitize construction activities and associate all data with a location reference. Oregon DOT maintains a mature PMS; however, construction QA data were not sufficiently available in an electronic format. Oregon DOT is making headways with the adoption of IC and IR technology. Recent projects have IC data and comprehensive QA data in an electronic format. These data include binder, aggregate, and HMA test results, as well as field acceptance data. Additionally, this State is rapidly adopting AMG for construction; however, the current specifications do not require the contractor to submit 3D as-built plans, and, as such, no cross-functional use of these data is envisioned at this point.

STATE PRACTICES WITH USE OF CIM

There is a growing movement under the umbrella of CIM to revisit how design and construction data are organized and shared so that the information provided is more consumable for downstream users. While plan sheets and PDF documents are durable, secure, and universally accessible, the information within these documents is less accessible. As States' e-Construction practices mature, there is growing capability maturity for presenting information digitally, which is presented in table 29.

Table 29. Capability maturity for electronic construction data.

Information Type	Level 1	Level 2	Level 3	Level 4
File format	PDF	PDF	PDF	Varies
Geometric data	Raster	Vector	Vector	Vector
Attribute data	Raster	Searchable text	Searchable text	Database fields
Searchable	No	Yes	Yes	Yes
Validated	No	No	Yes	Yes
Inquirable	No	No	No	Yes

At the first level, information is in a PDF document in a raster format. It is readable but cannot be searched or extracted. At the second level, information is in a vector PDF document. Now it is searchable, and geometric properties can be extracted and measured. At the third level, the vector PDF documents are created from fillable forms with drop-down fields. Now the documents have information that is prevalidated. At the fourth level, there is migration away from PDF documents. There is little precedent for the fourth level or beyond in practice, but many States have established their vision for the fourth level.

Increasingly, States recognize that the data created in design and collected in construction are an asset for the agency. While agency organization is still siloed, and collaboration is not as strong as it might be, many agencies have ongoing data governance initiatives. These agencies include Minnesota, Florida, and California.(98,99,100) This situation is raising awareness of the cross-functional value of data and the need to ensure that data are accessible, logically organized, and secure. In practice, data collection, organization, and storage are still not aligned for different functional uses, such as design, construction, and asset management and planning. However, the industry has much momentum around transforming processes with 3D engineered models and e-Construction. Many agencies are forming visions for level 4 electronic construction data practices and increasing the maturity of their current practices.

In recent years, there have been research efforts around BIM practices in which many agencies have participated. The themes of portable, durable, and accessible asset information that can be read and written from mobile devices frequently emerge. A domestic scan involved representatives from Iowa, Michigan, Arizona, Utah, Pennsylvania, and Florida DOTs. The scan tour also visited New York, Texas, Virginia, and Wisconsin DOTs to capture the practices in those States.(101)

Evolving practices for data management were also captured in surveys and case studies conducted in the development of a guidebook for CIM. These practices included electronic archiving and updating of plans, digital asset management, MMSs, and mobile devices. The specific software tools that were found for digital data management were ProjectWise, AASHTO Project, and Microsoft SharePoint®.(102) Microsoft SharePoint can manage single sign-on into multiple databases, which UDOT is pursuing. Another software tool that manages a single sign-on is Headlight from Pavia Systems. These single sign-on interfaces enable inspectors to collect various types of data in a single interface and push that data to different databases, one of which is AASHTO's SiteManager, another being Oracle MasterWorks. The success of these tools for managing construction data (for use in construction) sets a platform to build off for collecting and managing data in construction for future purposes, like reporting and predicting pavement conditions.

Iowa DOT has conducted several projects in which the 3D CADD data have superseded the PDF plans for highway construction and inspection. Building off this success, Iowa DOT has a vision to move quickly to implement what they call "Intelligent Plans," which are 3D CADD models connected to data in an Oracle database and accessed from mobile devices in the field. The intent of this effort is to provide design and construction data that meet the needs in construction, and it also serves maintenance and asset management. This vision includes advancing Iowa DOT's use of digital as-built records. The Design, Construction, and Maintenance Departments have collaborated to identify 23 priority assets and the associated spatial resolution and attributes to collect. To advance this initiative, Iowa DOT's inspectors need an easy tool to capture the electronic as-built data and a data warehouse in which to store and serve the data.[(103)]

While Montana DOT (MDT) is still piloting 3D design practices and using 3D data in construction inspection, it already has a vision to implement "Intelligent Models" throughout the lifecycle of select roadway assets. This vision includes using the 3D design data in construction inspection and providing asset inventory information, which would provide roadway geometric information, plant mix and surfacing depths, and other asset information for MDT's asset management system. MDT's target implementation date is 2022, with a staged implementation that began with piloting 3D design in 2016.[(104)]

UDOT has been implementing "Intelligent Design and Construction" since 2014, when the first implementation plan was drafted. UDOT's vision is to phase out plans and replace them with 3D models, receiving a 3D model as an as-built record from the contractor.[(105)] In a plans-free delivery, all annotations and other information normally contained in a plans set must be embedded in the 3D model. Utah's first pilot project, a widening project on SR-20, was completed successfully in the summer of 2016 using the Contract Manager/General Contractor procurement model. Challenges that UDOT are facing include data incompatibility between proprietary software and a need for user-friendly software for field staff.[(105)]

UDOT developed a data warehouse in 2013. This data warehouse includes geospatial data assets, as well as nonspatial data assets, such as UDOT's construction cost database. In 2012, UDOT initiated biennial statewide surface asset inventories to populate and maintain a current inventory. This inventory includes pavement types and areas and edge types and is integrated with pavement distress information that is collected using the same vehicle but a different sensor.[(106)] The data warehouse includes safety data, such as spatially located skid resistance, centerline and edge rumble strips, shoulder widths, and so on. The various data sources are aligned to the same spatial reference, which has enabled UDOT to create applications that query multiple databases in the data warehouse to aid in decisionmaking.

One pavement preservation design application queries the spatial asset inventory, safety database, and construction cost database to aid in preservation of the project design. In as little as 5 min, designers can extract quantities and estimate costs for preservation activities, such as mill and repaving, as well as identify any safety issues in the project limits and estimate the return on investment for a variety of safety improvements (for instance rumble strips or shoulder widening) based on the crash history in that location. UDOT estimates annual cost savings of over $1.5 million from automation efficiencies created by the data warehouse and applications.[(106)] These costs do not include the value of being able to make better, more informed decisions based on reliable data.

Pennsylvania DOT (PennDOT) began developing mobile applications for construction inspectors in 2013. Pavement materials testing was one of the first applications developed for PennDOT.[(107)] The application enables inspectors to collect materials testing information from the field and migrate it into PennDOT's back-end materials database via SharePoint.[(108)] PennDOT's application for project site activity documentation has an interface that lets inspectors select from prepopulated, validated lists, such as preapproved materials suppliers, and can store locations that are read directly from the mobile device's GPS and reconciled to project baselines (such as station and offset).[109]

DATA USED FOR PROJECT ANALYSES—PERFORMANCE MODELING AND CASE STUDIES

Summary of Agency Practices Leading to Selection of Data for Analyses

The survey of State DOTs to collect information on their QA and PMS databases and the potential for establishing correlations led to the following conclusions:

- No State is set up to automate or directly correlate QA to PMS.
- There is, at least to a fair degree, an interest in bridging the gap between the construction and PMS activities. However, the reasons for each DOT's interest in cross-linking these databases may vary.
- States recognize that there is an increased scope for facilitating the integration process by the enhancements in as-built data collection largely enabled by automation in construction technologies. Current practice does not permit the use of as-built records.
- The extent of QA data available, the types of data collected, the extent of data accessible electronically, and storage methods vary across agencies. The efforts involved in assembling and integrating databases will remain unique to each agency.
- Data integration allows mapping performance to QA data by project or by location and requires significant effort.

It was with the understanding of the preceding information that the project team selected agencies to obtain data for the analyses under this project. In addition, knowledge of specific details of databases in each agency was a factor in selecting agency databases for use in this study.

State Data Used for Performance Prediction Under Current Study

Based on State agency interviews and information obtained about datasets that can be potentially used to validate correlations between QA data and performance, the project team selected data from four States. The selection of these agencies enabled a wide range of analyses covering different pavement types, QA parameters, innovative technologies, and levels/tiers of analyses. The following factors were considered in selecting the States:

- The ability to include different material parameters in the analyses with these data. Data from multiple States were considered useful to highlight the similarities and differences in the outcomes from one State to another.
- The ability to perform both network- and project-level analyses.
- Historical condition data over an adequate period for performance forecasting.

- Agency’s general vision for improving PMS and desire to use QA data for forecasting.
- Maturity and advancements in the construction quality database system.
- The extent of data maintained in electronic format versus in paper records.
- Data from evolving QA and construction technologies.
- Suitable location referencing formats across different databases and the ability to identify data for a given project segment within each database.
- General efforts of the DOT that align with project goals.
- State DOT willingness to assist the project team.

Specific reasons for selecting individual States for analyses were as follows:

- State 1:
    - Comprehensive and well-organized data in both QA and PMS databases.
    - QA data organized by lots and assigned by specific dates of paving.
    - Ability to access traffic and climate data from other national databases to develop a case study, demonstrating the added value of integrating other agency databases.
- State 2:
    - Ability to analyze both PCC and HMA projects.
    - Availability of QA data and PMS data, with the ability to match the location references at both the network and project levels and, therefore, the ability to perform a project-level case study.
    - Ability to consider at least two innovative technologies: in this case, the MIT-Scan for PCC pavements and a continuous deflection monitoring device/RWD for HMA pavements.
- State 3:
    - Comprehensive and well-organized data in both QA and PMS databases.
    - Existing interest in pursuing the use of construction data for structural and functional performance measures. The main interest was in using aggregate properties, AC properties for the prediction of cracking, and rutting in HMA.
- State 4: Use of IC data from three construction projects with corresponding QA in-field HMA density data and QA material mix design data, which enabled a project-level case study.

A summary of the analyses performed using data from these States is presented in table 30 and table 31 for HMA pavement and in table 32 and table 33 for PCC pavements.

Note: Because of the lack of 3D data from as-built projects, the project team did not include case studies with data collected from 3D technologies under this project.

Table 30. Summary of State databases used for analyses of flexible pavements.

State	QA/Construction Parameters
State 1	• Conventional QA data. • Derived parameters. • Average and COV for variability analyses. • Other national database to integrate traffic and climate.[#]
State 2	• Conventional data. • Innovative technologies.[#] • Continuous deflection monitoring device.
State 3	• Conventional data. • Derived parameters.
State 4[#]	• IC.[#] • Conventional QA.[#]

[#]Used for case study to demonstrate potential integration in PMS.
COV = coefficient of variation.

Table 31. Performance indicators selected for modeling flexible pavements related to PMSs at network or project level.

State	Rutting	Cracking	IRI
State 1	Network*	Network*	—
State 2	Project	—	Project
	Project	Project	Project
State 3	Network	Network	—
State 4[#]	Project	Project	—

—No data.
*Considered both average values and variability through COV.
[#]Case study only.

Table 32. Summary of State databases used for analysis of rigid pavements.

State	QA/Construction Parameters
State 2	• Conventional data. • Innovative technologies. • MIT-Scan for dowel bar alignment.[#]

[#]Used for case study to demonstrate potential integration in PMS.

Table 33. Performance indicators selected for modeling rigid pavements related to pavement management at network or project level.

State	Faulting	Cracking	IRI
State 2	Network	Network	—
	8 projects	—	—

—No data.

CHAPTER 4. DATA IDENTIFICATION, DESCRIPTION, REVIEW, AND ASSEMBLY

INTRODUCTION

A key goal of this study was to assess the feasibility of utilizing QA test data as leading indicators of future highway pavement performance. Of specific importance is whether QA test data can be integrated into existing DOT PMS to improve accuracy and reliability of performance forecasting at the network level. Performance in the context of this study is described as pavement performance measures typically reported in DOT PMS, along with the performance measures recently established (defined and published) under the FHWA national performance management measures ruling. As described previously, the following broad QA and construction parameters were included in the analyses:

- Construction and QA data collected as part of traditional QC and acceptance testing. These data include lab and field measurements of layer thicknesses, HMA volumetrics, binder data, PCC mix design indexes, PCC strength data, and so on.

- Construction data collected from the adoption of innovative technologies. These data include advanced and expanded technologies, such as GPR, IC, IR, MIT-Scan, continuous deflection measuring devices (RWD, TSD), and so on.

Effectively determining feasibility of utilizing QA data as leading indicators of highway pavement performance requires the following:

- Determining QA/QC test data items available (i.e., type, extent of testing, storage) for inclusion in PMS as a leading indicator of performance.

- Investigating feasibility of integrating traditional and nontraditional QA/QC data into existing PMS.

- Analyzing statistically to determine whether QA/QC data aggregated at the PMS level (e.g., mean values for the typical PMS 0.1- to 1-mi sections) can be used as a leading indicator for pavement performance.

This chapter describes work done to determine QA test data available for inclusion in PMS as a leading indicator for performance.

Identification of DOT PMS and QA/QC Data

Identification of QA/QC test data available for inclusion in PMS requires reviewing the PMS of the DOT as well as construction QA programs to ascertain data items collected and stored as routine practice. Based on the outcome of State DOT interviews described in chapter 3, data were used from four State DOT databases for indepth analyses and case studies as described in table 30 and table 31 for HMA pavement and in table 32 and table 33 for PCC pavements. The project team conducted a comprehensive review of their databases and the information therein, which are described in the next sections. Please note that because the analyses in State 4 were restricted to a case study using IC data, reviews and assembly of the database for State 4 were limited to project-level QA and IC data from recent construction projects. No performance data were used to develop correlations at this point.

STATE 1 DOT

Pavement Management

State 1 DOT has a comprehensive PMS and QA/QC testing program. The latest generation of the DOT PMS, developed in the mid-2000s, provides a wide variety of capabilities, including corrective/preventive M&R treatment selection optimization and planning. This PMS database relies on several data sources developed and used as part of earlier versions of the DOT PMS. The data sources are presented as follows:

- State 1 pavement management database.
- State 1 transportation information system.
- State 1 highway log database.
- State 1 DOT SQL server-based maintenance activities.
- Image data.
- State 1 DOT Materials Database, State 1 Materials Database (actual name withheld).
- Feature inventory database.
- State information data warehouse.
- Traffic data files.

Using the information available in these tables, the State 1 DOT has developed a PMS database. Key data items included in the State 1 DOT PMS are presented in table 34.

Table 34. Summary of key data items included in the State 1 DOT PMS.

Data Items	Description
Highway ID and referencing	Route types, route number, route auxiliary ID, highway direction, and MP/reference nodes. Note the types of referencing used were mainly linear referencing or reference post and offset.
Jurisdiction	Districts, counties, cities.
Administrative	Functional class, elevation zones, and so on.
Environment	Environment (e.g., desert, mountain, transition), terrain (e.g., flat, rolling, and rugged).
Pavement/median	Pavement types (e.g., bituminous, concrete, or unpaved), median types (e.g., divided or undivided).
Shoulder/drainage	Shoulder, drainage, or curb types (shoulders, drainage, curbs, or sidewalks).
Construction	Construction activities, materials/layers, binders/aggregates, and aggregate sources.
Distress types	Performance measures that describe the units that are used in measuring the distress and severity defined as low, moderate, and high.
Traffic	Traffic counts, classes, and estimates of ESALs.
Deflection	Deflection information (device types).

QA Data

State 1 DOT maintains detailed information of construction activities (construction history) and QA/QC material testing. This information is maintained and stored in the following databases:

- State 1 DOT maintenance activities, which is SQL server based. The name of the database is not identified in the report but will be referred to as State 1 Maintenance Activities Database.

- State 1 DOT Materials Database. The name of the database is not identified in the report but will be referred to as the State 1 Materials Database.

The State 1 Maintenance Activities Database contains definitions of each maintenance activity and associated inventory feature and work unit. It also contains information regarding activity type, inventory feature, labor/equipment/material expended, and others. The State 1 Materials Database contains many data items that describe in detail materials types and properties used in maintenance activities. A summary of key data items in the State 1 Materials Database is presented in table 35. State 1 DOT also routinely collects material certification data that are not project specific and thus mostly reside in reports (PDF files) submitted by suppliers and contractors.

Table 35. Summary of key data items in State 1 Materials Database.

Data Item	Material Code	Description
Admix	AD	N/A
Aggregate	AG	Bituminous-treated base (BB) Cement-treated base (CB) Cement-treated subgrade (CS) Lean concrete base (LC) Lime-treated subgrade (LS) Road mix (RM) Soil cement (SC)
Aggregate base	AB	Class 1–3
Aggregate subbase	AS	Class 4–6
Asphaltic concrete	AC	½-inch asphaltic concrete (12) ½-inch fine band 417 AC (12F) ½-inch coarse band 417 AC (12K) ¾-inch asphaltic concrete (34) ¾-inch fine band 417 AC (34F) ¾-inch coarse band 417 AC (34K) Friction course (ACFC, FC) Asphalt rubber (AR–AC, RD) Asphalt-rubber asphaltic concrete friction course (AR–ACFC, RF) Base mix (BM) Bituminous-treated base (BB) Recycled asphaltic concrete (RC) Road mix (RM)
Coarse aggregate	CA	Size 1 through 10, 24, 56, 57, 67, 68, 78, 79, 89, 357, 467
Embankment	EM	N/A
Entrained air (air content)	ET	N/A
Filter material	FM	N/A
Fine aggregate	FA	N/A
Fly ash	FF	N/A
Mineral aggregate	MA	N/A
RAP	RP	Fine (F), coarse (C), other (O)
Subgrade	SG	N/A

STATE 2 DOT

Pavement Management

State 2 DOT pavement management program provides regions with information to facilitate pavement M&R decisionmaking. The program has the following purposes:

- Collect and provide pavement condition data and develop the condition data report.
- Investigate and report individual pavement sections remaining service life.
- Develop Good/Fair/Poor maps and graphs.
- Develop 20-yr network projections.
- Develop M&R recommendations.
- Develop regional budget allocation recommendations.
- Develop annual pavement management, preventive maintenance, and surface treatment reports.

Developing the reports listed previously requires comprehensive assessment of current pavement condition and forecasting of future (20-yr) pavement condition. PMS collects annual condition data for every highway on the State 2 DOT network (condition data collection dates back to 1991, and old data are archived). Condition data, reported in 0.1-mi PMS sections, includes cracking, rutting, and IRI reported for every highway functional class and pavement type in accordance with the LTPP *Distress Identification Manual*, which subcategorizes all cracking distress into severity levels of low, moderate, and high.(93) Condition data also includes a continuous highway image log comprising windshield, left, and right shoulder views of the pavement surface collected every 26 ft. The three views, when aligned properly, form a 120-degree panoramic view of the highway. Pavement surface photos taken every 5 ft, when stitched together, create a complete and continuous image of the data collection lane. From these images, all cracking distress is categorized and catalogued. Details of key pavement condition data collected are presented in table 36.

Table 36. Summary of pavement inventory and condition/distress information contained in PMS data.

Data Item	Description
ID	Unique PMS section identification number.
HWY*	Highway route number (e.g., 070A).
DIR*	Direction.
LENGTH	Section length in miles.
BMP*	Begin MP.
EMP*	End MP.
DATE	Date.
ENGREGION	State 2 DOT engineering region.
SPEED	Post speed limit.
PAVETYPE	Pavement type.
SHLDRT	Shoulder type.
SHLDRW	Shoulder width.
SHLDR_COND	Shoulder condition.
IRI (MEAN, LEFT, RIGHT, STD. DEV.)	Various smoothness (IRI) statistics.
RUT (LEFT, RIGHT, STD. DEV., MAX)	Various rutting statistics.
FAULT (AVERAGE, MAX)	Various transverse joint faulting statistics.
FATIGUE (L, M, H)	Fatigue cracking (low, medium, high severity).
TRANSCOUNT (L, M, H)	Number of transverse cracks (low, medium, high severity).
TRANSLENGTH (L, M, H)	Length of transverse cracks (low, medium, high severity).
LONG (L, M, H)	Length of longitudinal cracks (low, medium, high severity).
CORNER (L, M, H)	Number of corner breaks (low, medium, high severity).
CURVE	Curve or otherwise.
GRADE	Section grade and slope.
LONGITUDE (DD, UTM)	Longitude.
LATITUDE (DD, UTM)	Latitude.
ELEVATION	Elevation.
COLLECT_DATE	Data collection date.

*Key referencing data items.
DD = decimal degree; UTM = universal traverse mercader.

Construction QA Data

State 2 DOT maintains an in-house database, referred to as the QC/QA Master Database, to enter and store HMA QA data. This program contains three modules. The program can store information related to gradation, voids, and densities. The program is designed to generate reports in PDF format. Each report is project specific, identified by a subaccount (SUBAC) number. The program, clearly developed at a time when the practice was to manually produce QA reports, serves as a step up to electronic report generation. This program is not designed to provide access to the data in a "database" format but instead generates reports in a PDF format. However, the data do exist in the program and can be edited or redesigned.

The QA test files, accessed in a PDF format for this project, contain an agency accounting reference number (the SUBAC number) for characterizing project location. A summary of specific data items contained in the QA test files is presented in table 37. Table 38 presents an example of QA data as extracted from the PDF files.

Note that specific stations at which tests were performed are missing. The QC/QA Master Database includes a data field for entering station information, but the project team found that these data were generally missing in most project files.

Table 37. Summary of data items contained in the QA test files (PDF reports).

Data Items	Description
SUBAC*	Subaccount number.
MIX	HMA mix type.
TEST	Test type.
DATE	Test date.
YR	Year of testing.
AC	HMA binder/asphalt content.
DENSITY	HMA density.
VMA	HMA voids in mineral aggregate.
VOIDS	HMA lab air voids.
MAT	Material type/designation.
HWY	Highway/route.
BMP	Begin MP.
EMP	End MP.
Chainage*	Sampling location within project.

*Key referencing data items.

Table 38. Example of data contained in the QA records (PDF reports).

Mix	Date	AC	Density	VMA	Voids	Material
131343	9/17/2002	5.18	93.6	14.8	4.1	Bottom
131343	9/18/2002	5.39	92.8	14.9	4.4	Bottom
131343	9/18/2002	5.29	93.4	15.1	4.7	Bottom
131343	9/19/2002	5.29	93.4	15	4.7	Bottom
131343	9/20/2002	5.42	92.7	14.7	4.1	Bottom
131343	9/20/2002	5.38	92	14.8	4.5	Bottom
131343	9/23/2002	5.33	93.5	15	4.5	Bottom
131343	9/27/2002	5.34	93.4	15.3	4.8	Bottom
131343	10/2/2002	5.24	94	14.9	4.7	Bottom
131343	10/2/2002	5.21	92.6	14.9	4.4	Bottom
131343	10/2/2002	5.25	93.8	15.1	4.6	Bottom
131343	10/3/2002	5.27	92.6	15	4.5	Bottom
131343	10/3/2002	5.27	91.6	14.1	3.5	Bottom
131343	10/9/2002	5.37	93.6	14.5	3.7	Bottom
131343	10/9/2002	5.38	92.1	15.2	4.6	Bottom
131343	10/10/2002	5.26	94.8	15.4	4.8	Bottom
131343	10/10/2002	5.39	93.6	14.7	4	Bottom
131343	10/11/2002	5.42	93.7	14.9	4.3	Bottom
131343	10/11/2002	5.37	92.6	15	4.3	Bottom
131343	10/14/2002	5.33	93.1	14.9	4.2	Bottom

The challenge is to link this information to the PMS data in the absence of location references for each test data point. Information in project inventory database can be used to achieve this outcome.

Pavement Inventory and Construction History

State 2 DOT maintains pavement construction history data and inventory data in a database. The information in this construction history database is derived from construction or maintenance contracts. Each region of State 2 DOT maintains its own inventory databases in regional databases. It is the responsibility of each region to update the information and submit it to State 2 DOT Pavement Management for compilation into a statewide database. The construction history database is composed of four tables, one each for project data and maintenance data and two reference tables. The project table contains information for projects with pavement depth greater than 2 inches. Projects considered as design projects with pavement depth less than 2 inches were also found in this table. The maintenance table contains only maintenance projects with depth less than 2 inches. Two reference tables contain four-letter work-type codes for construction and maintenance activities. State 2 DOT QA testing data reside mostly in project-specific PDF reports generated from State 2 DOT's QA software programs.

The project and maintenance data table each contain construction history and construction, rehabilitation, and maintenance projects throughout the State. The construction history information includes inventory-type data for identifying project location, work type, costs, contractor, and acceptance date, as well as project SUBAC number and the MP limits for each SUBAC number. The State 2 DOT business/contracting office typically assigns a unique SUBAC number to a project. This number is used to track all payments and purchases made for a given project. Payments cover contractor works/labor, equipment hiring/rental, purchases of materials (e.g., HMA, PCC, aggregates), material testing, and characterization.

The contract SUBAC number and the highway, route, direction, and MP limits are the key for linking the dataset with State 2 DOT QA and PMS databases, respectively. A summary of key data items contained in the maintenance data tables is presented in table 39.

Table 39. Summary of key data contained in State 2 construction history database.

Data Items	Description	Comments
SUBAC*	Subaccount number	Links to QA
PROJ_NUM	Project number	—
DIR	Direction of travel	—
DESCRIPTION	Project description	—
HWY*	Highway route number	Link to PMS
BEG_MP*	Begin MP	
END_MP*	End MP	
LENGTH	Section/project length	—
REGION	State 2 DOT engineering region	—
WORK_TYPE	Work type (e.g., new construction, rehabilitation)	—
PAVE_TYPE	Pavement type	Validates with QA
DEPTH	New surface layer depth	
WIDTH	Project width	
PRIME_CONT	Prime contractor name	—
ACCEPT_DATE	Project acceptance date	Validates with QA
ITEM_COST	Cost	—
COST/SQYD/IN	Project costs per square yard/inch	—
TOTAL_COST	Total project cost	—
REJECTED-ADLP	Rejected construction type	Only in maintenance projects
REASON-ADLP	Reason for construction type	
KEY-ADLP	Key construction type	
YEAR-ADLP	Year of construction	

—No data.
*Key referencing data items.

Data Collected from Innovative QA Testing

A key aspect of this research was to assess the feasibility of assembling and reviewing QA-type data from new technologies and then determining their feasibility to be used as a leading indicator of future pavement performance. Two new technologies considered from State 2 DOT were:

- Continuous deflection monitoring device: State 2 DOT selected the RWD device to provide deflection information on a highway in 2008, soon after an overlay construction project on SH AA. The RWD data provide an indirect measure of the structural capacity of asphalt pavements. These data were used by the project team to correlate with field performance. Note that the RWD is not considered a QA tool, but rather a tool to monitor structural capacity. However, because RWD test data were available from a period soon after construction, a measure of the structural condition was treated as data collected at the time of construction.

- Magnetic tomography technology for dowel bar alignment: State 2 DOT developed QC specifications for the use of the MIT-Scan device to assess quality of construction of newly constructed JPCP joints. This device can measure the horizontal shift, the vertical shift, and the diagonal rotation of dowel bars at joints. The project team used data from several projects constructed between 2011 and 2013 in the analyses.

As noted earlier, data obtained from testing are typically reported directly to various contractors (which may be used internally) or to research staff (which may be published in research reports). Data collected from such activities are not included in the State 2 DOT construction history database or QA/QC database. Descriptions of the data obtained are presented in the following sections.

Travel Speed (Network-Level) Deflection Data

The research team obtained from an independent contractor RWD-measured maximum deflection data. The contractor collected test data from a State route and covered approximately 17 mi of pavement. Table 40 presents data samples obtained from the RWD. As shown in table 40, key data items—route ID, direction, and mile marker—were provided with deflection test data and pavement surface temperature. The inventory-type data items were of sufficient detail to enable the research team to link these data to the State 2 DOT PMS, the maintenance data tables of the construction history database, and other QA test data files.

Table 40. Example of deflection data recorded from the RWD device.

Route ID	Direction	Mile Marker	HMA Thickness (inches)	Bells Temperature (°F)	Total Deflection (mils)
SR 100XX	Northbound	1,030.325	4	58.47	14.14
SR 100XX	Northbound	1,030.425	4	58.47	9.59
SR 100XX	Northbound	1,030.525	4	58.47	11.47
SR 100XX	Northbound	1,030.625	4	58.47	18.01
SR 100XX	Northbound	1,030.725	4	58.47	19.21
SR 100XX	Northbound	1,030.825	4	58.47	16.56
SR 100XX	Northbound	1,030.925	4	58.47	16.52
SR 100XX	Northbound	1,031.025	4	58.47	18.28
SR 100XX	Northbound	1,031.125	4	58.47	15.27
SR 100XX	Northbound	1,031.225	4	58.47	15.29
SR 100XX	Northbound	1,031.325	4	58.47	12.67
SR 100XX	Northbound	1,031.425	4	58.47	20.28
SR 100XX	Northbound	1,031.525	4	58.47	17.95
SR 100XX	Northbound	1,031.625	4	58.47	16.73
SR 100XX	Northbound	1,031.725	4	58.47	16.82

MIT-Scan Data

The project team obtained MIT-Scan output data for several new JPCP projects in State 2. The projects were located on four highways: I-BB, US-CC, US-DD, and SR-EE. Information provided from MIT-Scan testing included:

- Station information (construction station).
- Test date.
- Mean dowel depth.
- Maximum vertical misalignment.
- Maximum horizontal misalignment.
- Maximum lateral position error (side shift).

State 2 DOT also provided inventory-type data for characterizing pavement and joint location. Examples of the data provided are presented in table 41, which also highlights the specific joints and bars with shorter dowel depth. The inventory-type data included route ID, station/mile marker, direction, and so on, along with the MIT-Scan test data; these data were easily integrated with State 2 DOT PMS and QA-type data.

Table 41. Example of MIT-Scan data obtained for analysis.

Highway	Joint	Bar Number	X Position (Xs) (inches)	Distance Between Adjacent Bars (Xd) (inches)	Depth (Zs) (inches)	Depth Deviation (dz) (inches)	Side Shift (dy) (inches)	Misalignment (s) (inches)	Horizontal Misalignment (sh) (inches)	Vertical Misalignment (sv) (inches)	Dowel Score	Joint Score
US DD	1	1	5.58	—	2.40*	2.10	−1.29	0.28	−0.28	−0.02	0	0
US DD	1	2	17.96	12.38	2.08*	2.42	−1.44	0.39	0.34	−0.19	0	
US DD	1	3	29.78	11.82	2.56*	1.94	−0.98	0.39	−0.17	−0.35	0	
US DD	1	4	41.67	11.89	2.70*	1.80	−1.22	0.38	−0.12	−0.36	0	
US DD	1	5	55.96	14.29	2.88*	1.62	−1.49	0.18	−0.04	−0.17	0	
US DD	1	6	89.12	33.16	3.48	1.02	−1.45	0.25	−0.06	−0.24	0	
US DD	1	7	101.75	12.64	3.25	1.25	−1.29	0.19	0.00	−0.19	0	
US DD	1	8	115.24	13.49	3.05	1.45	−1.53	0.58	0.55	−0.18	0	
US DD	1	9	125.94	10.70	2.96*	1.54	−1.81	0.21	−0.02	−0.21	0	
US DD	1	10	138.59	12.65	4.11	0.39	−0.94	0.55	−0.24	0.49	0	
US DD	2	1	5.80	—	3.84	0.66	−0.20	0.56	−0.44	−0.34	0	6
US DD	2	2	19.46	13.66	3.06	1.44	−0.94	0.12	−0.06	−0.10	0	
US DD	2	3	30.04	10.58	2.89*	1.61	−1.09	0.35	−0.30	−0.17	0	
US DD	2	4	41.30	11.26	3.04	1.46	−1.33	0.25	−0.13	−0.22	0	
US DD	2	5	55.56	14.26	3.49	1.01	−1.47	0.50	0.16	−0.48	0	
US DD	2	6	86.70	31.14	4.15	0.35	−1.88	1.12	−0.67	−0.90	5	
US DD	2	7	101.99	15.28	3.65	0.85	−0.83	0.45	−0.29	−0.34	0	
US DD	2	8	114.26	12.27	3.86	0.64	0.56	0.27	−0.11	0.24	0	
US DD	2	9	125.57	11.32	3.91	0.59	−1.46	0.38	−0.04	−0.38	0	
US DD	2	10	138.52	12.94	4.77	−0.27	−1.51	0.99	−0.97	−0.17	4	

—No data.
*Joints and bars with shorter dowel depth.

STATE 3 DOT

Pavement Management Data

The State 3 DOT PMS data are stored in a centralized data repository that contains the following:

- Pavement inventory database (traffic, road descriptions): roadway geometry, designation, and traffic. These data are referenced at 0.1-mi intervals.
- Pavement condition database (IRI, rutting, friction, cracking): ride quality, rutting, cracking, and friction condition data. These data also are segmented at 0.1-mi intervals.
- Pavement construction/maintenance history and M&R costs database: records that identify every layer in the pavement structure, including construction, material type, and thickness data. The data are segmented in various lengths based on consistent construction history; intervals typically vary between 0.1 and 2 mi.

The databases are merged and aggregated to provide summary information at the intervals defined in the construction history database to create the State 3 DOT PMS roadway section data required for analysis. A summary of State 3 DOT PMS data tables is presented in table 42.

Table 42. Summary of relevant pavement condition data extracted from State 3 DOT PMS.

Data Item	Description
SECTION ID	Section ID number.
TREATMENT ID	Treatment ID.
GLOBAL ROUTE ID	Route global ID.
SUB ROUTE ID	Subroute ID.
REGION/DISTRICT/COUNTY	Region, engineering district, and county.
ROUTE/RNUM/RSUFF	Route type, number, and suffix.
DIRECTION	Direction of travel.
BMP/EMP	Begin/end MP.
LANE NUMBER	Total number of lanes.
OUTER LANE	Outer lane number.
FUNC CLASS	Highway functional class.
GOVT CONTROL	Government control classification.
PAVEMENT TYPE	Pavement type designation.
TREATMENT THICKNESS	Treatment thickness.
CURRENT TREATMENT THICKNESS	Current treatment thickness.
LAYER NO	Surface layer number.
BIRTH/DEATH YEAR	Treatment placement/replacement year.
YEAR	Treatment replacement year.
AGE	Treatment age.
CONTRACT NUMBER	Treatment contract number.
FMIS	FMIS number.
LAYER DESCRIPTION	Layer description.
MATERIAL BAND SIZE	Material band size.

Data Item	Description
YEAR ORDER	Year material was ordered.
MAT UNIQUE ID	Material type unique ID.
MATERIAL DESCRIPTION	Material description.
TREATMENT	Treatment type description.
LAYER TYPE DESCRIPTION	Surface layer type description.
MATERIAL MIX METHOD DESC	Surface material mix type description.
MATERIAL MIX TYPE DESC	Surface material aggregate designation description.
MATERIAL BINDER	Treatment material binder type.
MATERIAL TRAFFIC LEVEL DESC	Material design traffic-level designation description.
CONSTRUCTION TYPE DESC	Construction type description.
RUT (AVG, CNT, STDEV)	Average rutting, count, standard deviation.
RUT FAMILY	Pavement family designation for forecasting.
FC (DENSITY, CNT, STDEV)	Functional cracking density, count, standard deviation.
FCI (DENSITY, STDEV)	Functional cracking index density, standard deviation.
SC (DENSITY, CNT, STDEV)	Structural cracking density, count, standard deviation.
SCI (DENSITY, STDEV)	Structural cracking index density, standard deviation.
CRACKING FAMILY	Family designation for forecasting structural cracking.
FRICTION	Surface friction.

FMIS = Financial Management Information System.

Construction QA Data

State 3 DOT collected and stored construction QA data in many tables and formats. The key datasets for which QA information were stored in the TestData020216 database (a Microsoft Access database containing several individual datasets with various QA test datasets) are presented as follows:

- BinderData.
- MixDesignAggSourceXXX.
- MixDesignXXX.
- TestDataQA.
- TestDataQC.

See table 43 and table 44 for a summary of data examples included in the datasets listed previously. The information presented in these tables shows that State 3 DOT routinely conducts a wide range of testing as part of pavement construction QA/QC, and a vast amount of detailed information from the QA/QC testing program is available in the various datasets. For example, the detailed and comprehensive data available include AC DSR shear modulus (G^*) origin and

DSR G^* pavement data, AC bending beam rheometer (BBR) temperature 1, BBR stiffness 1, and BBR mean value 1 information, as well as HMA gradation, air voids, VMA, and other data. Information about aggregate sources and coarse aggregate friction properties are also available.

Table 43. Summary of the State 3 DOT TestData020216 data tables.

Binder Data	Daily Sublot Production
• ID. • Material type. • Sample ID number. • Sample date. • Sample record date. • Project serial number. • HMA plant ID. • Contract number. • PG grade. • Supplier. • Tank number. • Lot number. • Mix temperature (minimum/maximum). • Compaction temperature (minimum/maximum). • Rotational viscosity. • DSR temperature, G^*, phase angle for original binder, RTFO, and PAV samples (from SHA and supplier). • BBR (temperature, stiffness). • MSCR. • Direct tension (temperature, strength, strain). • Critical crack temperature. • Project detail. • Sample taken from (truck number, truck tag number). • Viscosity test (SHA, supplier).	• Project ID. • Activity. • JMFID. • Plant. • Mix trim. • Mix method. • Sequence. • Year. • Quarter. • Month. • Date. • Lot. • Sublot. • Begin time. • End time. • Actual production.

MSCR = multiple stress creep recovery; PAV = pressure aging vessel; JMFID = job mix formula ID.

Table 44. Summary of the State 3 DOT TestData020216 data tables.

Mix Design Aggregate Source XXX	Mix Design XXX	Test Data QA/QC
1. Plant 2. PRODUCT ID 3. PRODUCT NUMBER 4. Source 5. Location 6. COMP_PRODUCT ID 7. Size 8. PERCENTAGE 9. Mat Type ID 10. Mat Type 11. Plant Reference	12. PRODUCT ID 13. PLANT Reference 14. Mix Method 15. Mix Type 16. Band 17. Gradation (2-in through No. 200 sieve sizes) 18. AC Producer 19. AC Type 20. AC Percent 21. Coarse Aggregate Angularity 22. Fine Aggregate Angularity 23. Gmb 24. Gmm 25. VA 26. VMA 27. VFA 28. Gse 29. Gsb 30. Mix Method, Temp, Type 31. Region 32. Sand Equivalent 33. TSR 34. Material Traffic Level 35. Initial Traffic	36. Project ID 37. Activity 38. JMFID 39. Mix Trim 40. Mix Method 41. Sequence 42. Year 43. Quarter 44. Month 45. Test Date 46. Lot 47. Sublot 48. Gradation (2-inch through No. 200 sieve sizes) 49. Core Density 50. Core Thickness 51. Dust-to-Asphalt 52. Gmb (Core) 53. Gmb (Gyro) 54. Gmb (meas.) 55. Gmm 56. Gmm (core) 57. Nuclear Density 58. Pb (percent) Ignition 59. VFA 60. VMA 61. VTM

Comp = compliance; Gse = effective aggregate specific gravity; TSR = tensile strength ratio; VTM = voids in total mix.

STATE 4 DOT

Data from State 4 were used only for a project-level case study on combining IC and QA data. State 4 is one of the agencies strongly adopting IC in construction and had major ongoing construction projects during the current research study. IC is being implemented by most States to capture a digital record of compaction coverage and the number of roller passes for each lift or layer of the pavement. Therefore, the agency can record the compaction history for the entire pavement, layer by layer and lift by lift. The IC vibratory rollers, which are equipped with accelerometers mounted on the axle of the drums, also have survey grade GPS tracking, IR temperature sensors, and on-board display of the construction area with IC measurements in color-coded maps. Typical IC measurements include CMV, number of roller passes, asphalt surface temperatures, and roller settings (vibration frequencies, amplitudes, and speeds). Several studies have been performed to authenticate the validity of IC measurements and to determine their use for pavement construction QA. A decision has not yet been made on this issue as outcomes of such studies to date have been less encouraging about the ability to correlate density and IC outputs.

Construction QA Data and IC Data

The project team used State 4 DOT data to evaluate the ability to spatially map IC output records with traditional QA data and to also investigate the potential for correlation between these two datasets. A wide range of data were assembled and integrated for analysis. The project team collected IC data from three construction projects on three roadways that will be referred to as US-KK, I-LLL, and I-MM. QA data collected at the time of construction, including field density and lab aggregate, binder, and HMA test data, were also obtained. A summary of the data assembled are presented in table 45 and table 46 for IC and field QA data, respectively.

Table 45. Description of IC data from State 4.

Number	Variable	Description
1	Time	Data collection time/date.
2	CellN_FT	Northing coordinates (ft).
3	CellE_FT	Easting coordinates (ft).
4	Elevation_FT	Elevation (ft).
5	PassNumber	Roller pass number.
6	LastRadioLtncy	—
7	DesignName	Project name.
8	Machine	Roller equipment manufacturer.
9	Speed_mph	Roller speed.
10	LastGPSMode	—
11	GPSAccTol_FT	—
12	TargPassCount	Target number of passes to achieve adequate compaction.
13	ValidPos	—
14	Lift	HMA lift number.
15	LastCMV	Last CMV value.
16	TargCMV	Target CMV value.
17	LastMDP	Last MDP value.
18	TargMDP	Target MDP value.
19	LastRMV	Last RMV value.
20	LastFreq_Hz	Roller vibratory frequency.
21	LastAmp_mm	Roller amplitude.
22	TargThickness_FT	Target HMA lift thickness.
23	MachineGear	—
24	VibeState	Roller vibratory state (on/off).
25	LastTemp_F	HMA placement (in situ) temperature.

—No data.
MDP = machine drive power; RMV = resonant meter value.

Table 46. Summary of field HMA test data from State 4.

Number	Variable	Description
1	Project	Project name
2	Description	Project description
3	ID	Test ID
4	Northing	Northing coordinates (ft)
5	Easting	Easting coordinates (ft)
6	Test type	HMA field cores density measurements
7	Value	Field density values
8	Date	Test date

DATA REVIEW AND ASSEMBLY

State 1 DOT

State 1 DOT PMS and QA/QC Test Data Collection and Assembly

The project team obtained from State 1 DOT several PMS data tables containing performance, rutting, and cracking data. The data tables STATE 1DOT_PERF_DATA, STATE1_RUTTING, and STATE1_CRACKING were assembled using data retrieved from State 1 DOT PMS. Data retrieval was facilitated by State 1 DOT-developed codes and queries. These data tables were received in Microsoft Excel format. All three data tables contained inventory-, traffic-, and performance-type data items. Inventory-type data items included unique PMS section identifiers (e.g., UNIQUEKEY and MPDIRID) as well as pavement location information defined by the PMS sections route type, route number, route suffix, highway direction, MP, and region. These tables included other data items such as pavement surface type and traffic. The three PMS data tables collectively contained several performance measures as well as the year in which condition data were collected. Performance data items reported in the three tables include the following:

- Load-related cracking/distress.
- Nonload-related cracking.
- Patching.
- Flushing.
- Raveling.
- Spalling.
- Potholes.
- Rutting.
- Ride.

From State 1 DOT, the project team obtained three data tables, in Microsoft Excel format, containing QA/QC type data items: dense graded asphaltic concrete, soil aggregate tabulation (aggregate base), and soil aggregate tabulation (subgrade). The State 1 DOT QA/QC data tables contained referencing-type information such as Transportation Accounting System (TRACS) number and Federal project number, code for material type, lot/sublot number, and material properties such as gradation, air voids, and VMA. For HMA materials, sampling of material for testing was done at the plant or in the field. When State 1 DOT completed testing, the results were included in the State 1 DOT QA/QC data tables, along with information about the test sample location, time of testing, testing lab, and other data. See table 47 for summaries of the data items contained in the State 1 DOT QA/QC test data tables.

Table 47. Summaries of the data items contained in the State 1 DOT QA/QC test data tables.

Dense Graded Asphaltic Concrete	Soil Aggregate Tabulation (Aggregate Base)	Soil Aggregate Tabulation (Subgrade)
• TRACS # • FEDERAL PROJECT # • MATTYPE • LOT • LOT_NUM • LOC DESC • LOT DATE • LOT_YR • VFA • IN PLACE AIR VOIDS • GRADATION • AC BINDER CONTENT • HMA BULK DENSITY • HMA RICE DENSITY • LAB HMA AIR VOIDS • HMA VMA • HMA VFA • HMA EFFECTIVE AGGREGATE SPECIFIC GRAVITY	• TRACS # • MAT CODE • MAT TYPE • LOT OR SUFFIX • SAMPLE DATE/TIME • SAMPLE LOCATION • LIFT NUMBER • ROADWAY ID • FED PROJECT NUMBER • GRADATION • ATTERBERG LIMITS • OPTIMUM MOISTURE CONTENT • MAX. DRY DENSITY • COARSE ABSORPTION • COARSE SPECIFIC GRAVITY • SAND EQUIVALENT • MOISTURE CONTENT	• TRACS # • MAT_TYPE • MAT_CODE • LOT_OR_SUFFIX • SAMPLE_NUMBER • SAMPLE_LOCATION • LIFT_NUMBER • ROADWAY_ID • SAMPLE_STATION • SAMPLE_OFFSET • ORIGINAL_SOURCE • FED_PROJECT_NUMBER • SAMPLE_DATETIME

A review of the data available in the Dense Graded Asphaltic Concrete data table showed that it contained 1,731 records (table 48). The records were from projects located throughout the State, with records per county ranging from 21 to 309. The review also revealed that the most common HMA mix types were M 34 (surface mix) and M BM (base material).

Table 48. Summary of number of AC material test results for State 1 counties in the DENSE_GRADED_ASPHALTIC_CONCRETE data table.

AC Mix Type	Counties										
	1	2	3	4	5	6	7	8	9	10	11
M 12	—	—	—	—	—	—	—	11	—	—	—
M 12K	—	20	—	—	—	—	—	—	—	—	—
M 34	—	25	—	45	278	16		255	19	239	81
M 34A	—	—	—	—	5	—	—	—	—	—	—
M 34F	70	—	—	—	—	20	—	—	—	—	—
M 34K	41	38	14	—	26	14	21	—	—	34	45
M 34KA	—	15	13	—	—	—	—	—	—	—	—
M 34KB	—	—	15	—	—	—	—	—	—	—	—
M BM	—	46	59	—	—	43	—	103	83	—	9
M RD	—	—	28	—	—	—	—	—	—	—	—
Total	111	144	129	45	309	93	21	369	102	273	135

—No data.

The STATE 1 DOT Soil Aggregate Tabulation (Aggregate Base) QA/QC dataset contained 18,034 records. None of the individual QA/QC test data items in the dataset reported data for all 18,034 records. The amount of data available for each data item ranged from 0.1 to 99.5 percent. In general, gradation data (i.e., for sieve sizes 1-inch through No. 200) were available for most of the records; Atterberg limits, maximum dry density, and so on, were available for approximately 10 percent of records. For the inventory-type data items such as TRACS_NUMBER, MAT CODE/TYPE, and SAMPLE DATE/TIME, information was available for all 18,034 records. See table 49 for a detailed summary of data availability in the table Soil Aggregate Tabulation (Aggregate Base).

Table 49. Summary of number of base/subbase aggregate material test results in the Soil Aggregate Tabulation (Aggregate Base) data table.

Test Property	Number of Records	Total Records (Percent)
TRACS number	18,034	100.0
Material code	18,034	100.0
Material type	18,034	100.0
Lot or suffix	2,682	14.9
Sample date/time	18,034	100.0
Sample location	17,942	99.5
Lift number	8,619	47.8
Roadway ID	13,564	75.2
Federal project number	16,726	92.7
Percent passing No. 4 sieve	17,147	95.1
Percent passing No. 40 sieve	17,052	94.6
Percent passing No. 200 sieve	17,057	94.6
Liquid limit	819	4.5
Plastic limit	888	4.9
Optimum moisture content	1,700	9.4
Maximum dry density	1,700	9.4
Coarse absorption	1,543	8.6
Coarse specific gravity	1,543	8.6
Sand equivalent	13	0.1
Moisture content	2,702	15.0

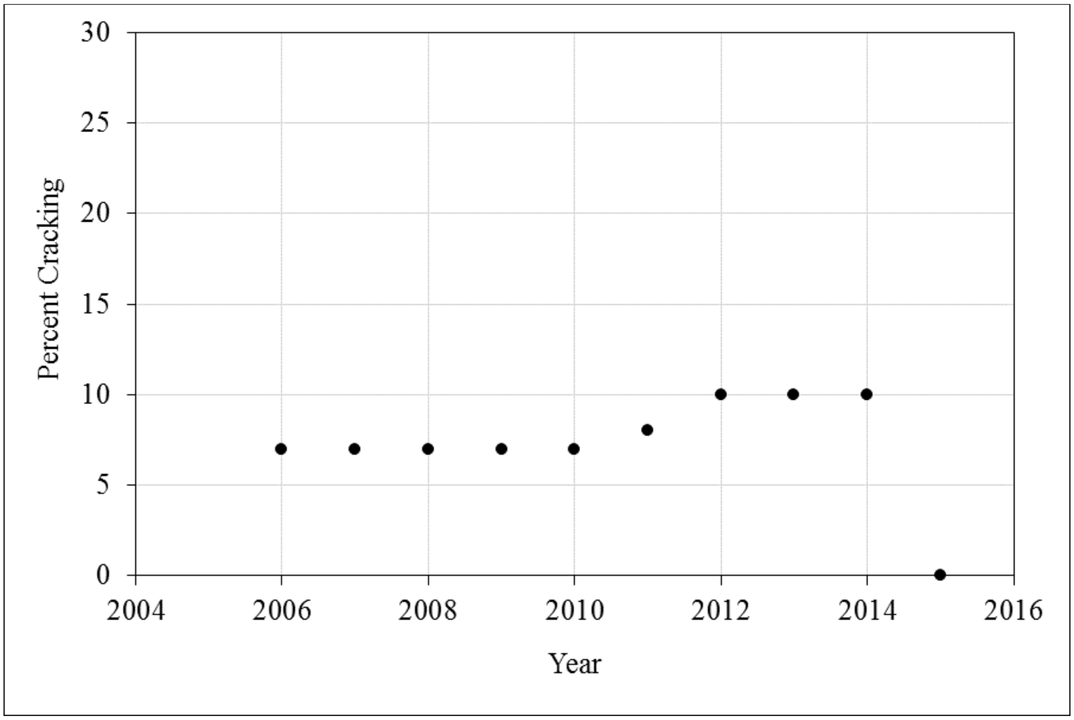
The State 1 DOT Soil Aggregate Tabulation (Subgrade) QA/QC dataset contained 9,684 records. The combination of TRACS number and Federal project number data items provided information for referencing the records in the data table. Inventory-type information was available for most records (more than 95 percent in general). Availability of QA/QC test data ranged from approximately 20 to 90 percent (e.g., gradation-type data availability was approximately 90 percent, whereas availability of Atterberg limits and density was closer to 20 percent). Note that several test data were reported for a given project (defined by the combination of TRACS number and Federal project number). See table 50 for a detailed summary of data availability in table Soil Aggregate Tabulation (Subgrade).

Table 50. Summary of number of subgrade QA test results in the Soil Aggregate Tabulation (Subgrade) data table.

Inventory Data Items	Records Available	All Records with Data (Percent)
TRACS number	9,683	100.0
Mat_Code	9,682	100.0
Lot_or_Suffix	581	6.0
Sample_Number	9,682	100.0
Sample_Location	9,564	98.8
Lift_Number	2,575	26.6
Roadway_ID	8,479	87.6
Sample_Station	8,829	91.2
Sample_Offset	8,488	87.7
Original_Source	9,163	94.6
Fed_Project_Number	8,921	92.1
Sample_Datetime	9,682	100.0

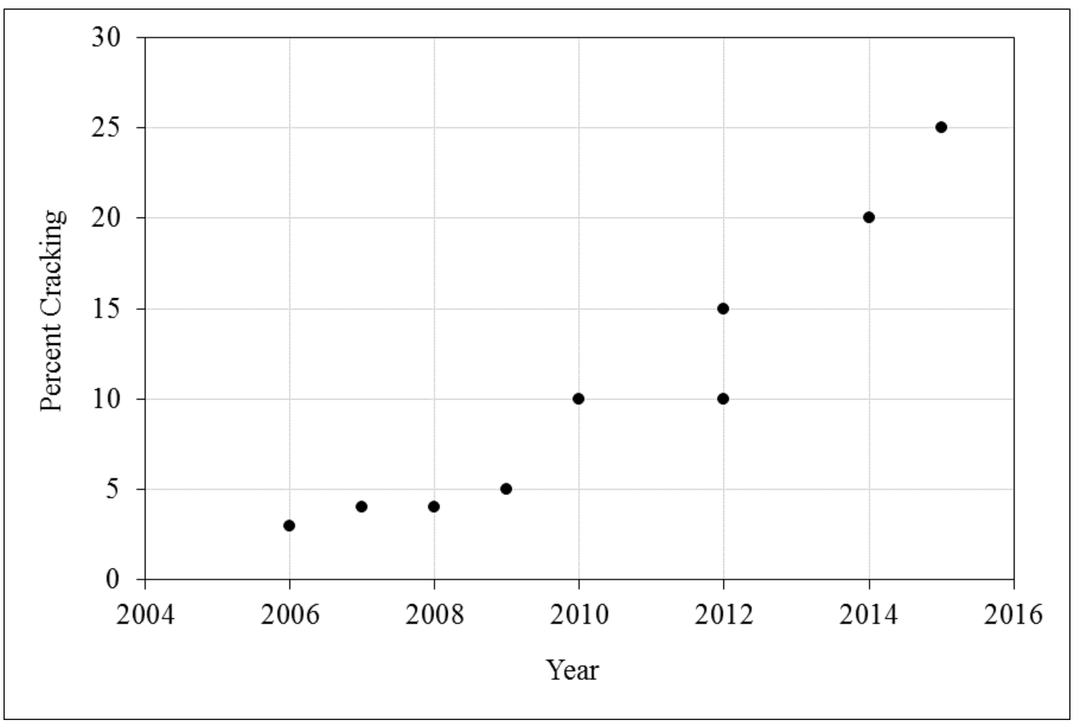
State 1 DOT PMS and QA/QC Test Data Review

The project team reviewed the assembled PMS and QA/QC data to assess accuracy and reasonableness. Data accuracy was assessed by developing plots of trends in performance measures (e.g., IRI versus data collection date) and histograms showing the distribution of QA/QC test data. See figure 45 through figure 48 for examples of plots of measured cracking and rutting versus data collection year for various State 1 DOT PMS sections. Note that rutting is reported for up to 10 offsets at a reference MP. The plots were generated for selected PMS sections and reviewed for reasonableness. Reasonableness was determined by assessing whether observed trends were as expected (e.g., increasing with time) and whether significant shifts in trends could be explained by construction/maintenance activity. The pavement construction history information was derived from State 1 DOT QA test data tables. The extent/amount of variability in measured data was also reviewed. For rutting, considerable amounts of variability were reported within PMS sections, as expected. Thus, the rutting and cracking data were found to be reasonable.



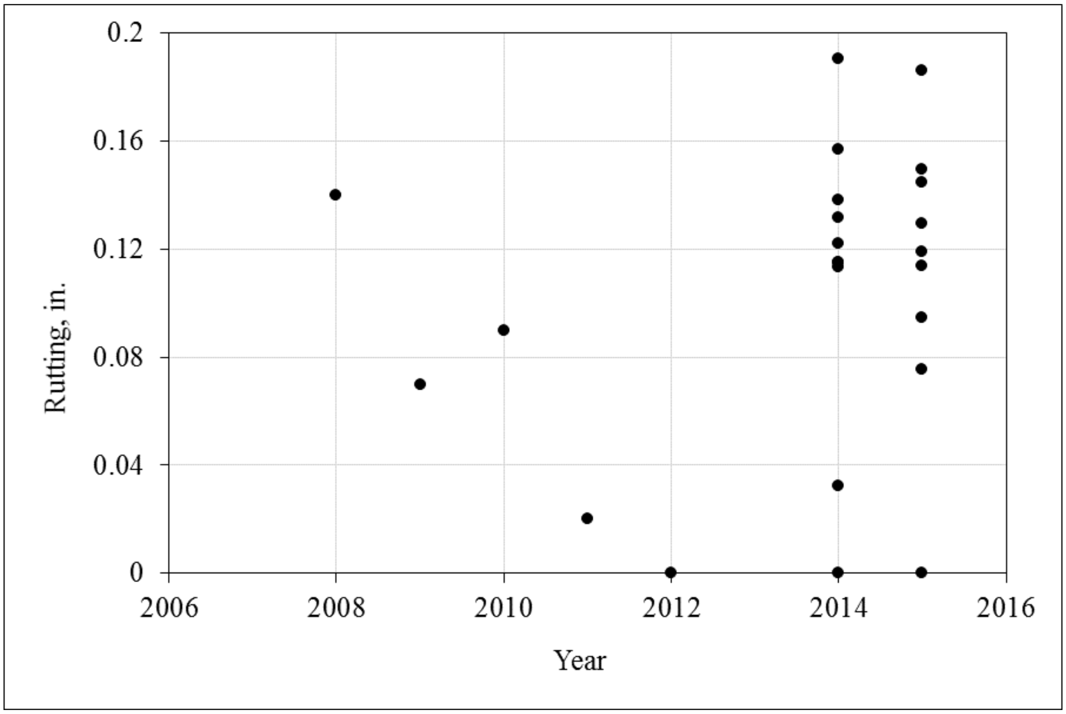
Source: FHWA.

Figure 45. Graph. Cracking in State 1 PMS section U-FF Northbound MP 42.



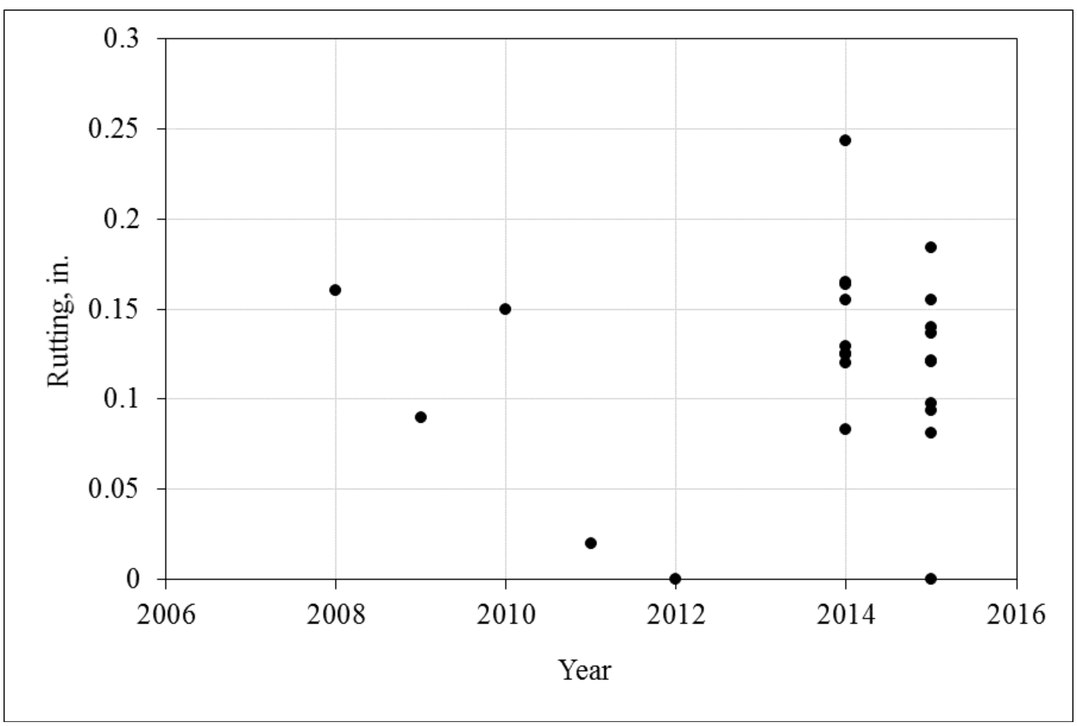
Source: FHWA.

Figure 46. Graph. Cracking in State 1 PMS section I-GG Eastbound MP 23.



Source: FHWA.

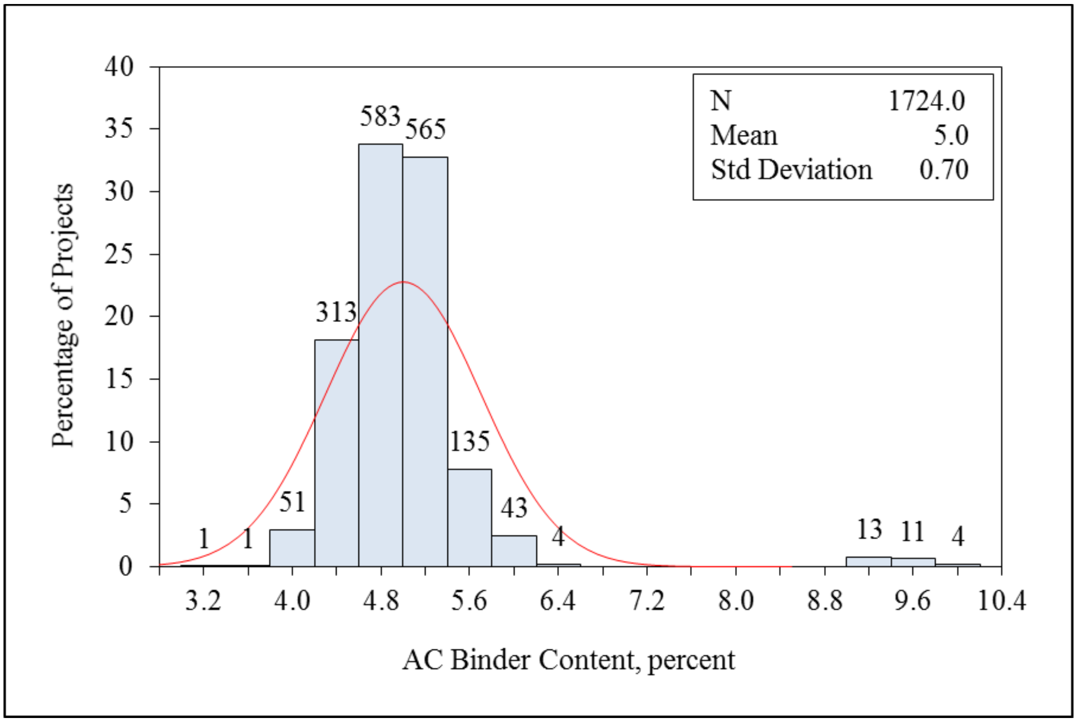
Figure 47. Graph. Rutting in State 1 PMS section I-HH Westbound MP 197.



Source: FHWA.

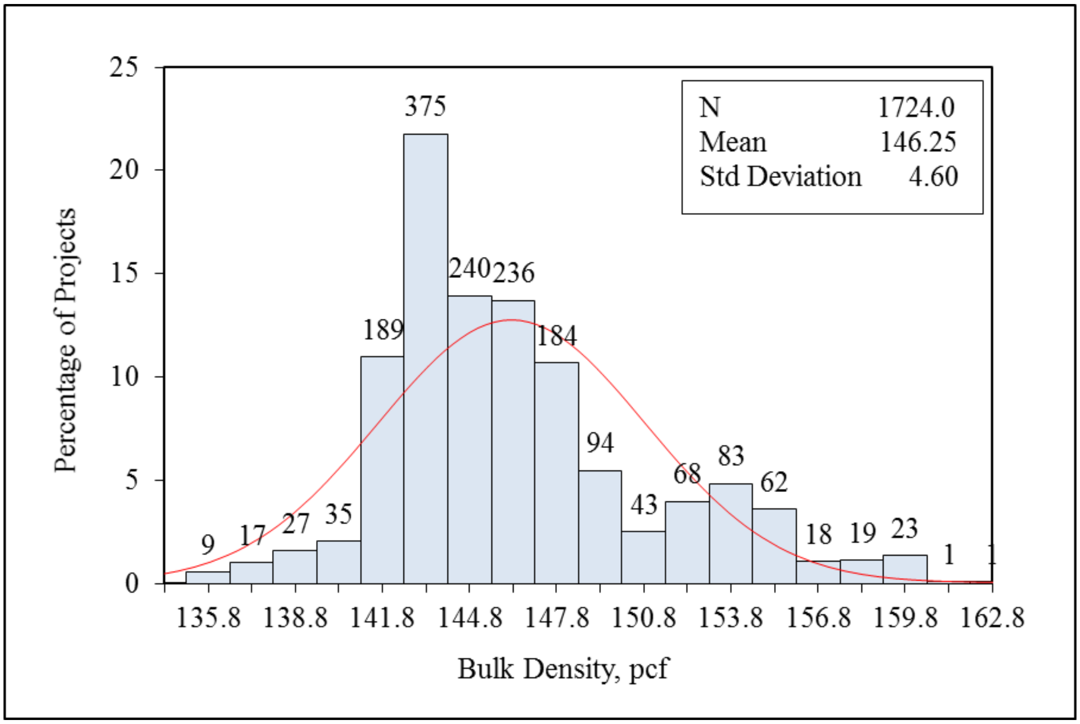
Figure 48. Graph. Rutting in State 1 PMS section I-GG Eastbound MP 37.

Figure 49 through figure 59 present distributions of HMA materials QA/QC test data items used to characterize key HMA material properties. Data presented in figure 49 through figure 59 showed significant range in key HMA mix properties (not for all mix types). Specifically, for all HMA mix types, asphalt binder content ranged from 3 to 6.5 percent (noting a few outliers greater than 9 percent), HMA bulk density ranged from 135 to 160 pcf, and field-measured in-place HMA air voids ranged from 4 to 11 percent. Although the wide range in test values can partly be attributed to the plots representing all the commonly applied HMA mix types in State 1, the considerable range reported in HMA QA/QC test properties implies considerable variability or differences in key HMA properties that are known to impact performance. These properties include air voids, gradation, and dynamic modulus.



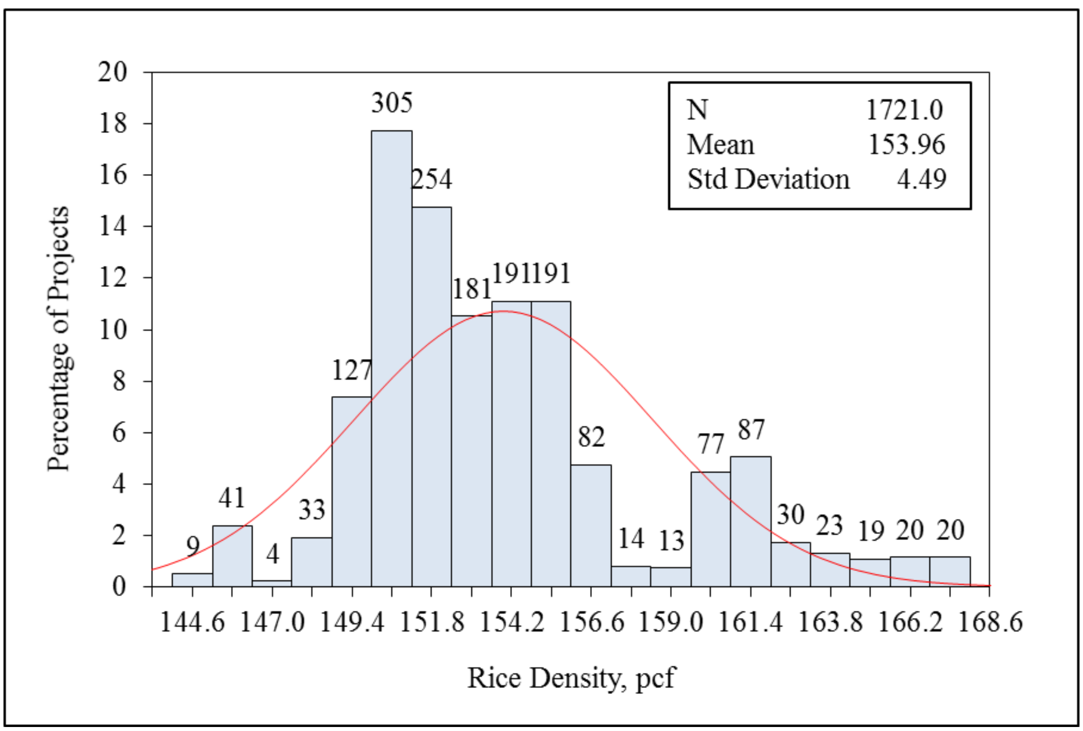
Source: FHWA.

Figure 49. Graph. Histogram showing distribution of AC mix binder content in State 1.



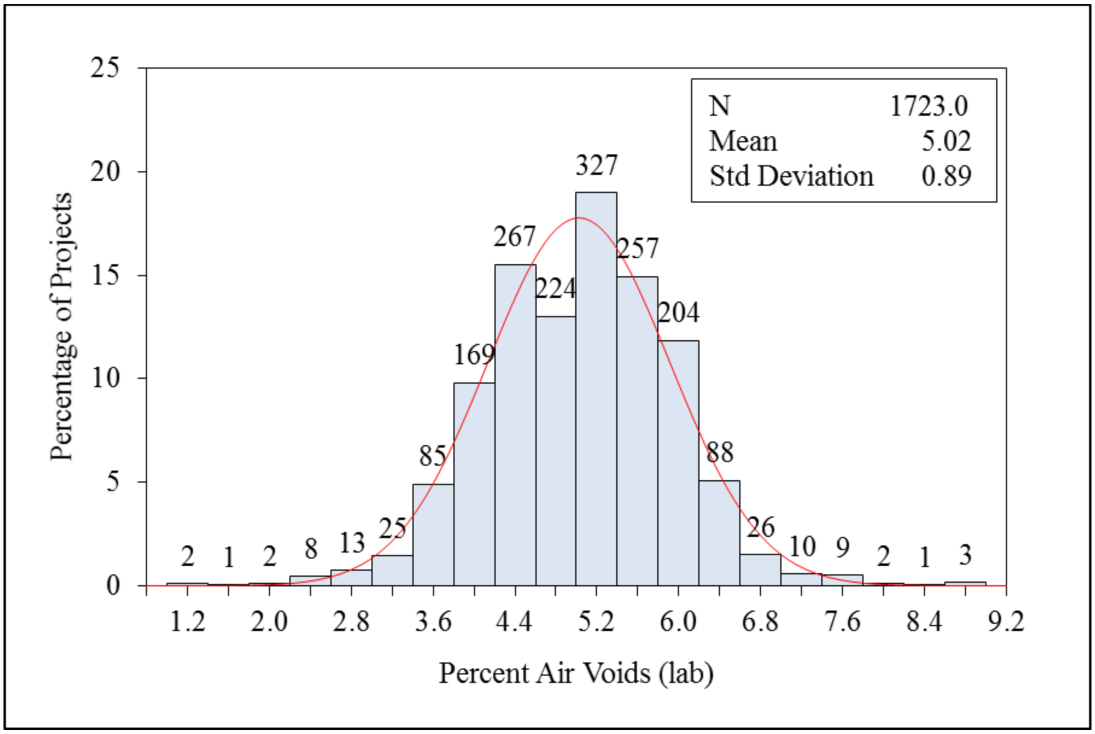
Source: FHWA.

Figure 50. Graph. Histogram showing distribution of AC mix bulk density in State 1.



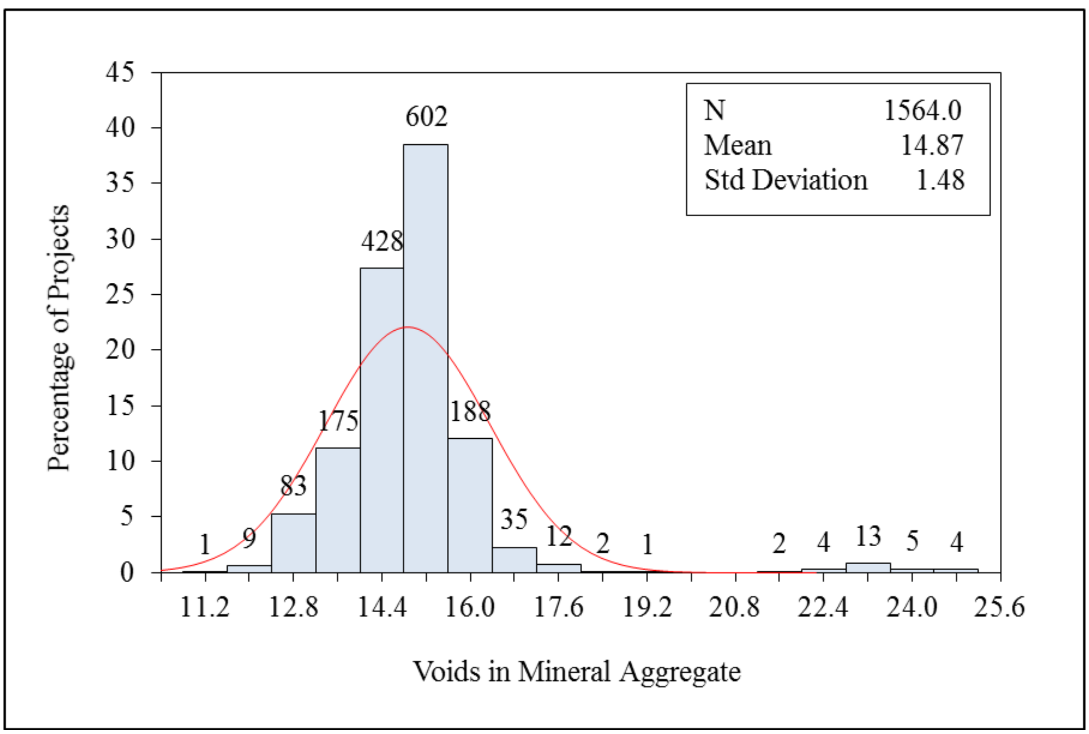
Source: FHWA.

Figure 51. Graph. Histogram showing distribution of AC mix rice density in State 1.



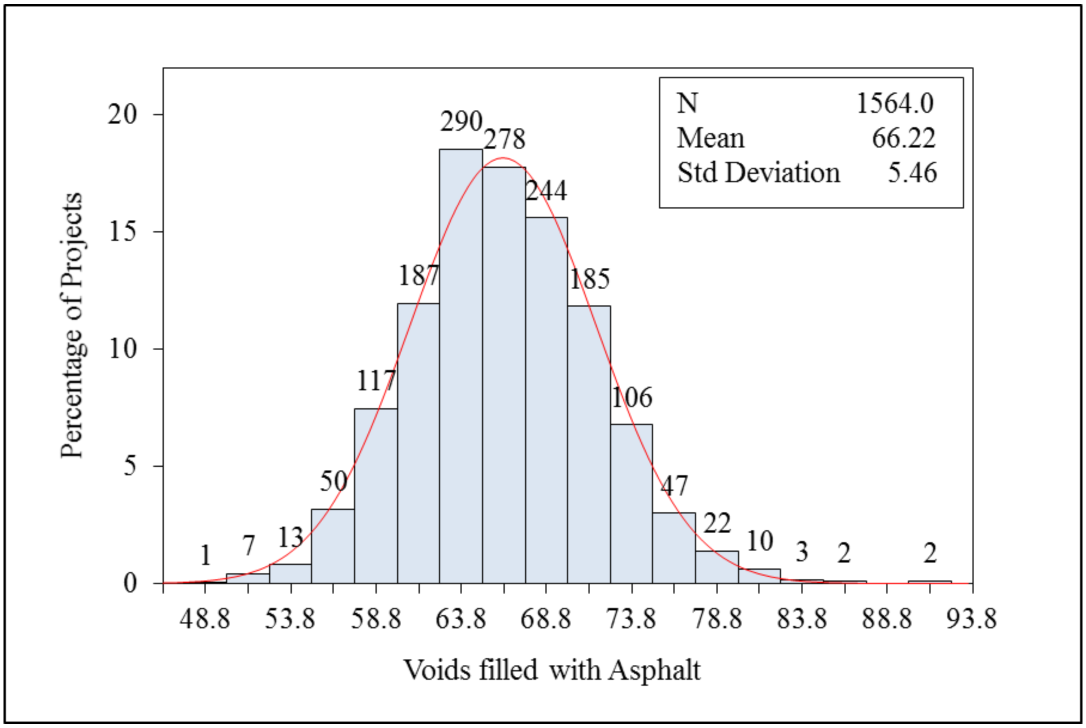
Source: FHWA.

Figure 52. Graph. Histogram showing distribution of AC mix lab tested percent air voids in State 1.



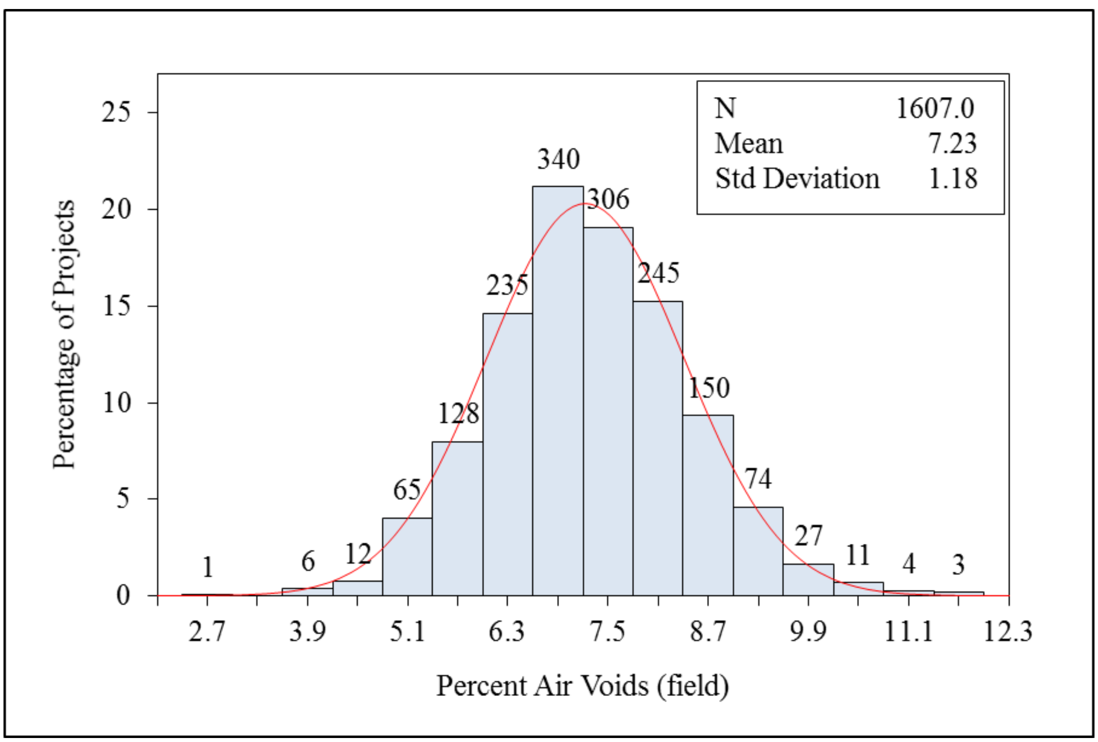
Source: FHWA.

Figure 53. Graph. Histogram showing distribution of AC mix VMA in State 1.



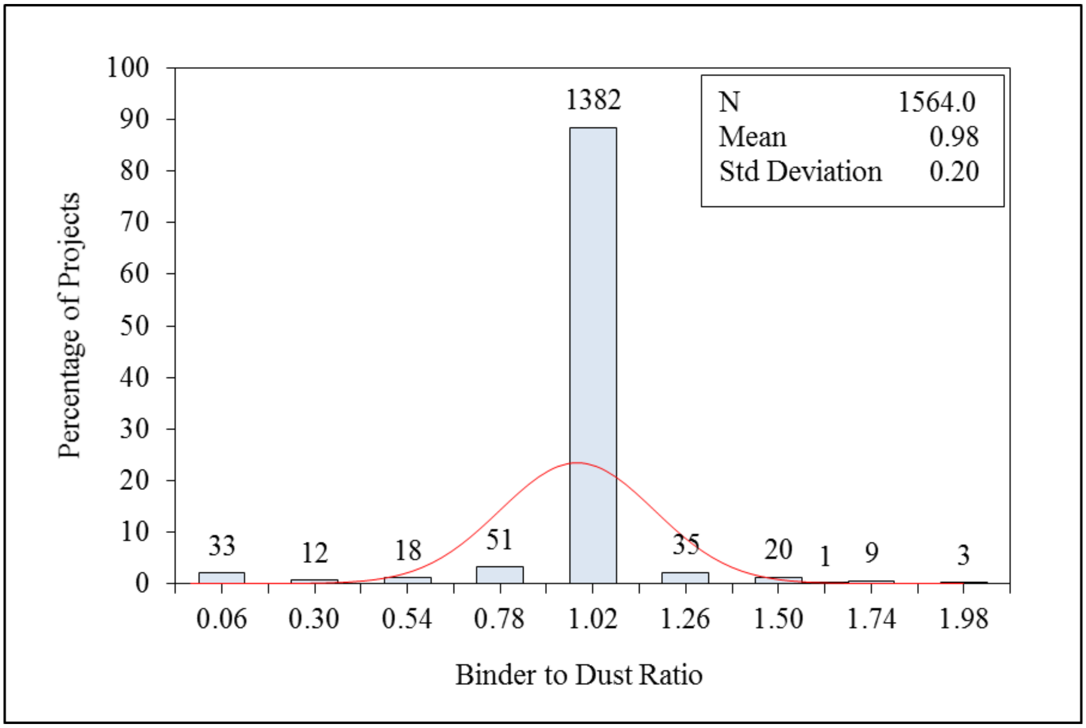
Source: FHWA.

Figure 54. Graph. Histogram showing distribution of AC mix VFA in State 1.



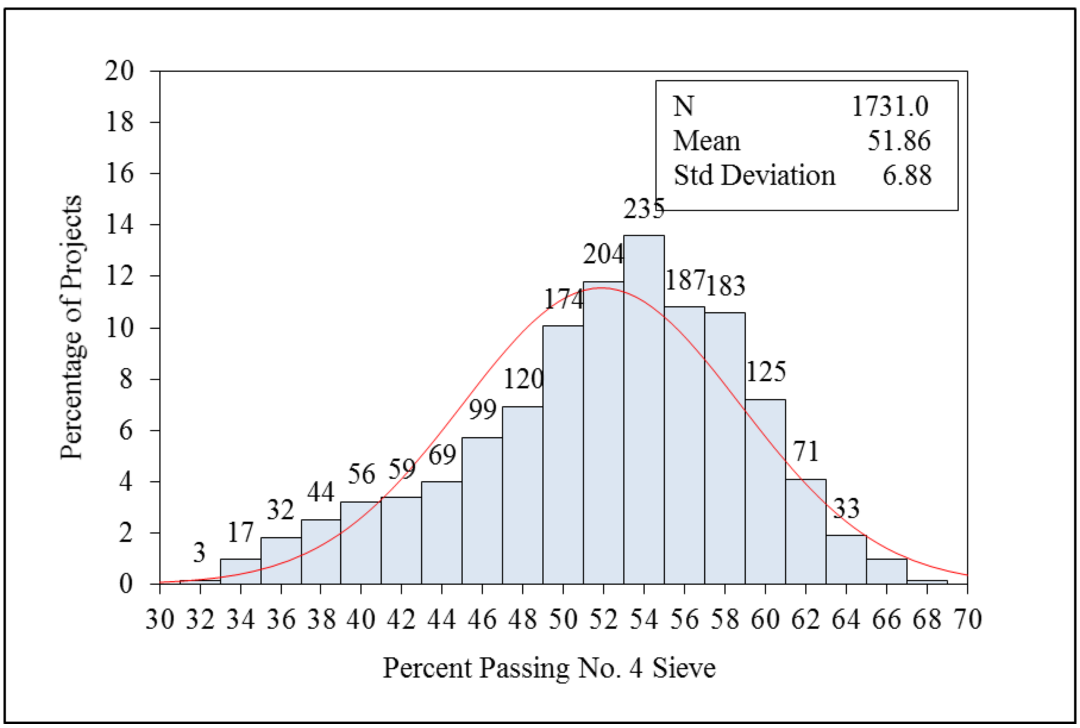
Source: FHWA.

Figure 55. Graph. Histogram showing distribution of AC mix in-place air voids in State 1.



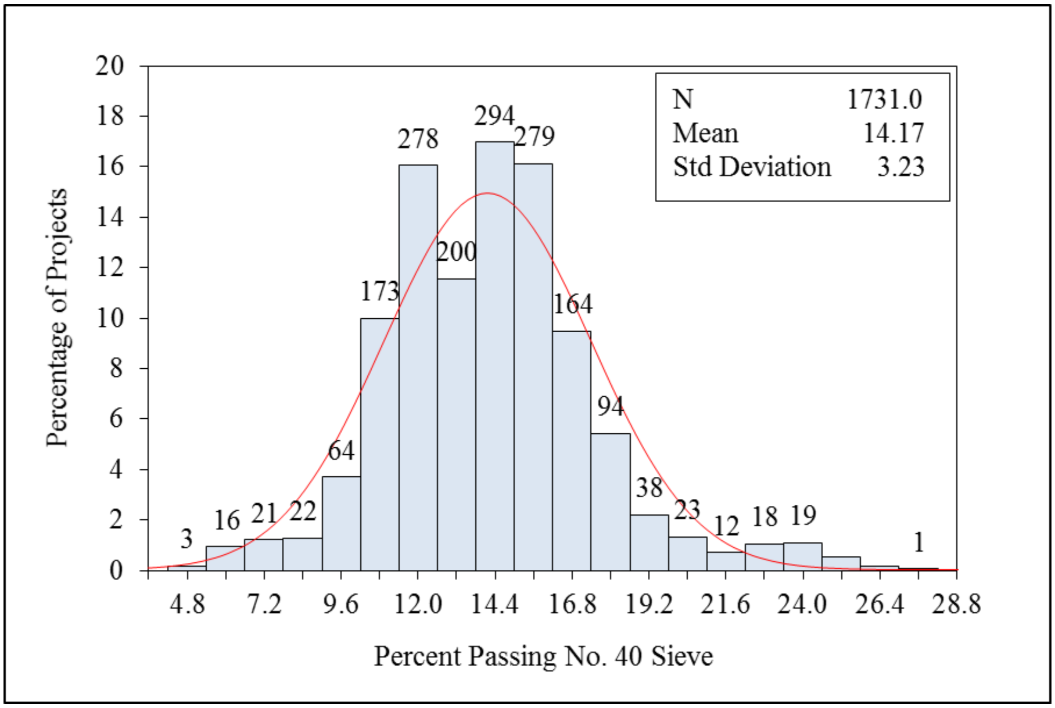
Source: FHWA.

Figure 56. Graph. Histogram showing distribution of AC mix binder-to-dust ratio in State 1.



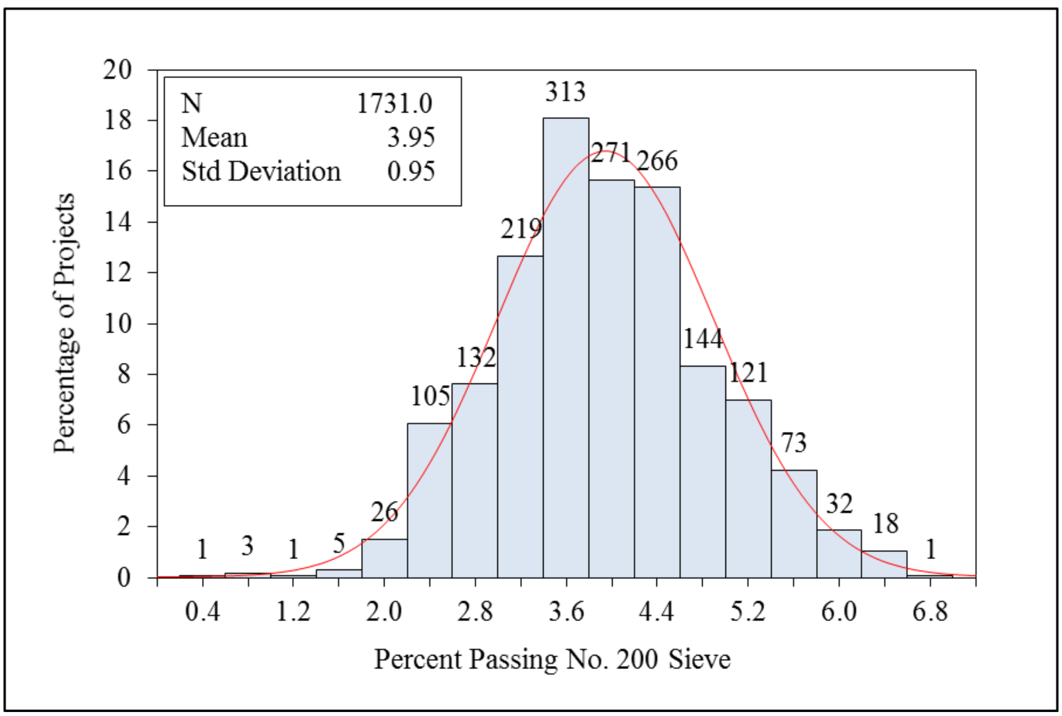
Source: FHWA.

Figure 57. Graph. Histogram showing distribution of AC mix percent passing No. 4 sieve in State 1.



Source: FHWA.

Figure 58. Graph. Histogram showing distribution of AC mix percent passing No. 40 sieve in State 1.



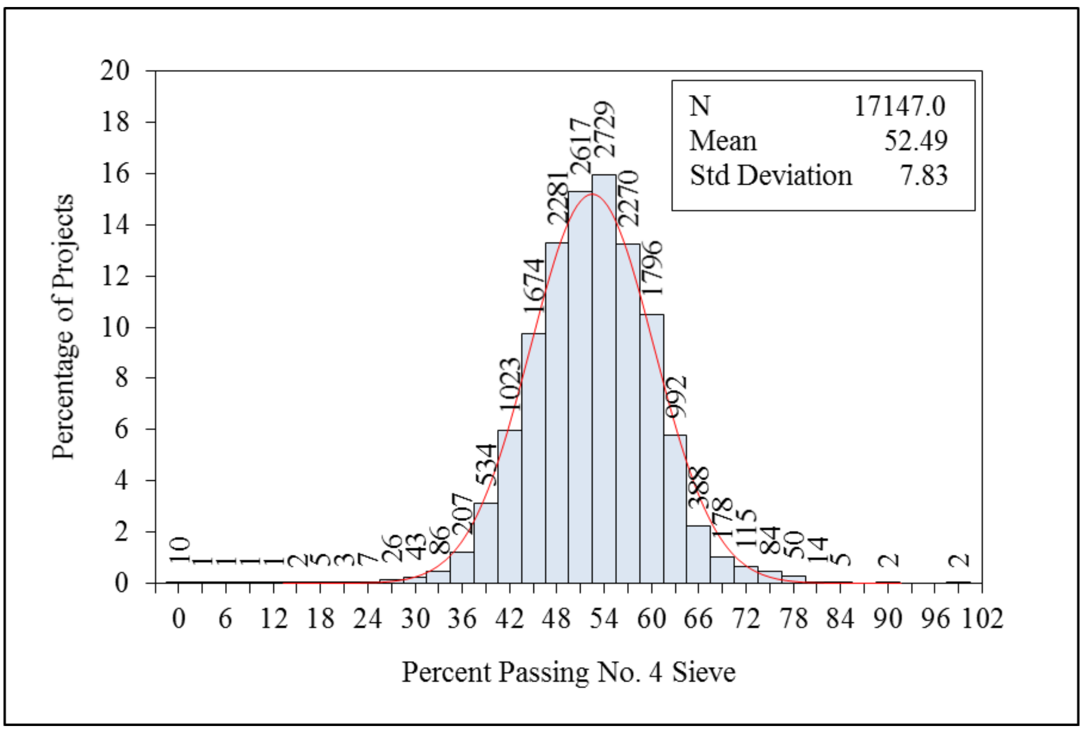
Source: FHWA.

Figure 59. Graph. Histogram showing distribution of AC mix percent passing No. 200 sieve in State 1.

Figure 60 through figure 66 present distributions of key aggregate base QA/QC test data used for characterizing aggregate base materials properties. Information in figure 60 through figure 66 indicates significant variations in aggregate base materials properties across projects. The amount passing the No. 4 sieve ranged from 24 to 78 percent, while the amount passing the No. 40 sieve size ranged from 6 to 42 percent. The amount passing the No. 200 sieve ranged from 0 to 12 percent.

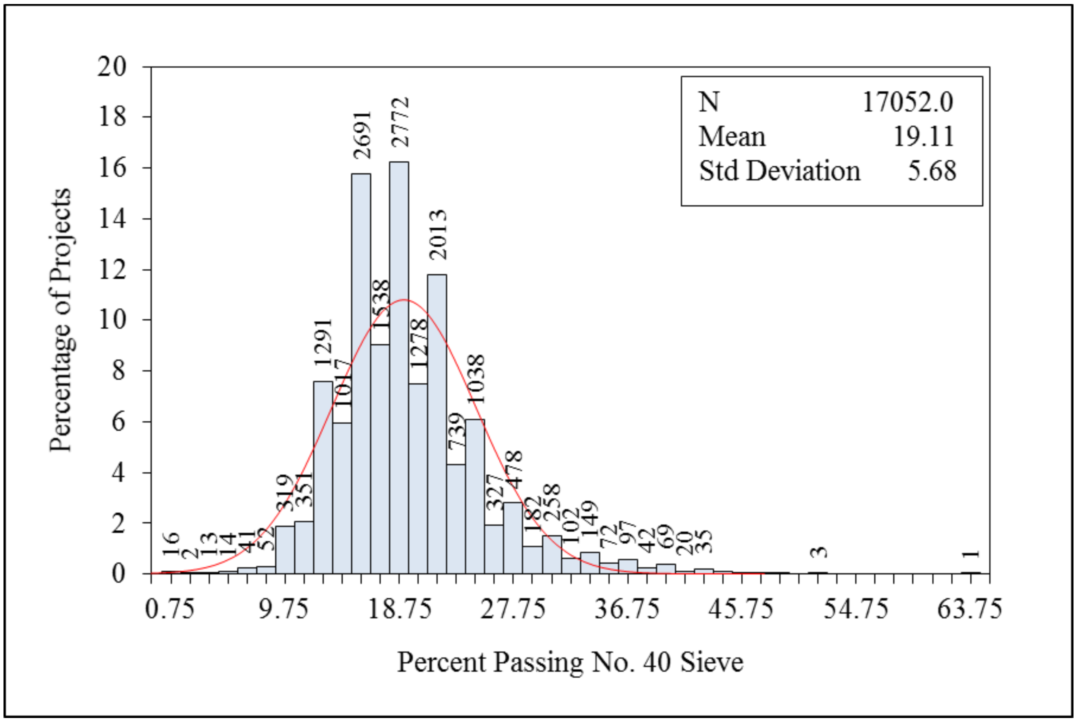
The project team used the gradation data available to estimate D_{60} (grain diameter at 60 percent finer), which was used to compute California bearing ratio (CBR) and resilient modulus (M_r). As gradation (D_{60}) is highly correlated to aggregate base CBR and M_r and impacts aggregate material sensitivity to moisture, significant variations within a project could lead to significant differences in project future performance. See figure 64 through figure 66 to view distributions of estimates of D_{60}, CBR, and M_r. The ranges for these computed parameters for aggregate base materials were found to be reasonable, except for a few outliers.

Figure 60 through figure 66 show that State 1 DOT aggregate base QA/QC data were of sufficient detail to estimate aggregate base M_r or CBR or determine the AASHTO soil class of the materials—basically level 3 aggregate material strength inputs for the AASHTOWare Pavement ME Design.



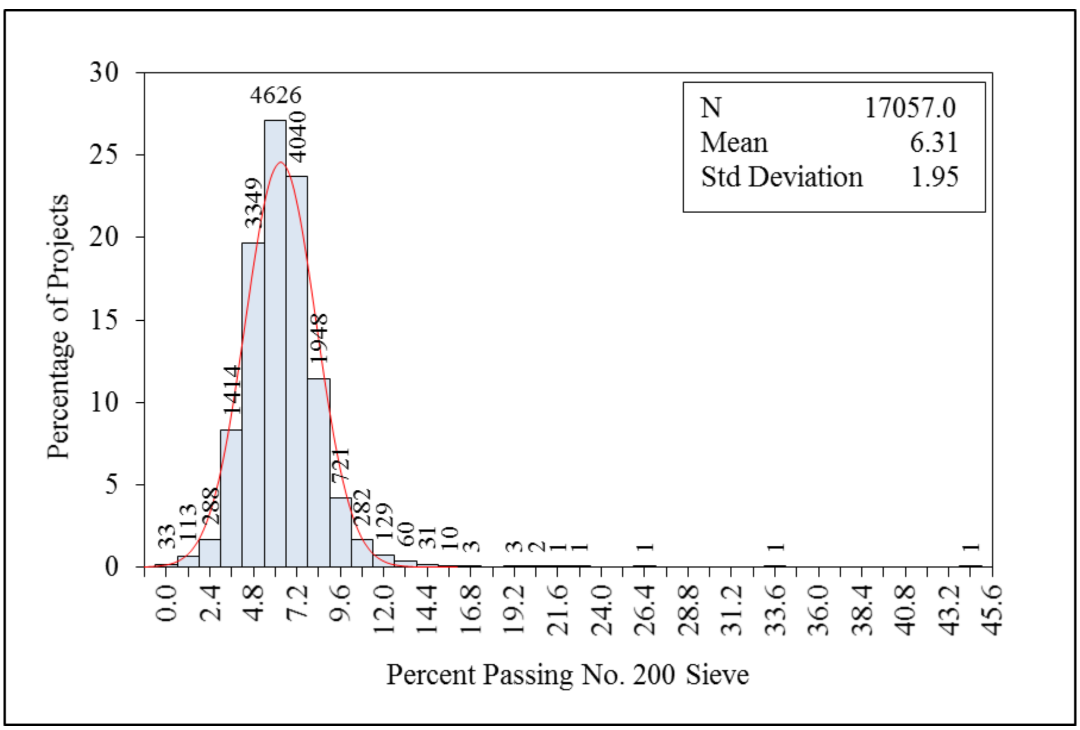
Source: FHWA.

Figure 60. Graph. Histogram showing distribution of aggregate base percent passing No. 4 sieve in State 1.



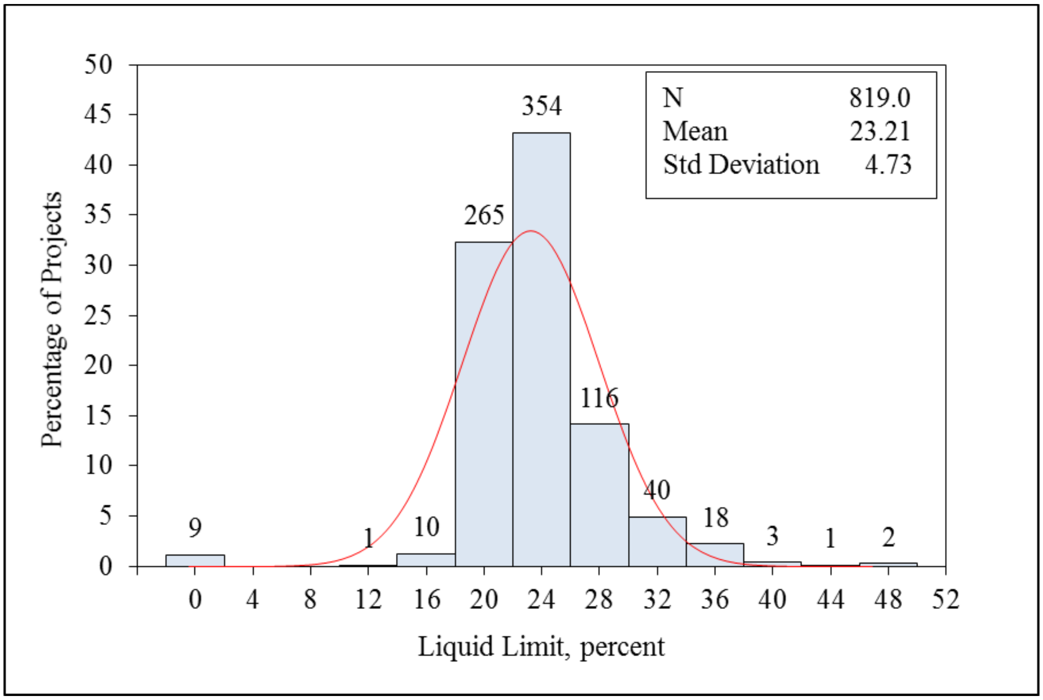
Source: FHWA.

Figure 61. Graph. Histogram showing distribution of aggregate base percent passing No. 40 sieve in State 1.



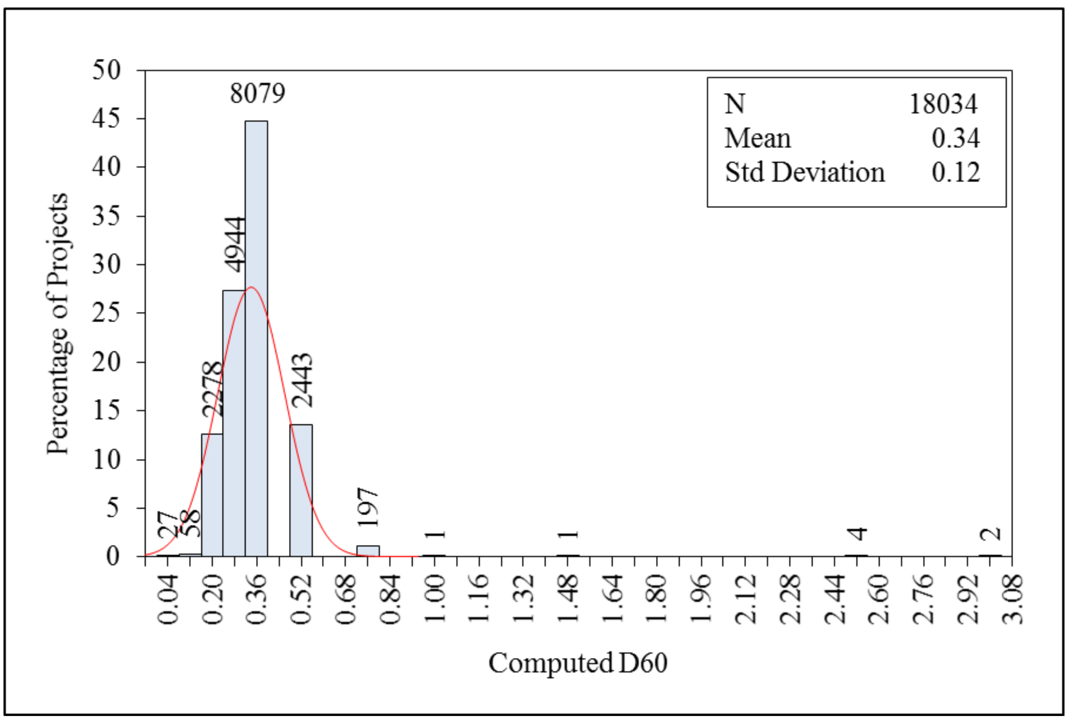
Source: FHWA.

Figure 62. Graph. Histogram showing distribution of aggregate base percent passing No. 200 sieve in State 1.



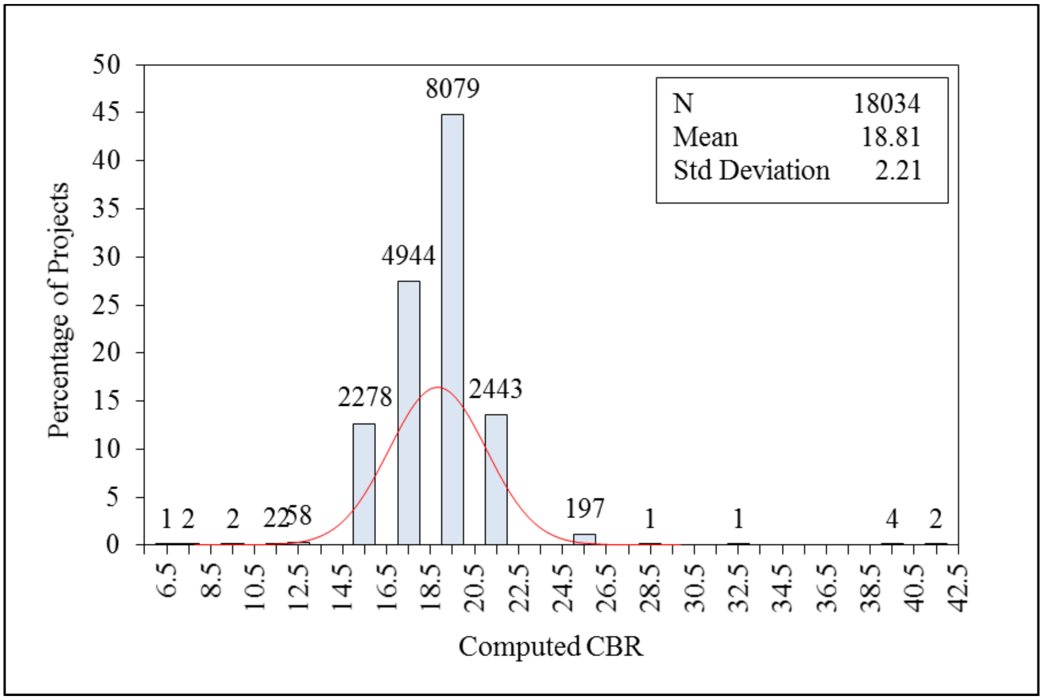
Source: FHWA.

Figure 63. Graph. Histogram showing distribution of aggregate base liquid limit in State 1.



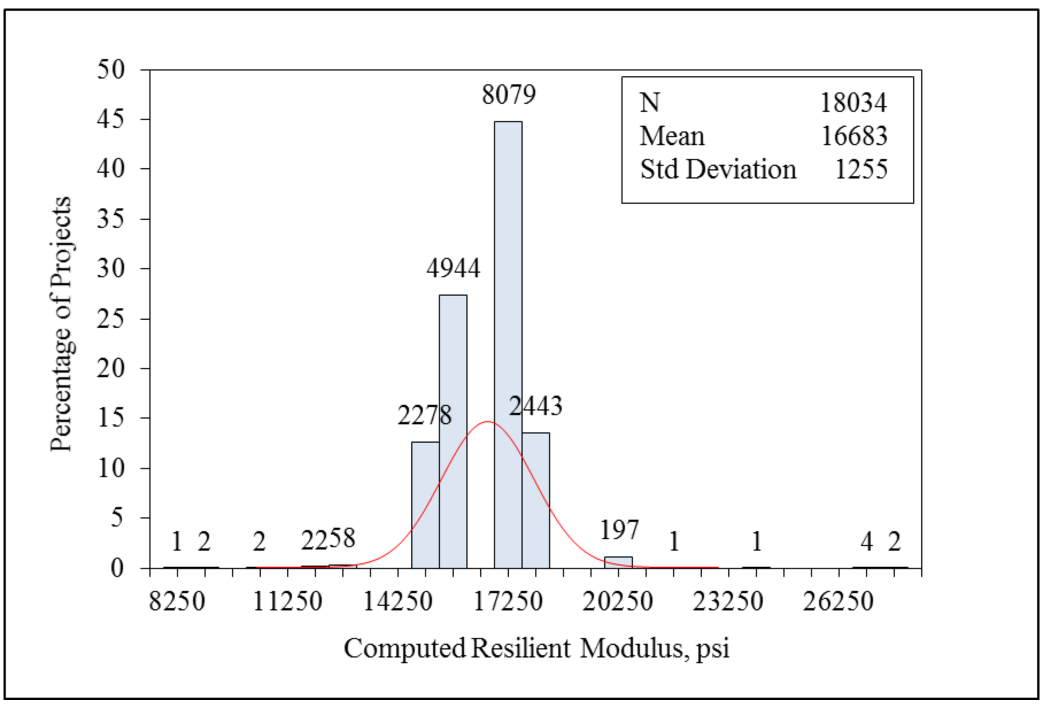
Source: FHWA.

Figure 64. Graph. Histogram showing distribution of aggregate base D_{60} in State 1.



Source: FHWA.

Figure 65. Graph. Histogram showing distribution of aggregate base computed CBR in State 1.

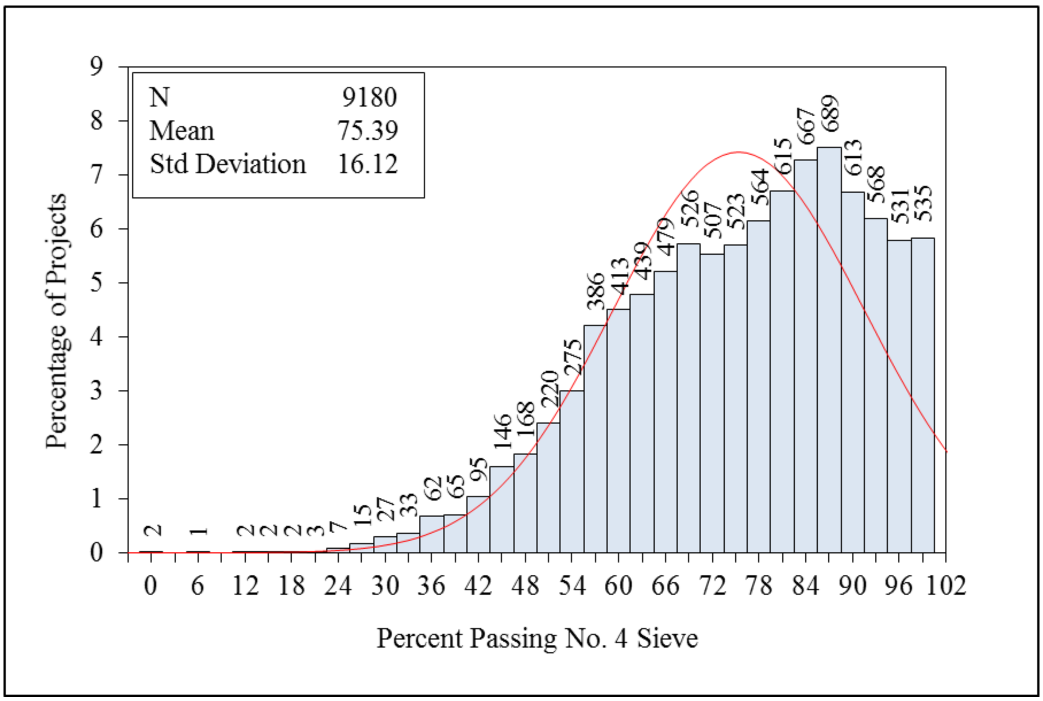


Source: FHWA.

Figure 66. Graph. Histogram showing distribution of aggregate base computed M_r in State 1.

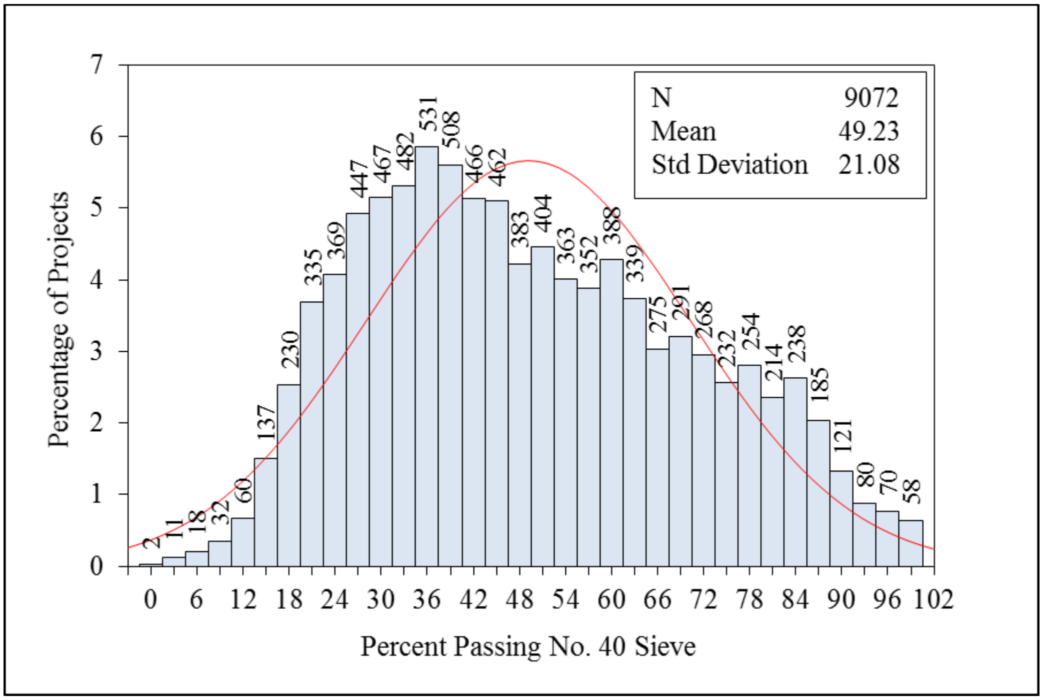
Figure 67 through figure 76 present distributions of key subgrade soil materials properties collected by State 1 DOT as part of QA. Information in figure 67 through figure 76 shows significant variations in subgrade soil properties across and within projects.

The amount passing the No. 4 sieve ranges from 24 to 100 percent, while the amount passing the No. 40 sieve size ranged from 0 to 100 percent. The amount passing the No. 200 sieve ranged from 1 to 90 percent. As gradation affects subgrade soil material strength properties and sensitivity to moisture, significant variations within a project could lead to significant differences in pavement support available (see figure 75 and figure 76, where a wide range of computed CBR and M_r are presented as a result of differences in gradation). The range of computed CBR and M_r values was deemed reasonable. The information presented in the QA dataset as shown was of sufficient detail to estimate subgrade M_r or CBR or determine the materials AASHTO soil class, which is a level 3 input for the AASHTOWare Pavement ME Design.



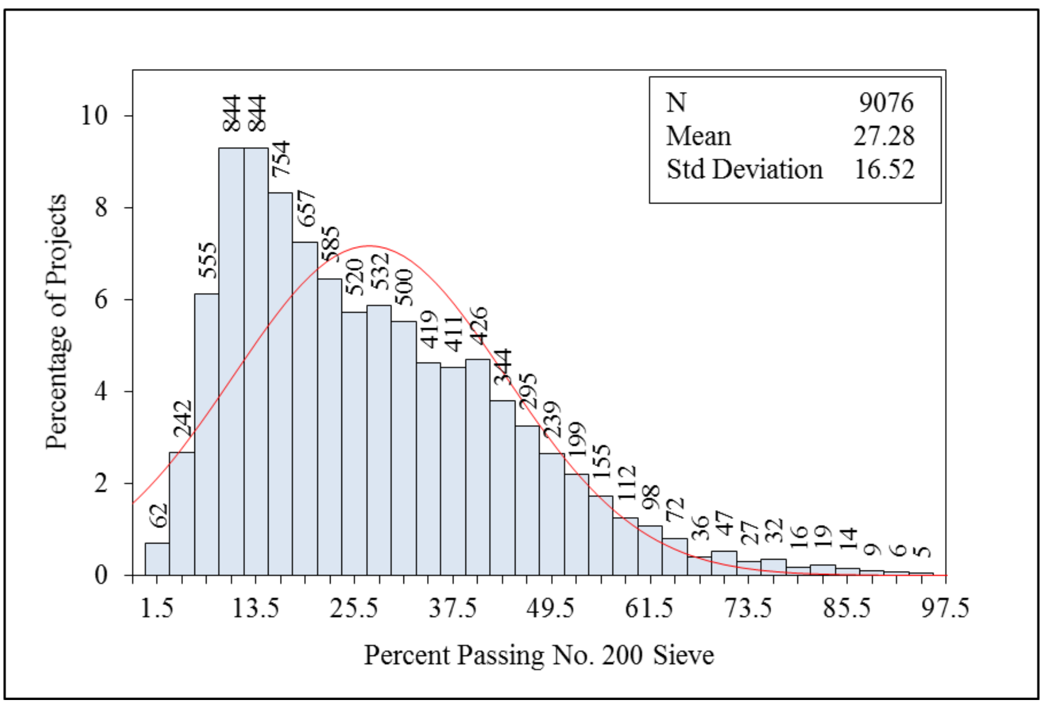
Source: FHWA.

Figure 67. Graph. Histogram showing distribution of subgrade soil percent passing the No. 4 sieve (State 1 subgrade soil QA data).



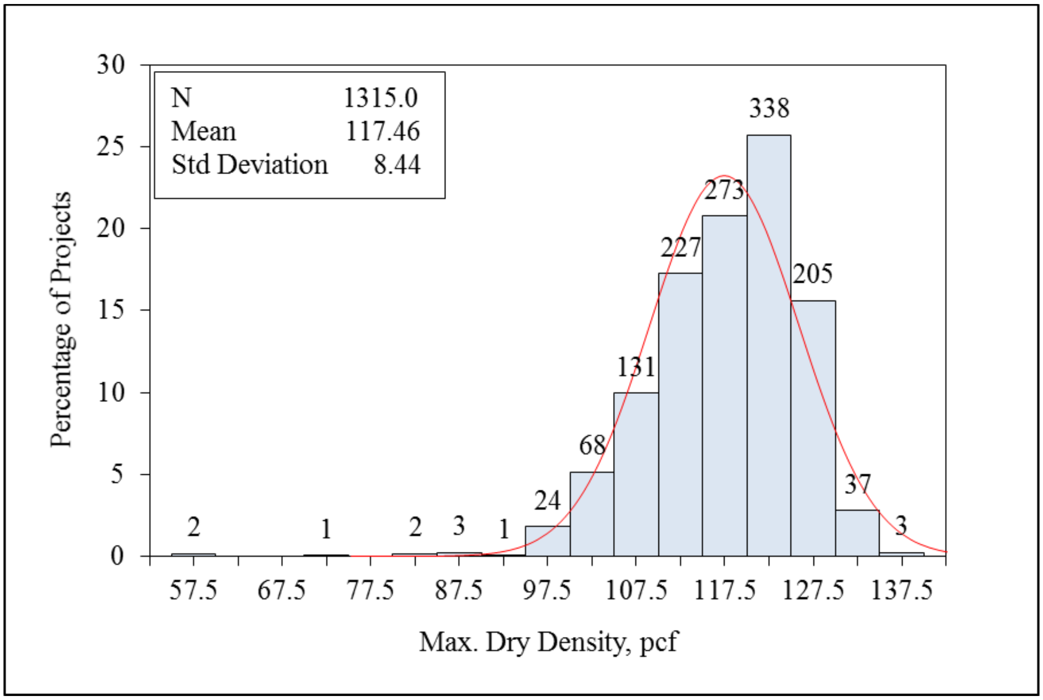
Source: FHWA.

Figure 68. Graph. Histogram showing distribution of subgrade soil percent passing the No. 40 sieve (State 1 subgrade soil QA data).



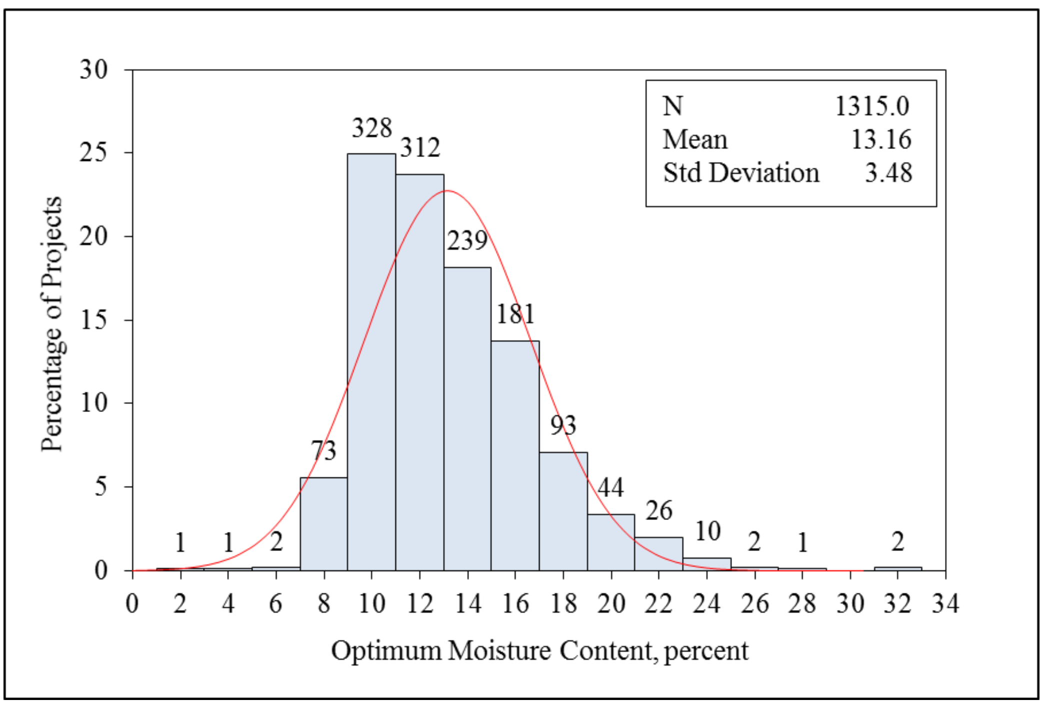
Source: FHWA.

Figure 69. Graph. Histogram showing distribution of subgrade soil percent passing the No. 200 sieve (State 1 subgrade soil QA data).



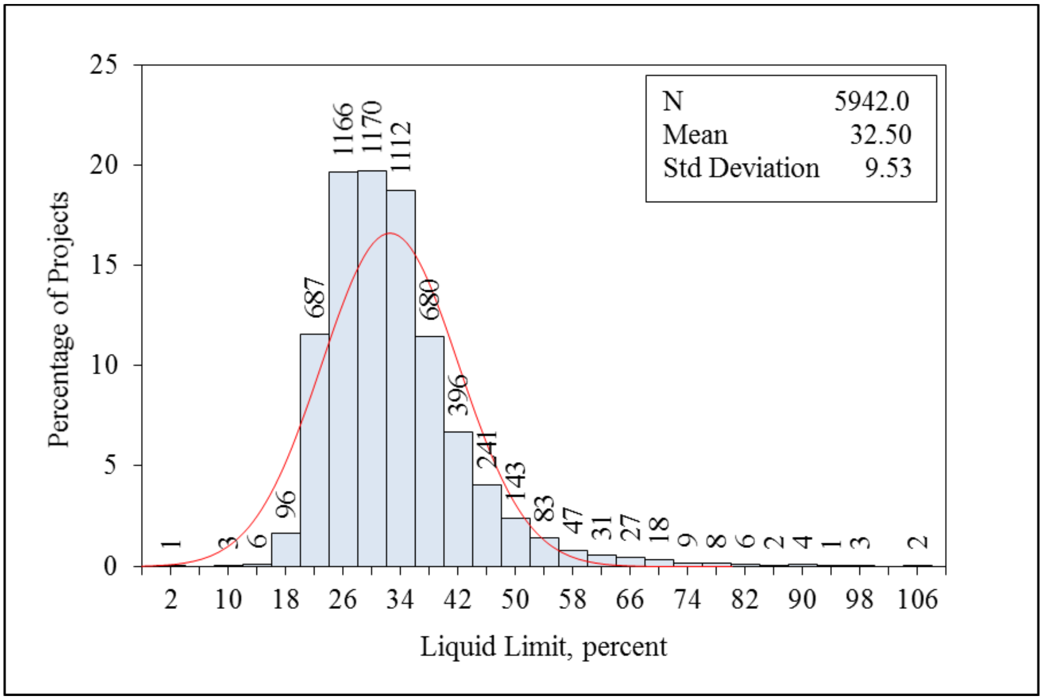
Source: FHWA.

Figure 70. Graph. Histogram showing distribution of subgrade soil maximum dry density (State 1 subgrade soil QA data).



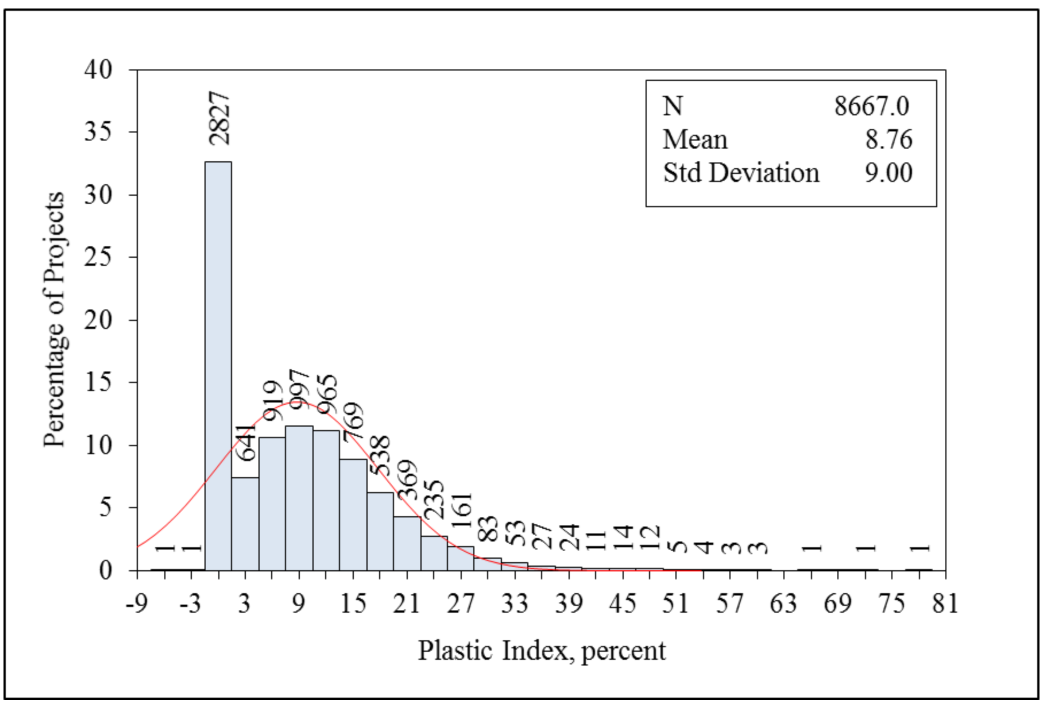
Source: FHWA.

Figure 71. Graph. Histogram showing distribution of subgrade soil optimum moisture content (State 1 subgrade soil QA data).



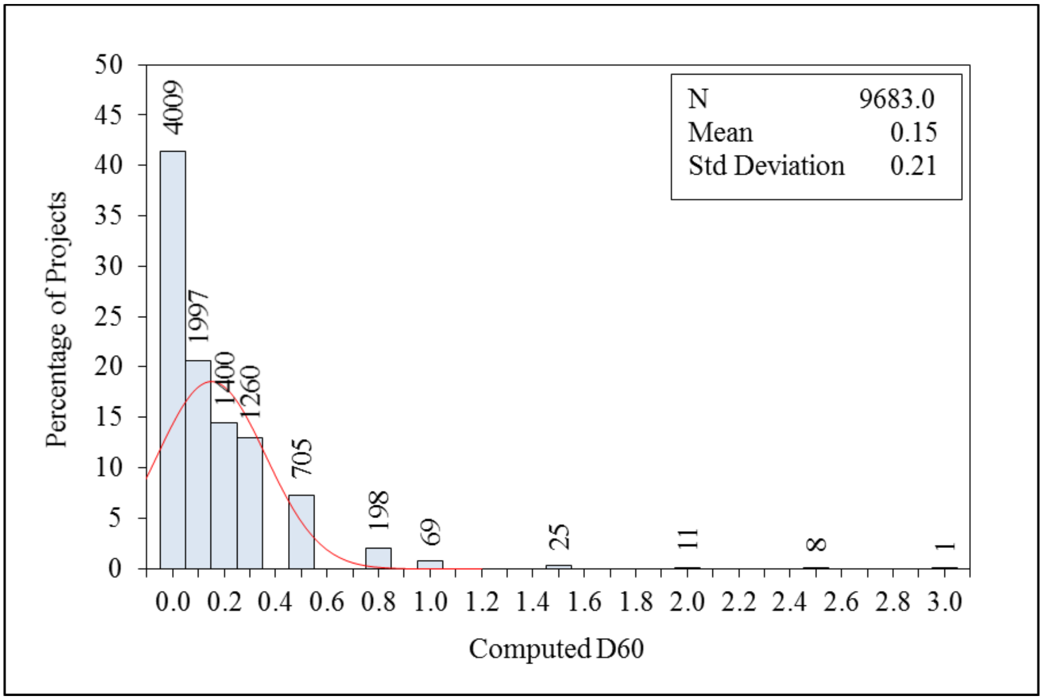
Source: FHWA.

Figure 72. Graph. Histogram showing distribution of subgrade soil liquid limit (State 1 subgrade soil QA data).



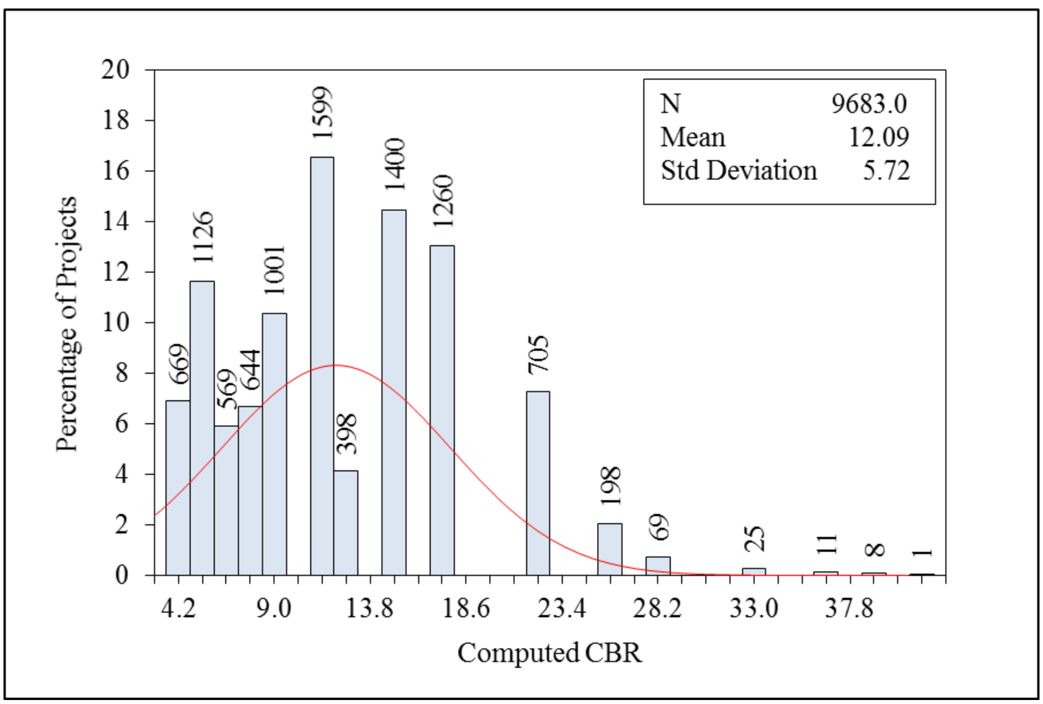
Source: FHWA.

Figure 73. Graph. Histogram showing distribution of subgrade soil plasticity index (State 1 subgrade soil QA data).



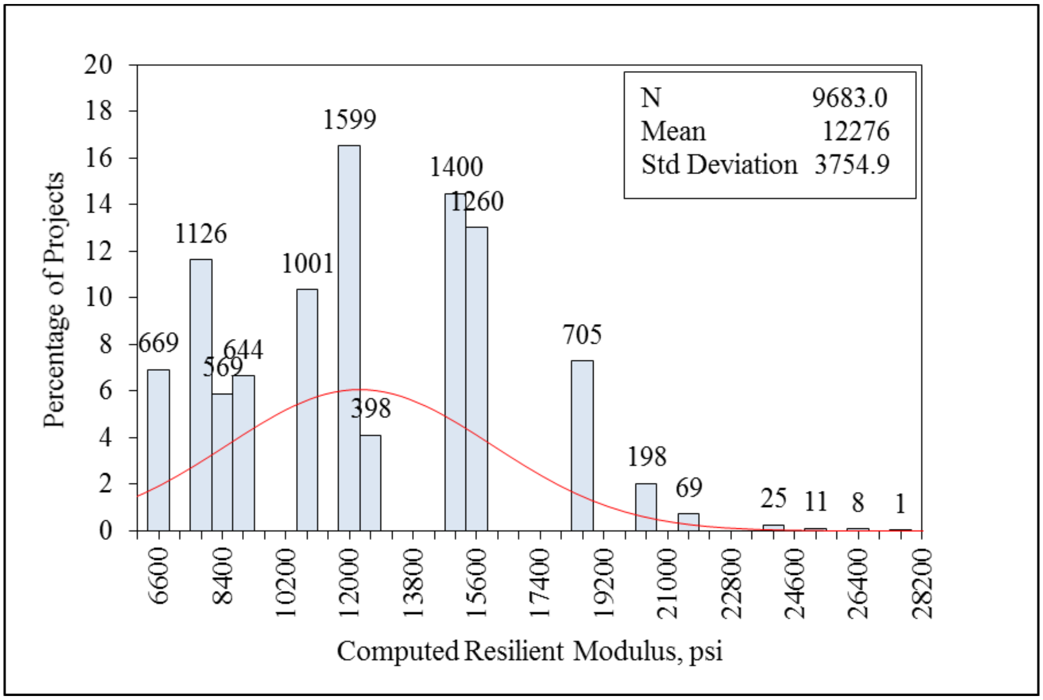
Source: FHWA.

Figure 74. Graph. Histogram showing distribution of subgrade soil D_{60} (State 1 subgrade soil QA data).



Source: FHWA.

Figure 75. Graph. Histogram showing distribution of subgrade soil computed CBR (State 1 subgrade soil QA data).



Source: FHWA.

Figure 76. Graph. Histogram showing distribution of subgrade soil computed M_r (State 1 subgrade soil QA data).

State 2 DOT

State 2 DOT PMS and QA/QC Test Data Collection and Assembly

The research team obtained from State 2 DOT several Microsoft Excel data tables with PMS data from 1998 through 2015 (table 51). The PMS files listed in table 51 contained approximately 60 pavement inventory and condition/distress data items that were used to characterize pavement condition. As shown in table 51, the pavement condition data represented approximately 11,000 lane miles of highway. Of the 11,000 mi, 89 percent were flexible pavements, 10.9 percent were rigid, while the remaining 0.1 percent was composite/other pavement types. State 2 DOT PMS data provided a detailed description of pavement location, type, traffic, and other descriptors (such as route type/number, begin MP [BMP], end MP [EMP], DIR, and longitude/latitude), along with condition data (characterized by load- and non-load-related distresses) and information about shoulder type, such as condition, grade, and speed. Table 52 presents a summary of data availability for the State 2 DOT PMS data table STATE 2DOTDataDelivery15.XLS. The research team selected table STATE 2DOTDataDelivery15.XLS as it represented current DOT data collection practices. The information in table 52 shows nearly 100 percent data availability, except for eight, for all the data items.

Table 51. Summary of State 2 DOT PMS data files assembled for analysis.

Data Files	No. of Observations	Length (mi)
Condition98.XLS	111,251	10,820
Condition99.XLS	112,268	10,815
Condition00.XLS	113,310	10,813
Condition01.XLS	111,195	10,657
Condition02.XLS	106,733	10,231
Condition03.XLS	106,876	10,426
Roadware04.XLS	110,519	11,039
Condition05.XLS	109,146	10,901
Condition06.XLS	111,203	11,121
Condition07.XLS	111,138	11,136
Condition08.XLS	109,616	10,555
Pathway09.XLS	109,804	10,642
Pathway10.XLS	110,291	10,743
Pathway11.XLS	110,888	10,651
Pathway12.XLS	178,418	17,568
Pathway13.XLS	109,453	10,700
STATE 2DOTDataDelivery14.XLS	113,316	10,475
STATE 2DOTDataDelivery15.XLS	113,676	11,265

Table 52. Summary of data availability for the State 2 DOT PMS data table STATE 2DOTDataDelivery15.XLS.

Data Item	Total Number of Records	Records with Data Available (Percent)
ID	113,676	100
HWY	113,676	100
DIR	113,676	100
REFPOST	113,676	100
SEGMENT	113,676	100
LENGTH	113,676	100
BMP	113,676	100
EMP	113,676	100
DATE	113,676	100
ENGREGION	113,676	100
SPEED	113,676	100
PAVETYPE	113,676	100
SHLDRT	113,676	100
SHLDRW	113,676	100
SHLDR_COND	113,676	100
CONST	113,676	100

Data Item	Total Number of Records	Records with Data Available (Percent)
IRI	113,676	100
IRILEFT	113,676	100
IRIRIGHT	113,676	100
IRILEFTSD	57,280	50.4
IRIRIGHTSD	57,280	50.4
RUT	113,676	100
RUTLEFT	113,676	100
RUTRIGHT	113,676	100
RUTLEFTSD	57,280	50.4
RUTRIGHTSD	57,280	50.4
RUTMAX	57,281	50.4
FAULTAVG	113,676	100
FAULTMAX	113,676	100
FATIGUE_L	113,676	100
FATIGUE_M	113,676	100
FATIGUE_H	113,676	100
FATIGUE	113,676	100
TRANSCOUNT_L	113,676	100
TRANSCOUNT_M	113,676	100
TRANSCOUNT_H	113,676	100
TRANSCOUNT	113,676	100
TRANSLENGTH_L	113,676	100
TRANSLENGTH_M	113,676	100
TRANSLENGTH_H	113,676	100
TRANSLENGTH	113,676	100
LONG_L	113,676	100
LONG_M	113,676	100
LONG_H	113,676	100
LONG	113,676	100
CORNER_L	113,676	100
CORNER_M	113,676	100
CORNER_H	113,676	100
CORNER	113,676	100
RUMBLE	113,676	100
CTYPE	57,280	50.4
CURVE	57,280	50.4
CLEN	57,280	50.4
GRADE	113,676	100
LATITUDE_DD	113,676	100

Data Item	Total Number of Records	Records with Data Available (Percent)
LONGITUDE_DD	113,676	100
LATITUDE_UTM	113,676	100
LONGITUDE_UTM	113,676	100
ELEVATION	113,676	100
COLLECT_DATE	113,676	100

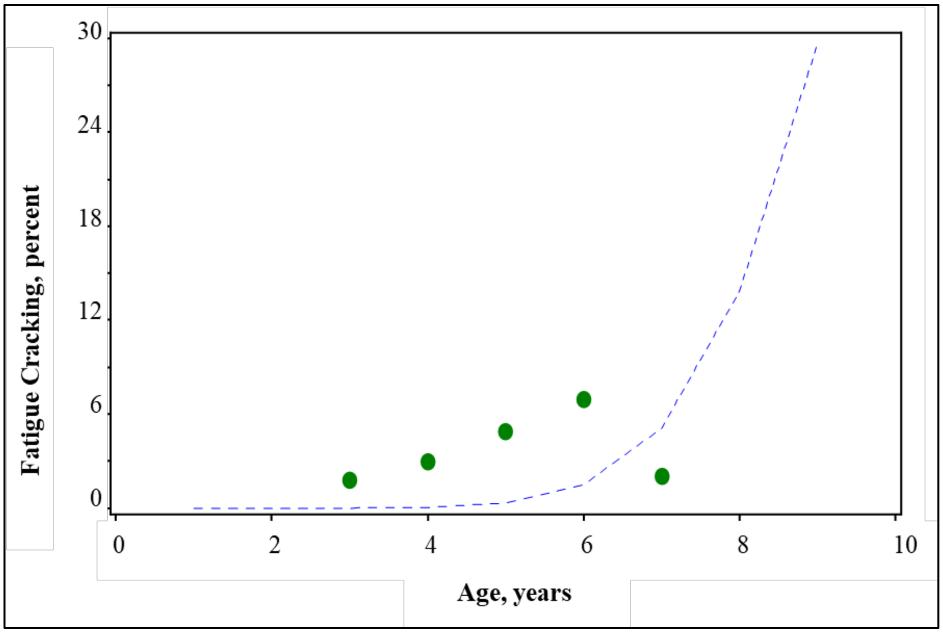
Table 53 presents a summary of data availability in the maintenance data tables of the construction history database, the Mtc_Dir1-2.xlsx data table. The information presented shows that the data table contained 3,610 records. Data availability ranged from 0 to 100 percent. Key location information HWY, DIR, BEG_MP, and END_MP were 100 percent available, along with WORK_TYPE. For the SUBAC number, which provides the link to QA/QC test data, only 24 percent of records reported this information. State 2 DOT provided the research team with electronic documents (PDF files) containing QA/QC test data summaries. The electronic documents provided information about the pavement location (HWY, DIR, BEG_MP, and END_MP) and SUBAC number. State 2 DOT also provided QA/QC test data, including gradation, VMA, and air voids. As it was not practical to review all QA/QC-related electronic documents in the DOT archives, the research team could not perform a full-scale assessment of QA/QC test data availability. However, for the projects for which such data were required, the DOT readily provided them. This outcome was an indicator that electronic documents containing QA/QC data were usually available. The research team did not analyze data availability for QA/QC testing using new technologies, as these were not collected and stored directly by the DOT.

Table 53. Summary of data availability for the State 2 DOT construction history database Dir1-2.xlsx data table.

Data Item	Total Number of Records	Records with Data Available (Percent)
Subac	876	24.3
Proj_Num	1,990	55.1
DIR	3,610	100.0
Description	1,097	30.4
HWY	3,610	100.0
Beg_MP	3,610	100.0
End_MP	3,610	100.0
Length	3,610	100.0
Region	3,610	100.0
Work_Type	3,610	100.0
Pave_Type	3,610	100.0
Depth	3,610	100.0
Width	1,679	46.5
Prime_Cont	703	19.5
Accept_Date	3,610	100.0
Item_Cost	436	12.1
Cost/SqYd/In	129	3.6
Total_Cost	738	20.4
REJECTED-ADLP	3,610	100.0
REASON-ADLP	0	0.0
KEY-ADLP	3610	100.0
YEAR-ADLP	3,610	100.0

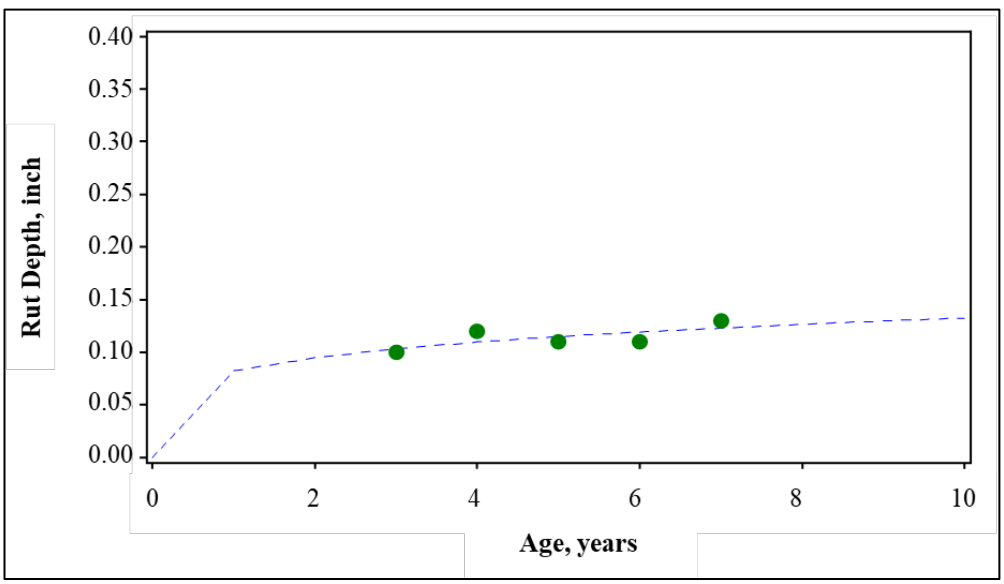
State 2 DOT PMS and QA Test Data Review

The research team reviewed the assembled PMS and QA data to assess accuracy and reasonableness. The team assessed data accuracy by developing plots of trends in performance measures (e.g., IRI versus data collection date) and histograms showing the distribution of QA/QC test data. Figure 77 through figure 79 present examples of plots of measured cracking, rutting, and IRI versus pavement age for various State 2 DOT PMS sections. The plots were generated for selected PMS sections and reviewed for reasonableness. Reasonableness was determined by assessing whether observed trends were as expected (e.g., increasing with time) and whether significant shifts in trends could be explained by construction/maintenance activity. The pavement construction history information was derived from State 2 DOT maintenance data tables. The trends in performance along with extent/amount of variability in measured data were as expected.



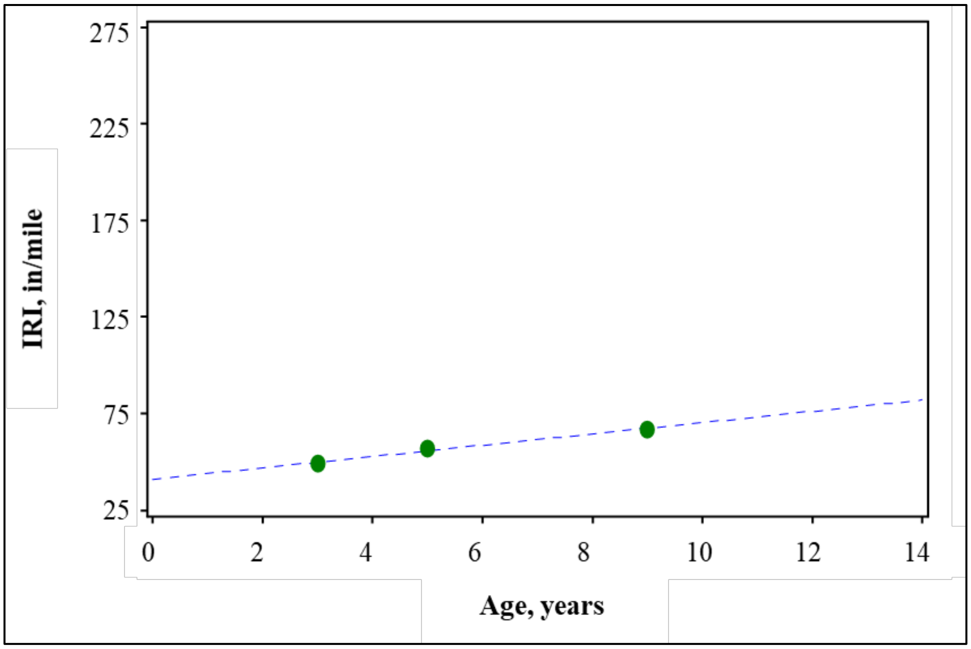
Source: FHWA.

Figure 77. Graph. Plot showing fatigue cracking development for State 2 PMS section HWY IIA, MP 226.5–226.6.



Source: FHWA.

Figure 78. Graph. Plot showing rut depth development for State 2 PMS section HWY IIA, MP 225.7–225.8.



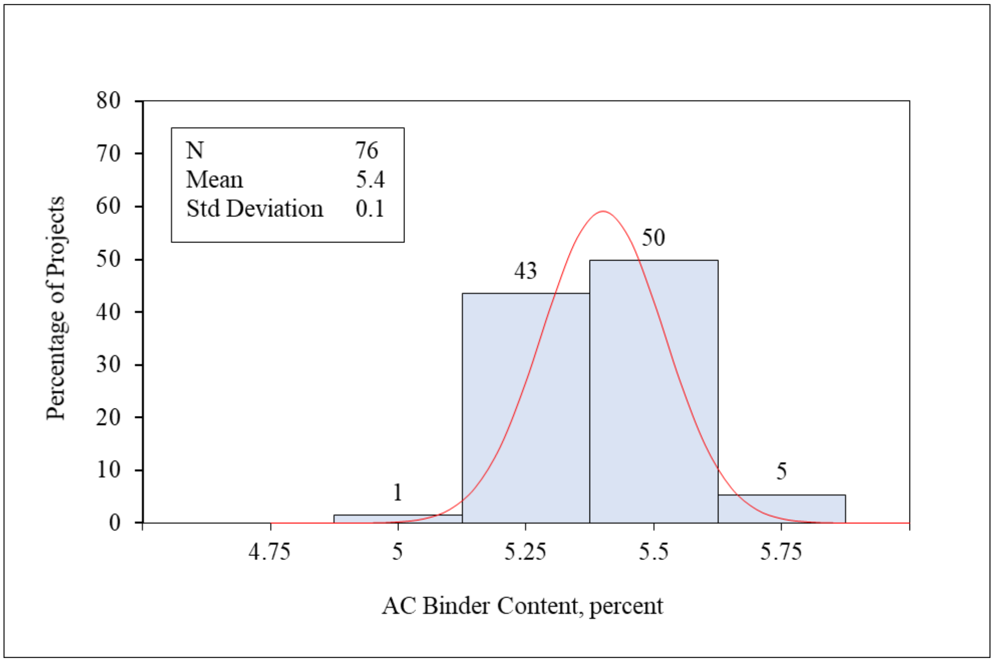
Source: FHWA.

Figure 79. Graph. Plot showing IRI development for State 2 PMS section HWY JJA, MP 14.6–14.7.

Figure 80 through figure 92 present plots of distributions of key QA test data obtained from the State 2 DOT records (PDF files) of acceptance testing for up to five projects and contractors. State 2 DOT collected QC data using new technologies (for a single TSDD and MIT-Scan project each). The data assembled were reviewed and found to be accurate and reasonable.

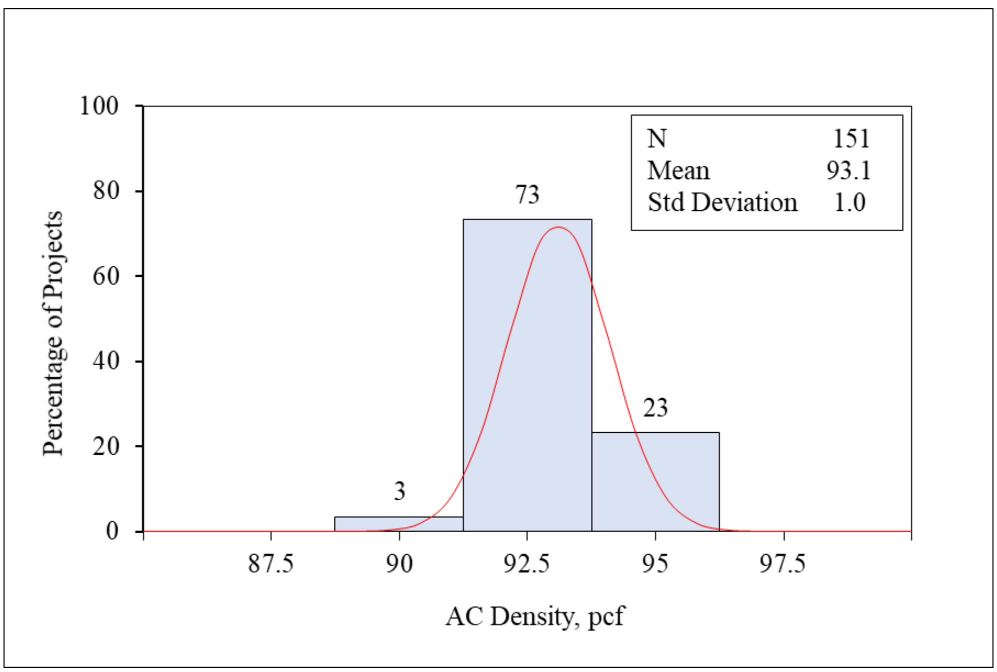
The following results were observed:

- Traditional QA test data were generally reasonable and were within expected ranges.
- Traditional QA/QC test data within project variability were as low as expected and reported the most variability.
- Maximum deflections measured from the RWD ranged from 2 to 30 mils. Thus, variability within the project was significant. This variability is an indication of significantly different pavement structural capacity along the project that could significantly impact structural performance.
- MIT-Scan data also exhibited considerable variability, which could affect future performance.



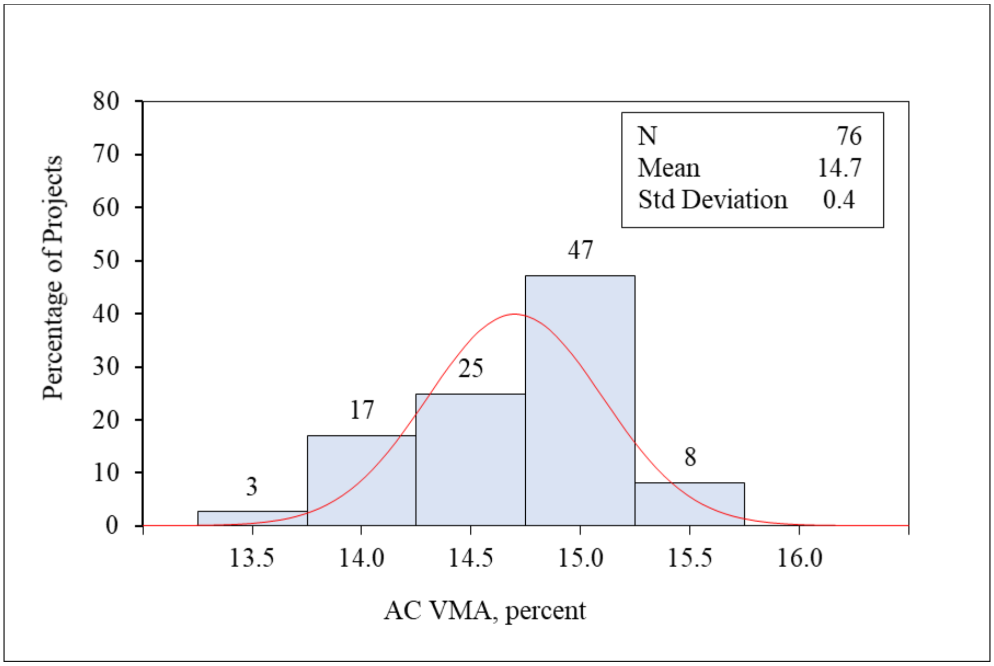
Source: FHWA.

Figure 80. Graph. Histogram showing distribution of State 2 DOT HMA binder content.



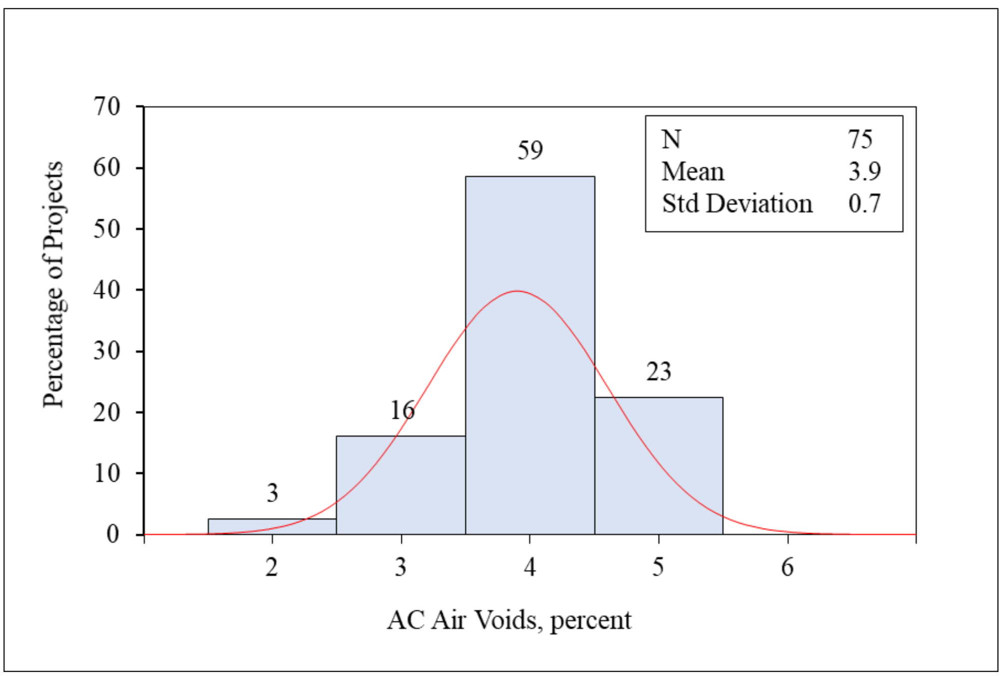
Source: FHWA.

Figure 81. Graph. Histogram showing distribution of State 2 DOT HMA mix density.



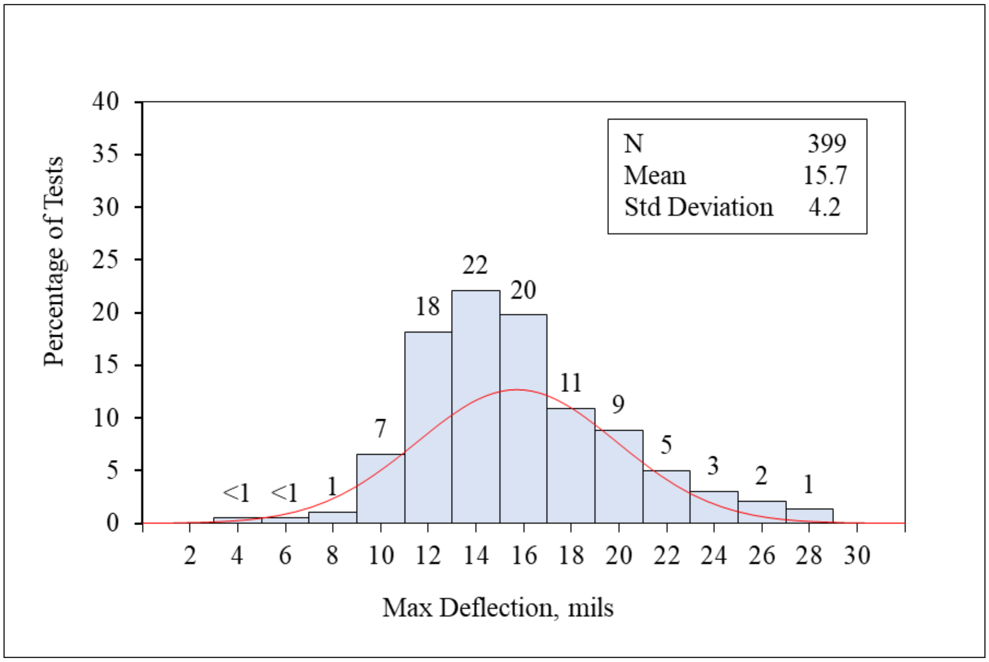
Source: FHWA.

Figure 82. Graph. Histogram showing distribution of State 2 DOT HMA VMA.



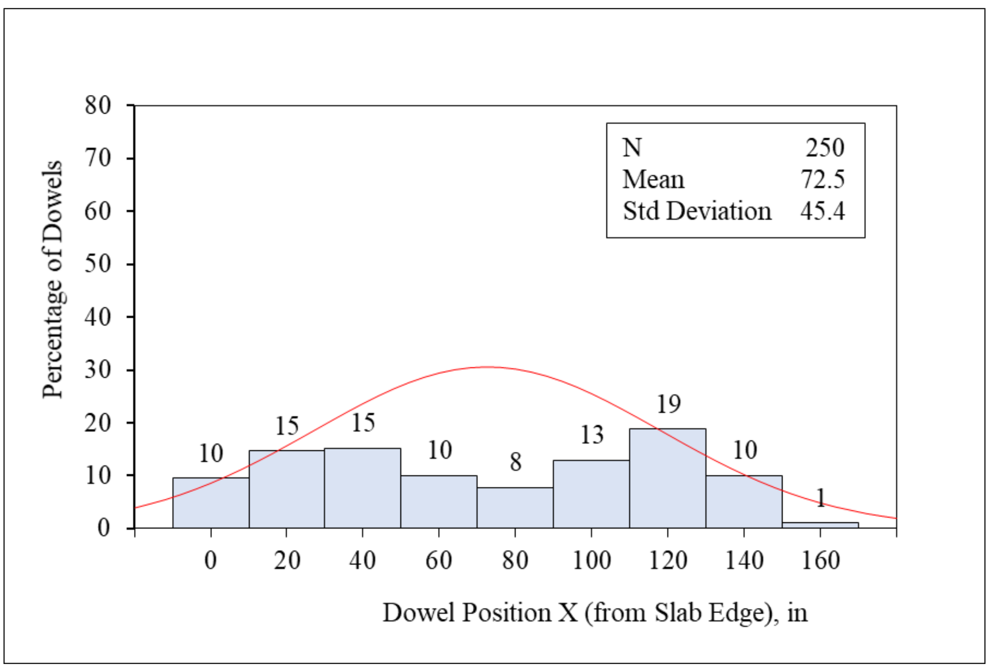
Source: FHWA.

Figure 83. Graph. Histogram showing distribution of State 2 DOT HMA lab air voids.



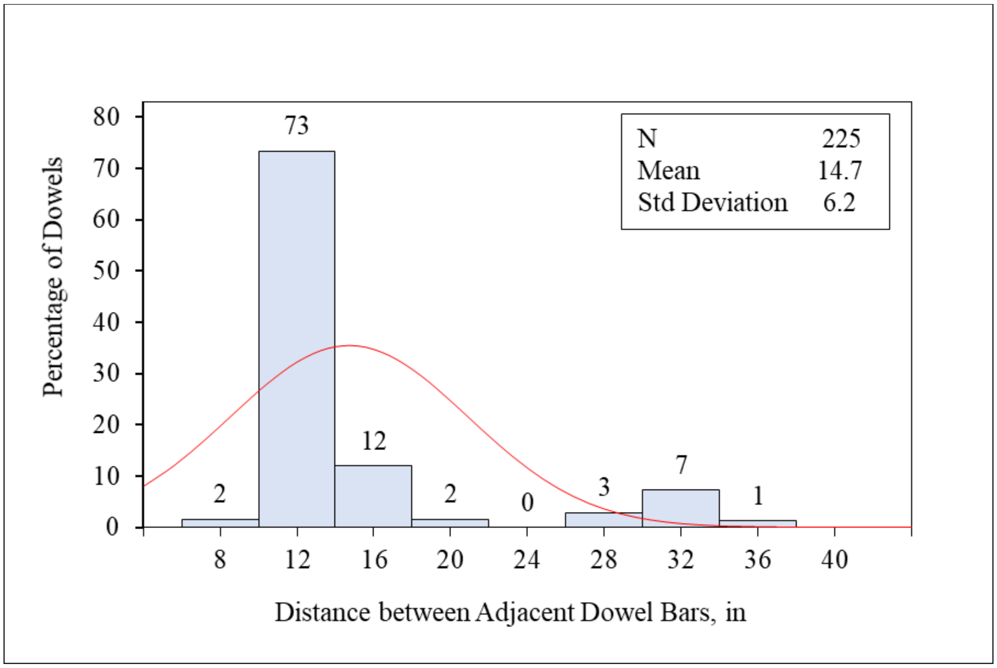
Source: FHWA.

Figure 84. Graph. Histogram showing distribution of RWD measured maximum deflections along 17 mi of a State route in State 2.



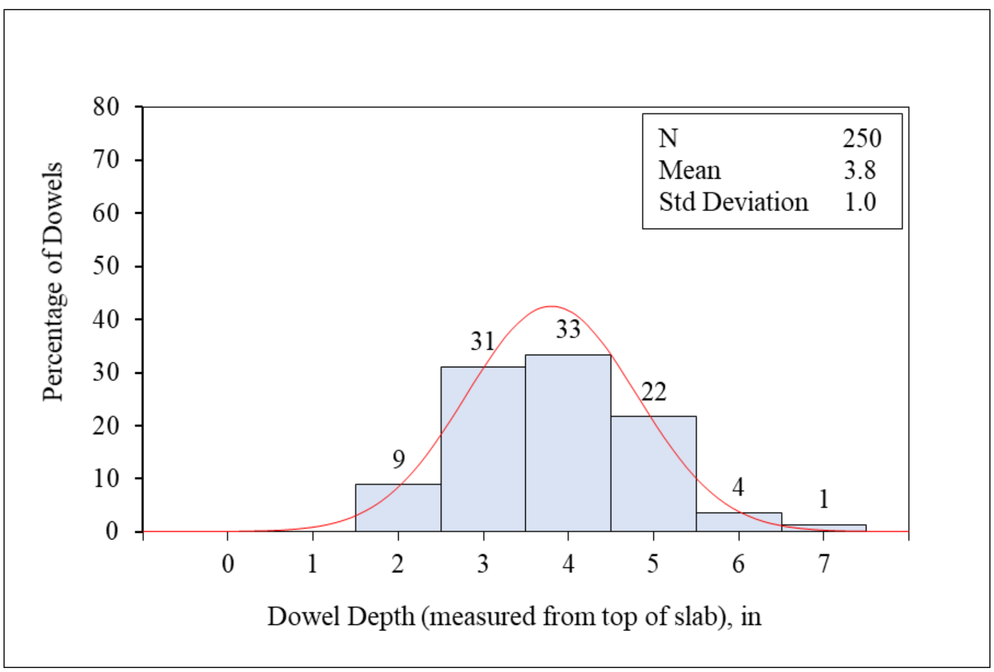
Source: FHWA.

Figure 85. Graph. Histogram showing distribution of MIT-Scan measured dowel position (measured from the slab edge) for a newly constructed JPCP in State 2.



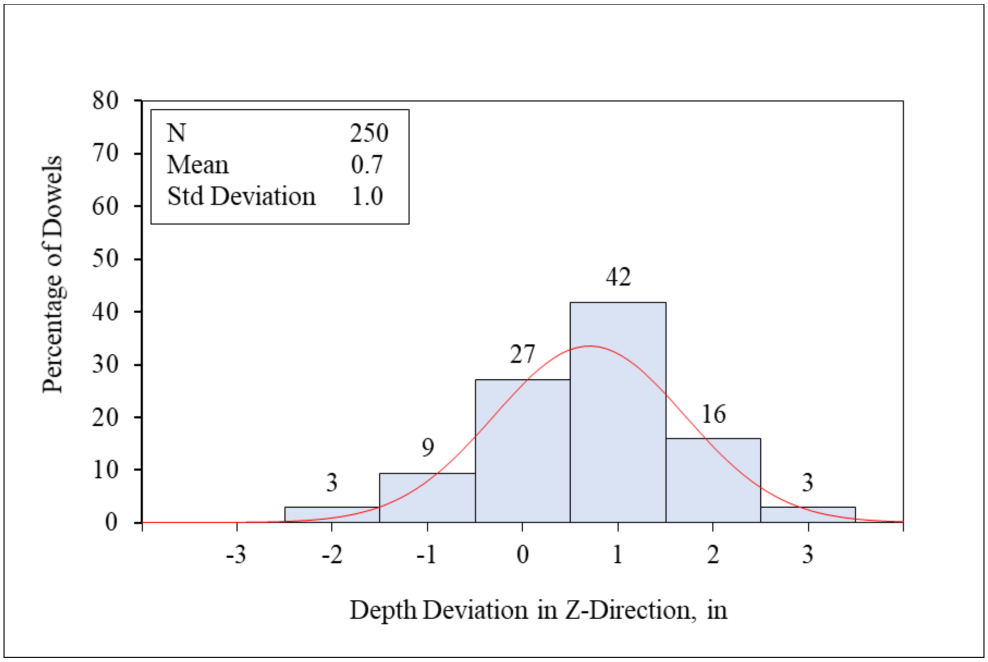
Source: FHWA.

Figure 86. Graph. Histogram showing distribution of MIT-Scan measured distance between adjacent dowel bars for a newly constructed JPCP in State 2.



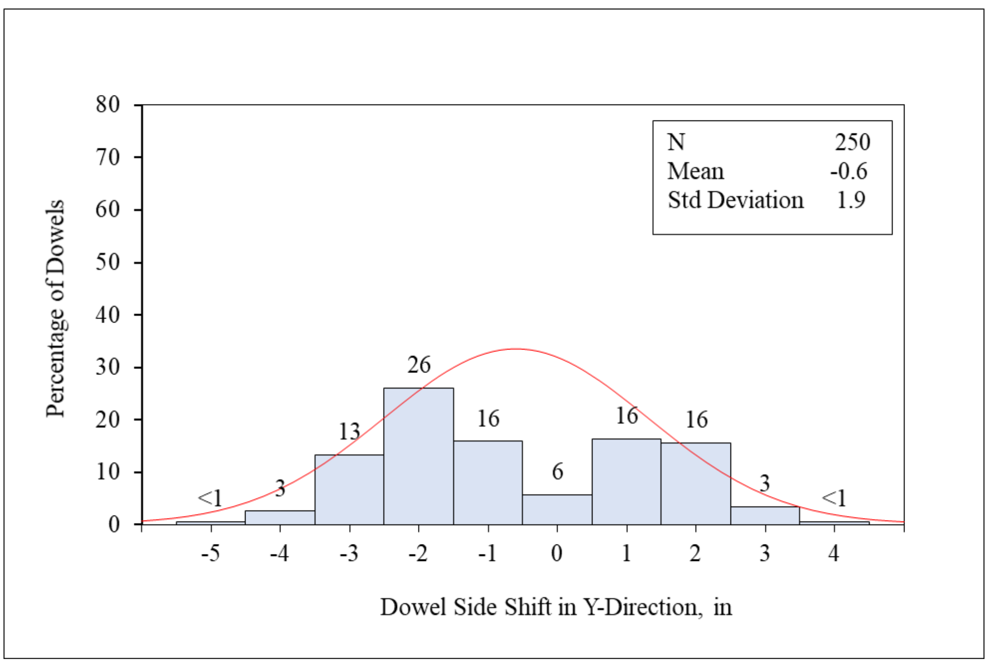
Source: FHWA.

Figure 87. Graph. Histogram showing distribution of MIT-Scan depth of dowel bars (measured from the top of the slab) for a newly constructed JPCP in State 2.



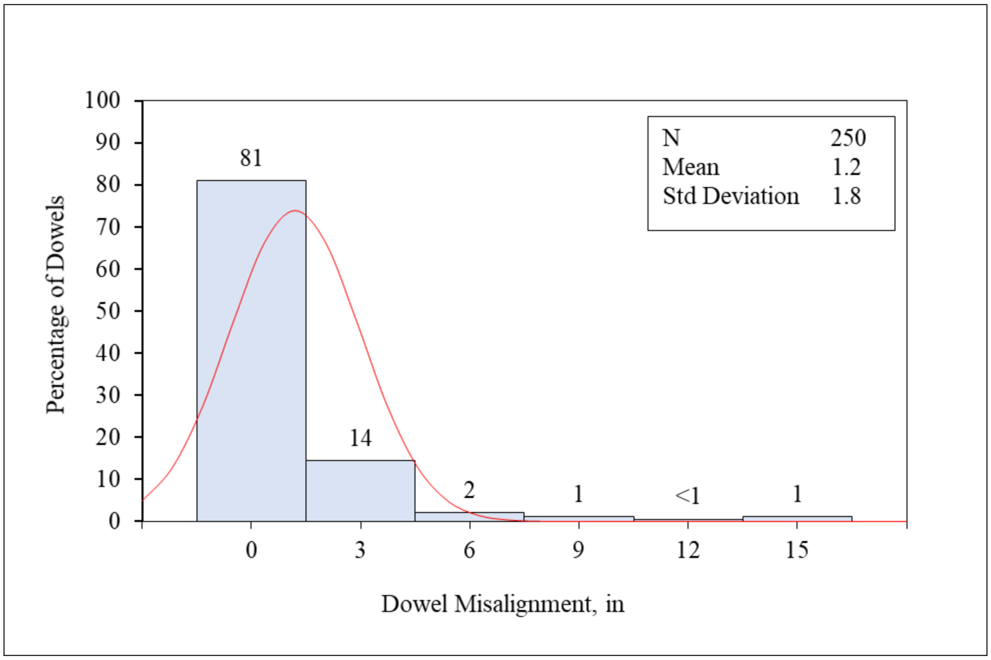
Source: FHWA.

Figure 88. Graph. Histogram showing distribution of MIT-Scan measured dowel deviations from vertical position (relative to midslab) for a newly constructed JPCP in State 2.



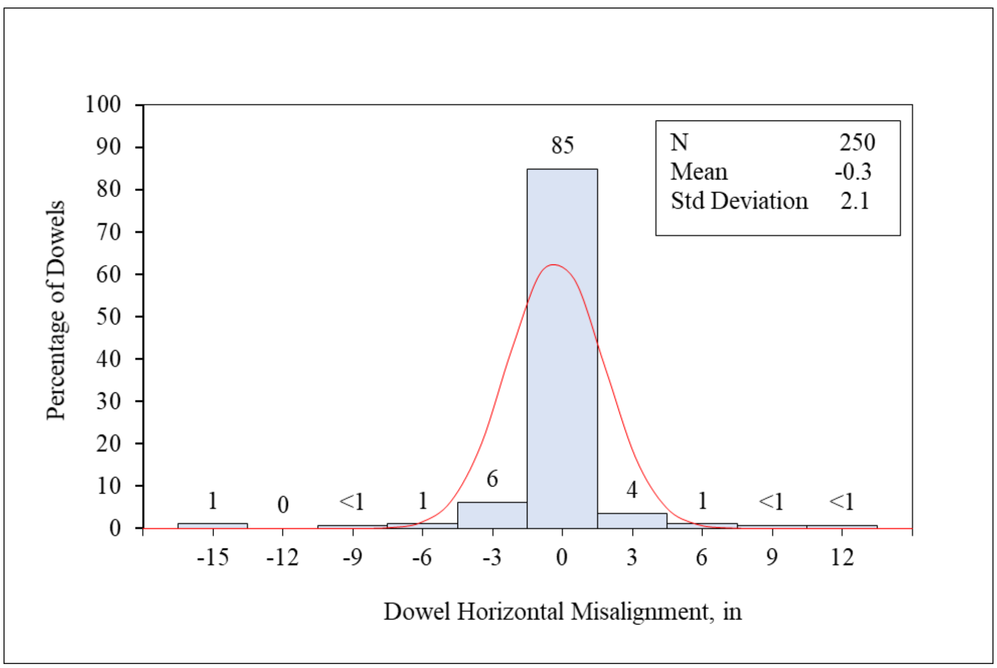
Source: FHWA.

Figure 89. Graph. Histogram showing distribution of MIT-Scan measured dowel deviations from lateral position (relative to design dowel location, i.e., 12-inch spacing) for a newly constructed JPCP in State 2.



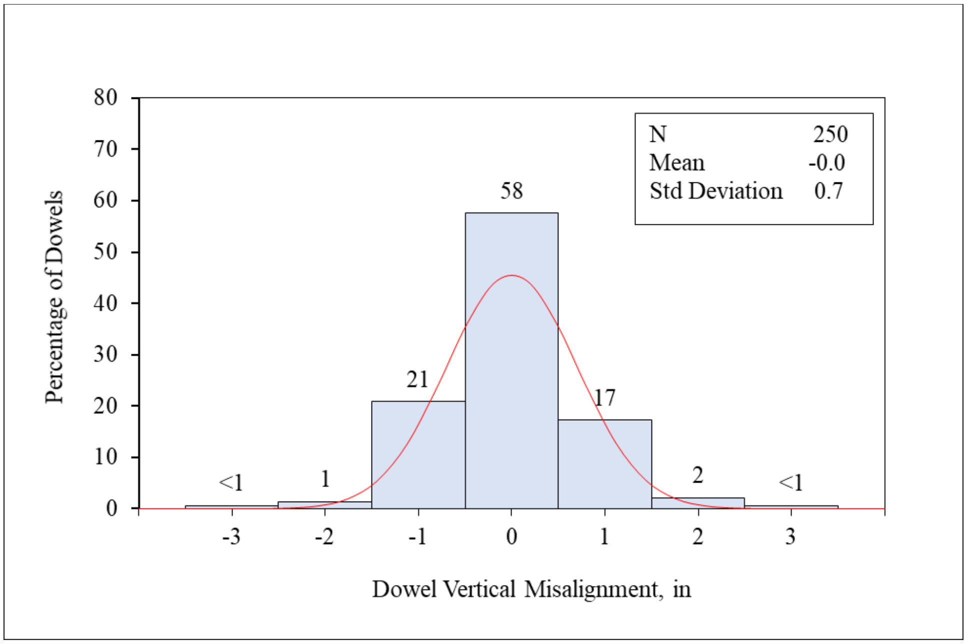
Source: FHWA.

Figure 90. Graph. Histogram showing distribution of MIT-Scan measured effective dowel misalignment for a newly constructed JPCP in State 2.



Source: FHWA.

Figure 91. Graph. Histogram showing distribution of MIT-Scan measured horizontal dowel misalignment for a newly constructed JPCP in State 2.



Source: FHWA.

Figure 92. Graph. Histogram showing distribution of MIT-Scan measured vertical dowel misalignment for a newly constructed JPCP in State 2.

State 3 DOT

State 3 DOT PMS and QA/QC Test Data Collection and Assembly

From State 3 DOT, the research team obtained three Microsoft Excel files containing summaries of the agencies cracking, rutting, and friction distress data, namely: TREND_CRACKING_SUMMARY_2-2-2016.xlsx, TREND_RUTTING_SUMMARY_2-2-2016.xlsx, and TREND_FRICTION_SUMMARY_2-2-2016.xlsx. The summaries were extracted from State 3 DOT's PMS database using agency-developed codes/queries for 2012, 2013, and 2014. A summary of information contained in the three files is presented in table 54.

Table 54. Summary of relevant pavement condition distress datasets extracted from the State 3 DOT PMS database.

Data Item	Description	Rut	Crack	Friction
ID NUMBER	Pavement ID number (e.g., 3)	✓	✓	✓
SECTION ID	Section ID number (e.g., 2)	✓	✓	✓
TREATMENT ID	Treatment ID (e.g., 32178)	✓	✓	—
GLOBAL ROUTE ID	Route global ID (e.g., 19981)	✓	✓	—
SUB ROUTE ID	Subroute ID (e.g., 2)	✓	✓	—
REGION	Region within the State (e.g., 2)	✓	✓	—
DISTRICT	Engineering district (e.g., 4)	✓	✓	—
COUNTY	County (e.g., BA)	✓	✓	✓
ROUTE	Route type (e.g., Interstate)	✓	✓	✓

Data Item	Description	Rut	Crack	Friction
RNUM	Route number (e.g., 83)	✓	✓	✓
RSUFF	Route number suffix (e.g., A)	✓	✓	✓
DIRECTION	Direction of travel (e.g., south)	✓	✓	✓
BMP	Begin MP (e.g., 10.5)	✓	✓	✓
EMP	End MP (e.g., 11.01)	✓	✓	✓
LANE NUMBER	Total number of lanes (e.g., 3)	✓	✓	✓
OUTER LANE	Outer lane number (e.g., 1)	✓	✓	✓
FUNC CLASS	Highway functional class (e.g., 1)	✓	✓	✓
GOVT CONTROL	Government control classification (e.g., 1)	✓	✓	✓
PAVEMENT TYPE	Pavement-type designation (e.g., flexible)	✓	✓	✓
TREATMENT THICKNESS	Treatment thickness (e.g., 1.5 inches)	✓	✓	—
CURRENT TREATMENT THICKNESS	Current treatment thickness (e.g., 1.5 inches)	✓	✓	—
LAYER NO	Surface layer number (e.g., 6)	✓	✓	✓
BIRTH YEAR	Treatment placement year (e.g., 1991)	✓	✓	✓
DEATH YEAR	Treatment replacement year (e.g., 1999)	✓	✓	✓
AGE	Treatment age (e.g., 5 yr)	✓	✓	✓
CONTRACT NUMBER	Treatment contract number (e.g., AW357451014)	✓	✓	✓
FMIS	FMIS number	✓	✓	✓
LAYER DESCRIPTION	Layer description (e.g., surface)	✓	✓	✓
MATERIAL BAND SIZE	Material band size (e.g., band SC)	✓	✓	✓
YEAR ORDER	Year material was ordered (e.g., 2008)	✓	✓	✓
MAT UNIQUE ID	Material-type unique ID (e.g., 2690)	✓	✓	✓
MATERIAL DESCRIPTION	Material description (e.g., gap-graded 12.5 mm 70–22)	✓	✓	✓
TREATMENT	Treatment-type description (e.g., grind overlay less than or equal to 1.5-inch grade increase)	✓	✓	—
LAYER TYPE DESCRIPTION	Surface layer-type description (e.g., asphalt)	✓	✓	✓
MATERIAL MIX METHOD DESC	Surface mix type (e.g., A-hot mix)	✓	✓	✓
MATERIAL MIX TYPE DESC	Surface material aggregate designation (H-high polish or G-gap graded)	✓	✓	✓

Data Item	Description	Rut	Crack	Friction
MATERIAL BINDER	Treatment material binder type (e.g., 70–22)	✓	✓	✓
MATERIAL TRAFFIC LEVEL DESC	Material design traffic-level designation	✓	✓	✓
CONSTRUCTION TYPE DESC	Construction-type description (e.g., minor rehabilitation or structural overlay)	✓	✓	—
AVG RUT	Average rutting	✓	—	—
CNT	Rutting measurements count	✓	—	—
STDEV	Rutting standard deviation	✓	—	—
RUT FAMILY	PMS pavement family designation for forecasting rutting (e.g., 99)	✓	—	—
FC DENSITY	Functional (load-related) cracking density	—	✓	—
FCD STDEV	Functional (load-related) cracking standard deviation	—	✓	—
FC CNT	Functional (load-related) cracking count	—	✓	—
FCI	Functional (load-related) cracking index	—	✓	—
FCI STDEV	Functional (load-related) cracking index standard deviation	—	✓	—
SC DENSITY	Structural (load-related) cracking density	—	✓	—
SCD STDEV	Structural (load-related) cracking standard deviation	—	✓	—
SC CNT	Structural (load-related) cracking count	—	✓	—
SCI	Structural (load-related) cracking index	—	✓	—
SCI STDEV	Structural (load-related) cracking index standard deviation	—	✓	—
CRACKING FAMILY	PMS pavement family designation for forecasting cracking (e.g., 99)	—	✓	—
FRICTION	Surface friction	—	—	✓

—No data.

On average, the datasets provided by State 3 DOT contained approximately 69,000 records. The 69,000 records represented approximately 28,170 individual PMS sections. A summary of the PMS sections according to pavement type and functional class is presented in table 55, which shows that, of the 28,170 individual PMS sections, 60.3 percent were flexible (F) pavements, 3.5 percent were rigid (R) pavements, and 35.8 percent were composite (FCJ) pavements. The remaining 0.5 percent of PMS sections were not classified.

Table 55. Summary of the PMS sections according to pavement type and functional class.

Functional Class	Pavement Type: Others	Pavement Type: F	Pavement Type: FC	Pavement Type: R
1	—	454	105	67
11	8	633	638	349
12	4	1,147	509	168
14	45	4,833	3,100	301
16	32	3,207	1,750	39
17	8	489	191	—
19	—	189	101	—
2	13	1,541	691	47
6	2	1,781	1,237	8
7	10	1,932	1,292	6
8	2	489	298	—
9	3	289	163	—

—No data.

Regarding data availability, the review of all three distress summary files indicated that key data items used to characterizing a PMS section location (ROUTE, RNUM, RSUFF, DIRECTION, BMP, and EMP) or pavement condition (CRACKING, RUTTING, and FRICTION) were close to 100 percent available. Contract identification information (key data items CONTRACT and Financial Management Information System [FMIS] used mostly for linking PMS datasets to other information sources to establish PMS section construction history) was also generally available. The dataset also provided basic pavement construction material types, and these were generally available for all records. Table 56 presents an example of data availability summary for TREND_CRACKING_SUMMARY_2-2-2016.xlsx.

Table 56. Summary of data availability for the State 3 DOT PMS cracking data table TREND_CRACKING_SUMMARY_2-2-2016.xlsx.

Data Item	Total Number of Records	Records with Data Available (Percent)
ID_	68,824	100.0
SECTION_ID	68,824	100.0
TREATMENT_ID	68,824	100.0
GLOBAL_ROUTE_ID	68,824	100.0
SUB_ROUTE_ID	68,824	100.0
REGION	68,824	100.0
DISTRICT	68,824	100.0
COUNTY	68,824	100.0
ROUTE	68,824	100.0
RNUM	68,824	100.0
RSUFF	4,788	6.9
DIRECTION	68,824	100.0

Data Item	Total Number of Records	Records with Data Available (Percent)
BMP	68,824	100.0
EMP	68,824	100.0
LANE_NUMBER	68,824	100.0
OUTER_LANE	68,824	100.0
FUNC_CLASS	68,824	100.0
GOVT_CONTROL	68,824	100.0
PAVEMENT_TYPE	68,824	100.0
TREATMENT_THICKNESS	6,8824	100.0
CURRENT_TREATMENT_THICKNESS	68,824	100.0
LAYER_NO	68,824	100.0
BIRTH_YEAR	68,824	100.0
CONTRACT	68,824	100.0
FMIS	68,824	100.0
LAYER_DESCRIPTION	68,824	100.0
MATERIAL_BAND_SIZE	68,824	100.0
YEAR_ORDER	68,824	100.0
MAT_UNIQUE_ID	68,824	100.0
MATERIAL_DESCRIPTION	68,824	100.0
TREATMENT	68,824	100.0
LAYER_TYPE_DESCRIPTION	68,824	100.0
MATERIAL_MIX_METHOD_DESC	68,824	100.0
MATERIAL_MIX_TYPE_DESC	68,824	100.0
MATERIAL_BINDER	68,824	100.0
MATERIAL_TRAFFIC_LEVEL_DESC	68,824	100.0
CONSTRUCTION_TYPE_DESC	68,824	100.0
DEATH_YEAR	68,824	100.0
AGE	68,824	100.0
FC_DENSITY	68,665	99.7
FCD_STDEV	68,665	99.7
FC_CNT	68,824	100.0
FCI	68,665	99.7
FCI_STDEV	6,8665	99.7
SC_DENSITY	68,663	99.7
SCD_STDEV	68,663	99.7
SC_CNT	68,824	100.0
SCI	68,663	99.7
SCI_STDEV	68,663	99.7

Data Item	Total Number of Records	Records with Data Available (Percent)
FC_DIFF	31,168	45.2
SC_DIFF	31,168	45.2
CRACKING_FAMILY	68,824	100.0
COLLECT_YEAR	68,824	100.0
FCI_ADJ	68,824	100.0
SCI_ADJ	68,824	100.0

For QA/QC-type information, the project team obtained the following data files:

- BinderData.
- ConstructionHistory.
- MixDesignAggSourceXXX and MixDesignXXX. (Filenames have been modified to not disclose State 3 DOT identity.)
- TestDataQA and TestDataQC.

Table 57 presents a summary of data availability for the BinderData table. Detailed information such as Binder PG grade, DSR *G**, and phase angle were available in this data table in significant quantities (greater than 90 percent of all records). Project/contract identification numbers for linking the QA/QC binder tests records to PMS and other datasets were also available.

The ConstructionHistory data table provided information for each unique PMS section regarding historical construction/maintenance activities (i.e., CONSTRUCTION_TYPE and ACTION_YEAR). Location information, such as ROUTE, RNUM, DIRECTION, BMP, and EMP, along with contract information (FUND, CONTRACT, and FMIS), were also available. In total, detailed ConstructionHistory data were available for 36,200 unique PMS sections.

Table 57. Summary of data availability for the State 3 DOT QA/QC data table BinderData.xlsx.

Data Item	Total Number of Records	Records with Data Available (Percent)
ID	3,993	100.0
MaterialType	3,985	99.8
SampleIDNumber	3,986	99.8
SampleDate	3,972	99.5
SampleRecDate	690	17.3
ProjectSerialNumber	630	15.8
HMAPlantID	3,696	92.6
ContractNumber	3,961	99.2
FMIS	—	0.0

Data Item	Total Number of Records	Records with Data Available (Percent)
PGGrade	3,985	99.8
SourceOfSupply	321	8.0
Supplier	3,942	98.7
TankNumber	3,568	89.4
LotNumber	3,766	94.3
Terminal	3,492	87.5
InLineBlended	3,993	100.0
SampleType	3,816	95.6
TechnicianName	2,635	66.0
SampleStarted	3,673	92.0
SampleCompleted	3,328	83.3
MixTempMin	3,829	95.9
MixTempMax	3,829	95.9
CompactionTempMin	3,829	95.9
CompactionTempMax	3,828	95.9
RotationalViscosity	3,796	95.1
SpindleSize	—	0.0
DSRTempORIG	3,839	96.1
DSRGStarORIG	3,840	96.2
DSRPhaseORIG	3,737	93.6
DSRTempRTFO	3,769	94.4
DSRGStarRTFO	3,771	94.4
DSRPhaseRTFO	3,736	93.6
MassChange	3,838	96.1
MassLossOrGain	3,661	91.7
DSRTempPAV	3,836	96.1
DSRGStarPAV	3,835	96.0
DSRPhasePAV	3,732	93.5
BBRTemp1	3,836	96.1
BBRStiffness1	3,831	95.9
BBRmvalue1	3,835	96.0
BBRTemp2	3,661	91.7
BBRStiffness2	3,661	91.7
BBRmvalue2	3,661	91.7
BBRTemp3	3,661	91.7
BBRStiffness3	3,661	91.7
BBRmvalue3	3,661	91.7
MSCR_1	—	0.0
MSCR_2	—	0.0

Data Item	Total Number of Records	Records with Data Available (Percent)
MSCR_3	—	0.0
MSCR_4	—	0.0
DTTemp1	3,660	91.7
DTStrengthAvg1	3,661	91.7
DTStrainAvg1	3,661	91.7
DTTemp2	3,661	91.7
DTStrengthAvg2	3,661	91.7
DTStrainAvg2	3,661	91.7
CritCrackTemp	3,661	91.7
Remarks	1,405	35.2
Cost	3,713	93.0
Tests	3,847	96.3
PASSFAILRV	—	0.0
PASSFAILDSRO	—	0.0
PASSFAILDSRR	—	0.0
PASSFAILMASS	—	0.0
PASSFAILDSRP	—	0.0
PASSFAILBBRS	—	0.0
PASSFAILBBRM	—	0.0
MeetsSpec	3,993	100.0
DoesNotMeetSpec	3,993	100.0
ProjectDetail	54	1.4
SampleTakenFrom	604	15.1
Truck.	108	2.7
TruckTag.	121	3.0
SampleRemarks	314	7.9
TestNotes	332	8.3
Visc_Test_Temperature	621	15.6
Visc_SHA	612	15.3
Visc_Supplier	256	6.4
Residue	633	15.9
Residue_Supplier	274	6.9
Sieve	518	13.0
Sieve_Supplier	264	6.6
SampleMeets	3,993	100.0
SampleDoesNotMeet	3,993	100.0
Other	3,993	100.0
OtherComment	154	3.9
SignedDate	117	2.9

Data Item	Total Number of Records	Records with Data Available (Percent)
SignedBy	117	2.9
M332_DSRTempORIG	12	0.3
M332_DSRGStarORIG	12	0.3
M332_DSRPhaseORIG	—	0.0
M332_DSRTempPAV	84	2.1
M332_DSRGStarPAV	84	2.1
M332_DSRPhasePAV	—	0.0
M332_MSCR_Temp	91	2.3
M332_MSCR_R01	91	2.3
M332_MSCR_R32	91	2.3
M332_MSCR_Rdiff	91	2.3
M332_MSCR_Jnr01	91	2.3
M332_MSCR_Jnr32	91	2.3
M332_MSCR_PDR_JnrDiff	90	2.3

—No data.

Data table MixDesignAggSourceXXX contained 7,926 records. Key data items provided include the name of the plant where the aggregate was produced or used, PRODUCTID, and PRODUCTNUMBER, along with the original aggregate source (name of supplier) and location (of quarry). Material type (e.g., coarse, sand) and size (e.g., number 9) were also provided. As shown in table 58, approximately 23 percent of the 7,926 records had the key information for the key data items.

Table 58. Summary of data availability for the State 3 DOT QA/QC data table MixDesignAggSourceXXX.xlsx.

Data Item	Total Number of Records	Records with Data Available (Percent)
Plant	7,926	100.0
PRODUCTID	1,830	23.1
PRODUCTNUMBER	1,830	23.1
Source	1,830	23.1
Location	1,830	23.1
Size2	1,830	23.1
COMP_PRODUCTID	1,830	23.1
Size	—	0.0
PERCENTAGE	338	4.3
Comp_Mat_Type_ID	1,789	22.6
COMP_MAT_TYPE	1,829	23.1
EXPIRATIONDATE	268	3.4
PlantRef	270	3.4
DESIGNFORMATREF	—	0.0

—No data.

Data table MixDesignXXX, a summary of which is provided in table 59, contained 1,830 records. Key data items provided were HMA mix type and properties such as gradation, percent binder, fine/coarse aggregate angularity, traffic (ESAL), aggregate specific gravity, air voids, VMA, and VFA. State 3 DOT provided additional, more detailed lab test data such as the tensile strength ratio (TSR). In general, over 80 percent of the records had some information about the key data items available. The data tables TestDataQA and TestDataQC contained over 600,000 records of HMA QA/QC test data. Data items of relevance included gradation, density, VFA, VMA, VTM, and HMA core thickness. The research team referenced the information presented in these tables using the data items ProjectID and job mix formula ID (JMFID). Information was available for 5,600 unique ProjectID and JMFID records.

Table 59. Summary of data availability for the State 3 DOT QA/QC data table MixDesignXXX.xlsx.

Data Item	Total Number of Records	Records with Data Available (Percent)
PRODUCTID	1,830	100.0
Mix	1,830	100.0
PLANTREF	1,830	100.0
Plant	1,830	100.0
MixMeth	1,830	100.0
MixType	1,830	100.0
Band	1,830	100.0
EXPIRATIONDATE	0	0.0

Data Item	Total Number of Records	Records with Data Available (Percent)
PRODCOMMENTS	338	18.5
STAPPROVED	1,789	97.8
ESTSTARTDATE	1,829	99.9
ACTSTARTDATE	268	14.6
ACTCOMPDATE	270	14.8
TSKCOMMENT	496	27.1
ASSIGNEDTO	269	14.7
Percent passing 2 inches through No. 200 sieve sizes	1,806	90–98.7
ACProducer	1,830	100.0
ACType	1,830	100.0
ACPercent	1,828	99.9
Coarse Agg Ang	1,606	87.8
Date Verified	415	22.7
ESAL	1,626	88.9
FE	1,588	86.8
Fine Agg Ang	1,618	88.4
Gb	1,773	96.9
Gmb	1,801	98.4
Gmb (design)	1,626	88.9
Gmm	1,801	98.4
VA	1,794	98.0
VMA	1,786	97.6
VFA	1,784	97.5
Gse	1,769	96.7
Gmm @ N (Max)	738	40.3
Gsb	1,789	97.8
Is Final	1,730	94.5
Mix Method	1,619	88.5
Mix Temp	1,798	98.3
Mix Type	1,398	76.4
Mold Temp	1,798	98.3
Region	1,822	99.6
Sand Eq	1,617	88.4
Sequence	736	40.2
TSR	1,590	86.9
PBA	1,756	96.0
PBE	1,756	96.0
D/B Ratio	1,804	98.6
TraffLevel	1,626	88.9

Data Item	Total Number of Records	Records with Data Available (Percent)
NIni	1,627	88.9
NDes	1,627	88.9
NMax	1,627	88.9

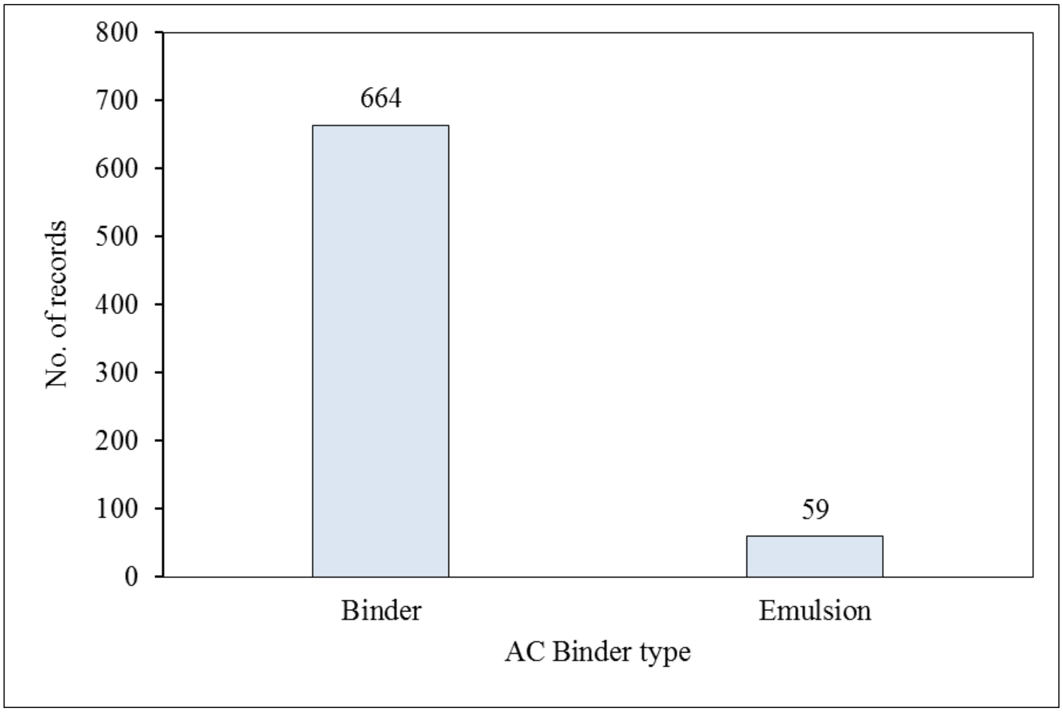
EST = estimated; ACT = actual; FE = flat and elongated; Gb = asphalt specific gravity; PBA = absorbed asphalt binder of aggregate; PBE = effective asphalt content; D/B = dust-to-effective binder ratio; NIni = initial traffic.

State 3 DOT PMS and QA/QC Test Data Review

The research team reviewed the assembled PMS and QA/QC data to assess accuracy and reasonableness. Data accuracy was assessed by developing plots of trends in performance measures (e.g., IRI versus data collection date) and histograms showing the distribution of QA/QC test data. Since only 5 yr of distress data were available, the plots are not presented in this section. However, the measured values were considered to be mostly reasonable.

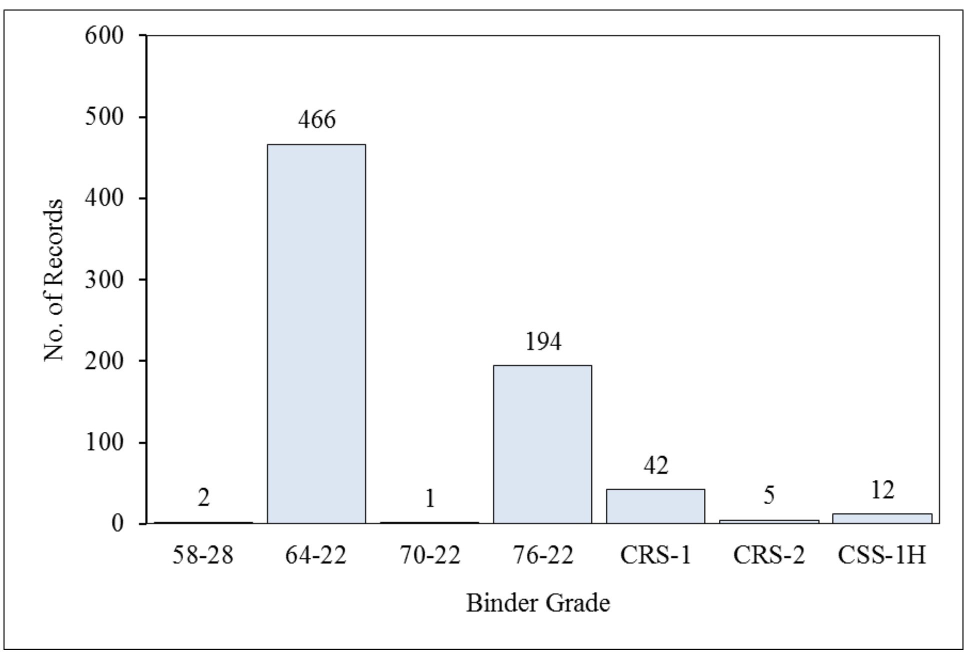
Figure 93 through figure 103 present data distributions of key QA test results obtained from the State 3 DOT Binder Test, MixDesignXXX, and QA/QC test datasets. The data assembled were reviewed and found to be accurate and reasonable. The following outcomes were generally observed:

- There were very few projects with emulsions compared with binders.
- PG 64-22 and PG 76-22 are the two most common binder types. A relatively small number of projects with PG 64-28 and PG 58-28 were also included. However, it was later found that corresponding performance data were limited for these projects.
- Approximately 60 percent of the test data were obtained from the QC testing program.
- QA/QC datasets included significantly more RAP mixes than Neat mixes.
- G^* and phase angle test values appeared reasonable.
- HMA core thickness ranged from 1 to 5 inches, which implies thin HMA pavements were very common.
- HMA mix properties density, VMA, VFA, and so on, appear to be reasonable.



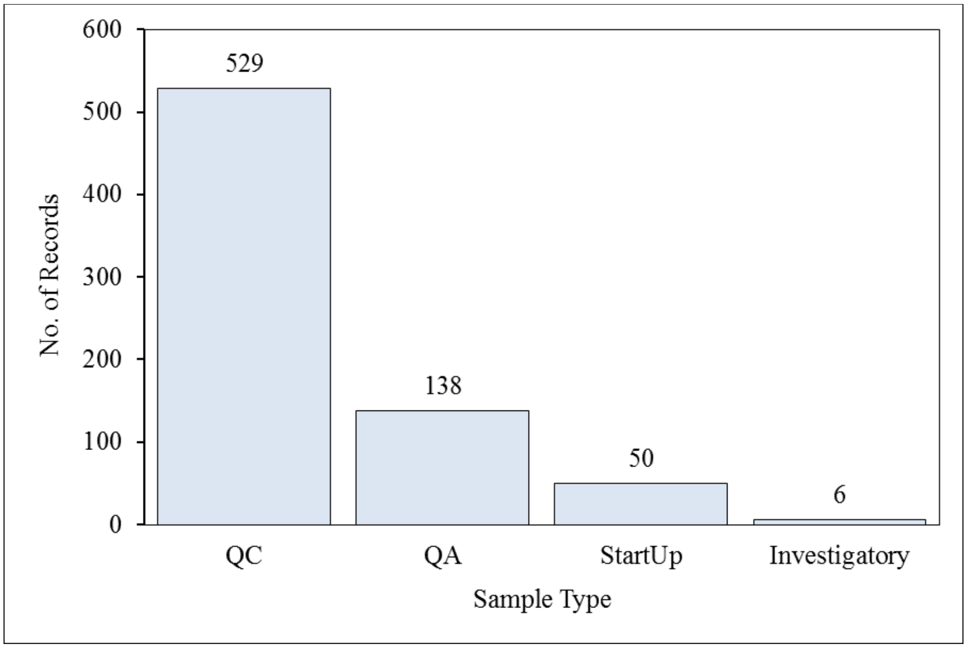
Source: FHWA.

Figure 93. Graph. Histogram showing distribution of AC binder type obtained from the State 3 DOT QA test data tables.



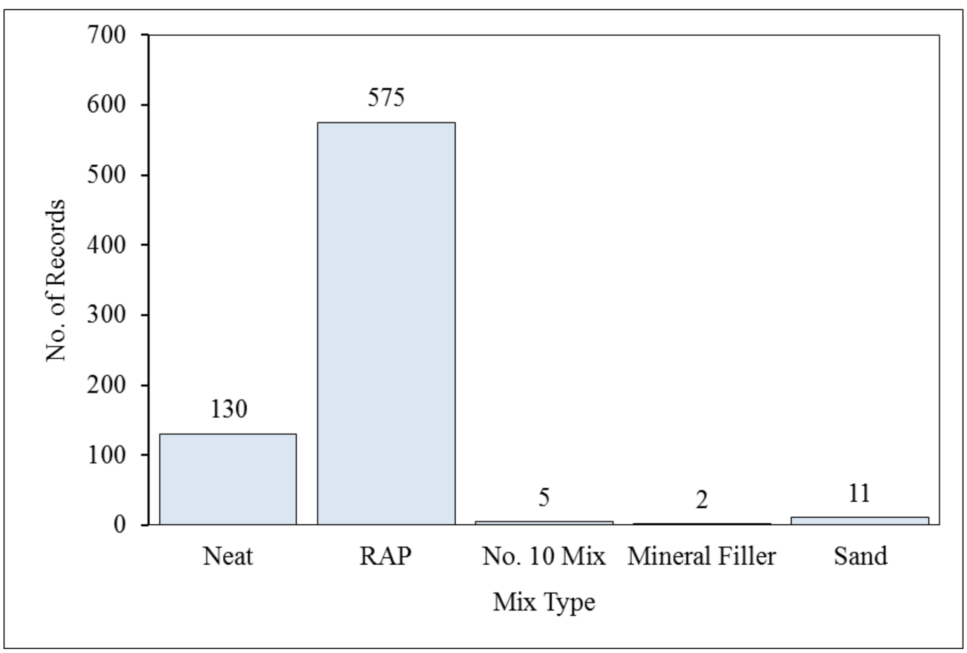
Source: FHWA.

Figure 94. Graph. Histogram showing distribution of binder grade obtained from the State3 DOT QA test data tables.



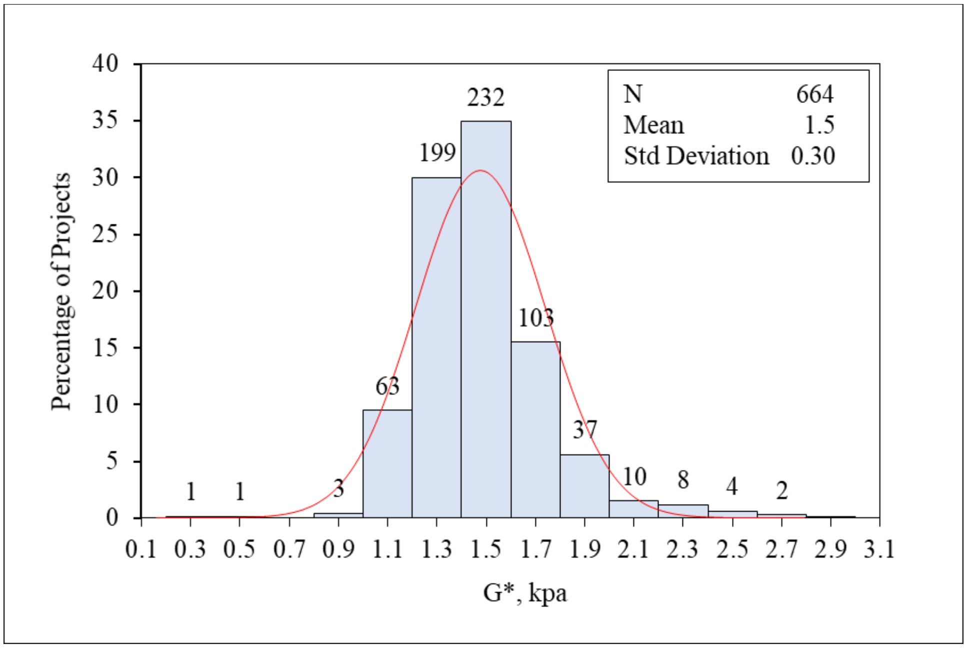
Source: FHWA.

Figure 95. Graph. Histogram showing distribution of AC binder sampling type obtained from the State 3 DOT QA test data tables.



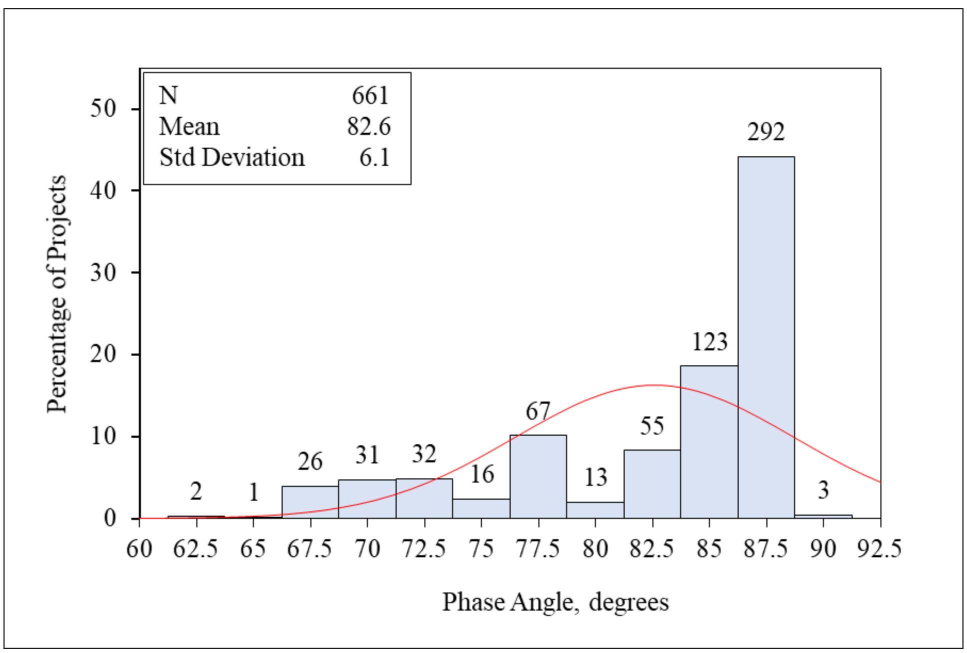
Source: FHWA.

Figure 96. Graph. Histogram showing distribution of HMA mix type obtained from the State 3 DOT QA test data tables.



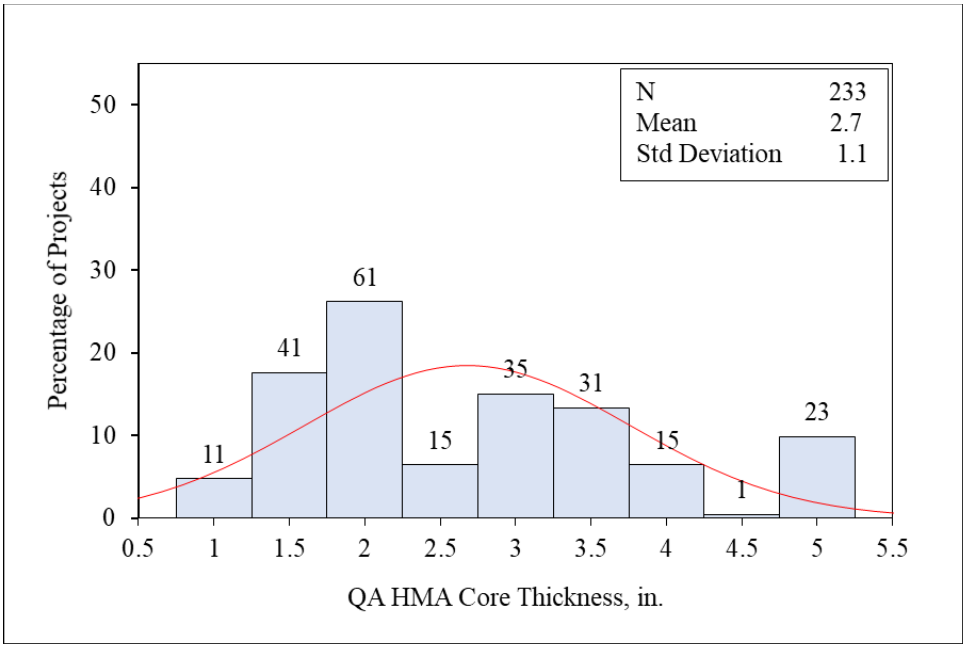
Source: FHWA.

Figure 97. Graph. Histogram showing distribution of AC binder *G (original binder) obtained from the State 3 DOT QA test data tables.**



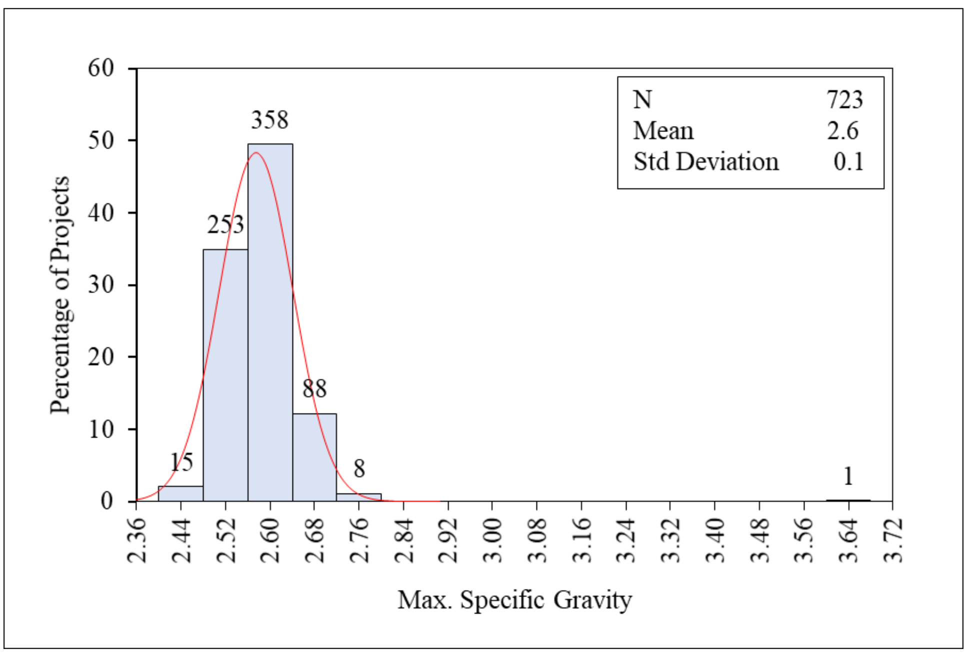
Source: FHWA.

Figure 98. Graph. Histogram showing distribution of AC binder phase angle (original binder) obtained from the State 3 DOT QA test data tables.



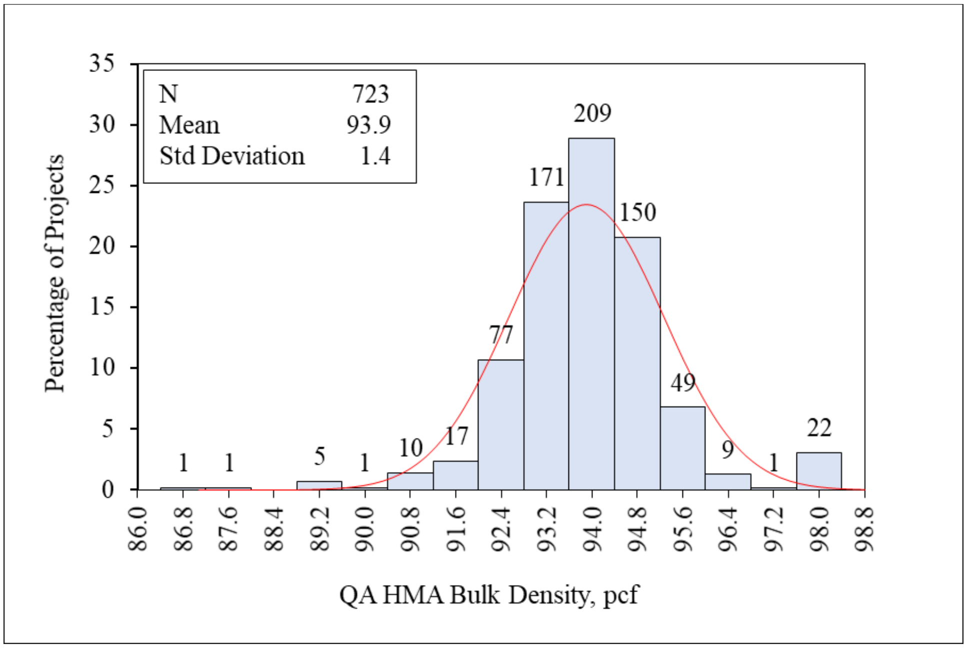
Source: FHWA.

Figure 99. Graph. Histogram showing distribution of HMA thickness (from field extracted cores) obtained from the State 3 DOT QA test data tables.



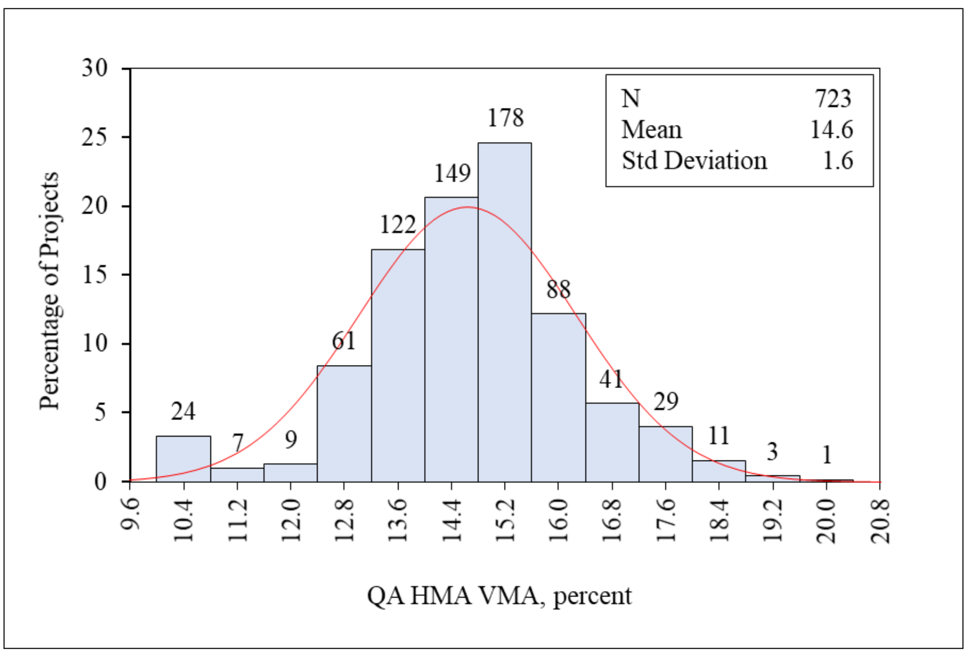
Source: FHWA.

Figure 100. Graph. Histogram showing distribution of HMA mix maximum specific gravity obtained from the State 3 DOT QA test data tables.



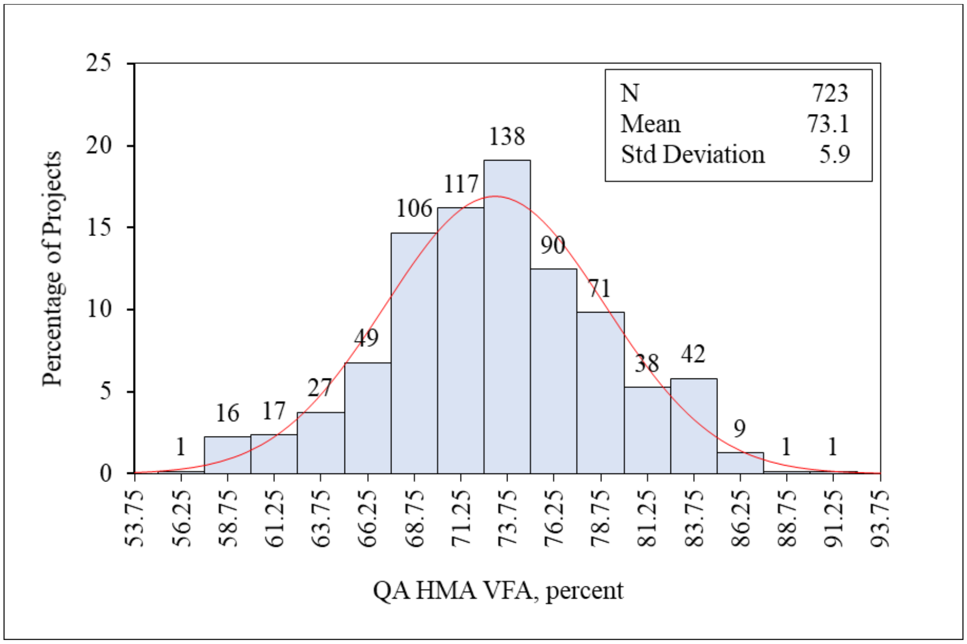
Source: FHWA.

Figure 101. Graph. Histogram showing distribution of HMA bulk specific gravity obtained from the State 3 DOT QA test data tables.



Source: FHWA.

Figure 102. Graph. Histogram showing distribution of HMA VMA obtained from the State 3 DOT QA test data tables.



Source: FHWA.

Figure 103. Graph. Histogram showing distribution of HMA VFA obtained from the State 3 DOT QA test data tables.

State 4 DOT

State 4 DOT IC and QA/QC and Test Data Assembly and Review

From all three projects, over 16 million IC readings were collected. The extent of IC data collected and assembled is summarized in table 60. Table 61 presents a summary of field core density measurements for all three projects. Figure 104 and figure 105 present examples of IC temperature data for short segments of the US-KK and I-LLL projects, respectively, i.e., this plot represents a subset of the data used in the analyses. These plots show the distribution of temperature across the mat for different passes. The lower temperature band was measured on the shoulder where no paving was performed. Figure 105 also shows the start station of the project.

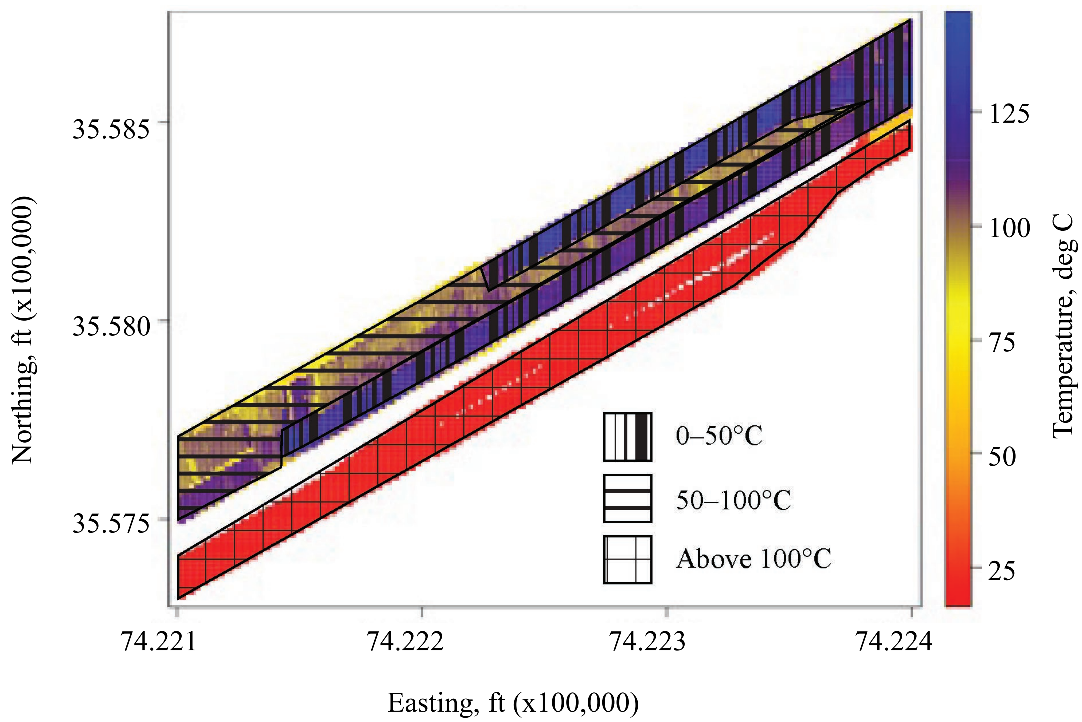
Table 60. Summary of IC data collected and assembled from the three projects in State 4.

Variable	Minimum Value	Average Value	Maximum Value
Easting (ft)	7,391,489	7,490,789	7,659,283
Northing (ft)	332,104	428,596	630,300
Elevation (ft)	110	473	865
Last Amp (mm)	0	0.61	2.99
Last CMV	0.2	35.39	200
Last frequency (Hz)	17.9	58.46	70.4
Last RMV	0	10.62	200
Last radio Ltncy	0	0	0
Last temperature (°F)	0	87.19	234.5
Lift number	1	1	1
Pass number	1	6	62
Speed (mph)	0	5.05	279.5
Target pass count	2	2.9	5
Target thickness (ft)	0.66	0.66	0.66

Amp = amplitude; Ltncy = latency.

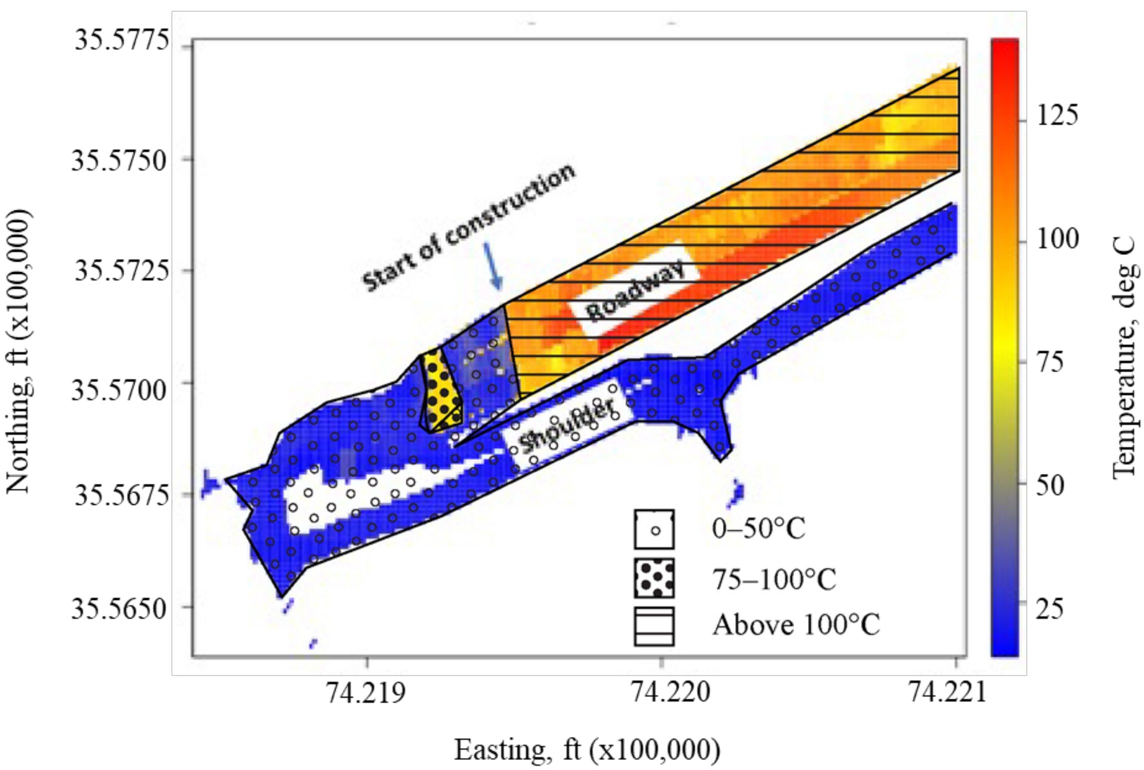
Table 61. Summary of field density from the three projects in State 4.

Project	Variables	Minimum Value	Average Value	Maximum Value
I-LLL	Easting (ft)	7,622,618	7,639,842	7,658,722
	Northing (ft)	620,067	626,196	630,289
	HMA density	90.1	93.96	96.9
I-MM	Easting (ft)	7,535,556	7,537,527	7,541,522
	Northing (ft)	369,577	384,330	413,155
	HMA density	91.5	94.22	97
US-KK	Easting (ft)	7,392,021	7,421,715	7,450,288
	Northing (ft)	332,194	351,729	358,685
	HMA density	91.6	96.37	97



Source: FHWA.

Figure 104. Graph. Heatmap showing field-measured IR HMA temperature from US-KK.



Source: FHWA.

Figure 105. Graph. Heatmap showing field-measured IR HMA temperature from I-LLL.

CHAPTER 5. DATA INTEGRATION METHODOLOGIES

DATA FORMATS OF DATA USED IN ANALYSES

Utilizing traditional QA/QC test data and outputs from new innovative pavement testing technologies as leading indicators of future pavement performance would be feasible only when integrating such data with construction history information, traffic, climate, and so on, along with existing DOT PMS. Data integration is described as a process comprising several technical, business, and coding tasks, leading to combining disparate data sources into a single dataset.

A review of DOT QA/QC test and PMS data collection and storage practices indicates myriad referencing systems, data formats, and aggregation levels being used by different units within the agency. The files are stored on various media, including centralized servers, desktop computers, paper files/reports, and DVDs. Typically, data are stored using a mix of agency in-house, customized, and commercial off-the-shelf (COTS) platforms; see table 62 and table 63 for examples. With the current state of the practice, DOTs have resorted to using a wide range of processes and protocols to facilitate data integration. The processes typically comprise:

- Identification of PMS, QA/QC, construction, traffic, and climate data items of interest.
- Identification of PMS, QA/QC, construction, traffic, climate data storage formats, aggregation methods, and referencing systems.
- Development of wrappers, queries, and codes for extracting datasets of interest.
- Development of wrappers, queries, and codes for integrating datasets of interest. This process typically requires DOTs to integrate the selected datasets incrementally as referencing systems across datasets vary considerably.

DOTs used various types of wrappers constructed around these data sources to extract data and update information. The wrappers are programming codes/executables, SQL codes, and scripts that are written in C#, SAS, and Visual Basic using software such as Microsoft Access, Oracle, SAS, and other applications. Wrappers can be as simple as an SQL script that links records in two datasets using common referencing systems (route number and MP) to more complex Visual Basic, SAS, and C# codes that combine logic and detailed programming to integrate databases. Also, the application of COTS software may be needed to covert hardcopies/PDF files into electronic data tables before integration with other datasets.

Specific to this project, PMS, QA/QC, and other required data used analyses that were obtained in a variety of formats, as shown in table 64. Effectively integrating the various data sources and formats required the use of several software and wrapper, queries, and coding. The level of detail of wrapper, queries, and coding very much depended on both the data formats and the referencing systems used to link records within the databases. The following sections present details of the procedures used for integrating the QA test and PMS databases obtained for this study.

Table 62. Examples of databases being used by different units within the agency.

Data Categories	Electronic Spreadsheets Oracle	Electronic Spreadsheets SAS	Electronic Spreadsheets Microsoft Access, Excel, CSV, TXT	Electronic Documents	Hardcopies (Paper)
PMS (condition information)	✓	✓	✓	—	—
Construction history (maintenance and rehabilitation records)	✓	✓	✓	✓	✓
QA/QC test data	—	—	✓	✓	✓
Climate	—	—	✓	✓	✓
Traffic	✓	✓	✓	✓	✓

—No data.

Table 63. Examples of referencing systems and aggregation levels being used by different units within the agency.

Data Categories	Per Pavement Section (0.1–1 mi)	Per Project or Lots/Sublots within Project	Per Supplier or Source
PMS (condition information)	✓	—	—
Construction history (maintenance and rehabilitation records)	✓	✓	—
QA/QC test data	—	✓	✓
Climate	—	—	—
Traffic	✓	✓	—

—No data.

Table 64. Summary of the data formats for the PMS/QA data used in this project.

Data Format	State 1	State 2	State 3	State 4
Paper (hardcopy)	✓	✓	✓	—
PDF*	✓	✓	✓	—
Microsoft Excel (XLS, CSV)	✓	✓	✓	✓
Microsoft Access	—	—	✓	✓

—No data.
*These data can be digitized by the agency with little to no effort.

METHODOLOGIES FOR DATA INTEGRATION

Integrating the assembled datasets from the State 1, State 2, State 3, and State 4 DOTs involved the following:

1. Identifying relevant referencing systems (note: this procedure varied with datasets).

2. Developing protocols and flowcharts for linking the referencing systems identified.

3. Developing wrappers, queries, and codes in the most appropriate software environment/platforms to perform integration actions.

4. Running wrappers, queries, and codes as needed and incrementally to effect actual dataset integration.

5. Assembling integrated datasets and assessing accuracy/reasonableness of data items.

A detailed step-by-step description of the data integration process is as follows:

1. Identify relevant referencing systems of datasets to be integrated.

    a. For PMS-type pavement condition and inventory datasets, the referencing system of interest was HWY/Route Type/Number and BEGIN/END Milepost, because for State 1, State 2, and State 3 DOTs, condition data were aggregated at the PMS section level (i.e., 0.1- to 1-mi increments of highway pavement), which was defined using the referencing systems described. It must be noted that, although State 2 DOT provided both route type/number and MP and GPS longitude/latitude as referencing systems in their PMS, the use of GPS was not applied in this analysis because no other databases used GPS as a referencing system.

    b. For the other data types (construction, rehabilitation, and maintenance history, materials QA test data, nontraditional testing from new technologies, and so on), three types of referencing systems were commonly used across the three DOTs:

        i. Route type/number and MP.

        ii. Accounting number, typically the agencies' SUBAC subaccount number, FMIS, or Federal project number.

        iii. DOT project/tracking (TRACS) number.

    The SUBAC and TRACS were key in retrieving information from datasets not typically maintained by the agency's pavement or traffic engineering units.

2. Develop procedures or flowcharts to format and normalize referencing systems. Although datasets may be using a common form of referencing systems (e.g., ROUTE TYPE/NUMBER and Milepost), the definitions of route type or MP may differ across datasets. For example, across datasets or sometimes within a given dataset, the highway

route type may be defined as I or IH, with both meaning interstate highways. Also, while a PMS system may be aggregating and reporting pavement condition for 0.1-mi sections, a construction database may report QA test data over a 5-mi project using a combination of SUBAC/TRACS number, ROUTE TYPE/NUMBER, BMP/EMP (which is greater than 0.1 mi), and SAMPLING or LOT/SUBLOT locations, defined mostly by chainage within the project. There was no need to develop wrapper, queries, or codes to convert the combination of SAMPLING or LOT/SUBLOT locations to actual MILEPOST or GPS (longitude/latitude) and redefine aggregation across datasets.

3. Convert the logic in the previously described developed procedures/flowcharts into software codes, wrappers, and executables as needed. The research team developed codes, wrappers, and queries based on the outcomes of the developed procedures and flowcharts. Coding was done using a small sample of data available and was tested thoroughly to ensure that it worked for all situations. This step was iterative, as several checks and modifications were necessary when developing required codes and executables that produced integrated datasets with minimum error.

4. Design and develop an integrated database.

    a. Define the objective of the integrated dataset (e.g., develop a database with the capability to store information and data items required to investigate the impact of HMA QA and QC test data for fatigue cracking). A dataset for this type of investigating must, as a minimum, contain the following:

        i. PMS section definition.

            1) Highway functional class.
            2) Pavement type.
            3) Pavement location (HWY, ROUTE TYPE/#, BEG/END MP, and so on).

        ii. Construction history.

            1) Last major construction event.

                a) M&R.
                b) New construction.
                c) Year.

            2) Previous major construction event.

                a) Type, year, and thickness.

        iii. Condition data.

            1) Fatigue cracking.

a) Extent.
b) Severity.
c) Collection date and year.

2) Age (collection date to construction date).

iv. QA test data from the last and previous major construction and maintenance activities:

1) HMA mix type.
2) Binder type and properties.
3) Aggregate sources.
4) Field and lab volumetric properties.
5) Field and lab gradation.
6) Layer thickness.
7) Others.

v. Historical traffic (ESALs, AADT, percent trucks, number of lanes, and so on).

b. Design a database to include all data items described in a logical and easy-to-understand manner. Note that historical cracking performance data corresponding to various stages of the pavement history (defined by age or traffic applications) must be available for analysis.

5. Run wrappers, codes, and queries as needed to assemble data into the integrated datasets described in the integrated database.

6. Check the assembled data for reasonableness and accuracy. Identify and correct anomalies as needed.

7. Finalize the integrated dataset.

The following sections describe in detail the project database development procedures used in this study to develop the integrated datasets required for analysis.

QA Test and PMS Data Integration for State 1

The research team integrated the State 1 DOT QA/QC test data and PMS/performance datasets using key PMS data ROUTE TYPE/MILEPOST and QA test data TRACS/PROJECT NUMBER referencing systems. The steps used for data integration are described as follows:

1. Identified datasets of interest.

a. Datasets of interest were described in detail in chapter 4. The information relevant for this discussion includes general content and referencing systems that are described as follows:

i. State 1 DOT_PERF_DATA: ROUTE TYPE/MILEPOST.
ii. STATE 1_RUTTING: ROUTE TYPE/MILEPOST.
iii. STATE 1_CRACKING: ROUTE TYPE/MILEPOST.
iv. Dense Graded Asphaltic Concrete: TRACS NUMBER.
v. Soil Aggregate Tabulation (Aggregate Base): TRACS NUMBER.
vi. Soil Aggregate Tabulation (Subgrade): TRACS NUMBER.

b. Information presented in step 1a shows that the PMS-type datasets had a common referencing system, ROUTE TYPE/MILEPOST, while the QA-type dataset referencing system was TRACS NUMBER. Thus, there was a need to develop means to link these two referencing systems. This step was done by using the State 1 DOT business office JOB SERVICE datasets, which provide information about both TRACS NUMBER and ROUTE TYPE/MILEPOST for State 1 DOT highway projects (table 65).

2. Combined State 1 DOT PMS datasets.

a. All three State 1 DOT PMS datasets—STATE 1DOT_PERF_DATA, STATE 1_CRACKING, and STATE 1_RUTTING—use the combination of ROUTE TYPE, RTE (i.e., ROUTE NUMBER), DIR (DIRECTION), AND MP (MILEPOST) to define PMS sections. The typical PMS section was 1 mi long, and thus performance data are aggregated over the 1-mi sections. For rutting, however, additional data are provided for offsets within the 1-mi PMS sections. Thus, all measured rutting data within a predefined PMS section were averaged and then reported the average rutting value for the given 1-mi PMS section.

b. STATE 1DOT_PERF_DATA, STATE 1_CRACKING, and STATE 1_RUTTING datasets are merged by linking the unique PMS section identifiers ROUTE TYPE, RTE, DIR, MP, and year for which the data were collected. The research team wrote code and a query in Microsoft Access to perform this task, as shown in figure 106.

3. Combined State 1 DOT QA/QC datasets. The QA datasets were merged using their unique TRACS NUMBER (figure 107).

4. Merged PMS and QA datasets. This action was done by using the STATE 1 DOT JOB SERVICES datasets as follows:

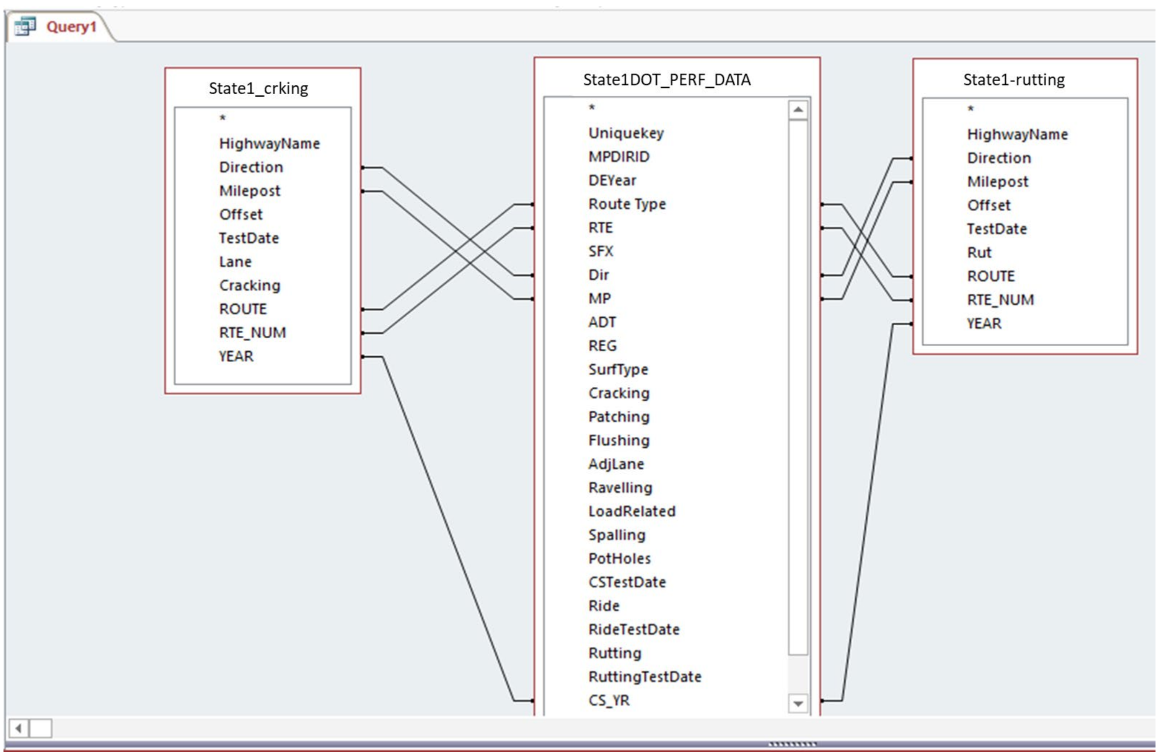
a. Link PMS and JOB SERVICES datasets using the ROUTE TYPE, RTE, DIR, MP information available in both data tables.

b. Link combination of PMS and JOB SERVICES QA test datasets using the TRACS NUMBER information available in both datasets.

c. Merger using code/queries developed using Microsoft Access. Examples are presented in figure 107 and figure 108.

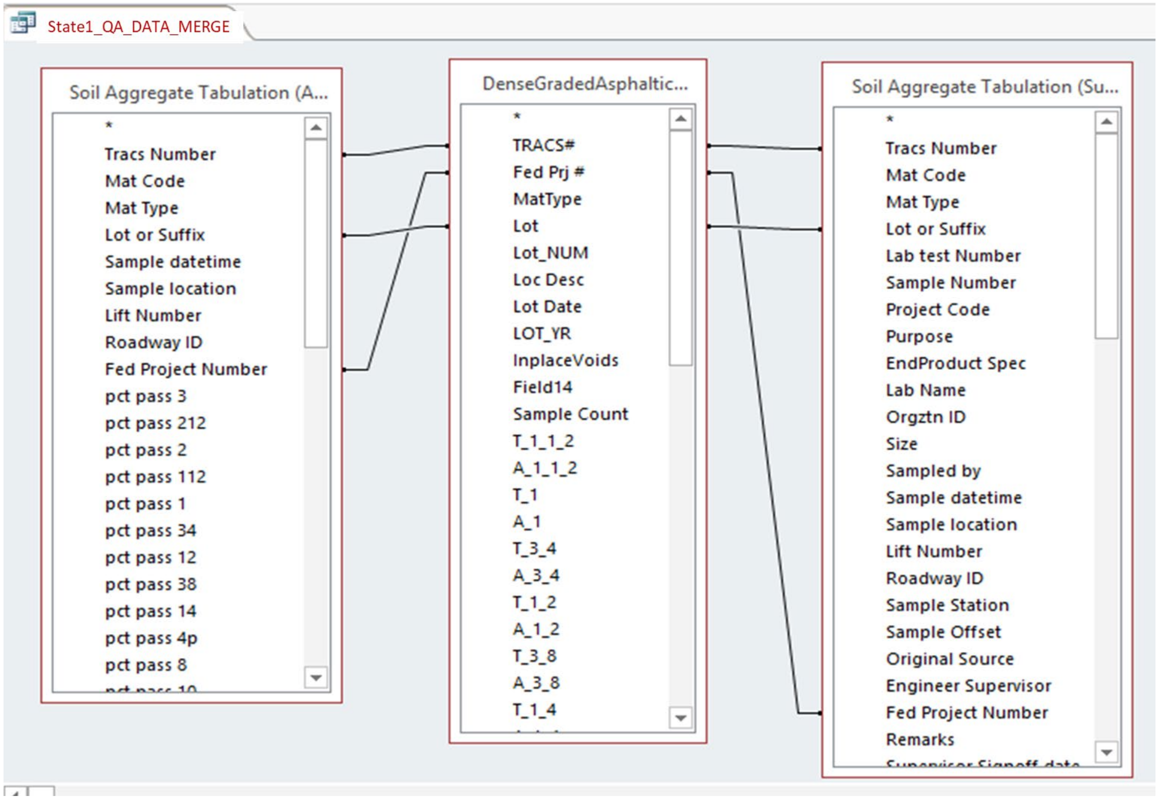
Table 65. Summary example of STATE 1 DOT JOB SERVICES dataset.

Route	Begin MP	Project Length (mi)	TRACS Number	Job Number
I-8	147.0	31.0	N/A	1012
I-8	19.8	0.2	H5453S1D	1088
I-8	29	0.1	H5240S1D	1089
I-8	117	3.3	H8000S1D	1146
I-8	13.7	7.8	H8158Y1D	1184
I-8	14.25	0.5	H8158R1D	1184R1
I-8	14.2	0.5	H8158R1D	1184R2
I-8	22.15	1.0	H869701D	1230
I-8	116.9	0.8	H6407S1D	3750
I-8	7.6	0.5	H810201D	3863
I-8	7.6	1.0	H810201D	3863R1
B-8	0	0.5	H7999S1D	1141
B-8	117	3.3	H8000Y1D	1146
I-8	122.9	0.2	H640701R	CS005



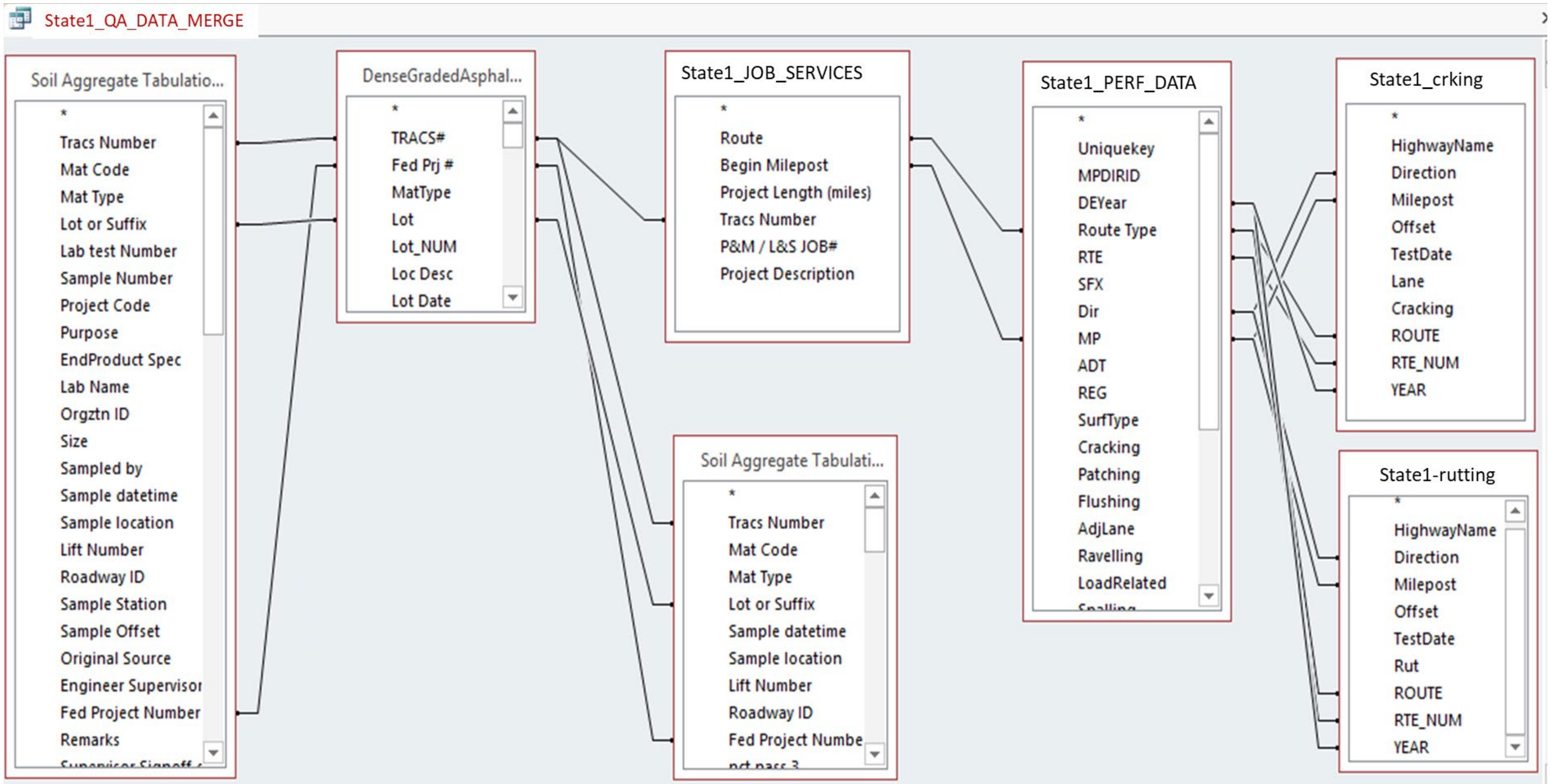
Source: FHWA.

Figure 106. Diagram. Microsoft Access code for merging STATE 1 DOT_PERF_DATA and STATE 1_RUTTING/STATE 1_RUTTING datasets by ROUTE TYPE/RTE/DIR/MILEPOST/YR.



Source: FHWA.

Figure 107. Diagram. Microsoft Access code for merging QA data tables of dense graded asphaltic concrete, soil aggregate tabulation (aggregate base), and soil aggregate tabulation (subgrade) by TRACS number.



Source: FHWA.

Figure 108. Diagram. Microsoft Access code for merging all PMS, performance, and QA test data for assembling the project database.

The preceding steps were used to assemble all needed information from the State 1 DOT PMS and QA/QC datasets required for performing the analysis under this study. Successful implementation of these steps indicated that it is possible to obtain and integrate required data using current State 1 DOT PMS and QA/QC database formats, aggregation, and reporting procedures to achieve study goals and objectives. Examples of detailed information assemble through integration the State 1 DOT datasets are presented in table 66 through table 69.

Table 66 highlights, for a given project, aggregate base sampling locations with sample retrieval times. This type of detailed information is key for determining exactly which batch of aggregate base material was placed at the given location (linking with engineer's notes and supplier records) and to which PMS section to link individual sample test results/data.

Table 67 shows similar information for subgrade soils. Linking the location information in table 66 and table 67 makes it possible to link the aggregate base and subgrade soil QA/QC test data for a given PMS sections, which in turn can be matched with the HMA QA/QC data for the same PMS section. Figure 109 presented a plot of station versus percent passing the No. 200 sieve for aggregate base and subgrade soils using the merged dataset presented in table 68 and table 69.

Table 66. QA aggregate base test data for State 1 DOT TRACS number H468101C.

TRACS No.	Material Code	Lot of Suffix	Sample Date and Time	Sample Location	Lift No.	Roadway ID	Fed Project No.
H468101C	AB	—	6/26/2003 1:15	WINDROW-WB. INTERIM RAMP	0	WB	AC*008A-A(014)B
H468101C	AB	—	6/26/2003 6:00	WINDROW-WB. INTERIM RAMP	1	WB	AC*008A-A(014)B
H468101C	AB	—	6/26/2003 6:00	WINDROW-WB. INTERIM RAMP	1	WB	AC*008A-A(014)B
H468101C	AB	—	6/26/2003 6:45	UNDER EXISTING PAVEMENT ON I-8	—	EB	AC*008A-A(014)B
H468101C	AB	—	6/27/2003 9:00	N. FRONTAGE RD. 2' LT OF CL	1	WB	AC*008A-A(014)B
H468101C	AB	—	6/27/2003 13:15	N. FRONTAGE RD. 10' RT OF CL	1	EB	AC*008A-A(014)B
H468101C	AB	0A	7/1/2003 8:30	INTERIM RAMP A	1	WB	AC*008A-A(014)B
H468101C	AB	—	7/2/2003 9:00	RAMP C; RT OF CL	1	RC	AC*008A-A(014)B
H468101C	AB	—	7/2/2003 9:00	RAMP C; RT OF CL	1	RC	AC*008A-A(014)B
H468101C	AB	—	7/8/2003 8:00	N. FRONTAGE RD.; @ CL	1	EB	AC*008A-A(014)B
H468101C	AB	—	7/24/2003 9:15	6' RT OF CL	1	RC	AC*008A-A(014)B
H468101C	AB	—	7/24/2003 9:20	W/R RT OF CL	1	RC	AC*008A-A(014)B
H468101C	AB	0A	7/25/2003 9:15	W/R RT OF CL	1	RC	AC*008A-A(014)B
H468101C	AB	—	9/2/2003 6:45	10' LT OF CL	1	NB	AC*008A-A(014)B

TRACS No.	Material Code	Lot of Suffix	Sample Date and Time	Sample Location	Lift No.	Roadway ID	Fed Project No.
H468101C	AB	—	9/11/2003 13:00	RAMP "D"	1	EB	AC*008A-A(014)B
H468101C	AB	—	9/12/2003 10:50	RAMP "B"	1	NB	AC*008A-A(014)B
H468101C	AB	—	9/12/2003 10:50	RAMP "B"	1	NB	AC*008A-A(014)B
H468101C	AB	0A	9/17/2003 11:00	RAMP "D"	1	EB	AC*008A-A(014)B
H468101C	AB	—	9/17/2003 11:00	GILA RIDGE RD.	—	EB	AC*008A-A(014)B
H468101C	AB	—	9/17/2003 11:00	GILA RIDGE RD.	—	EB	AC*008A-A(014)B
H468101C	AB	0A	9/18/2003 11:30	AVE. 3 E; S. OF BRIDGES	1	NB	AC*008A-A(014)B
H468101C	AB	—	9/26/2003 10:45	AVE 3E, S. OF GILA RIDGE	—	SB	AC*008A-A(014)B
H468101C	AB	—	9/29/2003 12:00	GILA RIDGE	—	SB	AC*008A-A(014)B
H468101C	AB	—	10/9/2003 9:30	MAINLINE	—	WB	AC*008A-A(014)B
H468101C	AB	—	10/10/2003 12:30	MAINLINE, EAST OF BRIDGE	—	WB	AC*008A-A(014)B
H468101C	AB	—	10/10/2003 12:30	MAINLINE, EAST OF BRIDGE	—	WB	AC*008A-A(014)B
H468101C	AB	0A	10/13/2003 8:00	MAINLINE	—	WB	AC*008A-A(014)B
H468101C	AB	—	10/21/2003 8:15	RAMP A	—	WB	AC*008A-A(014)B
H468101C	AB	—	1/8/2004 14:20	INTERIM RAMP A	1	WB	AC*008A-A(014)B

TRACS No.	Material Code	Lot of Suffix	Sample Date and Time	Sample Location	Lift No.	Roadway ID	Fed Project No.
H468101C	AB	—	1/19/2004 8:30	WINDROW @ CL	1	EB	AC*008A-A(014)B
H468101C	AB	—	1/27/2004 13:00	RDWY, (I-8 e.b.) 15' LT. OF CL	2	EB	AC*008A-A(014)B
H468101C	AB	—	3/18/2004 9:15	Windrow Ramp D	—	EB	AC*008A-A(014)B
H468101C	AB	—	3/18/2004 9:15	Windrow Ramp D	—	EB	AC*008A-A(014)B
H468101C	AB	—	4/21/2004 13:00	15' LT. OF AVE 3E C.L	1	NB	AC*008A-A(014)B

—No data.
NB = northbound; SB = southbound; EB = eastbound; WB = westbound.

Table 67. QA subgrade soil test data for State 1 DOT TRACS Number H468101C.

TRACS Number	Material Code	Lab Test No.	Sample No.	Purpose	Org. ID	Sample Date and Time	Sample Location	Lift No.	Roadway ID	Sample Station	Sample Offset	Original Source	Fed. Project No.	Sieve Test Type
H468101C	SG	03-330	1	Acceptance	8230	6/16/2006 11:00	IN PLACE-INTERIM RAMP	—	WB	27	0	NATIVE ON SITE	AC*008A-A(014)B	STATE 1 201-P12
H468101C	SG	03-331	2	Acceptance	8230	6/16/2003 11:15	IN PLACE INTERIM RAMP	—	WB	42	0	NATIVE ON SITE	AC*008A-A(014)B	STATE 1 248ALT1
H468101C	SG	03-337	3	Acceptance	8230	6/24/2003 7:45	FRONTAGE RD LT OF CL	—	WB	19	0	NATIVE ON SITE	AC*008A-A(014)B	STATE 1 201-P12
H468101C	SG	03-338	4	Acceptance	8230	6/24/2003 8:00	FRONTAGE RD RT OF CL	—	WB	11	0	NATIVE ON SITE	AC*008A-A(014)B	STATE 1 248ALT1

TRACS Number	Material Code	Lab Test No.	Sample No.	Purpose	Org. ID	Sample Date and Time	Sample Location	Lift No.	Roadway ID	Sample Station	Sample Offset	Original Source	Fed. Project No.	Sieve Test Type
H468101C	SG	03-393	4	Acceptance	8230	7/29/2003 13:30	I-8 #2 LN.	—	WB	19	0	—	AC*008A-A(014)B	STATE 1 201-P12
H468101C	SG	03-409	4	Acceptance	8230	8/12/2003 13:00	RAMP B	—	—	41	0	STOCK-PILE ON SITE	AC*008A-A(014)B	STATE 1 248ALT1
H468101C	SG	03-420	5	Acceptance	8230	8/21/2003 11:30	RAMP D	2	EB	14	0	ONSITE	AC*008A-A(014)B	STATE 1 248ALT1
H468101C	SG	03-339	5	Acceptance	8230	6/24/2003 8:15	INTERIM RAMP, RT OF CL	—	WB	45	0	NATIVE	AC*008A-A(014)B	STATE 1 201-P12
H468101C	SG	03-439	9	Acceptance	8230	9/12/2003 10:00	GILA RIDGE RD.	—	EB	75	0	ONSITE	AC*008A-A(014)B	STATE 1 248ALT1
H468101C	SG	03-442	12	Acceptance	8230	9/16/2003 15:00	AVE. 3E; S. OF BRIDGES	—	NB	44	0	ONSITE	AC*008A-A(014)B	STATE 1 201-P12
H468101C	SG	03-461	13	Acceptance	8230	9/25/2003 9:00	I-8 MAIN LINE	5	WB	240	—	NATIVE	AC*008A-A(014)B	STATE 1 201-P12
H468101C	SG	03-470	14	Acceptance	8230	10/2/2003 8:30	I-8 MAIN LINE	—	WB	20	0	ONSITE	AC*008A-A(014)B	STATE 1 248ALT1
H468101C	SG	03-485	15	Acceptance	8230	10/16/2003 8:00	RAMP A	3	WB	26	0	ONSITE	AC*008A-A(014)B	STATE 1 248ALT1
H468101C	SG	03-489	16	Acceptance	8230	10/17/2003 12:30	RAMP A; RT & LT OF CL	—	WB	27	0	BASIN A (NATIVE)	AC*008A-A(014)B	STATE 1 201-P12
H468101C	SG	03-0476	2	Correlation	9956	6/16/2003 12:30	INPLACE INTERIM RAMP	—	WB	42	0	NATIVE ONSITE	AC*008A-A(014)B	STATE 1 201-P12

TRACS Number	Material Code	Lab Test No.	Sample No.	Purpose	Org. ID	Sample Date and Time	Sample Location	Lift No.	Roadway ID	Sample Station	Sample Offset	Original Source	Fed. Project No.	Sieve Test Type
H468101C	SG	03-0491	5	Correlation	9956	6/24/2003 11:15	INTERIM RAMP, RT OF CL	—	WB	45	0	NATIVE	AC*008A-A(014)B	STATE 1 201-P12
H468101C	SG	03-0869	5	Correlation	9956	8/21/2003 11:30	RAMP D	2	EB	14	0	ON SITE	AC*008A-A(014)B	STATE 1 201-P12
H468101C	SG	03-1003	15	Correlation	9956	10/16/2003 8:00	RAMP A	3	WB	26	0	ON SITE	AC*008A-A(014)B	STATE 1 201-P12

—No data.

Table 68. Merged QA aggregate base and subgrade soil test data for State 1 DOT TRACS number H468101C.

TRACS No.	Material Code	Sample Location	Roadway ID	Sample Station	Sample Offset	Original Source	Subg_pct Pass 40	Subg_pct Pass 200
H468101C	SG	AVE. 3E; S. OF BRIDGES	NB	44	0	ON SITE	75	8.3
H468101C	SG	FRONTAGE RD LT OF CL	WB	19	0	NATIVE ON SITE	89	7.8
H468101C	SG	FRONTAGE RD RT OF CL	WB	11	0	NATIVE ON SITE	98	10
H468101C	SG	GILA RIDGE RD.	EB	75	0	ON SITE	80	18.9
H468101C	SG	—	—	—	—	—		
H468101C	SG	I-8 #2 LN.	WB	19	0	NATIVE	56	8.5
H468101C	SG	I-8 MAINLINE	WB	24	—	ONSITE	74	9.4
H468101C	SG	I-8 MAINLINE	WB	20	0	—	78	11.6

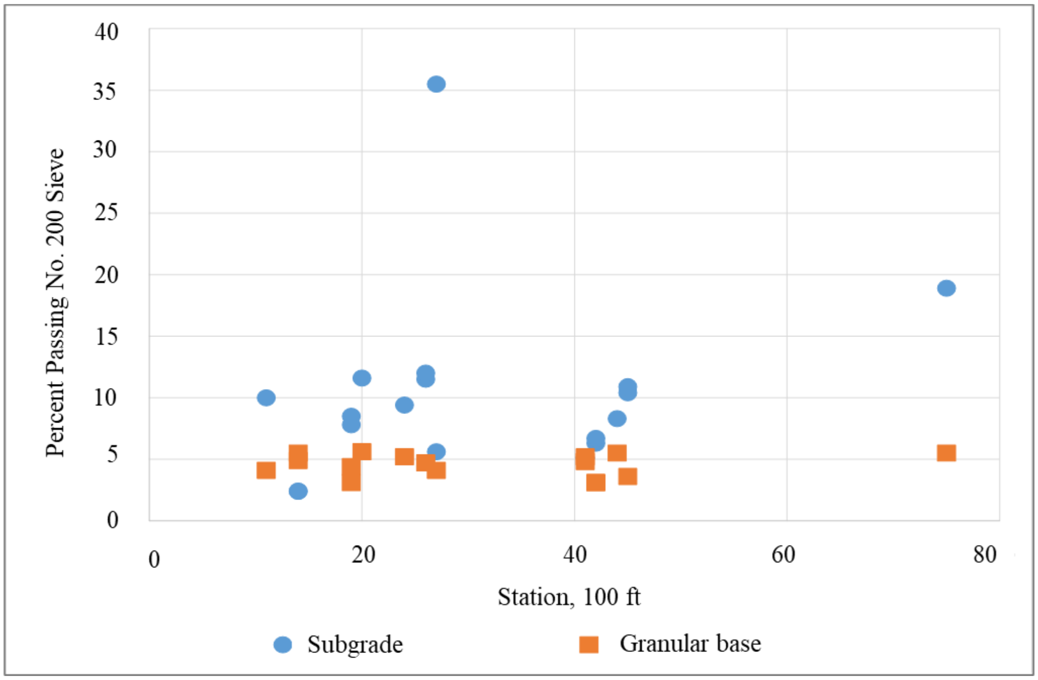
TRACS No.	Material Code	Sample Location	Roadway ID	Sample Station	Sample Offset	Original Source	Subg_pct Pass 40	Subg_pct Pass 200
H468101C	SG	—	—	—	—	NATIVE ON SITE	—	—
H468101C	SG	IN PLACE INTERIM RAMP	WB	27	0	NATIVE ON SITE	66	5.6
H468101C	SG	IN PLACE INTERUM RAMP	WB	42	0	NATIVE ON SITE	79	6.3
H468101C	SG	IN PLACE INTERIM RAMP	WB	42	0	NATIVE ON SITE	76	6.7
H468101C	SG	INTERIM RAMP, RT OF CL	WB	45	0	NATIVE	88	10.4
H468101C	SG	INTERIM RAMP, RT OF CL	WB	45	0	NATIVE	88	10.9
H468101C	SG	RAMP A	WB	26	0	ONSITE	77	11.5
H468101C	SG	RAMP A	WB	26	0	ONSITE	78	12
H468101C	SG	RAMP A; RT & LT OF CL	WB	27	—	BASIN A (NATIVE)	93	35.5
H468101C	SG	RAMP B	—	41	0	STOCKPILE ONSITE	83	5.1
H468101C	—	RAMP B	—	41	0	STOCKPILE ONSITE	83	5.1
H468101C	—	RAMP D	EB	14	0	OSNITE	83	2.4
H468101C	—	RAMP D	EB	14	0	ONSITE	83	2.4

—No data.
Subg_pct Pass = Subgrade percent passing sieve.

Table 69. Merged QA aggregate base and subgrade soil test data for Federal project number AC*008-A (014) B.

Sample Location	Lift No.	Roadway ID	Federal Project No.	Pct Pass 40	Pct Pass 200	Sample Date and Time
AVE 3E; S. OF BRIDGES	1	NB	AC*008A-A(014)B	29	5.5	9/18/2003 11:30
N. FRONTAGE RD. 2' LT OF CL	1	WB	AC*008A-A(014)B	30	3.1	6/27/2003 9:00
N. FRANTAGE RD. 10' RT OF CL	1	EB	AC*008A-A(014)B	35	4.1	6/27/2003 13:15
GILA RIDGE RD.	—	EB	AC*008A-A(014)B	33	5.5	9/17/2003 11:00
GILA RIDGE RD.	—	EB	AC*008A-A(014)B	34	6.1	9/17/2003 11:00
I-8 MAINLINE	—	WB	AC*008A-A(014)B	27	4.4	10/9/2003 9:30
I-8 MAINLINE, EAST OF BRIDGE	—	WB	AC*008A-A(014)B	33	5.2	10/10/2003 12:30
I-8 MAINLINE, EAST OF BRIDGE	—	WB	AC*008A-A(014)B	35	5.6	10/10/2003 12:30
I-8 MAINLINE	—	WB	AC*008A-A(014)B	30	4.7	10/13/2003 8:00
INTERIM RAMP A	1	WB	AC*008A-A(014)B	29	4.1	1/8/2004 14:20
WINDOW-WB. INTERIM RAMP	0	WB	AC*008A-A(014)B	32	3.1	6/26/2003 1:15
WINDOW-WB. INTERIM RAMP	1	WB	AC*008A-A(014)B	28	3.1	6/26/2003 6:00
WINDOW-WB. INTERIM RAMP	1	WB	AC*008A-A(014)B	29	3.6	6/26/2003 6:00
RAMP A	—	WB	AC*008A-A(014)B	31	4.7	10/21/2003 8:15
RAMP "B"	1	NB	AC*008A-A(014)B	36	4.8	9/12/2003 10:50
RAMP "B"	1	NB	AC*008A-A(014)B	35	5.2	9/12/2003 10:50
RAMP "D"	1	EB	AC*008A-A(014)B	19	4.9	9/11/2003 13:00
RAMP "D"	1	EB	AC*008A-A(014)B	33	5.5	9/17/2003 11:00

—No data.



Source: FHWA.

Figure 109. Graph. Plot of station versus percent passing the No. 200 sieve for aggregate base and subgrade soils using the merged dataset presented in table 68 and table 69.

QA Test and PMS Data Integration for State 2

Data integration of the State 2 DOT PMS, QA test, and other nontraditional datasets was done using key inventory/location data items HWY, DIR, BMP, and EMP; QA test data tables SUBAC/PROJECT NUMBER; and SAMPLING/LOT location information. Data integration was done as follows:

1. Identified datasets of interest:

    a. Datasets of interest are described in detail in chapter 4. The relevant information for this discussion includes general content and referencing systems that are described as follows:

        i. ConditionXX.csv (XX ranges from 98 through 15 for 1998 to 2015, respectively): HWY, DIR, BMP, and EMP.

        ii. Construction history database, maintenance data tables: SUBAC NUMBER.

        iii. State 2 DOT PDF files containing QA test data/records: SUBAC NUMBER. The PDF files contain descriptions of project location (e.g., HWY, DIR, and BMP). However, these were organized in a consistent manner.

        iv. Excel spreadsheets with RWD deflection and MIT-Scan data from contractors: HWY, DIR, and BMP.

b. Information presented in step 1a shows that the PMS-type datasets and the contractors' new technology datasets had a common referencing system for HWY, DIR, BMP, and EMP, whereas the QA- and QC-type dataset referencing system included SUBAC NUMBER and some description of project/sample location. The maintenance dataset in the construction history database, however, contained both SUBAC number and project HWY, DIR, BMP, and EMP information.

c. Since the maintenance dataset of the construction history database provides both referencing systems, it was adopted as the central link from which all the other datasets could be merged, as described in steps 2 through 5.

2. Defined unique State 2 DOT PMS sections, which are defined in the State 2 DOT PMS datasets using a combination of HWY, DIR, BMP, and EMP. For State 2 DOT PMS, pavement performance data are aggregated and reported as the average or representative value for a given 0.1-mi PMS pavement section.

3. Established a comprehensive PMS dataset by performing a vertical integration of the PMS data tables, since State 2 DOT provided individual Microsoft Excel datasets with annual (1998 through 2015) summaries of condition data. This step was done by appending or adding the records and observations from one PMS dataset to the end of another PMS dataset. This function was done in Microsoft Access; the outcome was the creation of a master State 2 DOT PMS database containing condition data from 1998 through 2015.

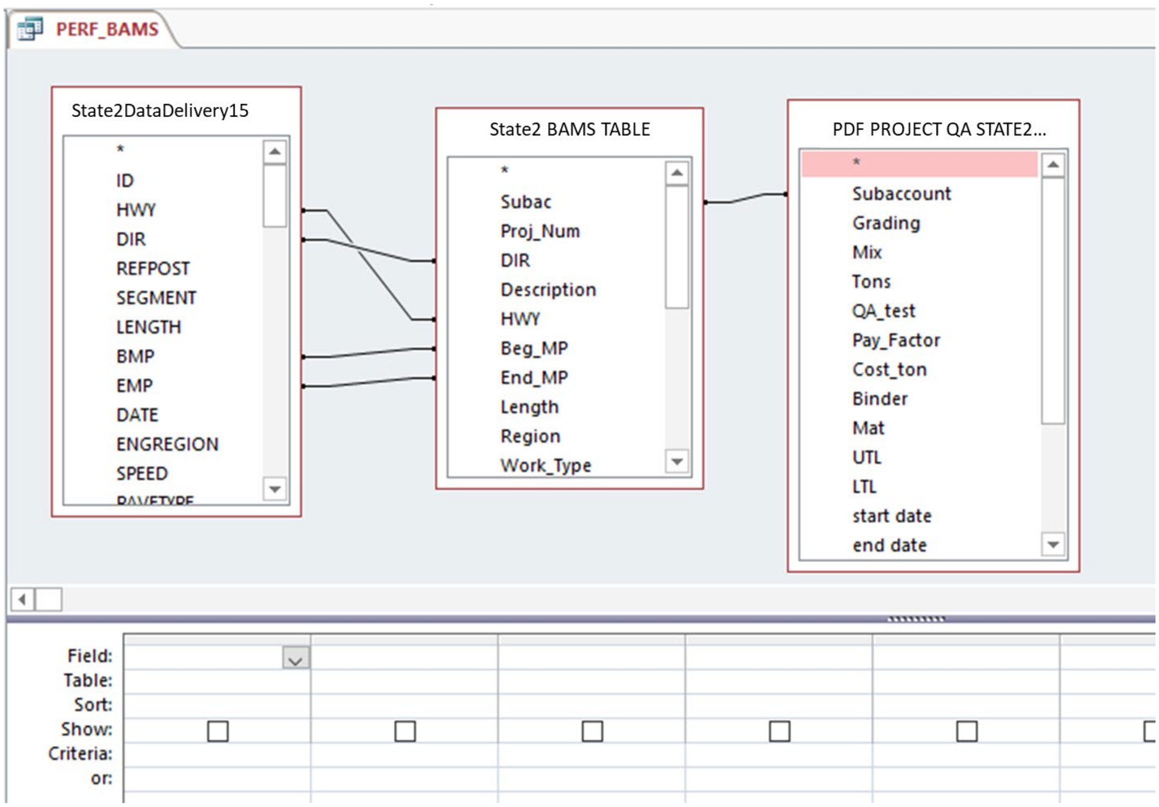
4. Developed codes/queries for integrating PMS and maintenance dataset of the construction history database. This step was done by linking HWY, DIR, and BMP in each dataset. A key outcome of this step was to link the two referencing systems: HWY, DIR, and BMP; and State 2 DOT SUBAC number. The SUBAC number is the key referencing data item that was used to link QA and QC data to PMS.

5. Merged the State 2 DOT PMS DATA and the maintenance dataset of the construction history database with individual project QA and QC test data. For State 2 DOT, the QA and QC data were provided as electronic documents, mostly in PDF format. The information in these documents was referenced and identified by SUBAC number. The merger was done as follows:

    a. Converted electronic document information in PDF format to Microsoft Excel electronic databases (e.g., XLS, CSV, or TXT data formats). Adobe® Acrobat® version 9.0 and after can directly convert data tables into Excel format. This action, however, must be done manually, one table at a time.

    b. Merged the converted electronic document PDF file with the master PMS maintenance dataset of the construction history database when the conversion was complete, using the SUBAC number and sample location information (ROUTE TYPE/NUMBER, MILEPOST, CHAINAGE, and so on).

The preceding steps are shown graphically in figure 110. Running the Microsoft Access query displayed in figure 110 produced a merged dataset with State 2 DOT PMS, maintenance dataset of the construction history database SUBAC number, and project-specific QA and QC test data. Note the SQL and VB coding developed to effect this merger is not shown in figure 110. The research team added other data (i.e., MIT-SCAN and RWD deflection) to the project data by linking HWY, DIR, BMP, and EMP to the respective datasets.



Source: FHWA.

Figure 110. Diagram. Microsoft Access code for merging State 2 DOT PMS, construction history database SUBAC number, and project-specific QA test datasets.

QA Test and PMS Data Integration for State 3

The research team integrated data of the State 3 DOT PMS and QA and QC test datasets using key inventory and location data items ROUTE, RNUM, RSUFF, DIRECTION, BMP, EMP, and LANE_NUMBER; QA test data tables CONTRACTNUMBER, PROJECTID, JMFID, and LOT#; and SUBLOT# location information. Data integration was done as follows:

1. Identified datasets of interest:

    a. Datasets of interest are described in detail in chapter 4. The relevant information for this discussion is general content and reference systems that are described as follows:

        i. Cracking: ROUTE, RNUM, RSUFF, DIRECTION, BMP, EMP, and LANE_NUMBER.

ii. Rutting: ROUTE, RNUM, RSUFF, DIRECTION, BMP, EMP, and LANE_NUMBER.

iii. Friction: ROUTE, RNUM, RSUFF, DIRECTION, BMP, EMP, and LANE_NUMBER.

iv. BinderData: CONTRACT_NUMBER.

v. MixDesignAggSourceMM: CONTRACT_NUMBER.

vi. MixDesignXXX: CONTRACT_NUMBER.

vii. TestDataQA/QC: CONTRACT_NUMBER, PROJECTID, JMFID, LOT#, AND SUBLOT#.

b. Information presented in step 1a shows that the PMS-type datasets had a common referencing system—ROUTE, RNUM, RSUFF, DIRECTION, BMP, EMP, and LANE_NUMBER—while the QA-type dataset referencing systems was a combination of CONTRACT_NUMBER, PROJECTID, JMFID, LOT#, and SUBLOT#.

c. State 3 DOT Soils and Aggregate Technology Division routinely publishes the Office of Materials Technology Aggregate Bulletin Test Data, which contains information pertaining to the qualified list of aggregate producers and fine/coarse aggregate physical test data such as:

i. Specific gravity and absorption.
ii. Soundness.
iii. Los Angeles (LA) abrasion.
iv. ASR.
v. British pendulum test.
vi. Dynamic friction test.
vii. Petrography for noncarbonate aggregate.
viii. Acid insoluble residue for carbonate aggregate.

Referencing for these data is defined by AGGREGATE SOURCE, TYPE, and CATEGORY.

d. State 3 DOT Office of Construction (Contract Payment Section) assigns a FMIS charge number to all contract categories to ensure proper billing. The FMIS information includes general information about project location. The information available online provided details on the county, location, description of the highway and number of lanes, length and the phasing of construction, scope of the construction project, and details of the specific items being studies under the project, if applicable.

e. Table 70 presents sample route and contract data for State 3.

2. Integrated the datasets with the referencing systems described is done as follows:

a. Defined unique State 3 DOT PMS sections. These sections were defined in the State 3 DOT PMS datasets using a combination of RNUM, RSUFF, DIRECTION, BMP, EMP, and LANE_NUMBER. For State 3 DOT PMS, pavement performance data were aggregated and reported as the average or representative value for a given 1-mi PMS pavement section.

b. Established a comprehensive PMS dataset by performing a horizontal integration of these PMS datasets linking the key referencing data items described in step 2a, since State 3 DOT provides individual Microsoft Excel datasets with annual summaries of cracking, rutting, and friction condition data. Merge the PMS datasets using Microsoft Access.

c. Merged the combined PMS dataset with the State 3 DOT contract information dataset. This merger created a link between PMS data and project contract-type referencing data items (CONTRACT NUMBER, FMIS, and so on).

d. Performed horizontal integration between the PMS and contract dataset and the QA test data tables using relevant set of CONTRACT NUMBER, FMIS, and other information. Note that the data table MixDesignAggSourceXXX provides information about aggregate sources.

e. Used the aggregate source information provided in MixDesignAggSourceXXX to perform a horizontal merger with the State 3 DOT Materials Technology Aggregate Bulletin Test Data tables. Note the PDF tables containing this information was digitized prior to merger and horizontal integration.

The research team developed several codes and queries to make the mergers described possible. These were similar to those shown for State 1 and State 2 and thus will not be repeated.

Table 70. Example of State 3 DOT route and contract data.

Route	RNUM	RSUFF	DIR	BMP	EMP	Contract No.	Contract	FMIS
IS	68	—	E	2.53	3.21	AL3265177	AL3265177	AL326B51
IS	68	—	E	3.85	4.04	GA6565177	GA6565177	GA656B51
IS	68	—	E	7.24	7.62	XY1115168	XY1115168	GA382K55
IS	68	—	E	19.8	20.15	XX0015177	XX0015177	AL877B59
IS	68	—	E	22.1	22.9	AL3125177	AL3125177	AL312B51
IS	68	—	W	0.3	0.68	XY1115168	XY1115168	GA382K55
IS	68	—	W	3.28	3.351	AL3265177	AL3265177	AL326B51
IS	68	—	W	3.85	4.04	GA6565177	GA6565177	GA656B51
IS	68	—	W	4.76	7.42	AW201B51	AW201B51	AW201B51
IS	68	—	W	5.176	5.35	GA6565177	GA6565177	GA656B51
IS	68	—	W	8.9	9.25	XY1015168	XY1015168	AL453A54
IS	68	—	W	22.1	22.9	AL3125177	AL3125177	AL312B51
IS	68	—	W	37.26	37.47	XY1015168	XY1015168	AL433K5A
IS	70	—	E	1.8	2.25	FR5775176	FR5775176	FR577B51
IS	70	—	E	24.85	25.2	AW221B51	AW221B51	AW221B51
IS	70	—	W	0	1.2	FR297B51	FR297B51	FR297B51

—No data.

IC and QA Data Integration for State 4

Information in the IC and density data files was merged using the position referencing northing and easting. Note that for a given northing and easting position, density measurements were obtained from field QA, and several IC measures from difference roller passes were available for each location on the project. Thus, for data integration, IC measurements closest within 1 ft of the extracted field AC core were deemed as most representative. On average, up to six IC passes were reported for each core location. An example subset of the data assembled is presented in table 71.

Table 71. Example of IC and QA merged dataset for State 4.

Project	Machine	Vibe State	Pass No.	Northing	Easting	Distance (ft) (Core to IC Reading)	Last Amp (mm)	Last CMV	Last Frequency (Hz)	Last RMV	Density Value
I-LLL	15-57-10	On	5	628589.3	7622627	0.61479	0.75	50.5	62.1	6.1	95
			7			0.57058	0.73	19.8	62.5	2.3	95
			8			0.57058	0.75	50.5	62.1	6.1	95
			10			0.57058	0.72	6.1	62.1	4.9	95
			12			0.57058	0.69	36.2	62.5	4.9	95
I-MM	NM74896	On	5	369578	7535556	0.45414	0.48	26.4	63.7	5.1	95.5
			6			0.45414	0.44	21.2	63.7	8	95.5
			7			0.66446	0.48	26.4	63.7	5.1	95.5
			8			0.45414	0.45	21.2	64.1	2.4	95.5
			10			0.45414	0.51	46.9	63.7	4.9	95.5
			11			0.45414	0.45	36	63.3	4.9	95.5
			12			0.66446	0.48	20.8	64.9	1.9	95.5
			13			0.66446	0.45	44.6	63.7	7.3	95.5
			14			0.45414	0.49	41.5	64.1	3.1	95.5
			16			0.66446	0.5	45.7	63.7	7.3	95.5
			17			0.66446	0.45	28.4	63.7	6.1	95.5
			20			0.66446	0.52	38.7	63.7	3	95.5

Project	Machine	Vibe State	Pass No.	Northing	Easting	Distance (ft) (Core to IC Reading)	Last Amp (mm)	Last CMV	Last Frequency (Hz)	Last RMV	Density Value
US-KK	NM74896	On	1	370213.6	7535661	0.85207	0.45	11.5	63.3	6.5	96.3
			2			0.29518	0.44	13.2	63.3	0.7	96.3
			3			0.29518	0.44	24.1	63.3	9.8	96.3
			5			0.85207	0.43	12.4	63.3	2.3	96.3
			6			0.29518	0.43	12.4	63.3	2.3	96.3
			7			0.29518	0.4	23.8	63.3	4.6	96.3
			8			0.85207	0.41	20.3	63.3	2.9	96.3
			9			0.29518	0.42	25.7	63.7	2.4	96.3
			11			0.85207	0.52	31.7	63.7	8	96.3
			12			0.29518	0.52	31.7	63.7	8	96.3
			13			0.85207	0.48	33.1	62.1	1.9	96.3
			14			0.29518	0.48	31.6	61.3	2.2	96.3

The integrated dataset was reviewed for anomalies and errors and cleansed as needed. Examples of anomalies and error included:

- Distance between cores and IC roller passes. Distances greater than 1.0 ft were not included in the analysis. The value of 1.0 was determined from multiple trials to examine correlations discussed in the next chapter.

- IC reported HMA placement temperatures. Temperatures ranged from 0°F to 230°F. For analysis, HMA placement temperatures less than 175°F were excluded as compaction at such temperatures was considered to be erroneous or anomalous.

- Erroneous values for IC outputs. Zero values for key IC outputs such as Last Amp, Last CMV, Last Frequency, and Last RMV.

- Target pass number ranged from 1 to 6. Actual pass number ranged from 1 to 62. The significantly high pass numbers (e.g., greater than 10) were investigated to determine whether they were anomalies or errors. In general, locations reporting significantly high pass numbers were removed from the assembled dataset.

SUMMARY

This chapter presented a detailed description of data integration procedures, methodologies, and tools used in combining data and information from disparate datasets. As stated, there is very little commonality in designs of the datasets used by DOTs for storing PMS, QA and QC, construction history, and other data types. Thus, there is a need for many different codes and queries for data integration. Also, there is still some element of manual integration required for older data because not all data are available in electronic format or are easy to integrate with file formats (XLS, CSV, TXT, DAT, and so on). Data from newer construction projects are more likely to be existing in an electronic format.

The information presented in this chapter shows that data merger and integration are possible, although the details of the methodologies and tools required will remain DOT specific and data format dependent. Data integration was a significant step in this project. Standardization of DOT data collection and storage practices will, in the long term, provide the opportunity for performing the tasks described in a more efficient, timely, and cost-effective manner.

CHAPTER 6. PREDICTION MODEL DEVELOPMENT AND USE CASES

UTILIZING QA TEST DATA AS LEADING INDICATORS OF PAVEMENT PERFORMANCE

A primary goal of this research was to assess the feasibility of DOTs utilizing pavement construction QA data as leading indicators of future pavement condition and performance. Condition and performance in this context were characterized based on a combination of performance measures published under the national performance management measures ruling as summarized in table 72.(2) A leading indicator, for the purposes of this study, is described as a measurable pavement QA measure (including thickness, strength, air voids, or density) whose value or change in value does significantly impact and determine the path or trend taken by a given performance measure.

Table 72. Metrics used in national performance management measures ruling.

Surface Type	Metric
All pavements	IRI (inches/mi)
Asphalt pavement and jointed concrete pavement	Cracking (percent)
Asphalt pavement	Rutting (inches)
Jointed concrete pavement	Faulting
CRCP	Cracking (percent)

Effectively assessing the feasibility of utilizing QA data as a leading indicator of highway pavement performance required developing and implementing a robust data analysis plan. The plan was to identify preliminary/basic trends in relationships between distress/IRI and QA data items and then establish where the trends are reasonable and significant.

This chapter describes the procedures and outcomes of statistical analysis to identify QA data items that significantly impact future performance; these data could potentially be utilized within a PMS framework as leading indicators for future performance. Data were used from four States, as described in chapter 4 and chapter 5. A summary of the analyses performed using data from these States is presented in table 31 for HMA pavement and in table 32 for PCC pavements. As indicated in these tables, the QA parameters included both traditional QA parameters as well as derived parameters that are indicators of performance.

This chapter also presents case studies demonstrating how the correlations developed can be implemented in a State PMS. The case studies presented in this report are the following:

- State 1: This case study highlights how performance predictions can be enhanced using additional data, such as those with traffic and climate information, which are known to impact performance. The basic QA-PMS-based correlations can be enhanced by incorporating traffic and climate data parameters in the prediction models.

- State 2: This case study highlights how data from innovative QA technologies can be potentially used to estimate long-term performance trends. Measurements and outputs from new innovative technologies, such as RWD and MIT-Scan, were correlated to performance at a project level.

- State 3: This case study attempts to show an example of how performance predictions using QA data can be implemented into an agency PMS, which is the true application of the findings from this project.

- State 4: This case study attempts to show the correlation between IC and QA data to demonstrate an indirect correlation of data collected from newer construction technologies to performance.

Case studies for State 1 and State 3 were performed at the network, and the case studies for State 2 and State 4 were performed at the project level. A summary of the analyses included is shown in table 73.

Table 73. Summary of analyses types, performance prediction models, and case studies.

State	Performance Indicator: Rutting	Performance Indicator: Faulting	Performance Indicator: Cracking	Performance Indicator: IRI	Case Study
State 1	F, N, Q, A F, N, Q, V F, N, Q, D, A F, N, Q, D, V F, N, Q, D, A, T, C#	—	F, N, Q, A F, N, Q, V F, N, Q, D, A F, N, Q, D, V F, N, Q, D, A, T, C#	—	Benefit of adding traffic and climate data.
State 2	F, N, Q, A F, P, Q, RW, A#	R, N, Q, A R, P, Q, M, A#	F, N, Q, A R, N, Q, A F, P, Q, RW, A#	F, N, Q, A R, N, Q, A	Data from nontraditional QA/network-level tests correlated to performance.
State 3+	F, N, Q, A F, N, Q, D, A F, N, Q, A	—	F, N, Q, A F, N, Q, D, A F, N, Q, A	—	Implementation of improved prediction model in the DOT's PMS.
State 4	F, P, Q, IC, A#	—	F, P, Q, IC, A#	—	Demonstration of methods to "indirectly" link modern technologies to performance.

—No data.
#In-case study.
+State has functional and structural cracking in pavement management database.
Pavement type: F = flexible, R = rigid; analysis level: N = network level, P = project level; data types: Q = traditional QA data, D = QA derived parameters, M = MIT-Scan, RW = RWD, IC = IC data, T = traffic, C = climate. Data used: A = averages; V = COV/variability.

OVERVIEW OF DATA ANALYSIS METHODOLOGY

This section presents statistical analysis done to assess feasibility of using QA test data as leading indicators for pavement performance. Analysis was done at three levels of intensity: identification of preliminary correlations between distress, IRI, and QA test data; formation of basic models relating distress, IRI, and QA test data using automated techniques; and final model formulation and assessment of the model's independent QA test data variables' significance and sensitivity to distress and IRI. The analysis methodology is as follows:

1. Review assembled integrated PMS and QA test databases for accuracy and reasonableness and estimate computed parameters that can be derived from QA test data (e.g., HMA dynamic modulus, SA1, resistivity, aggregate/soil D_{60}, CBR, M_r). Estimate computed parameters only when key inputs for estimation are available.

2. Use time-series PMS distress (cracking, rutting, faulting, IRI) data to develop simple linear regression models for forecasting future distress and IRI.

3. Estimate for each PMS section baseline distress IRI. For this analysis, baseline distress/IRI was defined as distress and IRI measured or forecasted after 10 or 15 yr in service. The choice of 10 or 15 yr was based on the amount of historical data available (i.e., when less than 6 yr, a baseline age of 10 yr was selected; otherwise, 15 yr was selected).

4. Perform statistical analysis.

    a. Identify preliminary correlations between distress and IRI and QA test data. This step comprised computing Pearson's correlation statistic, r, to characterize correlation between QA data items and distress and IRI. Pearson's correlation statistic is a parametric measure that measures the strength and direction of a linear relationship between two variables. For an exact linear relationship between two variables, a positive relationship exists if the correlation is 1; a negative relationship exists if the correlation is −1. If there is no linear predictability between the two variables, the correlation is 0. Thus, the value of computed r was an indicator of potential QA test data influencing future pavement performance. An indication of strong correlation between distress and IRI and QA test data items, however, does not imply causality because, in some cases, an underlying causal relationship might not exist. Also, obtaining an r of 0 may simply imply the nature of the relationship between two variables is not linear. A test of the hypothesis Prob > $|r|$ under $H0$: $r = 0$ was performed to determine probability $r = 0$. For this study, a p-value less than 0.15 was considered an indication of $r \neq 0$. The outcomes of the correlation analysis were used as the bases for characterizing correlations between distress or IRI and QA test data as strong, fair, or weak, based on the criteria presented in table 74.

    b. Form basic models relating distress/IRI and QA test data using automated techniques. Using the QA test data items identified in step 4a and elsewhere, conduct automated stepwise regression analysis to establish feasible basic regression models. Note that stepwise regression analysis is an automated procedure for establishing potential regression models. The following parameters were considered in selecting feasible QA data items:

i. Selection method: stepwise.

ii. Selection criterion: significance level of independent variables (QA data items).

   1) Entry significance level (SLE): 0.15.
   2) Stay significance level (SLS): 0.15.

iii. Stop criterion: minimal predicted residual error sum of squares (PRESS) statistic value.

iv. Choose criterion: Mallows' C_p (optimum number of independent variables).

c. Formulate final model and assess model's independent QA test data variables' significance and sensitivity to distress and IRI. Perform analysis of variance (ANOVA) to confirm or modify the preliminary models developed in step 4b. The outcome is a selection of a more robust model that identifies QA data items that significantly influences distress and IRI and is reasonably sensitive to distress and IRI. For example, increasing QA data item value results in a reasonable increase or decrease in distress and IRI. The final model is selected based on several factors, including diagnostic statistics, R^2, root mean square error (RMSE), correlation coefficient, variance inflation factor (VIF), and *p*-value, and evaluation of the models' reasonableness.

Table 74. Criteria for characterizing Pearson's correlation estimates.

Pearson's Correlation Coefficient	Significant Test ($r = 0$) *p*-value	Characterization
$\|r\| > 0.2$	*p*-value < 0.05	Strong
$0.1 < \|r\| < 0.2$	0.1 > *p*-value > 0.05	Fair
$\|r\| < 0.1$	*p*-value > 0.1	Weak

The research team examined and evaluated the final models' reasonableness by comparing trends and sensitivities of changes in QA data item values with corresponding changes in distress and IRI trends reported in published literature from past studies. For example, sensitivity analysis conducted under many studies using the AASHTOWare Pavement ME has shown that increasing HMA air voids does increase HMA rutting, while decreasing PCC compressive strength results in increased cracking. See table 26 and table 27 for a comprehensive summary of expected trends and sensitivities for flexible and rigid pavements, respectively.

STATISTICAL ANALYSIS FOR STATE 1

Data analysis was done using the integrated State 1 DOT PMS and QA test database described in chapter 4 and chapter 5, as well as the analysis methodologies previously described in this chapter. The results are described in the following sections.

State 1 DOT Correlation Analysis

This section presents the analysis conducted to characterize correlations of cracking and rutting to HMA QA test data. Table 75 through table 77 presents the outcome of Pearson's correlation analysis to determine the impact of HMA QA test data variables on HMA fatigue cracking and rutting. The strength of correlation assessment is based on Pearson's correlation coefficient and *p*-value (test of significance) for the given data items. The results, shown in table 76 and table 77, show gradation (specifically, the percent passing ¾-inch, ½-inch sieve, 3/8-inch, No. 100, and No. 200 sieve sizes), along with asphalt binder content, VMA, and VFA as the QA data items that had a strong impact on fatigue cracking. For rutting, the strongest correlations were between computed dynamic *E* modulus and percent passing No. 100 and No. 200 sieve sizes.

Note that dynamic *E* modulus estimates were not measured directly from the lab or reverse calculated but rather estimated using QA test data (gradations and air voids) and the Witczak model. Key inputs, such as binder type, were assumed. The E^* included in this analysis was like the level 3 type estimates utilized in the AASHTOWare Pavement ME.

The information presented in table 75 through table 77 was reasonable. For cracking, HMA gradation does significantly impact strength, modulus, voids, and durability. Thus, a strong correlation between cracking and HMA gradation is as expected. Also, AC binder content does significantly impact HMA air voids, VFA, strength, and modulus, and thus cracking. Therefore, a strong correlation between cracking and VFA seems reasonable. For rutting, strong correlations between QA data items HMA fines (percent passing No. 100 and No. 200 sieve sizes) and E^* was observed. Increasing fines in HMA does lead to mix instability, thus increasing plastic strain and rutting potential. Also, E^* highly influences the amount of elastic and plastic strain developed when HMA is subjected to traffic loading and thus rutting (accumulation of plastic strain). The relationship may be nonlinear or interactive with other data items.

Table 75. STATE 1 HMA QA data basic statistics.

QA Variables	No. Data Points	Mean	Standard Deviation	Minimum	Maximum
Percent passing 1-inch sieve	72	99.9	0.4	97.8	100.0
Percent passing ¾-inch sieve	72	96.6	3.2	87.3	100.0
Percent passing ½-inch sieve	72	80.8	5.3	67.5	96.5
Percent passing 3/8-inch sieve	72	69.7	5.2	55.6	78.9
Percent passing ¼-inch sieve	72	57.6	6.1	41.0	68.8
Percent passing No. 4 sieve	72	51.7	6.6	36.6	64.0
Percent passing No. 8 sieve	72	37.8	6.1	21.1	48.2
Percent passing No. 10 sieve	72	34.7	5.8	18.6	45.8
Percent passing No. 16 sieve	72	26.4	5.0	12.8	37.7
Percent passing No. 30 sieve	72	18.1	3.8	7.8	29.2
Percent passing No. 40 sieve	72	14.2	2.9	6.3	24.0
Percent passing No. 50 sieve	72	11.0	2.2	5.1	18.6
Percent passing No. 100 sieve	72	6.5	1.3	3.8	9.5
Percent passing No. 200 sieve	72	4.1	0.9	2.3	6.3
Percent AC binder content	72	5.0	0.6	4.2	9.5
HMA bulk density (pcf)	72	146.2	4.0	137.2	159.1
HMA rice density (pcf)	72	153.9	4.0	145.5	166.6
HMA lab air voids (percent)	72	5.0	0.7	3.2	6.6
HMA VMA (percent)	63	14.8	1.4	12.6	23.3
HMA VFA (percent)	63	66.1	4.3	56.7	75.6
Coarse aggregate specific gravity	63	3.0	0.0	3.0	3.0
Effective binder-to-dust ratio	63	1.0	0.1	0.0	1.3
HMA in-place air voids (percent)	71	7.3	0.9	4.3	10.0
Computed E^* (psi) (millions)	71	5.6	0.66	4.6	7.6

Table 76. Pearson's correlation tables for STATE 1 HMA PMS cracking.

QA Variables	Pearson's Correlation	Test of Significance	Comments
Percent passing 1-inch sieve	0.149	0.2605	Fair
Percent passing ¾-inch sieve	0.330	0.0107	Strong
Percent passing ½-inch sieve	0.379	0.0031	Strong
Percent passing 3/8-inch sieve	0.237	0.0705	Strong
Percent passing ¼-inch sieve	0.055	0.6800	Weak
Percent passing No. 4 sieve	0.056	0.6744	Weak
Percent passing No. 8 sieve	0.041	0.7564	Weak
Percent passing No. 10 sieve	0.033	0.8062	Weak
Percent passing No. 16 sieve	0.044	0.7404	Weak
Percent passing No. 30 sieve	0.095	0.4733	Weak
Percent passing No. 40 sieve	0.151	0.2536	Fair
Percent passing No. 50 sieve	0.204	0.1204	Fair
Percent passing No. 100 sieve	0.267	0.041	Strong
Percent passing No. 200 sieve	0.288	0.0268	Strong
Percent AC binder content	0.290	0.0261	Strong
HMA bulk density (pcf)	0.011	0.9325	Weak
HMA rice density (pcf)	−0.028	0.8342	Weak
HMA lab air voids (percent)	−0.142	0.2829	Fair
HMA VMA (percent)	0.262	0.0611	Strong
HMA VFA (percent)	0.330	0.0168	Strong
Coarse aggregate specific gravity	−0.073	0.6052	Weak
Effective binder-to-dust ratio	−0.131	0.3558	Fair
HMA in-place air voids (percent)	0.007	0.9587	Weak
Computed E^* (psi) (millions)	0.061	0.6488	Weak

Table 77. Pearson's correlation tables for STATE 1 HMA PMS rutting.

QA Variables	Pearson's Correlation	Test of Significance	Comments
Percent passing 1-inch sieve	0.129	0.2984	Fair
Percent passing ¾-inch sieve	0.215	0.0805	Weak
Percent passing ½-inch sieve	0.175	0.1566	Fair
Percent passing 3/8-inch sieve	0.094	0.4479	Weak
Percent passing ¼-inch sieve	−0.066	0.5976	Weak
Percent passing No. 4 sieve	−0.122	0.3272	Weak
Percent passing No. 8 sieve	−0.148	0.2324	Fair
Percent passing No. 10 sieve	−0.149	0.2302	Fair
Percent passing No. 16 sieve	−0.11814	0.341	Fair
Percent passing No. 30 sieve	−0.07432	0.55	Weak
Percent passing No. 40 sieve	−0.02419	0.846	Weak
Percent passing No. 50 sieve	0.08812	0.4783	Weak
Percent passing No. 100 sieve	0.34981	0.0037	Strong
Percent passing No. 200 sieve	0.334	0.0057	Strong
Percent AC binder content	−0.0054	0.9649	Weak
HMA bulk density (pcf)	−0.0531	0.6694	Weak
HMA rice density (pcf)	−0.0374	0.7636	Weak
HMA lab air voids (percent)	0.0681	0.5835	Weak
HMA VMA (percent)	0.0316	0.8102	Weak
HMA VFA (percent)	−0.0721	0.5838	Weak
Coarse aggregate specific gravity	0.0757	0.5651	Weak
Effective binder-to-dust ratio	0.12748	0.3317	Fair
HMA in-place air voids (percent)	−0.0677	0.5888	Weak
Computed E^* (psi) (millions)	0.28603	0.0199	Strong

State 1 DOT Stepwise Regression Analysis

Average Cracking Versus State 1 DOT QA Data items

The research team performed stepwise regression to develop basic model formations and to identify QA test data items that may be included in a finalized cracking prediction model. The basic model is presented in table 78.

Table 78. Stepwise selection of basic cracking prediction models developed using State 1 DOT QA test data.

Step	Effect Entered	Effect Removed	Number Effects In	Model R^2	C_p Statistic	PRESS Statistic	$Pr > F$**	Coefficient Estimate**
0	Intercept	—	1	0.0000	13.4733	238.9724	1.0000	6.072716
1	Percent passing ⅜-inch sieve	—	2	0.1127	8.6571	222.5405	0.0184	—
2	HMA bulk density	—	3	0.1737	6.9698	211.9421	0.0719	−0.254286
3	Computed HMA *E**	—	4	0.2596	3.7716	198.4376	0.0270	0.000005259
4	Percent passing No. 4 sieve	—	5	0.3392	0.9626	182.0810	0.0262	0.387546
5	Percent passing ⅜-inch sieve	—	4	0.3384	−0.9911	173.7097	0.8223	—
6	HMA in-place air voids	—	5	0.3821	−1.6315	177.5877	0.0848	1.373192
7	Percent passing ¾-inch sieve	—	6	0.4384	−3.0411*	167.8665*	0.0437	−0.259129

Stepwise selection summary: RMSE = 1.73053, R^2 = 0.4384, N = 67.
—No data.
*Optimal value of criterion.
**Values at step 7.

Information presented in table 78 shows the following:

- HMA bulk density, computed HMA E^*, percent passing No. 4 sieve, HMA in-place air voids, and percent passing ¾-inch sieve were significant data items included in the model (p-value less than 10 percent).

- Increasing HMA bulk density and intermediate aggregate size fraction (percent passing ¾-inch sieve size) resulted in a decrease in cracking.

- Increasing as-placed HMA air voids and the number of fines in the HMA mix percent passing No. 4 sieve resulted in increased cracking.

- Increasing computed HMA E^* did increase cracking. This result was not as expected and may be due to lack of interaction variables, such as traffic and layer thicknesses, along with assumption of HMA binder type.

Except for percent passing ¾-inch sieve, all other data items included in this preliminary model were classified as weak in table 75. The model R^2 of 44 percent and RMSE of 1.7 was deemed reasonable.

Average Rutting Versus State 1 DOT QA Data Items

Table 79 presents the outcome of stepwise regression performed to develop basic model formations and to identify QA test data items that may be included in a finalized rutting prediction model. The results in table 79 show HMA bulk density, computed HMA E^*, and HMA lab and in-place air voids as the QA data items that influenced average HMA rutting after 15 yr in service. Criteria for selecting these data items were described in the previous section, Overview of Data Analysis Methodology. All three data items had a weak-to-strong correlation to average rutting, as shown in table 75. The relationship presented in table 79 shows that increasing HMA VMA or HMA in-place air voids resulted in an increase in rutting, which is as expected. However, the trend showing an increase in computed HMA E^*, increasing rutting, was not in agreement with expected trends. This finding may be due to absence of other interacting factors such as traffic and layer thicknesses or assumptions made in estimating the parameter. The model's R^2 of 24 percent and RMSE of 0.065 inch were deemed reasonable.

Table 79. Stepwise selection summary for relationship between average rutting and State 1 DOT QA test data items.

Step	Effect Entered	Effect Removed	No. Effects In	Model R^2	C_p Statistic	PRESS Statistic	*Pr* > *F***	Coefficient Estimate**
0	Intercept	—	1	0.0000	22.17	0.3078	1.0000	−0.686590
1	Computed HMA *E**	—	2	0.1335	13.93	0.2899	0.0056	0.025682
2	HMA lab VMA	—	3	0.2105	10.08	0.2781	0.0271	0.022777
3	HMA lab air voids	—	4	0.2461	9.37*	0.2764*	0.1230	5.642E-8

Stepwise selection summary: RMSE = 0.06561, R^2 = 0.2461, *N* = 67.
—No data.
*Optimal value of criterion.
**Values at step 4.

State 1 DOT Finalized Generalized Linear Model/ANOVA Regression Analysis

Average Cracking Versus State 1 DOT QA Data Items

Table 80 presents the outcome of generalized linear model (GLM) regression performed to finalize the average cracking and HMA QA test data items' relationship and model. The results in table 80 confirm that the QA data items identified in table 79 (i.e., HMA bulk density, computed HMA *E**, percent passing No. 4 sieve, HMA in-place air voids, and percent passing ¾-inch sieve) are the QA data items that most influenced average HMA cracking. A review of the finalized model showed a reasonable R^2 of 42 percent and RMSE of 1.7 percent, which implied that QA data items measured in the lab and field and then aggregated by project or PMS sections can be leading indicators of future pavement performance.

Table 80. GLM summary for relationship between average cracking and State 1 DOT QA test data items.

Parameter	Estimate	*Pr* > |*t*|
Intercept	7.574451395	0.5593
Percent passing ¾-inch sieve	−0.281488073	0.0254
Percent passing No. 4 sieve	0.350628747	<0.0001
HMA bulk density	−0.244028349	0.0008
HMA in-place air voids	1.519550924	0.0018
Computed HMA *E**	0.000005222	<0.0001

R^2 = 0.421515, COV = 47.86, RMSE = 1.755694.

Key trends observed from the model in table 80 are as follows:

- The increase of fines in the HMA mix (i.e., increased percent passing the No. 4 sieve) does increase cracking, while increasing the amount of intermediate aggregate sizes (percent passing ¾-inch sieve size) does decrease cracking.

- The increase of field-measured HMA air voids does increase cracking.

- The increase of E^* does influence cracking development and progression. The trend shown by E^* is, however, not as expected, as increasing E^* generally does reduce cracking. It is, however, believed that the observed trend may be influenced by the absence of interacting factors, such as layer thickness, traffic, and base/subgrade support.

- The model's diagnostic statistics (R^2 = 42 percent, COV = 47.8 percent, and RMSE = 1.75 percent cracking) were deemed reasonable.

Average Rutting Versus State 1 DOT QA Data Items

Table 81 presents the finalized rutting prediction model based on the measured State 1 DOT HMA QA test data items. The results in table 81 confirm the trends observed in table 79—increasing voids in the HMA mix does increase measured rutting. Additional QA data items were included in the finalized model as they were found to significantly impact rutting distress with little correlation with other QA data items included in the model (VIF less than 10). The additional variables indicated the following:

- Increasing the proportion of intermediate aggregates (less than the ¾-inch sieve size) reduced rutting, which is as expected. However, increasing the number of fines in the HMA mix (percent passing No. 40 sieve) does increase the amount of rutting observed.

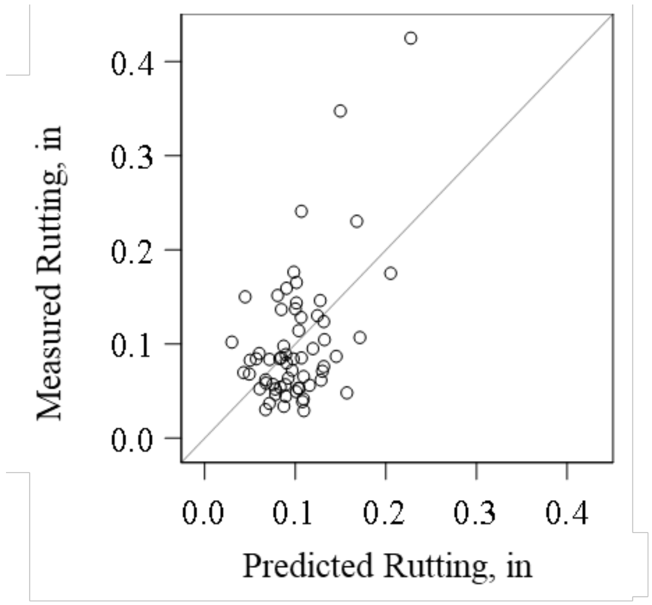
- Increasing HMA asphalt binder content does increase observed rutting. Excessive amounts of binder in HMA can lead to deficiencies in mix stability, leading to increased plastic strain when subjected to traffic loading and thus rutting.

Table 81. GLM summary for relationship between average rutting and State 1 DOT QA test data items.

Variable	Parameter Estimate	$Pr > \|t\|$	Variance Inflation
Intercept	−0.76223	0.0073	0
HMA percent passing ¾-inch sieve	−0.00801	0.0925	3.73795
HMA percent passing No. 40 sieve	0.00849	0.0272	1.61257
HMA percent asphalt binder	0.09536	0.0144	2.42105
HMA lab air voids	0.03434	0.0261	1.35317
HMA field-measured air voids	0.03716	0.0313	3.16334
Computed HMA E^*	1.060164E-7	0.0005	5.19951

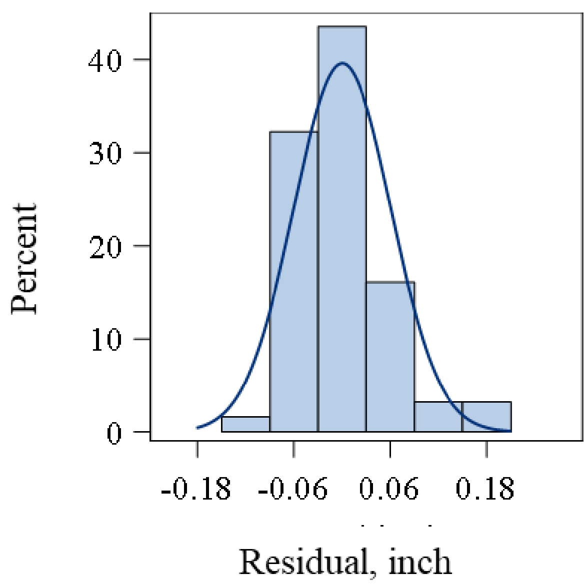
R^2 = 0.2689, COV = 63.33, RMSE = 0.06363.

The final model presented in table 81 appears to be mostly reasonable and does indicate that QA test data values collected in the field and lab can be used to predict future rutting performance. The model presented an R^2 of 0.27 and RMSE of 0.063. The low R^2 was deemed reasonable, considering that only QA data items were included. Figure 111 shows plots of predicted versus measured rutting, and figure 112 shows the residual (error) between measured and predicted rutting. Figure 113 through figure 118 shows plots of residual versus the model presented in the regressor variables. The plots show minimal or no bias.



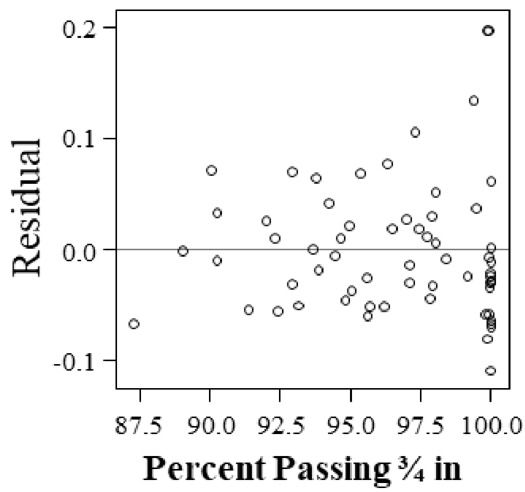
Source: FHWA.

Figure 111. Graph. Plots of predicted versus measured rutting in State 1.



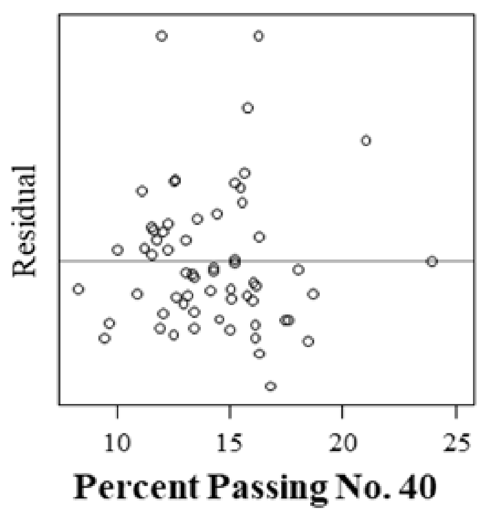
Source: FHWA.

Figure 112. Graph. Residual (error) between measured and predicted rutting in State 1.



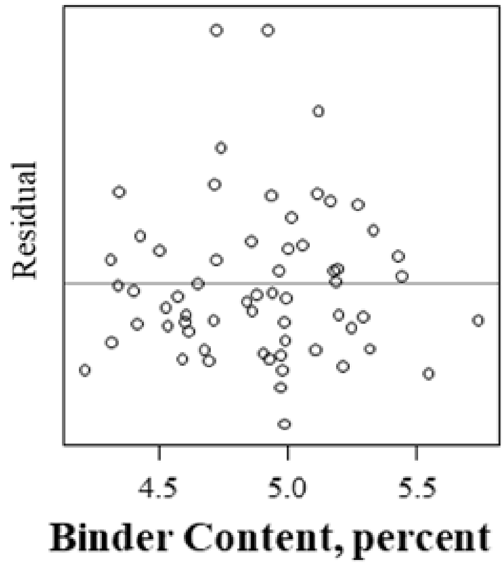
Source: FHWA.

Figure 113. Chart. Plot of residual in State 1-predicted rutting versus percent passing ¾ inch.



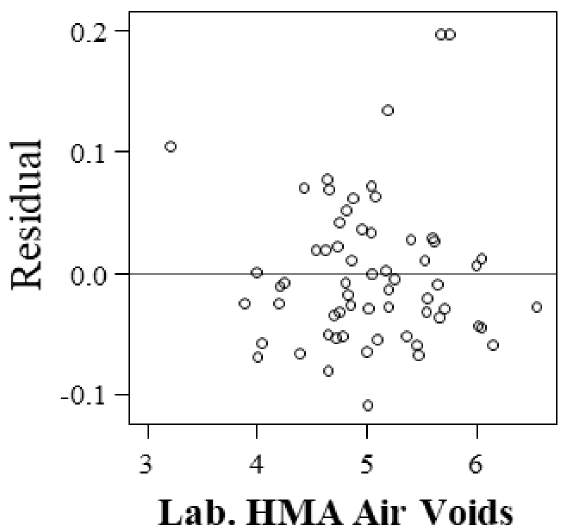
Source: FHWA.

Figure 114. Chart. Plot of residual in State 1-predicted rutting versus percent passing No. 40.



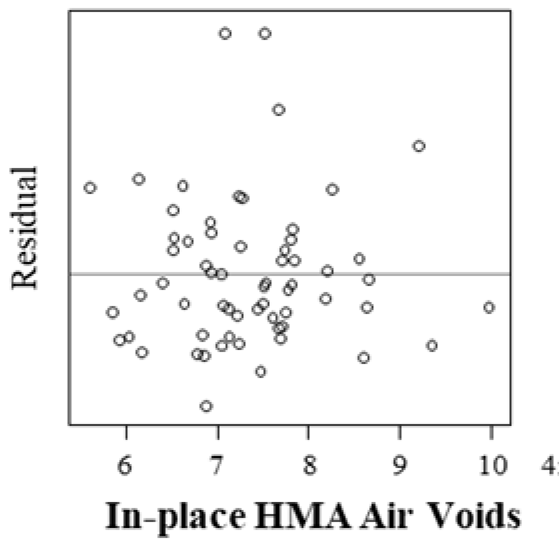
Source: FHWA.

Figure 115. Chart. Plot of residual in State 1-predicted rutting versus binder content.



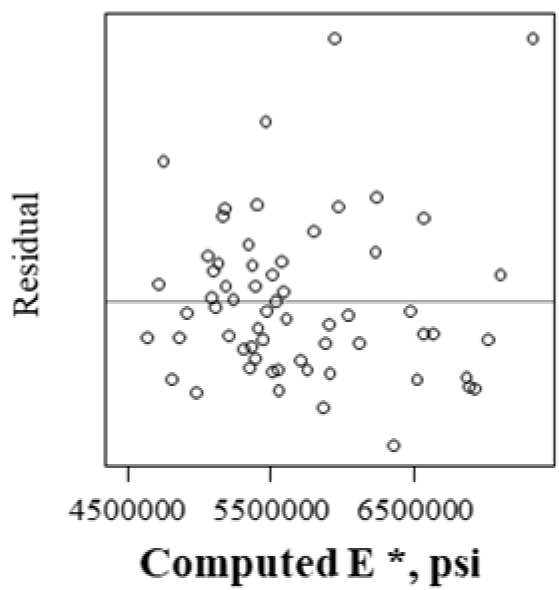
Source: FHWA.

Figure 116. Chart. Plot of residual in State 1-predicted rutting versus HMA air voids in the lab.



Source: FHWA.

Figure 117. Chart. Plot of residual in State 1-predicted rutting versus in-place HMA air voids.



Source: FHWA.

Figure 118. Chart. Plot of residual in State 1-predicted rutting versus computed *E.**

Impact of Construction Variability on Cracking/Rutting

Variability in QA test values within a PMS section or construction project is typically an indicator of consistency in construction. For PRS, pay factors for estimating contract fees are determined based on many factors, including variability along the given project (an indication of construction quality). Also, excessive variability in construction quality can lead to localized early failures along the project, as several localized areas may exhibit significant deficiencies, including thickness, strength, modulus, and air voids.

Thus, additional analysis was done using the State 1 DOT QA test data to determine whether, within projects (comprising several 1-mi PMS sections), variability in QA data items does impact variability in observed cracking and rutting. Variability was characterized as COV of measured cracking/rutting and COV of QA test data item along a given project. Analysis was limited to performing an ANOVA to determine the COV of QA data items that had a significant impact on COV of cracking/rutting. The results of the analysis for cracking and rutting are presented in table 82 and table 83, respectively.

The results in table 82 shows that COV of HMA gradation, density, air voids, and VFA had a significant influence on COV of cracking. For rutting, the significant variables were COV of gradation, air voids, and *E**. These QA test data items, therefore, could serve as a measure of overall construction quality and can be included in PMS as a leading indicator of early failures with a given project.

Table 82. ANOVA results for relationship between COV of cracking and COV of State 1 DOT QA test data items.

Source	Type III SS	Mean Square	*F* Value	*Pr* > *F*
COV of HMA percent passing ¾-inch sieve	6,915.249	6,915.249	2.31	0.1355
COV of HMA percent passing ½-inch sieve	13,477.919	13,477.919	4.51	0.0395
COV of lab-measured HMA maximum density	26,435.744	26,435.744	8.85	0.0048
COV of lab-measured HMA air voids	51,461.185	51,461.185	17.22	0.0002
COV of lab-measured HMA VFA	45,390.820	45,390.820	15.19	0.0003

R^2 = 0.3948, COV = 59.54, RMSE = 54.663.

Table 83. ANOVA results for relationship between COV of rutting and COV of State 1 DOT QA test data items.

Source	Type III SS	Mean Square	*F* Value	*Pr* > *F*
COV HMA percent passing No. 50 sieve	6,919.341	6,919.34	6.05	0.0174
COV HMA coarse aggregate specific gravity	2,712.017	2,712.01	2.37	0.1298
COV of in-place HMA air voids	10,325.891	10,325.89	9.03	0.0041
COV of computed *E**	5,285.990	5,285.99	4.62	0.0364

R^2 = 0.259733, COV = 65.03, RMSE = 33.81.

Use of Derived Parameters to Predict Performance

Previous chapters of the report discussed that parameters "derived" as a function of mix volumetrics and binder properties tend to be strong indicators of performance. There is a potential for derived parameters such as the dynamic modulus (level 3 input for AASHTOWare

ME), effective air void content (correlated to the specific surface of the aggregate in mixture, S_a, and durability), and resistivity (correlated to rutting resistance) to be incorporated into PMS-type performance forecasting models. These parameters offer the benefit of combining mix design and binder properties to characterize overall HMA material property rather than relying on a single QA data item that may not fully capture the overall characteristic of the HMA material. Computed parameters thus should correlate better with performance.

The project team explored the use of "derived" parameters for the development of performance prediction models. The data used in the statistical analyses presented in the preceding section were used to calculate derived parameters discussed in chapter 2; these parameters have proven correlation to performance. These parameters were resistivity, effective air void content, and specific surface of aggregate mixture. The results of the statistical analyses, which followed the same steps as those presented earlier in this section for conventional QA parameters, are presented in the following tables:

- Table 84, for average cracking in State 1 DOT data. The derived parameter included in the model is effective air void content. The corresponding results for a model with conventional QA parameters are presented in table 80.
- Table 85, for COV cracking in State 1 DOT data. The derived parameter included in the model is COV of effective air void content. The corresponding results for a model with conventional QA parameters are presented in table 81.
- Table 86, for average rutting in State 1 DOT data. The derived parameter included in the model is effective air void content. The corresponding results for a model with conventional QA parameters are presented in table 82.
- Table 87, for COV rutting in State 1 DOT data. The derived parameter included in the model is COV of specific surface of aggregate (SAI). The corresponding results for a model with conventional QA parameters are presented in table 83.

Results presented in table 84 through table 87 were a means to assess the improvements that can be expected with the inclusion of the derived parameters, rather than the use of the conventional QA test results. Table 88 summarizes the R^2 obtained for the prediction models based on the conventional QA parameters directly obtained from State QA databases and the derived parameters. It is clear, at least based on goodness of fit, that the models were improved in some cases or of similar predictive capacity, i.e., for average cracking, COV cracking, and average rutting. These results are encouraging for recommending the use of derived parameters as agencies consider integrating QA data for performance prediction.

Table 84. GLM summary (model coefficients) for relationship between average cracking and "derived" parameters from State 1 DOT QA test data items.

Parameter	Estimate	Standard Error	*t* Value	*Pr* > |*t*|
Intercept	47.49796215	11.44532672	4.15	0.0001
Percent passing No. 200	0.88585615	0.31857024	2.78	0.0077
Asphalt content	−2.25062843	0.83891162	−2.68	0.0100
Bulk density	−0.24485616	0.06643955	−3.69	0.0006
Effective air void content	−0.58676683	0.24078475	−2.44	0.0186

R^2 = 0.414821, COV = 48.87, RMSE = 1.780556, *N* = 53.

Table 85. GLM summary (model coefficients) for relationship between COV cracking and "derived" parameters from State 1 DOT QA test data items.

Parameter	Estimate	Standard Error	*t* Value	*Pr* > |*t*|
Intercept	47.497962	11.44532672	4.15	0.0001
COV percent passing 1½ inches	0.88585615	0.31857024	2.78	0.0077
COV percent passing No. 4	−2.25062843	0.83891162	−2.68	0.0100
COV rice density	−0.24485616	0.06643955	−3.69	0.0006
COV aggregate specific gravity	−0.58676683	0.24078475	−2.44	0.0186
COV effective air void content	—	—	—	—

R^2 = 0.587730, COV = 55.33669, RMSE = 51.13055, *N* = 36.
—No data.

Table 86. GLM summary (model coefficients) for relationship between average rutting and "derived" parameters from State 1 DOT QA test data items.

Parameter	Estimate	Standard Error	*t* Value	*Pr* > |*t*|
Intercept	−0.40708	0.26291	−1.55	0.1275
Average percent passing ¾-inch sieve	−0.00758	0.00450	−1.68	0.0981
Average percent asphalt content	0.08178	0.03480	2.35	0.0225
Average air voids	0.02792	0.01417	1.97	0.0540
Average in-place air voids	0.03880	0.01676	2.31	0.0245
Average computed HMA *E**	7.735148E-8	2.421006E-8	3.20	0.0024
Average effective air void content	−0.02361	0.00886	−2.66	0.0102

R^2 = 0.2940, COV = 62.99837, RMSE = 0.06364, *N* = 60.

Table 87. GLM summary (model coefficients) for relationship between COV rutting and "derived" parameters from State 1 DOT QA test data items.

Parameter	Estimate	Standard Error	*t* Value	*Pr* > |*t*|
Intercept	54.45676	16.20627	3.36	0.0015
COV effective aggregate specific gravity	29.15084	18.32730	1.59	0.1183
COV in-place voids	5.18733	1.58622	3.27	0.0020
COV computed HMA *E**	−4.93920	2.22859	−2.22	0.0314
COV specific surface of aggregate mixture	−3.95614	1.33326	−2.97	0.0047

R^2 = 0.2898, COV = 63.03090, RMSE = 33.442404, N = 60.

Table 88. Summary of goodness of fit using QA data and using derived parameters.

State	Model	R^2 for Models with Conventional QA Data	R^2 for Models with Derived Parameters
State 1	Average cracking	42	42
	COV cracking	40	59
	Average rutting	27	46
	COV rutting	26	25

Case Study 1: Use of QA Variables to Improve Performance Forecasting for PMS

As shown in the preceding sections, several QA variables show a significant impact on future pavement cracking and rutting performance. A summary of the identified QA variables is presented in table 89 for cracking and rutting from the previous analyses. As the primary objective of this study was to identify and determine feasibility of incorporating QA variables that potentially impact future performance into PMS, this case study was performed to understand:

- If the variables identified in table 89 can be incorporated in PMS-type models.
- If, once incorporated, they improve the model's predictive capacity.

The outcomes of the analyses done to assess impact of QA variables on a PMS-type cracking forecasting model is summarized in this section.

Table 89. Summary of QA variable types that impact AC pavement cracking and rutting distresses.

Parameter	Cracking	Rutting
Intercept	X	—
Percent passing ¾-inch sieve	X	X
Percent passing No. 4 sieve	X	—
Percent passing No. 40 sieve	—	X
HMA bulk density	X	—
HMA in-place air voids	X	X
HMA lab air voids	—	X
HMA percent asphalt binder	—	X
Computed HMA E^*	X	X

—No data.

Incorporation of QA Data Into PMS-Type Database

For this example case study, data were obtained from multiple sources, namely:

- State 1 DOT QA data tables.
- State 1 DOT PMS cracking and rutting data tables.
- FHWA HPMS data for State 1.
- FHWA modern-era retrospective analysis for research applications climate data tables.

By integrating the four data sources, a PMS grade dataset containing basic pavement type/structure data, traffic, rutting/cracking performance, and climate data was assembled for HMA pavement in State 1. Data from the four sources were integrated using a variety of tools and codes as they had considerably different linear referencing systems (LRS) (e.g., GPS, highway type and MP, project/contract numbers). The assembled data were reviewed for quality and reasonableness. Remedial action was taken to remove significant outliers and erroneous records. Mechanistic-type clusters such as SA1 and VTMeff were estimated using the raw QA data to obtain parameters that have been demonstrated through research to impact pavement performance and thus can be incorporated into the performance forecasting models. The assemble data included over 1,400 records.

Cracking Forecasting Model

PMS mostly rely on basic polynomial-type models/equations to forecast future distresses and condition. An example of such a model relating cracking to pavement age or cumulative truck traffic applications is shown in the equation presented in figure 119, while the equation in figure 120 presents a modified version, which includes QA and other data types.

$$CRK = \beta_0 + \beta_1 * AGE + \beta_2 * AGE^2 + \beta_3 * AGE^3 + \cdots \ldots \ldots + \beta_n * AGE^n$$

Figure 119. Equation. Typical model forms for cracking prediction model.

$$CRK = a_0 + \sum_{n=1}^{N} a_n AGE^n + \sum_{k=1}^{K} a_k QA^k + \sum_{j=1}^{J} a_j CLIM^j + Others$$

Figure 120. Equation. Modified version of PMS cracking prediction model form.

Where:

a_0, a_n, a_k, a_j = regression coefficients.
β_0, β_1 = regression coefficients.
CRK = alligator fatigue cracking.
AGE = pavement age in years.
QA = QA variables.
CLIM = climate-related variables.
Others = other variables such as layer thickness.

Under this case study, the assembled data were fit to the equation forms shown in figure 119 and figure 120. The outcomes are as presented in equations shown in figure 121 and figure 122.

$$CRK = 0.994 - 0.262 * AGE + 0.0705 * AGE^2 - 0.0014 * AGE^3$$

Figure 121. Equation. Cracking prediction model based on age.

$$CRK = 5.011 + 0.557 * AGE - 0.0094 * THK - 0.2184 * DENSITY + 0.8265 * VMA$$
$$+1.354 * SA1 + 0.109 * VTMeff + 0.742 * SUBG + 0.169 * MAXTEMP$$

Figure 122. Equation. Cracking prediction model using age, QA data, and other parameters derived from QA data.

Where:

THK = HMA thickness.
DENSITY = HMA density.
VTM_{eff} = AV + 1.87 − 1.53*SA1.
AV = HMA as-placed air voids.
SA1 = (PCT_N50 + PCT_N100 + PCT_N200)/5.
SUBG = subgrade type (1 = coarse, 0 = fine).
MAXTEMP = maximum ambient temperature.

The model statistics for the equations in figure 121 and figure 122, presented in table 90, show the significant improvement to the performance prediction model by incorporating data from other QA databases, such as traffic and climate. This case study is intended to serve as an example of how this study can be implemented.

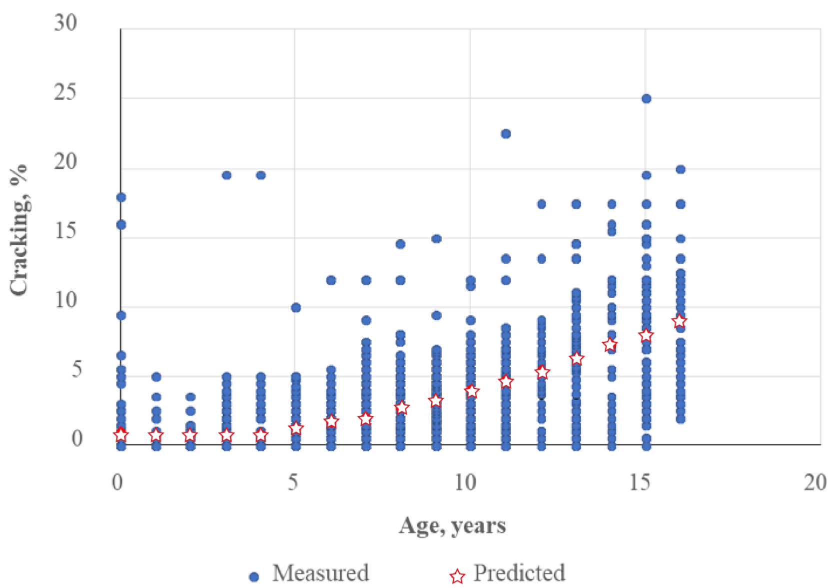
Table 90. Model statistics for example PMS cracking prediction models using age and additional QA parameters.

Model	*N*	R^2	COV	RMSE (percent)
Model using age (figure 121)	1,589	0.38	96.3	2.86
Model using age and QA parameters (figure 122)	1,393	0.55	80.9	2.35

Assessment of Impact of QA Variables on Cracking Prediction

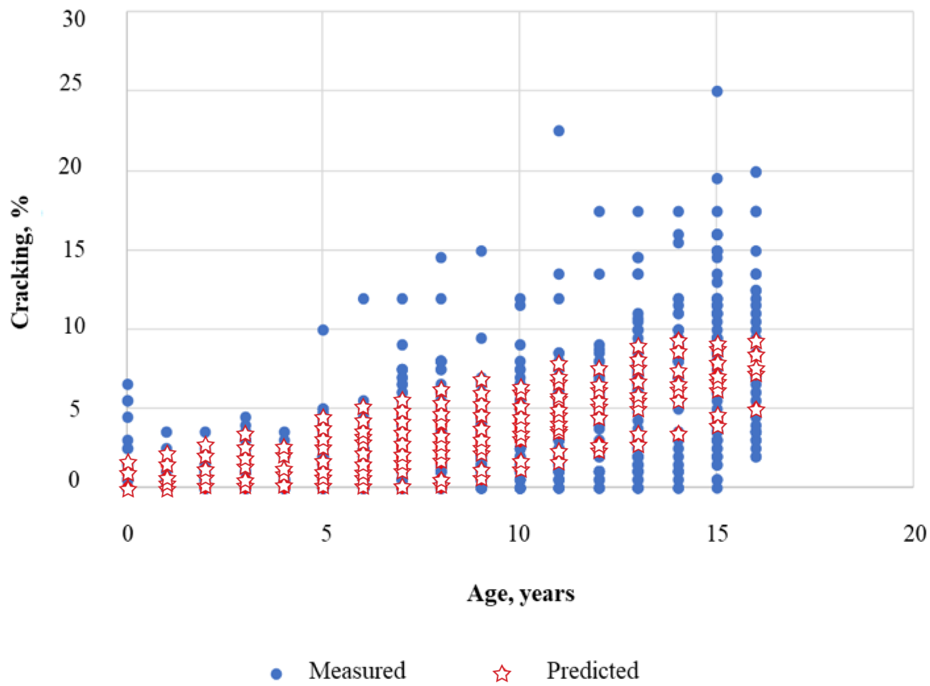
The predictive capacity of the models in figure 121 and figure 122 is shown through the model's diagnostic statistics presented in table 90. Including QA and other parameters resulted in a 45 percent increase in R^2, 17 percent decrease in COV, and 18 percent decrease in standard error of the estimate (SEE).

Figure 123 shows a plot of measured and predicted cracking versus age for the model in figure 121 using only age as a variable, whereas figure 124 shows the same for the predictive model in figure 122 using age, climate, traffic, and QA variables. A review of the plots presented shows the superior predictive capacity of the model using age, QA, traffic, and climate parameters. It covers a wider range of measured cracking compared with predictions from age alone. Thus, both the diagnostic statistics and plots show a significant increase in the model's predictive capacity with the inclusion of QA and other variables. This increase confirms the earlier analyses that shows that QA parameters do impact future pavement performance. It is also in agreement with past research that demonstrated the impact of pavement design parameters such as HMA thickness and site factors such as climate and subgrade type on performance.



Source: FHWA.

Figure 123. Graph. Plot of measured and predicted cracking versus age for model with age only.



Source: FHWA.

Figure 124. Graph. Plot of measured and predicted cracking versus age for model using age and QA data.

STATISTICAL ANALYSIS FOR STATE 2

This section presents the results of analysis conducted to assess feasibility of utilizing State 2 DOT QA test data as a leading indicator of pavement performance. Analysis was done using the integrated State 2 DOT PMS and QA test database described in chapter 4 and chapter 5 and analysis methodologies previously described in this chapter. Analysis used both network and project-specific data. The results are described in the following sections.

State 2 DOT Correlation Analysis

Summary of Correlations Between Rutting/IRI and HMA QA Test Data

Table 91, table 92, and table 93 present the statistics and results of correlation analysis (Pearson's correlation coefficient, *r*) to assess strength of relationships between rutting and State 2 DOT QA test data items. As shown in table 92 and table 93, asphalt binder content and HMA mix air voids exhibit strong correlations with both rutting and IRI. HMA density and VMA have a weak to fair correlation with both rutting and IRI. The results presented are as expected, as binder content has a significant impact on HMA material modulus/stability. HMA modulus/stability has significant influence on rutting development and progression. HMA air voids significantly impact initial consolidation of the HMA mix and thus plastic strain development. The HMA air voids also impact E^*, as shown by the Witczak model, and thus rutting progression and smoothness loss. The impact of binder content and air voids on smoothness loss is as expected, as HMA stability/modulus deficiencies influenced by these QA test data items does result in distress development in general, leading to loss of smoothness.

Table 91. Summary statistics of State 2 HMA QA data items.

QA Variables	No. Data Points	Mean	Standard Deviation	Minimum	Maximum
HMA binder content (top layer)	188	5.38	0.13	5.12	5.67
HMA binder content (bottom layer)	188	5.41	0.14	5.18	5.80
HMA density (top layer)	185	92.98	0.92	90.40	95.60
HMA density (bottom layer)	188	93.10	1.08	89.90	95.60
VMA (top layer)	188	14.51	0.42	13.70	15.60
VMA (bottom layer)	188	14.89	0.36	13.60	15.40
HMA air voids (top layer)	188	4.06	0.70	1.50	4.80
HMA air voids (bottom layer)	183	4.07	0.70	1.50	4.80

Table 92. Pearson's correlation tables for State 2 HMA PMS rutting.

QA Variables	Pearson's Correlation	Test of Significance	Comments
HMA binder content (top layer)	−0.3308	<0.0001	Strong
HMA binder content (bottom layer)	−0.3540	<0.0001	Strong
HMA density (top layer)	0.0593	0.4226	Weak
HMA density (bottom layer)	−0.1435	0.0494	Fair
VMA (top layer)	0.1462	0.0452	Fair
VMA (bottom layer)	0.0582	0.4269	Weak
HMA air voids (top layer)	0.2624	0.0003	Strong
HMA air voids (bottom layer)	0.2801	0.0001	Strong

Table 93. Pearson's correlation tables for State 2 HMA PMS IRI.

QA Variables	Pearson's Correlation	Test of Significance	Comments
HMA binder content (top layer)	−0.159	0.029	Fair
HMA binder content (bottom layer)	−0.2533	0.0005	Strong
HMA density (top layer)	0.01388	0.8512	Weak
HMA density (bottom layer)	−0.06119	0.4042	Weak
VMA (top layer)	0.08789	0.2304	Weak
VMA (bottom layer)	0.14032	0.0548	Fair
HMA air voids (top layer)	0.23458	0.0012	Strong
HMA air voids (bottom layer)	0.23318	0.0015	Strong

Summary of Correlations between Cracking/Faulting and PCC QA Test Data

Table 94 through table 97 present the summary of data and outcome of correlation analysis for cracking and faulting, respectively. As presented in table 94 and table 95, the QA test data items categorized as having strong correlations with cracking were PCC mix constituents (cementitious materials content [i.e., cement and fly ash], sand, and additives) and coarse aggregate absorptivity (correlates well with coarse aggregate and thus PCC strength and durability). PCC w/c ratio, compressive strength, and coarse aggregate content were among the data items with a fair correlation with cracking. The QA data items identified as having fair/strong correlation with cracking were deemed reasonable as they collectively influence PCC strength and modulus—the two key parameters that impact fatigue damage and cracking. Table 96 and table 97 show PCC mix constituents (PCC fly ash, coarse aggregate, water, additives, and cement content) along with PCC strength and coarse aggregate specific gravity, absorptivity, and LA abrasion as the QA data items with a strong correlation to faulting. The identified QA data elements were deemed as reasonable, as they affect PCC strength/modulus and joint aggregate interlock (which correlates well with coarse aggregate strength/durability characterized by absorptivity), the two parameters that significantly influence faulting development and progression.

Table 94. Summary statistics of State 2 PCC QA data items used for JPCP transverse cracking.

QA Variables	No. Data Points	Mean	Standard Deviation	Minimum	Maximum
PCC fly ash content	382	117	10	113	141
PCC coarse aggregate content	382	1,342	336	940	1,630
PCC sand content	382	1,256	84	1,080	1,326
PCC cement content	382	682	10	678	706
w/c ratio	382	0.37	0.02	0.35	0.39
Additive (AEA) amount	382	6.2	3.5	2.5	11.5
Additive (WRA) amount	340	21.2	3.7	14.0	30.0
PCC water content	382	251	11	240	270
PCC slump	382	2.7	0.5	1.8	3.0
PCC air content	382	6.1	0.6	4.9	6.7
PCC unit weight	382	144.4	1.0	143.6	146.4
PCC yield strength	382	13.3	13.0	1.0	27.1
PCC 28-d compressive strength	382	5,752	274	5,390	6,190
Coarse aggregate specific gravity	382	2.7	0.1	2.7	2.8
Coarse aggregate absorptivity	382	0.6	0.2	0.3	0.8
Coarse aggregate LA abrasion	382	26.7	7.2	15.0	33.4
Intermediate aggregate specific gravity	160	2.6	0.0	2.6	2.6
Intermediate aggregate absorptivity	160	1.0	0.1	0.8	1.2
Intermediate aggregate LA abrasion	160	41.2	1.9	38.0	43.0
Fineness modulus	382	3.0	0.2	2.6	3.2
Fine aggregate specific gravity	382	2.6	0.0	2.6	2.6
Fine aggregate absorptivity	382	0.7	0.1	0.6	0.9
Sand equivalent	382	94.0	0.9	93.0	97.0

WRA = water-reducing admixture.

Table 95. Pearson's correlation tables for State 2 JPCP transverse cracking.

QA Variables	Pearson's Correlation	Test of Significance	Comments
PCC fly ash content	0.2349	<0.0001	Strong
PCC coarse aggregate content	−0.1544	0.0025	Fair
PCC sand content	−0.2541	<0.0001	Strong
PCC cement content	0.2349	<0.0001	Strong
w/c ratio	0.1119	0.0288	Fair
Additive (AEA) amount	−0.0527	0.3046	Weak
Additive (WRA) amount	0.3474	<0.0001	Strong
PCC water content	0.1928	0.0002	Fair
PCC slump	0.1375	0.0071	Fair
PCC air content	0.0505	0.3251	Weak
PCC unit weight	—	0.007	Fair
PCC yield strength	−0.0926	0.0708	Weak
PCC 28-d compressive strength	0.1947	0.0001	Fair
Coarse aggregate specific gravity	0.1272	0.0128	Fair
Coarse aggregate absorptivity	−0.2459	<0.0001	Strong
Coarse aggregate LA abrasion	−0.2038	<0.0001	Fair
Intermediate aggregate specific gravity	0.2580	0.001	Fair
Intermediate aggregate absorptivity	−0.1980	0.0121	Fair
Intermediate aggregate LA abrasion	0.2733	0.0005	Strong
Fineness modulus	−0.0655	0.2014	Weak
Fine aggregate specific gravity	0.1317	0.01	Fair
Fine aggregate absorptivity	0.0789	0.1236	Weak
Sand equivalent	0.1163	0.023	Fair

Table 96. Summary statistics of State 2 PCC QA data items used for JPCP transverse joint faulting.

QA Variables	No. Data Points	Mean	Standard Deviation	Minimum	Maximum
PCC fly ash content	382	117	10.20	113	141
PCC coarse aggregate content	382	1,342	335.78	940	1,630
PCC sand content	382	1,256	84.19	1,080	1,326
Additive (AEA) amount	382	6.2	3.46	2.5	11.5
Additive (WRA) amount	340	21.2	3.66	14	30
PCC water content	382	251.0	11.25	240	270
PCC slump	382	2.7	0.51	1.75	3
PCC air content	382	6.1	0.60	4.9	6.7
PCC unit weight	382	144.4	0.95	143.6	146.4
PCC yield strength	382	13.3	13.02	0.99	27.05
PCC 7-d compressive strength	382	4,370	299.78	3,920	5,370
PCC 28-d compressive strength	382	5,752	274.21	5,390	6,190
PCC placement month	382	7	2.67	2	11
Coarse aggregate specific gravity	382	2.74	0.07	2.665	2.83
Coarse aggregate absorptivity	382	0.64	0.16	0.3	0.8
Coarse aggregate LA abrasion	382	26.69	7.16	15	33.4
Fineness modulus	382	2.96	0.22	2.64	3.18
Fine aggregate specific gravity	382	2.61	0.01	2.6	2.62
Fine aggregate absorptivity	382	0.72	0.12	0.6	0.9
Sand equivalent	382	93.95	0.95	93	97
PCC elastic modulus	382	4,321,854	103,288	4,184,747	4,484,564
w/c ratio	382	0.37	0.016	0.35398	0.38938

Table 97. Pearson's correlation tables for JPCP transverse joint faulting.

QA Variables	Pearson's Correlation	Test of Significance	Comments
PCC fly ash content	−0.2095	<0.0001	Strong
PCC coarse aggregate content	0.28847	<0.0001	Strong
PCC sand content	0.32929	<0.0001	Strong
Additive (AEA) amount	−0.1372	0.0072	Fair
Additive (WRA) amount	−0.2534	<0.0001	Strong
PCC water content	−0.3453	<0.0001	Strong
PCC slump	0.05704	0.2661	Weak
PCC air content	0.21032	<0.0001	Strong
PCC unit weight	−0.1253	0.0142	Fair
PCC yield strength	0.3116	<0.0001	Strong
PCC 7-d compressive strength	−0.1192	0.0198	Fair
PCC 28-d compressive strength	0.11032	0.0311	Fair
PCC placement month	0.05639	0.2716	Weak
Coarse aggregate specific gravity	−0.315	<0.0001	Strong
Coarse aggregate absorptivity	0.3676	<0.0001	Strong
Coarse aggregate LA abrasion	0.34132	<0.0001	Strong
Fineness modulus	0.24387	<0.0001	Strong
Fine aggregate specific gravity	−0.1103	0.0311	Fair
Fine aggregate absorptivity	−0.2674	<0.0001	Strong
Sand equivalent	−0.1494	0.0034	Fair
PCC elastic modulus	0.11194	0.0287	Fair
w/c ratio	−0.2794	<0.0001	Strong

State 2 DOT Stepwise Regression Analysis

Average Rutting/IRI Versus State 2 DOT QA Data items

Table 98 and table 99 present the outcomes of stepwise regression analysis for developing the preliminary relationship and models for rutting and IRI, respectively, based on QA test data items. For both relationships, HMA binder content (bottom layer) was the only data item selected. As binder content is a key indicator of many key HMA properties, such as VFA, air voids, and E^*, selection of this data item was deemed reasonable. Review of the models' coefficients shows that, for both models, increasing HMA mix binder content results in a decrease of rutting and IRI.

Table 98. Stepwise selection summary for relationship between rutting and State 2 DOT QA test data items.

Step	Effect Entered	Effect Removed	No. Effects In	Model R^2	C_p Statistic	PRESS Statistic	*Pr* > *F***	Coefficient Estimate**
0	Intercept	—	1	0.0000	24.93	0.9075	1.0000	1.1788
1	HMA binder content (bottom layer)	—	2	0.1177	1.699*	0.8025*	<0.0001	−0.125

Stepwise selection summary: RMSE = 0.06597, R^2 = 0.135, *N* = 181.
—No data.
*Optimal value of criterion.
**Values at step 1.

Table 99. Stepwise selection summary for relationship between IRI and State 2 DOT QA test data.

Step	Effect Entered	Effect Removed	No. Effects In	Model R^2	C_p Statistic	PRESS Statistic	*Pr* > *F***	Coefficient Estimate**
0	Intercept	—	1	0.0000	13.31	52,103	1.0000	239.08
1	HMA binder content (bottom layer)	—	2	0.0642	2.7187*	49,217*	0.0005	−29.8127

Stepwise selection summary: RMSE = 16.23508, R^2 = 0.0814, *N* = 184.
—No data.
*Optimal value of criterion.
**Values at step 1.

Average Cracking/Faulting Versus State 2 DOT QA Data Items

Table 100 and table 101 present outcomes of basic model development through stepwise regression analysis for JPCP cracking and faulting, respectively. The results in table 100 indicate that PCC 7-d compressive strength, w/c ratio, and sand equivalent were the three QA data items that met the independent variables selection criteria and thus were included in the preliminary model. A detailed examination of the preliminary model shows that, although all three data items do impact JPCP faulting development, the model coefficients do present trends that were not as expected. The reasons for this situation might include interactions between the selected data items and lack of completeness of this model, as key inputs such as traffic and climate are not included. The selection of the three data items, however, shows that there is a strong correlation between QA data items and JPCP cracking.

For transverse joint faulting, table 101 shows that PCC coarse aggregate absorptivity, sand equivalent, and coarse aggregate content were the three QA data items that met the independent variables selection criteria and thus were included in the preliminary model. Detailed examination indicated that all three data items are reasonable. The trends, as shown by model coefficients, were also deemed reasonable, because increasing coarse aggregate absorptivity (less strength/durability) does decrease load transfer due to aggregate interlock and thus increases faulting. Also, increasing PCC coarse aggregate content increases PCC strength/modulus and thus reduces faulting, as indicated by the models' coefficients.

Table 100. Stepwise selection summary for the relationship between JPCP transverse cracking and State 2 DOT QA test data items.

Step	Effect Entered	Effect Removed	No. Effects In	Model R^2	C_p	PRESS	*Pr* > *F*	Estimate
0	Intercept	—	1	0.0000	140.101	26,581.41	1.0000	−270.61
1	PCC 7-d compressive strength	—	2	0.1577	60.092	22,601.51	<0.0001	0.015
2	w/c ratio	—	3	0.2458	16.263	20,343.20	<0.0001	155.53
3	Sand equivalent	—	4	0.2763	2.3923*	19,795.69*	<0.0001	1.584

R^2 = 0.2763, RMSE = 7.11510, N = 382.
—No data.
*Optimal value of criterion.

Table 101. Stepwise selection summary for relationship between JPCP transverse joint faulting and State 2 DOT QA test data items.

Step	Effect Entered	Effect Removed	No. Effects In	Model R^2	C_p	PRESS	*Pr* > *F*	Estimate
0	Intercept	—	1	0.0000	80.2788	84.3902	1.0000	10.000748
1	Coarse aggregate absorptivity	—	2	0.1416	23.0699	72.8125	<0.0001	2.370160
2	Sand equivalent	—	3	0.1869	6.0956	69.1270	<0.0001	−0.107917
3	PCC coarse aggregate content	—	4	0.1991	3.0071*	68.1633*	0.0245	−0.000597

R^2 = 0.44719, RMSE = 0.0991, N = 382.
—No data.
*Optimal value of criterion.

State 2 DOT Finalized GLM/ANOVA Regression Analysis

Average Rutting/IRI Versus State 2 DOT QA Data Items

Table 102 and table 103 present the outcomes of GLM regression analysis for developing the finalized relationship/models for rutting/IRI (based on QA test data items). For the rutting model, table 102 shows binder content as the significant variable included in the model. As expected, increasing binder content resulted in a decrease in rutting. The R^2, COV, and RMSE of this model were deemed reasonable (note that the model does not include other key variables such as traffic, climate, and thickness). For IRI, in table 103, the significant variables were binder content and air voids. As expected, increasing binder content reduced IRI, while increasing air voids increased IRI. Thus, the model was deemed reasonable. Model diagnostic statistics R^2, COV, and RMSE were deemed as reasonable, as this was not a full model with all parameters included.

Table 102. GLM summary for relationship between average rutting and State 2 DOT QA test data items.

Parameter	Estimate	$Pr > \|t\|$
Intercept	1.17446	<0.0001
HMA binder content (bottom layer)	−0.1679	<0.0001

R^2 = 0.1346, COV = 25.9, RMSE = 0.0652.

Table 103. GLM summary for relationship between average IRI and State 2 DOT QA test data items.

Parameter	Estimate	$Pr > \|t\|$
Intercept	274.32	0.0052
HMA binder content (bottom layer)	−25.946	0.0299
HMA air voids (top layer)	3.7107	0.1172

R^2 = 0.0814, COV = 20.73, RMSE = 16.122.

Average Cracking/Faulting Versus State 2 DOT QA Data Items

Table 104 and table 105 present the outcomes of GLM regression analysis for developing the finalized relationship and models for cracking and faulting, respectively (based on PCC QA test data items). For the cracking model, table 104 shows that PCC unit weight and w/c ratio as the significant variables included in the model. PCC compressive strength decreases with increasing w/c ratio. Therefore, increasing w/c ratio would result in increased cracking, as shown by the model in table 104. Also, in general, PCC strength increases with increased unit weight; thus, as expected, the model shows that increasing PCC unit weight does reduce cracking. The models' R^2 was low, while COV was high. Model SEE was deemed reasonable. The low R^2 and high COV values were due mostly to the fact that this was not a full model that considered other key parameters such as climate, traffic, and joint load transfer mechanism characterization.

Table 104. GLM summary for relationship between average JPCP transverse cracking and State 2 DOT QA test data items.

Parameter	Estimate	Standard Error	*t* Value	*Pr* > |*t*|
Intercept	218.2	64.5	3.38	0.0008
w/c ratio	91.1	27.2	3.34	0.0009
PCC unit weight	−1.721	0.46	−3.70	0.0002

R^2 = 0.0469, COV = 255.74, RMSE = 8.1.

Table 105 shows that increasing coarse aggregate absorptivity (indicator of lower aggregate durability and aggregate interlock) results in an increase in faulting. This increase is as expected. Increasing both PCC sand equivalent and 7-d compressive strength reduces faulting. As a higher sand equivalent value indicates that there is less claylike material in the PCC (i.e., increased durability and higher PCC strength), the two trends were found to be reasonable and as expected. The R^2, COV, and RMSE of this model were deemed reasonable (note that the model does not include other key variables such as traffic, climate, or thickness).

Table 105. GLM summary for relationship between average JPCP transverse joint faulting and State 2 DOT QA test data items.

Parameter	Estimate	Standard Error	*t* Value	*Pr* > |*t*|
Intercept	11.42	2.376	4.81	<0.0001
Coarse aggregate absorptivity	1.15	0.141	8.13	<0.0001
Sand equivalent	−0.11	0.024	−4.65	<0.0001
PCC 7-d compressive strength	−0.000206	0.0000768	−2.69	0.0075

R^2 = 0.188236, COV = 70.568, RMSE = 0.437632.

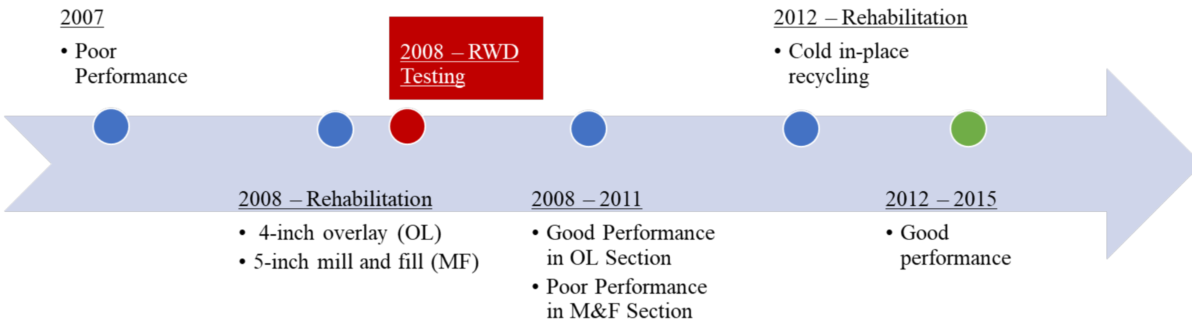
Use of Derived Parameters to Predict Performance

With the types of QA data elements available with State 2 DOT, the evaluation of the use of derived parameters was not possible. Therefore, models with the use of derived parameters are not presented in this section.

Case Study 2: Utilizing Data from Innovative Technologies as Leading Indicators of Performance

Case Study 2a: Evaluation of Impact of RWD-Measured Maximum Deflection on Fatigue Cracking Observed in HWY NN (MP 33.1–47.3)

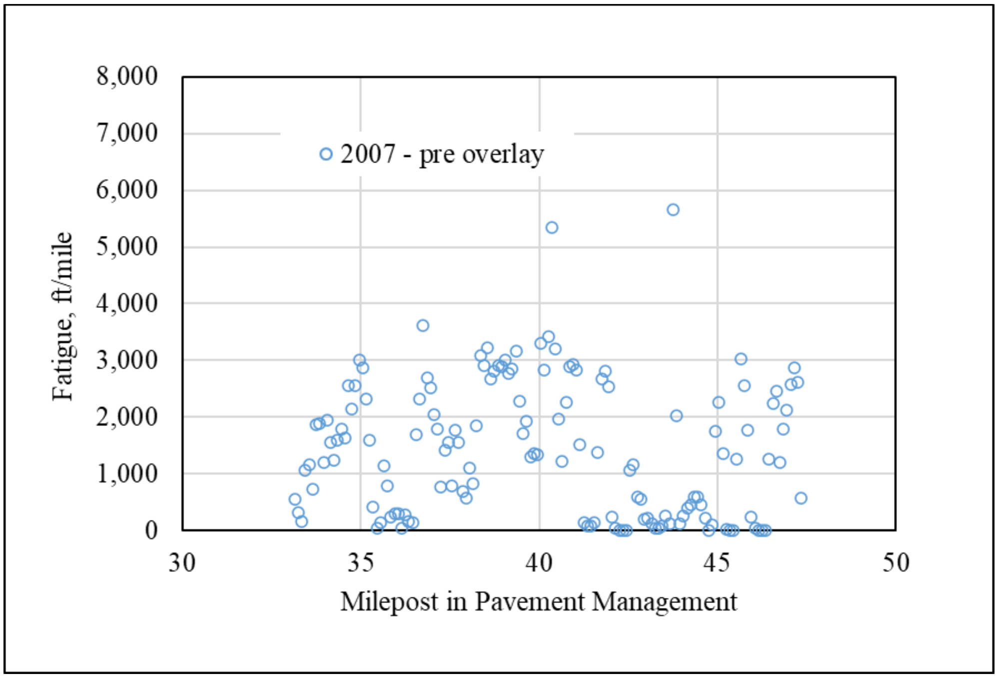
The research team selected an overlay construction project from 2008 to evaluate the ability of continuous deflection monitoring devices to identify structural conditions that might affect future pavement performance. The construction project selected is located along SH NN in State 2. The selected project corridor spans between MP 33.1 and MP 47.3, while the duration of performance evaluation was between 2007 and 2013 for this case study. The project timeline is illustrated in figure 125.



Source: FHWA.
OL = overlay; M&F = mill and fill.

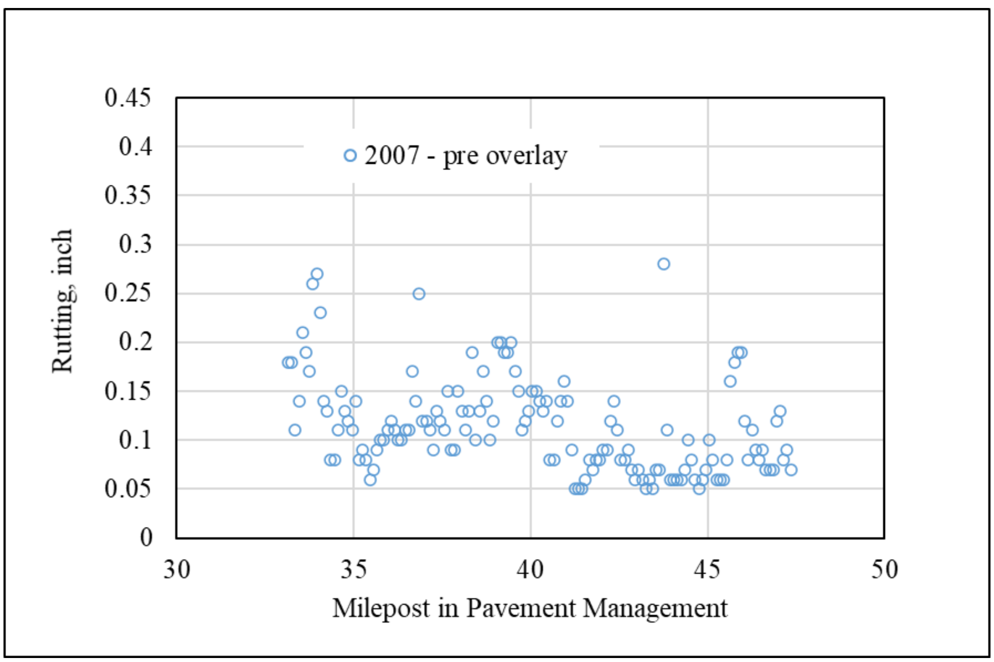
Figure 125. Illustration. Timeline of project performance evaluation.

The project corridor considered showed poor performance and recorded high levels of distress in 2007, based on pre-overlay data aggregated in the State PMS. The reported fatigue, rutting, and IRI are shown in figure 126, figure 127, and figure 128. A rehabilitation activity was performed between MP 33.1 and MP 45.2 in 2008 as noted in the State 2 DOT QA and contracts databases. The 2008 rehabilitation activity involved a 4-inch overlay between MP 33.1 and MP 41.2, followed by a 5-inch mill and fill between MP 41.2 and MP 45.2. The QA materials data indicated that two mixes were used in this effort, as shown in table 106 through table 109, a virgin mix and a RAP mix. However, the location references for the mixes were not evident, as the stationing data were missing, i.e., not recorded (although the database offers the feature to record the location reference), in the construction records. Table 108 and table 109 show that the RAP mix had higher air voids and VMA. Construction was completed in September 2008. The focus of this specific evaluation was not on the QA records, but instead was on the ability of an innovative technology, such a continuous deflection monitoring device, to identify structural deficiencies that might result from either low-quality materials or construction and could affect future pavement performance.



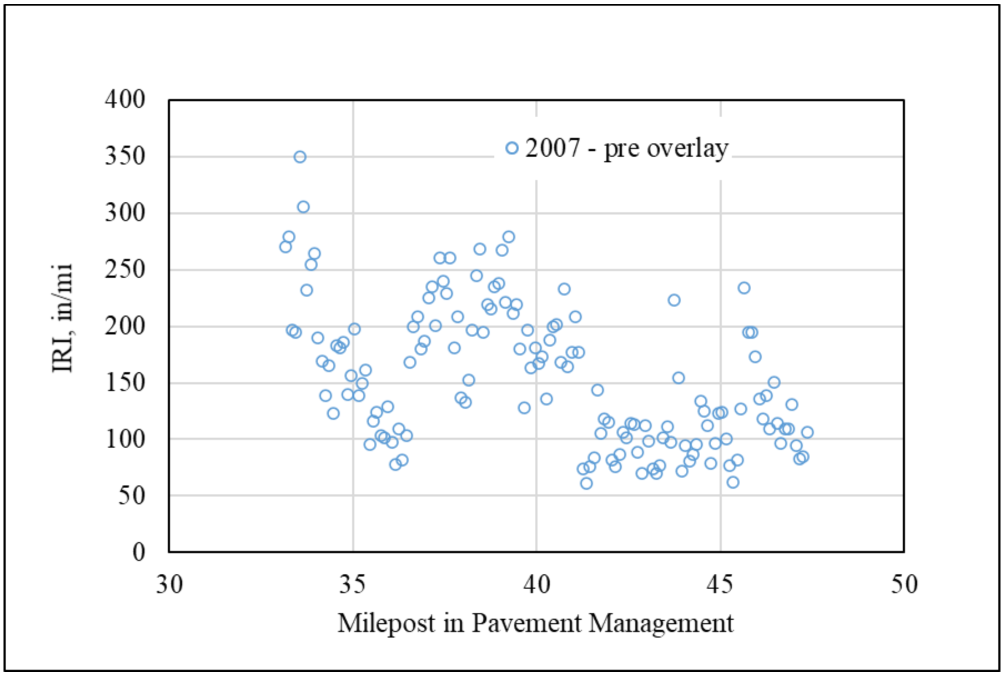
Source: FHWA.

Figure 126. Chart. Fatigue cracking in selected segment of SH NN in 2007 pre-overlay.



Source: FHWA.

Figure 127. Chart. Average rutting in selected segment of SH NN in 2007 pre-overlay.



Source: FHWA.

Figure 128. Chart. Average IRI in selected segment of SH NN in 2007 pre-overlay.

Table 106. QA test result summary of asphalt content for the SH NN project.

Mix ID	Quantity (Tons)	Number of Tests	QL	PF	I/DP (Dollars)
Mix 168525	17,404	18	96.500	1.05000	4,612.06
64-28 W/RAP	14,568	15	99.165	1.05000	4,370.40

QL = Quality Level; PF = Pay Factor; I/DP = incentive and disincentive payment.

Table 107. QA test result summary of mat density for the SH NN project.

Mix ID	Quantity (Tons)	Number of Tests	QL	PF	I/DP (Dollars)
Mix 168525	17,404	36	95.274	1.04440	14,332.69
64-28 W/RAP	14,568	30	97.857	1.05000	16,826.04

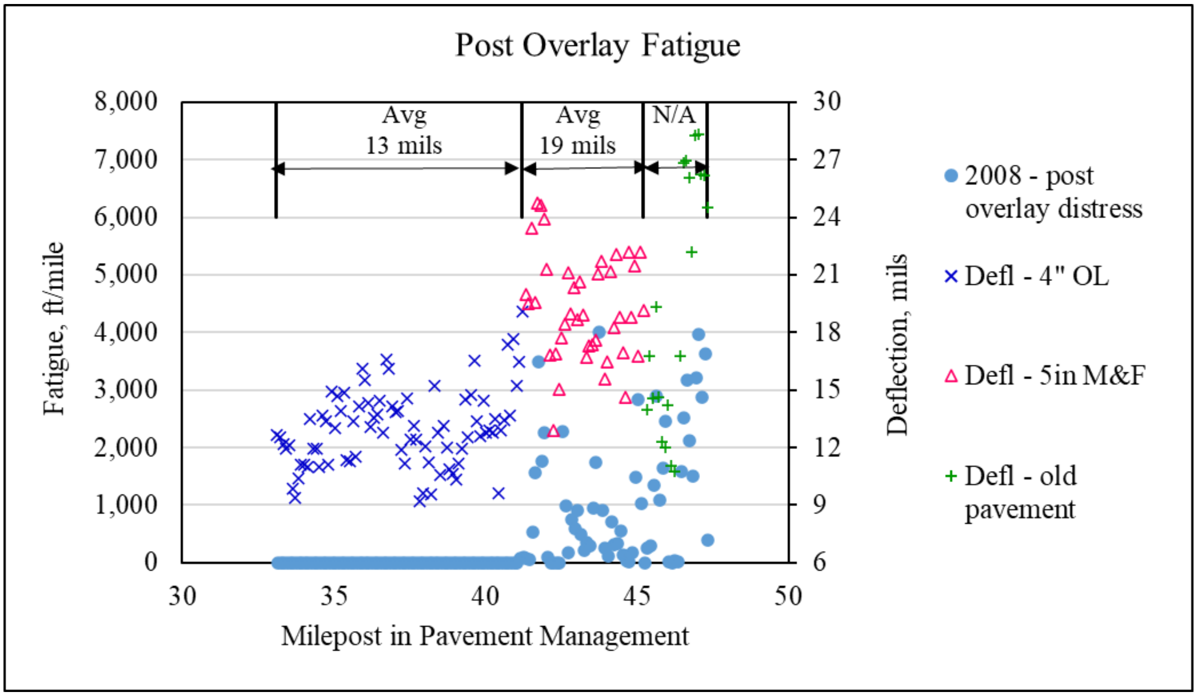
Table 108. QA test result summary of VMA for the SH NN project.

Mix ID	Quantity (Tons)	Number of Tests	QL	PF	I/DP (Dollars)
Mix 168525	17,404	18	99.877	1.05000	4,612.06
64-28 W/RAP	14,568	15	75.067	0.93359	–5,804.55

Table 109. QA test result summary of air voids for the SH NN project.

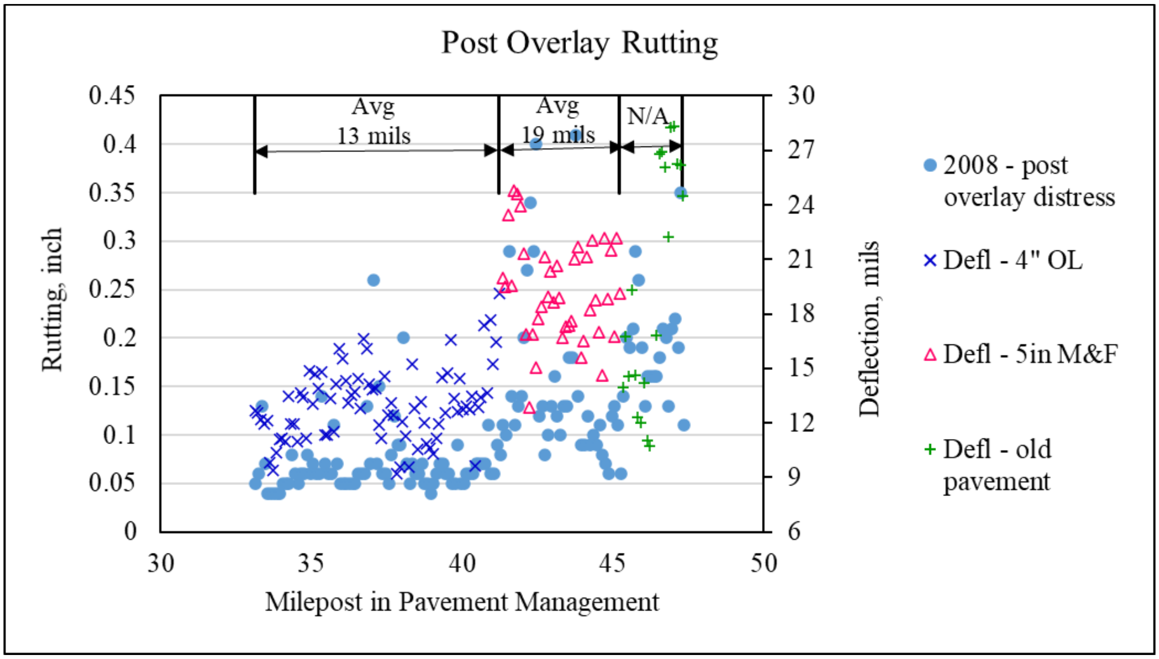
Mix ID	Quantity (Tons)	Number of Tests	QL	PF	I/DP (Dollars)
Mix 168525	17,404	18	97.333	1.05000	13,836.18
64-28 W/RAP	14,568	15	53.905	0.76109	–62,649.13

The continuous deflection monitoring device that provided structural response data was the RWD. Deflection data were collected within 12 mo of pavement construction for this project. Deflection data are plotted in figure 129, figure 130, and figure 131, overlapping field fatigue cracking, average rutting, and IRI at every 1/10th of a mile. Deflection data are distinguished for the segments that underwent 4-inch overlay and 5-inch mill and fill. Please note that the segment between MP 45.2 and MP 47.3 did not have a rehabilitation treatment. The average measured deflections were 13 mils and 19 mils, suggesting a reduced structural capacity of the latter segment. The performance data agree with the observed lower structural capacity, indicating that the higher distress in the latter segment is a consequence of a downside in the construction event.



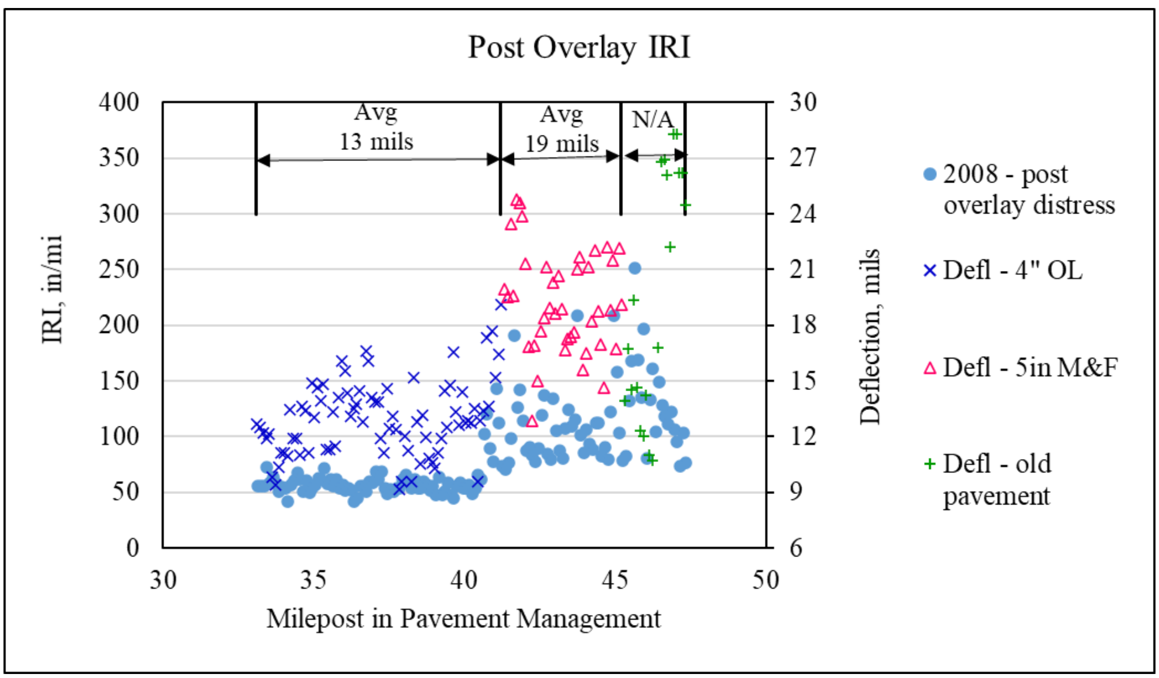
Source: FHWA.

Figure 129. Chart. Fatigue cracking in selected segment of SH NN in 2008 post-overlay.



Source: FHWA.

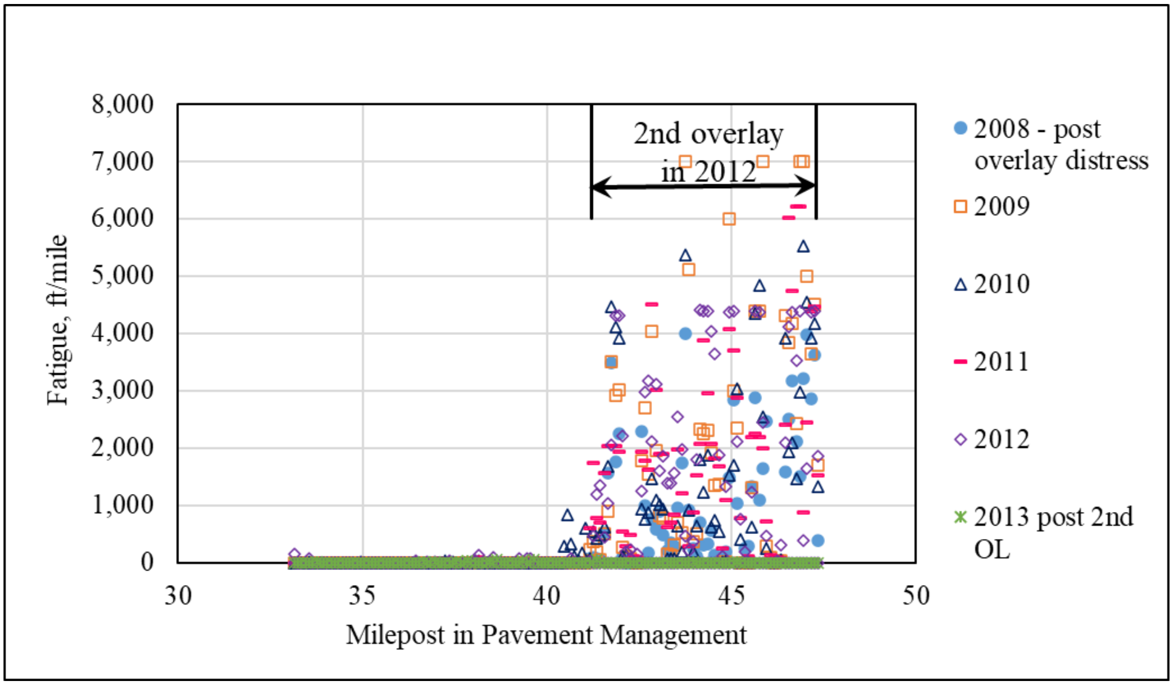
Figure 130. Chart. Average rutting in selected segment of SH NN in 2008 post-overlay.



Source: FHWA.

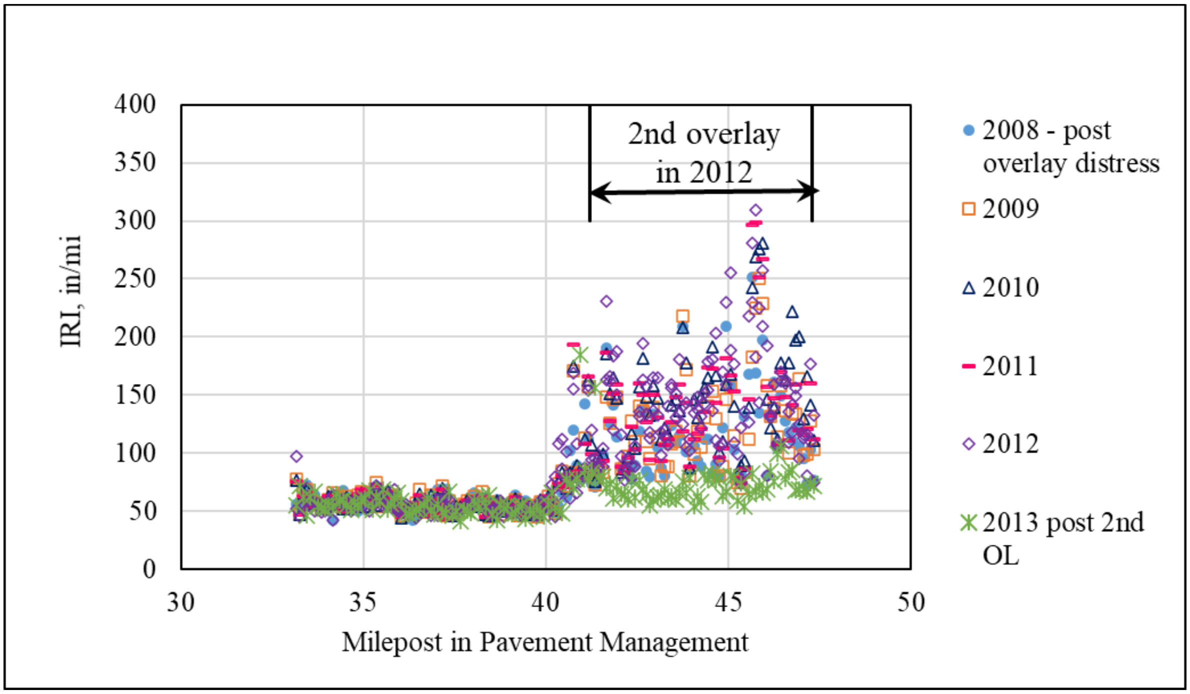
Figure 131. Chart. Average IRI in selected segment of SH NN in 2008 post-overlay.

Clearly, the QA data available do not allow the research team to fully corroborate this fact, which is not the intent of this analysis. However, the data do verify that the RWD deflections can signal the presence of a weaker section that is likely to develop distresses sooner than anticipated. Communication with the State DOT and a review of the roadway images did not indicate the presence of traffic-altering operations (the presence of warehouses or intersections with other high-traffic roadways). Performance data tracked over the next several years indicated that the latter segment continued to deteriorate until a second rehabilitation activity (cold in-place recycling) was performed between MP 41.2 and MP 47.3, which reduced all critical distresses. Figure 132 and figure 133 show the fatigue cracking and IRI within the highway corridor being evaluated and highlight the increase in distresses in the latter segment. Performance data post-2012 rehabilitation, however, show reduced cracking and IRI in the project.



Source: FHWA.

Figure 132. Chart. Average fatigue cracking in selected SH NN corridor from 2009 to 2013.



Source: FHWA.

Figure 133. Chart. Average IRI in selected SH NN highway corridor from 2009 to 2013.

Detailed Statistical Analysis

The observed trends in figure 129 through figure 131 were further investigated by performing detailed ANOVA to determine whether RWD maximum deflection measured within 12 mo of construction had a significant impact on fatigue cracking, rutting, and IRI (after 5 yr in service). Analysis, as described previously, used the model form in figure 134:

$$Distress\ or\ IRI = \beta_0 + \beta_1 * \delta$$

Figure 134. Equation. Model form to estimate distress or IRI.

Where:

Distress or IRI = fatigue cracking or rutting or IRI.

δ = maximum deflection class.

<15 mils = low.

>15 mils = high.

Results are presented in table 110 through table 112 for fatigue cracking, rutting, and IRI, respectively.

Table 110. Summary of ANOVA results indicating significance of RWD maximum deflection on future fatigue cracking distress.

Parameter	Estimate	Standard Error	*t* Value	*Pr* > |*t*|
Intercept	1,156.351	79.3692	14.57	<0.0001
Maximum deflection, low	−1,108.223	107.5032	−10.31	<0.0001
Maximum deflection, high	0.000	—	—	—

R^2 = 0. 40513, COV = 151.41, RMSE = 836.20, N = 244.
—No data.

Table 111. Summary of ANOVA results indicating significance of RWD maximum deflection on future rutting distress.

Parameter	Estimate	Standard Error	*t* Value	*Pr* > |*t*|
Intercept	0.143963	0.00267188	53.88	<0.0001
Maximum deflection, low	−0.0307308	0.00361897	−8.49	<0.0001
Maximum deflection, high	0.000	—	—	—

R^2 = 0. 22956, COV = 22.128, RMSE = 0.02815, N = 244.
—No data.

Table 112. Summary of ANOVA results indicating significance of RWD maximum deflection on future IRI.

Parameter	Estimate	Standard Error	*t* Value	*Pr* > |*t*|
Intercept	115.1869	4.20600	27.39	<0.0001
Maximum deflection, low	14.2745	13.60403	1.05	0.2949
Maximum deflection, high	−41.3936	5.67421	−7.30	<0.0001

R^2 = 0. 1774, COV = 49.55, RMSE = 46.646, N = 285.

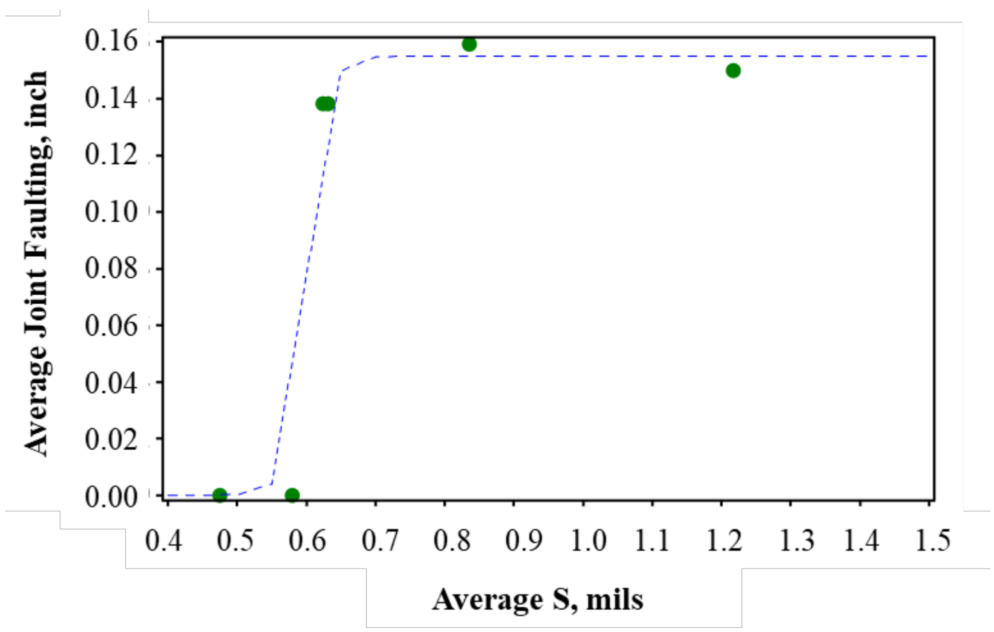
The results in table 110 through table 112 show the following:

- RWD-measured pavement deflection shows an impact on all three performance measures (cracking, rutting, and IRI).
- Pavement sections with measured maximum deflection less than 15 mils exhibited the least amount of distress.
- Pavement sections with measured maximum deflection greater than 25 mils exhibited the highest amount of distress.
- Fatigue cracking had the highest R^2 with RWD deflections (40 percent). For rutting and IRI, R^2 was 15 percent to 18 percent.

The results show that, at the project level, RWD-measured deflection can be a good indicator of future performance. The suitability of RWD-measured deflection data at the network level as a leading indicator of performance will need to be investigated by agencies. Please note that it is not the intent of this research to determine whether RWD can serve as a valuable QA tool. This case study does not validate or disprove the potential of any TSDD for use in QA.

Case Study 2b: Evaluation of Field-Measured Dowel Misalignment on Future Faulting Distress

Field-measured JPCP transverse joint dowel misalignment (*S*) data were evaluated to assess the feasibility of using such data as a leading indicator for future faulting performance. The data were obtained for four projects in State 2. The projects were constructed between 2011 and 2013, and, within the selected project segment, each project showed varying levels of faulting. Figure 135 shows the relationship between overall *S* and JPCP transverse joint faulting (after 2-4 yr in service). The information presented in figure 135 shows that, for this project, joints with *S* less than 0.6 experience no significant levels of faulting. However, for joints with *S* greater than 0.6, faulting after 2–4 yr in service increased significantly to over 0.12 inches (the threshold design value). The plot also shows the relationship between *S* and faulting was nonlinear.



Source: FHWA.

Figure 135. Chart. Relationship between overall *S* and JPCP transverse joint faulting (after 2–4 yr in service).

The nonlinear relationship between *S* and faulting implied that fitting a linear model to the *S* parameter and faulting measurements would not produce meaningful models. Also, there were insufficient data for performing a full-scale ANOVA test. A more appropriate methodology for analysis was thus development of a nonlinear model relating *S* to measured faulting and assess the reasonableness of the model faulting predictions (i.e., goodness of fit and bias). The research team assessed fitness based on model diagnostic statistics R^2 RMSE. Bias was assessed by performing a paired *t*-test to determine whether measured and predicted faulting were from the same population. The nonlinear model form is as presented in figure 136.

$$Fault = \alpha S^{\beta}$$

Figure 136. Equation. Faulting.

Where:

Fault = average transverse joint faulting, inches.

S = dowel misalignment, mils.

α, β = regression coefficients.

The models' diagnostic statistics and *t*-test results are presented in table 113 and table 114. Table 113 shows model diagnostic statistics (R^2 = 0.9778, COV = 14.5, RMSE = 0.01156), which were all deemed reasonable. Figure 137 shows plot of predicted and measured faulting, which was reasonable. The paired *t*-test results in table 114 showed that, at the 5 percent significance level, measured and predicted faulting were essentially from the same population. The results presented showed a very reasonable relationship between dowel misalignment measure *S* and faulting. This result implies that the level of *S* measured postconstruction can effectively indicate future faulting levels. Thus, the measure of dowel alignment is potentially a leading indicator of faulting development. There is a potential benefit to using this parameter in the development of faulting prediction models.

Table 113. Faulting and dowel misalignment property *S* nonlinear model diagnostic statistics.

Source	DF	Sum of Squares	Mean Square	*F* Value	*Pr* > *F*
Model	1	0.0845	0.0845	388.88	<0.0001
Error	7	0.00152	0.000217	—	—
Uncorrected total	8	0.0860	—	—	—

R^2 = 0.9778, COV = 14.5, RMSE = 0.01156.

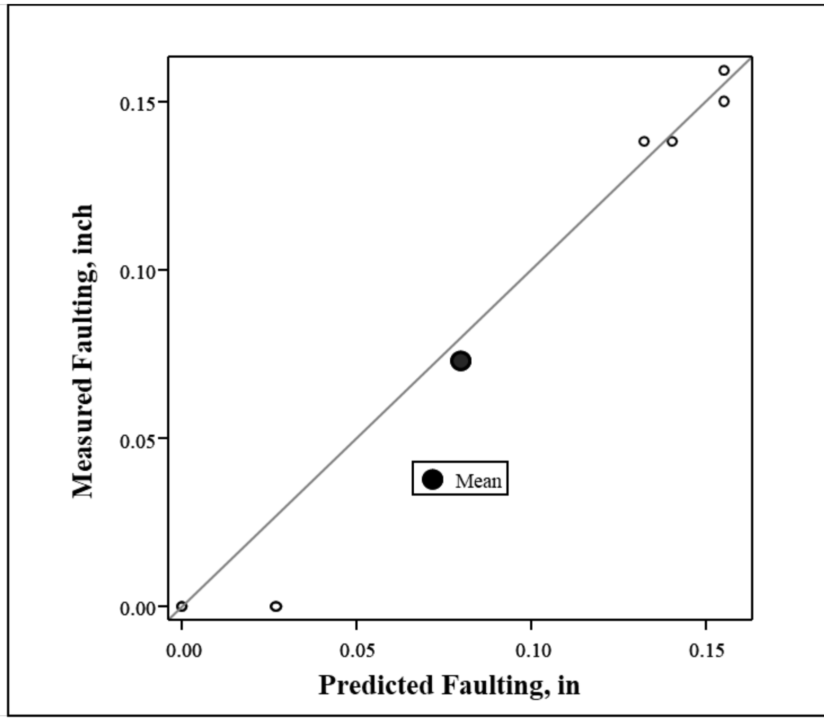
—No data.

DF = degrees of freedom.

Table 114. Bias testing for outputs from the faulting and dowel misalignment property *S* nonlinear model (paired *t*-test of measured versus predicted faulting).

Mean	95th Percent CL Mean		Standard Deviation	95th Percent CL Standard Deviation		*t* Value	*Pr* > |*t*|
0.00635	−0.00458	0.0173	0.0131	0.00865	0.0266	1.37	0.2120

CL = confidence level.



Source: FHWA.

Figure 137. Chart. Plot of measured versus predicted faulting.

STATISTICAL ANALYSIS FOR STATE 3

Statistical analysis was done to determine feasibility of utilizing State 3 DOT QA test data as a leading indicator of pavement performance, as characterized by three performance measures: structural cracking index (SCI), functional cracking index (FCI), and rutting. Analysis was done using the integrated State 3 DOT PMS and QA test database, described in chapter 4 and chapter 5, and analysis methodologies previously described in this chapter. Analysis was done using network-level data. The results are described in the following sections.

State 3 DOT Correlation Analysis

Summary of Correlations between SCI, FCI, Rutting, and HMA QA Test Data

Table 115 through table 117 present the results of correlation analysis between SCI and FCI and State 3 DOT QA data items. Table 118 and table 119 present similar results for rutting. The analysis identified gradation (large, intermediate, and fine aggregate sizes), mix volumetrics (VFA, VMA, and VTM), and binder properties *G** and phase angle as the QA data items with strong correlation with SCI. All these data items impact key HMA properties (strength, modulus, and stability) and thus fatigue and structural distress.

Table 115. HMA QA data basic statistics.

QA Variables	No. Data Points	Mean	Standard Deviation	Minimum	Maximum
HMA core thickness	64	3.68	0.33	2.7	4.0
Percent passing 0.075-mm sieve	199	6.47	1.14	5.1	8.8
Percent passing 1.18-mm sieve	199	18.24	2.01	16.3	22.0
Percent passing 1.5-mm sieve	199	8.36	1.15	6.5	11.0
Percent passing 2.36-mm sieve	199	25.66	3.19	21.8	32.9
Percent passing 3.0-mm sieve	199	10.80	1.03	9.0	13.0
Percent passing 4.75-mm sieve	199	39.37	5.10	30.0	59.0
Percent passing 6.0-mm sieve	199	14.06	1.48	12.0	17.0
Percent passing 9.5-mm sieve	199	64.29	8.92	48.0	90.0
Percent passing 12.5-mm sieve	199	76.59	10.25	58.0	96.0
Percent passing 19.0-mm sieve	199	90.86	7.78	78.5	100.0
Percent passing 25.0-mm sieve	140	93.73	5.70	85.9	100.0
VFA	197	75.41	3.32	70.0	84.3
VMA	197	11.83	1.36	10.0	15.0
VTM	197	3.03	0.65	2.1	4.5
HMA core density	139	95.26	1.04	92.8	96.5
SA1	199	5.13	0.64	4.2	6.6
$\|G^*\|\sin\delta$	199	1.36	0.25	1.1	1.9
DSR G^* (ORIG)	199	1.37	0.25	1.2	1.9
DSR δ (ORIG)	199	84.59	3.49	78.6	87.2
G_{sb}	199	2.72	0.28	0.0	2.9
G_{mm}	199	2.57	0.26	0.0	2.7
G_{mb}	199	2.47	0.25	0.0	2.6
TSR	43	5.00	18.72	0.9	90.1

Table 116. Pearson's correlation tables for State 3 DOT PMS SCI.

QA Variables	Pearson's Correlation	Test of Significance	Comments
HMA core thickness	0.183	0.1551	Fair
Percent passing 0.075-mm sieve	−0.377	<0.0001	Strong
Percent passing 1.18-mm sieve	−0.425	<0.0001	Strong
Percent passing 1.5-mm sieve	−0.393	<0.0001	Strong
Percent passing 2.36-mm sieve	−0.487	<0.0001	Strong
Percent passing 3.0-mm sieve	−0.374	<0.0001	Strong
Percent passing 4.75-mm sieve	−0.482	<0.0001	Strong
Percent passing 6.0-mm sieve	−0.403	<0.0001	Strong
Percent passing 9.5-mm sieve	−0.565	<0.0001	Strong
Percent passing 12.5-mm sieve	−0.583	<0.0001	Strong
Percent passing 19.0-mm sieve	−0.467	<0.0001	Strong
Percent passing 25.0-mm sieve	−0.297	0.0004	Strong
VFA	0.400	<0.0001	Strong
VMA	−0.532	<0.0001	Strong
VTM	−0.499	<0.0001	Strong
HMA core density	−0.086	0.3203	Weak
SA1	−0.397	<0.0001	Strong
$\|G^*\|\sin\delta$	−0.253	0.0003	Strong
DSR G^* (ORIG)	−0.247	0.0005	Strong
DSR δ (ORIG)	−0.256	0.0003	Strong
G_{sb}	−0.076	0.2896	Weak
G_{mm}	−0.036	0.6134	Weak
G_{mb}	−0.032	0.6591	Weak
TSR	0.285	0.0706	Strong

Table 117. Pearson's correlation tables for State 3 DOT PMS FCI.

QA Variables	Pearson's Correlation	Test of Significance	Comments
HMA core thickness	0.105	0.4152	Strong
Percent passing 0.075-mm sieve	−0.160	0.0252	Fair
Percent passing 1.18-mm sieve	−0.165	0.0208	Fair
Percent passing 1.5-mm sieve	−0.154	0.0307	Fair
Percent passing 2.36-mm sieve	−0.241	0.0006	Strong
Percent passing 3.0-mm sieve	−0.100	0.1636	Fair
Percent passing 4.75-mm sieve	−0.280	<0.0001	Strong
Percent passing 6.0-mm sieve	−0.094	0.1911	Fair
Percent passing 9.5-mm sieve	−0.256	0.0003	Strong
Percent passing 12.5-mm sieve	−0.234	0.001	Strong
Percent passing 19.0-mm sieve	−0.223	0.0017	Strong
Percent passing 25.0-mm sieve	−0.068	0.4267	Strong
VFA	0.166	0.0207	Weak
VMA	−0.279	<0.0001	Strong
VTM	−0.234	0.001	Strong
HMA core density	0.000	0.9968	Weak
SA1	−0.145	0.0427	Fair
$\|G^*\|\sin\delta$	−0.052	0.4696	Weak
DSR G^* (ORIG)	−0.054	0.4526	Weak
DSR δ (ORIG)	0.034	0.6313	Weak
G_{sb}	0.384	<0.0001	Strong
G_{mm}	0.397	<0.0001	Strong
G_{mb}	0.400	<0.0001	Strong
TSR	0.257	0.1043	Strong

Table 118. HMA QA data basic statistics.

QA Variables	No. Data Points	Mean	Standard Deviation	Minimum	Maximum
Percent passing 0.075-mm sieve	190	6.15	0.92	5.10	11.87
Percent passing 1.18-mm sieve	190	17.65	1.70	16.34	26.67
Percent passing 1.5-mm sieve	190	8.02	0.82	7.00	14.11
Percent passing 2.36-mm sieve	190	24.76	2.94	19.70	40.93
Percent passing 3.0-mm sieve	190	10.52	0.81	9.00	15.27
Percent passing 4.75-mm sieve	190	38.25	4.96	30.00	64.27
Percent passing 6.0-mm sieve	190	13.64	1.13	12.83	18.60
Percent passing 9.5-mm sieve	190	62.60	8.93	48.00	97.53
Percent passing 12.5-mm sieve	189	74.30	9.79	58.00	96.71
Percent passing 19.0-mm sieve	186	89.02	7.78	78.46	100.0
Percent passing 25.0-mm sieve	129	91.93	5.33	85.89	98.67
VFA	190	76.11	3.48	68.77	86.68
VMA	190	11.54	1.34	10.03	18.07
VTM	190	2.87	0.61	2.09	4.07
HMA core density	150	95.21	1.02	93.10	96.49
SA1	190	4.94	0.47	4.22	8.25
Resistivity	190	1.49×10^{-5}	2.04×10^{-6}	0.58×10^{-5}	2.34×10^{-5}
DSR G^* (ORIG)	190	1.39	0.25	1.16	1.86
DSR δ (ORIG)	190	84.25	3.68	78.60	87.20
G_{sb}	190	2.76	0.04	2.71	2.88
G_{mm}	190	2.60	0.05	2.53	2.65
G_{mb}	190	2.51	0.05	2.44	2.55
Lab air void	190	0.96	0.00	0.96	0.97
$G^*/\sin\delta$	190	1.40	0.25	1.18	1.86

Table 119. Pearson's correlation s for State 3 DOT PMS rutting.

QA Variables	Pearson's Correlation	Test of Significance	Comments
Percent passing 0.075-mm sieve	−0.08878	0.2232	Weak
Percent passing 1.18-mm sieve	−0.07548	0.3006	Weak
Percent passing 1.5-mm sieve	−0.06463	0.3757	Weak
Percent passing 2.36-mm sieve	−0.01488	0.8386	Weak
Percent passing 3.0-mm sieve	0.01623	0.8242	Weak
Percent passing 4.75-mm sieve	0.01488	0.8386	Weak
Percent passing 6.0-mm sieve	−0.08071	0.2683	Weak
Percent passing 9.5-mm sieve	−0.03268	0.6544	Weak
Percent passing 12.5-mm sieve	−0.06199	0.3968	Weak
Percent passing 19.0-mm sieve	0.05486	0.457	Weak
Percent passing 25.0-mm sieve	0.2453	0.0051	Strong
VFA	−0.06328	0.3857	Weak
VMA	0.05284	0.469	Weak
VTM	0.01339	0.8545	Weak
HMA core density	−0.32	<0.0001	Strong
SA1	−0.05191	0.4769	Weak
Resistivity	−0.18524	0.0105	Fair
DSR G^* (ORIG)	0.09586	0.1883	Weak
DSR δ (ORIG)	0.25318	0.0004	Strong
G_{sb}	0.04525	0.5353	Weak
G_{mm}	0.02402	0.7422	Weak
G_{mb}	0.09539	0.1905	Weak
Lab air void	0.39005	<0.0001	Strong
$G^*/\sin\delta$	0.08781	0.2283	Weak

HMA core thickness, gradation (mostly intermediate and fine sizes), and mix volumetrics were identified as the QA data items with strong correlations with FCI. Gradation and volumetrics affect HMA tensile strength and stability, which significantly impacts HMA's ability to resist cracking and fracture. Table 118 and table 119 identify the percentage passing the 25-mm sieve size (large aggregates), HMA density and air voids, and DSR δ (ORIG) as having a strong correlation with rutting. HMA mixes with larger sized aggregate, higher density, and lower air voids are mostly more resistant to rutting, and thus these data items are highly correlated with the distress. Also, increasing the phase angle (δ) of asphalt binders produces binders that are less resistant to rutting. Phase angle is an indicator of modification. Modified binders have lower phase angle. Phase angle is thus highly correlated with rutting.

State 3 DOT Stepwise Regression Analysis

Average Cracking (SCI/FCI) Versus State 3 DOT QA Data Items

Table 120 and table 121 present outcomes of preliminary model development through stepwise regression analysis for SCI and FCI, respectively. The results in table 120 indicate that HMA core density is the only data item selected. HMA density correlates well with strength and modulus and thus has a significant impact on SCI. The preliminary model shows that increasing HMA density decreases SCI, which is as expected. For FCI, a preliminary model was not developed, as none of the data items met the selection criteria.

Table 122 presents outcomes of preliminary model development through stepwise regression analysis for rutting.

Table 120. Stepwise selection summary for relationship between SCI and State 3 DOT QA test data items.

Step	Effect Entered	Effect Removed	No. Effects	Model R^2	C_p	PRESS	*Pr* > *F*	Estimate
0	Intercept	—	1	0.0000	2.3283	1539.8612	0.00	169.3
1	HMA core density	—	2	0.0437	−0.7063*	1495.8259*	5.16	−0.757

R^2 = 0.0437, RMSE = 3.57862, N = 115.
—No data.
*Optimal value of criterion.

Table 121. Stepwise selection summary for relationship between FCI and State 3 DOT QA test data items.

Step	Effect Entered	Effect Removed	No. Effects	No. Parameters	Model R^2	C_p	PRESS	*Pr* > *F*
0	Intercept	—	1	1	0.0000	0.41006	6623.89	—

R^2 = 0.0000, RMSE = 7.55634, N= 114.
—No data.

Table 122. Stepwise selection summary for relationship between rutting and State 3 DOT QA test data items.

Step	Effect Entered	Effect Removed	No. Effects	No. Parameters	Model R^2	C_p	PRESS	*Pr* > *F*
0	Intercept	—	1	1	0.0000	42.84	0.5602	1.0000
1	Lab air voids	—	2	2	0.2098	9.420	0.4511	<0.0001
2	Traffic level (for material selection)	—	3	3	0.2414	6.084	0.4385	0.0242
3	$G^*/\sin\delta$	—	4	4	0.2712	3.050*	0.4243*	0.0261

—No data.

Average Rutting Versus State 3 DOT QA Data Items

For rutting, lab-measured air voids, traffic level, and the computed parameter $G^*/\sin\delta$ were selected. These three data items affect rutting development and progression. The selection was deemed reasonable.

State 3 DOT Final GLM/ANOVA Regression Analysis

Cracking (SCI/FCI) Versus State 3 DOT QA Data Items

Table 123 through table 128 present the finalized SCI, FCI, and rutting prediction models. It must be noted that the final models are not full-scale models and do not include all the other key variables, such as measured traffic and loading, layer thickness, and climate, that influence these distresses.

For the SCI model, table 123 and table 124 show that lab air voids, the interaction between HMA type*binder PG grade, and percent passing 19.0 mm were the QA data items that significantly influenced HMA structural cracking development and progression. Other variables included in the preliminary models were dropped or replaced with similar variables due to interactions among these variables. The final SCI model reported R^2 equaled 35 percent, COV equaled 7.0 percent, and RMSE equaled 6.55 percent cracking, all of which were deemed reasonable. For the interaction of HMA type and binder PG grade, the RAP mixes performed better than the Neat mixes, while PG grade 64-22 performed better than PG 76-22. Several studies have shown that the presence of RAP in HMA mixes can and does reduce mix rutting potential while improving fatigue resistance.[110]

For FCI, table 125 and table 126 show that the interaction of HMA type*binder PG grade and percent passing 19.0-mm sieve were the significant variables included in the prediction model. Further evaluation of the model showed that the PG 76-22 mixes performed better than the PG 64-22 mixes; the 76-22 performed the best, which was as expected. Also, increasing the percent aggregate material passing the 19.0-mm sieve reduced FCI. This trend was deemed reasonable and expected. The models' statistics (R^2 = 0.207490, COV = 8.892089, RMSE = 8.096364) were deemed reasonable.

Rutting Versus State 3 DOT QA Data Items

For rutting, information in table 127 and table 128 showed that binder PG grade, percent passing 19.0-mm sieve, and lab air voids were the significant variables included in the rutting prediction model. Further review showed that the PG 76-22 mixes performed better than the PG 64-22 mixes, as expected. Increasing air voids increased rutting, while increasing the amount of coarse material passing the 19.0-mm sieve reduced the distress. These trends are as expected. The models statistics (R^2 = 0.189, COV = 32.5, RMSE = 0.053509) were deemed reasonable.

Table 123. GLM summary (type III SS) for relationship between SCI and State 3 DOT QA test data items.

Source	DF	Type III SS	Mean Square	*F* Value	*Pr* > *F*
Lab air voids	1	658.588	658.588	15.34	0.0001
HMA type*binder PG grade	2	182.543	91.271	2.13	0.1222
Percent passing 19.0-mm sieve	1	1615.538	1615.538	37.63	<0.0001

Table 124. GLM summary (model coefficients) for relationship between SCI and State 3 DOT QA test data items.

Parameter	Estimate	Standard Error	*t* Value	*Pr* > |*t*|
Intercept	−702.445	222.7146	−3.15	0.0019
Lab air voids	893.989	228.2634	3.92	0.0001
HMA type*binder PG grade, Neat 76-22	13.850	6.8855	2.01	0.0457
HMA type*binder PG grade, RAP 64-22	2.558	2.5512	1.00	0.3172
HMA type*binder PG grade, RAP 76-22	0.000	—	—	—
Percent passing 19.0-mm sieve	−0.725	0.1182	−6.13	<0.0001

R^2 = 0.356221, COV = 7.00, RMSE = 6.5525, N = 196.
—No data.

Table 125. GLM summary (type III SS) for relationship between FCI and State 3 DOT QA test data items.

Source	DF	Type III SS	Mean Square	*F* Value	*Pr* > *F*
HMA type*binder PG grade	2	2,520.050	1,260.025	19.22	<0.0001
Percent passing 19.0-mm sieve	1	903.129	903.129	13.78	0.0003

Table 126. GLM summary (model coefficients) for relationship between FCI and State 3 DOT QA test data items.

Parameter	Estimate	Standard Error	*t* Value	*Pr* > |*t*|
Intercept	131.8672	10.69441	12.33	<0.0001
HMA type*binder PG grade, Neat 76-22	−19.9196	5.42704	−3.67	0.0003
HMA type*binder PG grade, RAP 64-22	6.2831	2.43707	2.58	0.0107
HMA type*binder PG grade, RAP 76-22	0.0000	—	—	—
Percent passing 19.0-mm sieve	−0.4977	0.13410	−3.71	0.0003

R^2 = 0.207490, COV = 8.892089, RMSE = 8.096364, N = 189.
—No data.

Table 127. GLM summary (type III SS) for relationship between rutting and State 3 DOT QA test data items.

Source	DF	Type III SS	Mean Square	*F* Value	*Pr* > *F*
PG Grade	1	0.016656	0.016656	5.82	0.0169
Percent passing 19.0 mm sieve	1	0.027502	0.027502	9.61	0.0022
Lab air voids	1	0.013408	0.013408	4.68	0.0318

Table 128. GLM summary (model coefficients) for relationship between rutting and State 3 DOT QA test data items.

Parameter	Estimate	Standard Error	*t* Value	*Pr* > |*t*|
Intercept	−4.10286	2.1401	−1.92	0.0568
Binder PG grade, 64-22	0.06270	0.0259	2.41	0.0169
Binder PG grade, 76-22	0.00000	—	—	—
Percent passing 19.0-mm sieve	−0.00361	0.0011	−3.10	0.0022
Lab air voids	4.72390	2.1829	2.16	0.0318

R^2 = 0.189, COV = 32.5, RMSE = 0.053509, *N* = 185.
—No data.

Use of Derived Parameters to Predict Performance

Comparable to the analysis presented for State 1, QA data from State 3 permitted the calculation of derived parameters that were evaluated for their potential to correlate to performance. The results of the performance modeling efforts using derived parameters are presented in the following tables:

- Table 129, for structural cracking in State 3 DOT data. The derived parameter included in the model is SAI and $|G^*|\sin\delta$. The corresponding results for a model with conventional QA parameters are presented in table 126.

- Table 130, for functional cracking in State 3 DOT data. The derived parameter included in the model is SAI. The corresponding results for a model with conventional QA parameters are presented in table 127.

- Table 131, for rutting in State 3 DOT data. The derived parameter included in the model is the resistivity for each binder grade. The corresponding results for a model with conventional QA parameters are presented in table 128.

Table 129. GLM summary (model coefficients) for relationship between structural cracking and "derived" parameters from State 3 DOT QA test data items.

	Estimate	Standard Error	*t* Value	*Pr* > |*t*|
Intercept	80.13613094	4.67558595	17.14	<0.0001
Material selection for traffic level 2	−17.45812051	1.81654994	−9.61	<0.0001
Material selection for traffic level 3	0.92842423	1.00432963	0.92	0.3563
Material selection for traffic level 4	0.00000000	—	—	—
PG grade 64-22	−4.67946000	1.18334310	−3.95	0.0001
PG grade 76-22	0.00000000	—	—	—
Specific surface of aggregate mixture	−1.07258698	0.52490001	−2.04	0.0422
$\|G^*\|\sin\delta$	19.34588546	3.19129916	6.06	<0.0001

R^2 = 0.447885, COV = 6.247186, RMSE = 5.869310, *N* = 223.
—No data.

Table 130. GLM summary (model coefficients) for relationship between functional cracking and "derived" parameters from State 3 DOT QA test data items.

Parameter	Estimate	Standard Error	*t* Value	*Pr* > |*t*|
Intercept	84.97296915	6.17358166	13.76	<0.0001
Material selection for traffic level 2	−12.80765353	2.45024861	−5.23	<0.0001
Material selection for traffic level 3	−3.27748265	1.37387600	−2.39	0.0179
Material selection for traffic level 4	0.00000000	—	—	—
Specific surface of aggregate mixture	−1.90733083	0.73839655	−2.58	0.0104

R^2 = 0.130512, COV = 9.248507, RMSE = 8.421056, N = 223.
—No data.

Table 131. GLM summary (model coefficients) for relationship between rutting and "derived" parameters from State 3 DOT QA test data items.

QA Test Data Item	Estimate	Standard Error	*t* Value	*Pr* > |*t*|
Intercept	0.270024	0.036680	7.36	<0.0001
Material selection for traffic level 2	−0.032741	0.019709	−1.66	0.0984
Material selection for traffic level 3	0.037899	0.009813	3.86	0.0002
Material selection for traffic level 4	0.000000	—	—	—
Resistivity*PG grade 64-22	−6067.280796	2,185.201499	−2.78	0.0061
Resistivity*PG grade 76-22	−8325.828849	2,370.921206	−3.51	0.0006

R^2 = 0.137212, COV = 33.61180, RMSE = 0.055265, N = 190.
—No data.

Results presented in table 129 through table 131, again (as with derived parameters models in State 1), were used to evaluate the value of using these derived parameters to predict performance. Table 132 summarizes the R^2 obtained for the prediction models based on the conventional QA parameters directly obtained from State QA databases and the derived parameters. It is clear, at least based on goodness of fit, that the structural cracking model was improved. The lack of improvement in functional cracking is not unexpected, because the derived parameters capture the material parameters that affect the mechanism of structural cracking. Clearly, the QA data in State 3 suggest the rutting performance has been well controlled with the existing specifications and may not be well explained through QA indicators.

Table 132. Summary of goodness of fit using QA data and using derived parameters.

State	Model	R^2 for Models with Conventional QA Data	R^2 for Models with Derived Parameters
State 3	Functional cracking	21	13
	Structural cracking	36	45
	Rutting	19	14

Clearly, the analyses presented in this report are intended to evaluate the ability of QA and construction data to predict performance. The results of the models using derived parameters suggest that these parameters have a potential for improving performance predictions and may be an approach for agencies to consider for integrating QA data to predict performance. Based on the premise that these parameters were fundamentally derived to combine mix volumetrics and binder properties to effectively relate to performance, it is worthwhile to consider them in modeling for future applications of integrating QA data for performance prediction in PMS. These results are encouraging for recommending the use of derived parameters to agencies.

Case Study 3: Integrating QA Data Into PMS for Improved Performance Modeling

Results from the analyses of data from State 1, State 2, and State 3 are encouraging for the use of QA data as leading indicators of performance. This case study demonstrates an example of procedures to materialize the use of QA to improve PMS prediction models, i.e., to integrate QA and construction parameters into the PMS system, for improving the performance model. This case study example presents a procedure for incorporating into State 3 DOT PMS systems the QA data items identified as having a significant impact on pavement performance. The example was developed using data from State 3 DOT PMS and QA data tables, and it uses existing State 3 DOT performance forecasting models.

Example Methodology for Incorporating QA Data Items as Leading Indicator of Performance

The methodology presented in this case study involves the following steps:

1. Identify the pavement type of interest.
2. Determine the QA data items that impact performance for utilization as leading indicators of performance.
3. Determine existing (State 3 DOT) PMS performance forecasting models for the identified pavement types of interest.
4. Develop correction factors for the performance forecasting models identified in step 3 using the QA data items identified as leading indicators and adjust/correct existing PMS models outputs as needed.
5. Evaluate predictions of performance with correction factors and characterize improvements in goodness of fit and bias.

The project team developed the methodology described previously based on current State 3 DOT performance forecasting models. This methodology might not necessarily be suitable for other agencies, however. The goal is to illustrate enhancements in prediction capacity of existing forecasting models with the inclusion of QA-type data. Another goal is to illustrate that QA-type data can be included in the PMS forecasting models without significant modifications to existing processes/procedures and analysis tools.

Identify Pavement Type of Interest

State 3 DOT classified new and overlaid HMA pavement types into families based on pavement type, traffic, climate, and so on. The selected pavement families for this case study were 17, 19, 20, 22, 26, 40, 42, 45, and 47 in the agency's PMS.

Determine QA Data Items That Impact Performance for Utilization as Leading Indicators of Performance

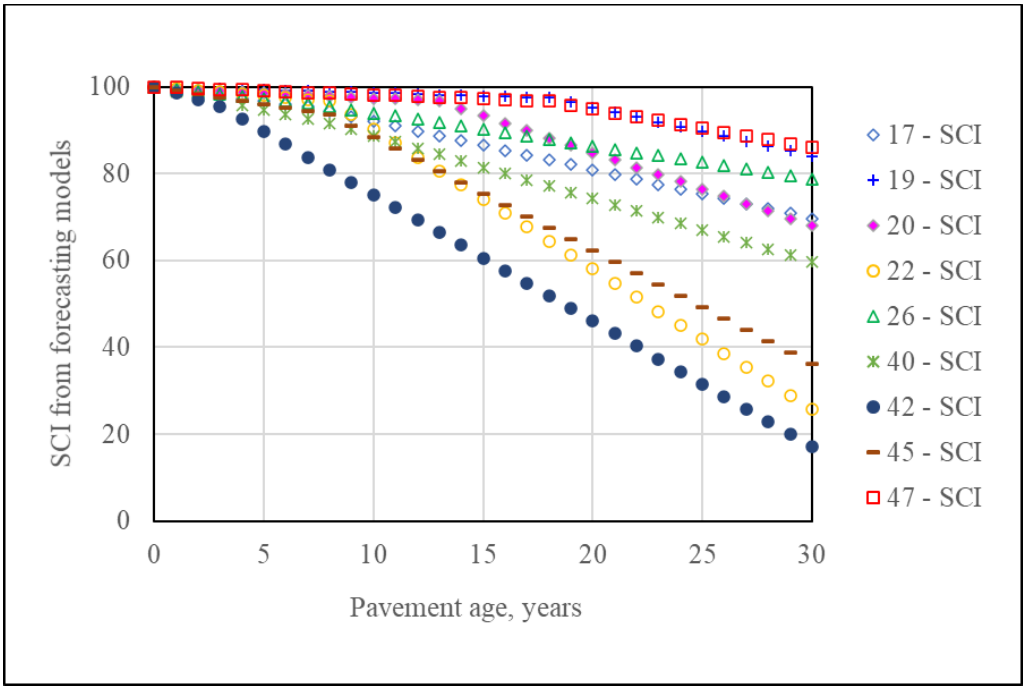
State 3 DOT QA test data items included in the final SCI prediction model are presented in table 133. As shown in this table, lab air voids, the interaction between HMA type and binder PG grade, and percentage passing 19.0-mm sieve were the QA data items found to have a significant impact on future flexible pavement SCI. These variables form the basis for developing adjustment factors to adjust the State 3 DOT SCI forecasting models and predicted SCI (for pavement families 17, 19, 20, 22, 26, 40, 42, 45, and 47).

Table 133. GLM summary for relationship between SCI and State 3 DOT QA test data.

Source	DF	Type III SS	Mean Square	*F* Value	*Pr* > *F*
Lab air voids	1	658.588	658.588	15.34	0.0001
HMA type*binder PG grade	2	182.543	91.271	2.13	0.1222
Percent passing 19.0-mm sieve	1	1,615.538	1,615.538	37.63	<0.0001

Determine Existing State 3 DOT PMS Performance Forecasting Models for the Identified Pavement Types of Interest

State 3 DOT SCI forecasting models currently incorporated in the DOTs' PMS are based on pavement age (time since last significant construction event) and are presented in figure 138 for the selected families 17, 19, 20, 22, 26, 40, 42, 45, and 47 for SCI. The plot shows significant variations in SCI for the different pavement families. SCI after 15 yr in service rage from 60 to 97, and at 30 yr range from 86 to 17.



Source: FHWA.

Figure 138. Graph. Plots of predicted SCI versus age for selected families of HMA pavements in State 3 DOT.

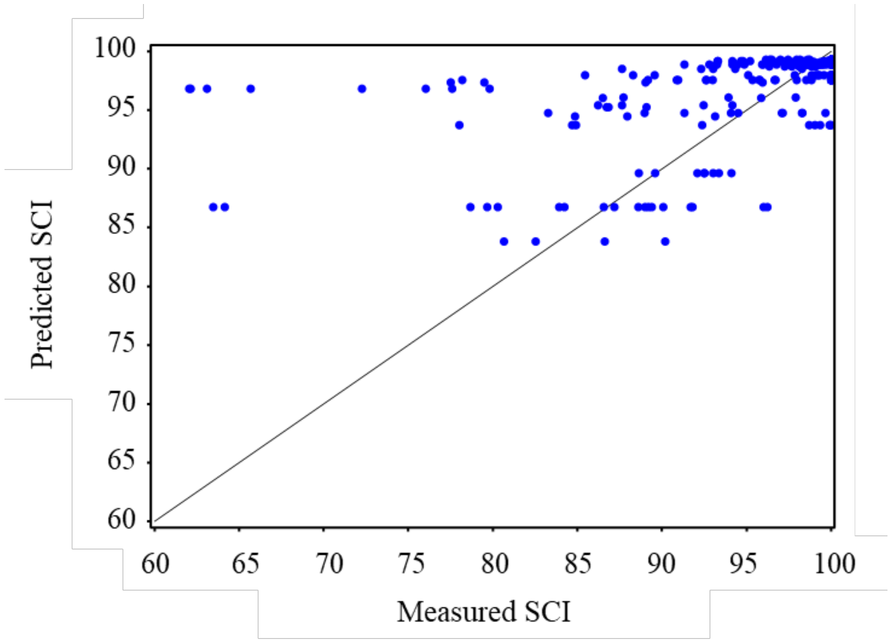
Determine Reasonableness of Forecasting Models

This step involved comparing measured SCI and forecasted SCI from the State 3 DOT models to determine goodness of fit and presence of bias. Reasonableness of goodness of fit was assessed using diagnostic statistics R^2 and RMSE. Bias was assessed by developing simple linear relationship between measured and predicted SCI and checking if the slope of the measured versus predicted SCI linear model with no intercept was 1.0. A slope of 1.0 implies there are not significant levels of bias. Bias was also assessed by performing a paired *t*-test using the measured and predicted SCI. A *p*-value greater than 0.05 (i.e., 5 percent significance) implied that the difference between measured and predicted SCI was not significantly different, and thus they belong to the same populations.

Outcomes of the analysis described are presented as follows:

- Goodness of fit: RMSE = 3.66, $R^2 = 0.2187$.
- Bias:
  - Slope of measured versus predicted SCI linear curve = 1.02.
  - 95 percent CI of slope ranges from 1.01 to 1.03.
  - *p*-value for testing hypothesis that slope = 0: less than 0.0001.
  - Pair *t*-test *p*-value: less than 0.0001.

The results presented showed an average goodness of fit for PMS models but significant bias in predictions (1 to 2 percent greater than measured values on average). This bias is shown in figure 139.



Source: FHWA.

Figure 139. Graph. Plot of predicted versus measured SCI using State 3 DOT SCI forecasting models for selected families of HMA pavements.

Develop Correction Factors

Under this step, using the QA data items identified as leading indicators, adjustment/correction factors for existing PMS SCI forecasting models were developed. Correction factors were developed in the form of the model presented in figure 140:

$$ADJ_{SCI} = \frac{100}{(1 + SCI^{CORR_{FACTOR}})}$$

Figure 140. Equation. Correction factors model.

Where:

ADJ_{SCI} = adjusted SCI.
SCI = estimated from State 3 DOT SCI forecasting models.
$CORR_{FACTOR}$ = *P1***LAB_AV* + *P2**PG64-22 + *P3**PG76-22 + *P4**Neat + *P5**RAP + P6*%PASS3/4.
LAB_AV = lab-measured HMA air voids.
PG64-22 =1.0 if binder grade is PG64-22.
PG76-22 =1.0 if binder grade is PG76-22.
Neat = 1.0 if HMA is a neat mix.
RAP = 1.0 if HMA contains RAP.
%PASS3/4 = Percent passing ¾-inch sieve size.
P1 = −23.6294.
P2 =17.5694.
P3 = 17.4206.

P4 = −0.4805.
P5 = 0.000010.
P6 = 0.0479.

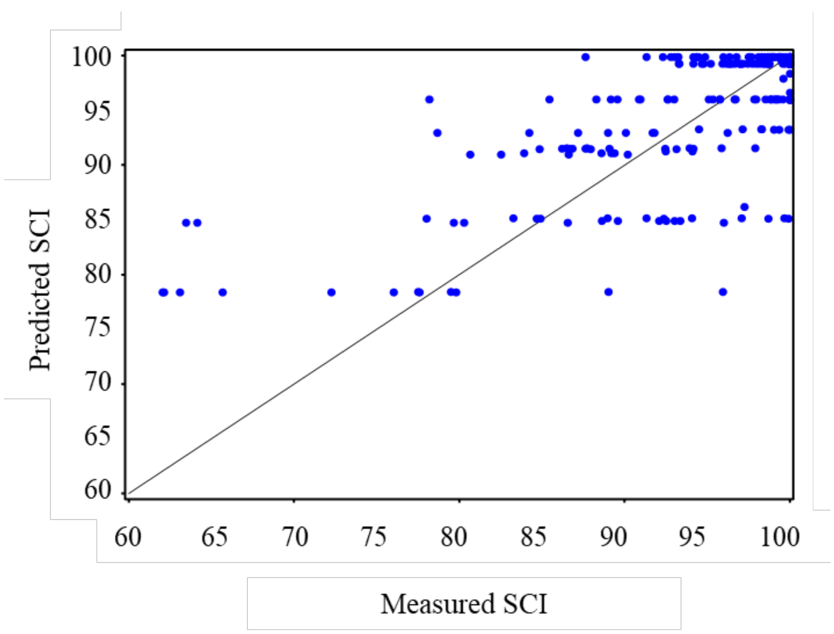
As shown in figure 140, a common adjustment factor was used, regardless of pavement family. Also, all the identified QA data leading indicators were included in the formula for estimating the adjustment factor.

Evaluate Predictions of Performance with Correction Factors and Characterize Improvements in Goodness of Fit and Bias

Figure 141 shows the plot of measured versus corrected and adjusted State 3 DOT-predicted SCI. The plot shows a significant improvement in goodness of fit and bias. The project team confirmed these results using the diagnostic statistics previously described and summarized as follows:

- Goodness of fit: RMSE = 4.38, R^2 = 0.4995.
- Bias:
  - Slope of measured versus predicted SCI linear curve = 1.0046.
  - 95 percent CI of slope ranges from 0.99659 to 1.01269.
  - *p*-value for testing hypothesis that slope = 0: 0.2575.
  - Pair *t*-test *p*-value: 0.0563.

The results presented show that there is no significant bias in corrected SCI predictions, and goodness of fit improved significantly from 0.22 to 0.5. RMSE increased marginally from 3.6 to 4.4 percent cracking. It was expected that the R^2 of 0.5 would have been greater (better goodness of fit) if adjustment factors were developed individually for each family of pavements.



Source: FHWA.

Figure 141. Graph. Plot of "corrected" State 3 DOT predicted versus measured SCI.

This example illustrated that adjusting existing forecasted SCI values with QA data-derived adjustment factors (within State 3 DOT PMS) does improve forecasted SCI significantly (improved goodness of fit and less bias). This example is also a preliminary analysis performed to illustrate the project team's vision to incorporate QA parameters into an agency's PMS.

SUMMARY OF STATISTICAL ANALYSIS FOR STATE 4

As explained in the first section of this chapter, Utilizing QA Test Data as Leading Indicators of Pavement Performance, data from State 4 were used only for a case study to examine the value of incorporating IC data from construction as a dataset to improve pavement management performance models. There is clear evidence from current State practices that IC specifications are used to control coverage and number of passes, which is worthy of recommending IC data for future use in asset management and for purposes of evaluating anomalies in pavement condition data. It has also been found that the consistency in IC outputs in relation to in situ material properties is machine dependent. It is, therefore, of interest in this study to determine the extent to which IC data correlate to traditional QA parameters. Success in establishing this correlation provides the opportunity to use IC data as an indirect measure to relate construction data to performance, which was the goal of this case study.

Case Study 4: Using Data from Innovative Technologies as Leading Indicators of Performance

Chapter 4 and chapter 5 discussed the data elements and the integration of IC and QA data. This section presents the analyses performed with the assembled datasets to establish a correlation between field density and IC outputs. Other laboratory QA test data were also available for each mix used in the three IC projects.

Approach Adopted for the Analysis

Mostly, basic regression techniques, such as single and multiple linear regression, are good investigative tools that can be used to establish the relationships between dependent and several independent variables. For more complicated relationships, the application of nonlinear regression techniques may be suitable. For this analysis, multivariate regression analysis techniques were adopted due to the nature of the data available and implied experimental design. For multivariate regression analysis to be viable (assessing whether one or more independent variables explain the dependent variable), the following key assumptions must be satisfied:

- Sample size—In general, a sample size of 20 or more is required for regression analysis. The assembled database contained over 150 individual field-measured HMA density records with accompanying IC measurements close enough (less than 5 inches) to be deemed as representative of the density measurements.

- No auto-correlation—Placement and compaction of HMA in the field to achieve density specifications require several passes of the vibratory roller. Thus, as IC observations and outputs are "compaction stage" dependent, it is reasonable to assume that output (i) value will be correlated with output ($i - 1$) value. This situation was overcome by estimating averaged IC outputs that represented the whole HMA placement and compaction in-place process. Statistics such as the average, maximum, minimum, and last IC outputs were used for analysis.

- Linear relationship—Pearson's correlation estimates are presented in table 134. The estimates show a fair degree of correlation between the key IC responses and outputs. Also, the relationship between the dependent variable (density) and independent variables (IC outputs) was relatively weak. This weakness indicates a nonlinear relationship between dependent and independent variables, if any exists. The use of mathematical clusters derived empirically using the IC outputs or nonlinear models may be more appropriate for model development.

- No or little multicollinearity—A key requirement for a stable and reliable predictive model with multiple independent variables is the absence of multicollinearity in the independent data. Multicollinearity is the presence of a strong correlation between two or more independent variables, resulting in the inability to isolate the relationship between each independent variable and the dependent variable. One or more variables, hence, become redundant in the model. The coefficient estimated for a given variable (broadly defining how critical the variable is) may vary widely, depending on which other independent variable is included in the model, thereby affecting the overall sensitivity of the model.

- Homoscedasticity—This assumption relates to the requirement for equal variance in the data and is also the basis for other statistical analyses, such as ANOVA and the *t*-test. There should be a uniform spread along the entire range of the data used in the model, implying the error in the model also has a uniform spread.

Table 134. Correlation analysis of field-measured HMA density and key IC outputs.

Variables	HMA Density (Percent)	Amplitude (mm)	CMV	Roller Frequency (Hz)	RMV	No. of Passes
HMA density (percent)	1.00000	0.06476	0.01961	−0.00253	0.05520	0.09432
Amplitude (mm)	0.06476	1.00000	0.50326	−0.47037	0.47223	0.16613
CMV	0.01961	0.50326	1.00000	−0.20014	0.51060	0.31523
Roller frequency (Hz)	−0.00253	−0.47037	−0.20014	1.00000	−0.04412	0.21221
RMV	0.05520	0.47223	0.51060	−0.04412	1.00000	0.19021
Number of passes	0.09432	0.16613	0.31523	0.21221	0.19021	1.00000

Regression Analysis

Appropriate regression analysis was conducted to identify IC outputs that significantly impact field-measured HMA density. Furthermore, this analysis helped evaluate the feasibility of modeling/predicting field-measured HMA density. The regression model adopted the related density with interaction of categorical variables "Project"; compaction equipment, "Machine"; and key IC outputs "CMV" and "amplitude" (figure 142). The outputs of the regression analysis are presented in table 135.

$$CRK = \beta_0 + \beta_1 * Project + \beta_2 * Project * machine + \beta_3 * Project * machine * AMP + \beta_4 * Project * machine * CMV$$

Figure 142. Equation. Regression model adopted to relate density to IC.

Table 135. Regression statistics to correlate field HMA density to key IC outputs.

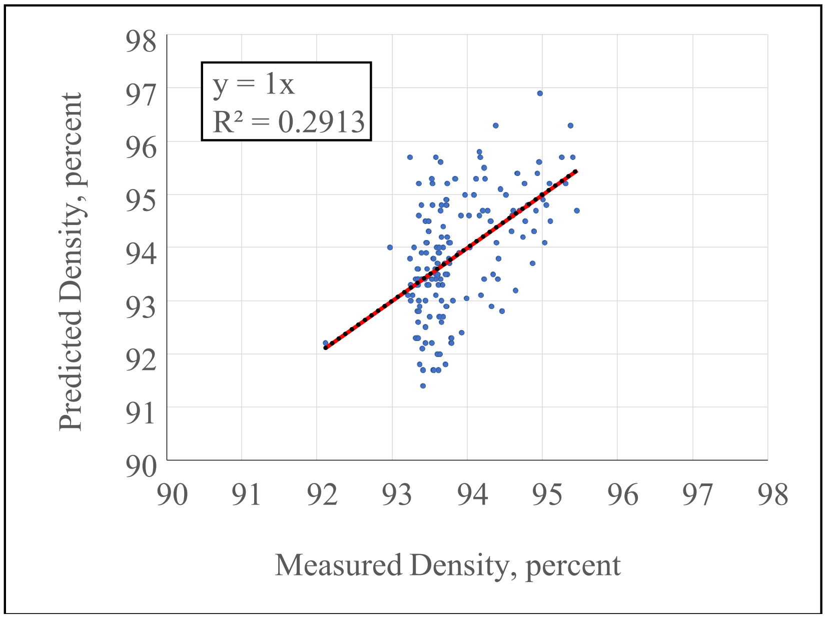
Source	DF	Type I SS	Mean Square	*F* Value	*Pr* > *F*
Project	2	9.113	4.557	4.57	0.012
Project*Machine	5	9.410	1.882	1.89	0.1004
AMP*Project*Machine	7	24.551	3.507	3.52	0.0017
CMV*Project*Machine	7	12.649	1.807	1.81	0.0896

N = 157; R^2 = 0.291284; COV = 1.063607; RMSE = 0.998459.

The information in table 135 shows the following:

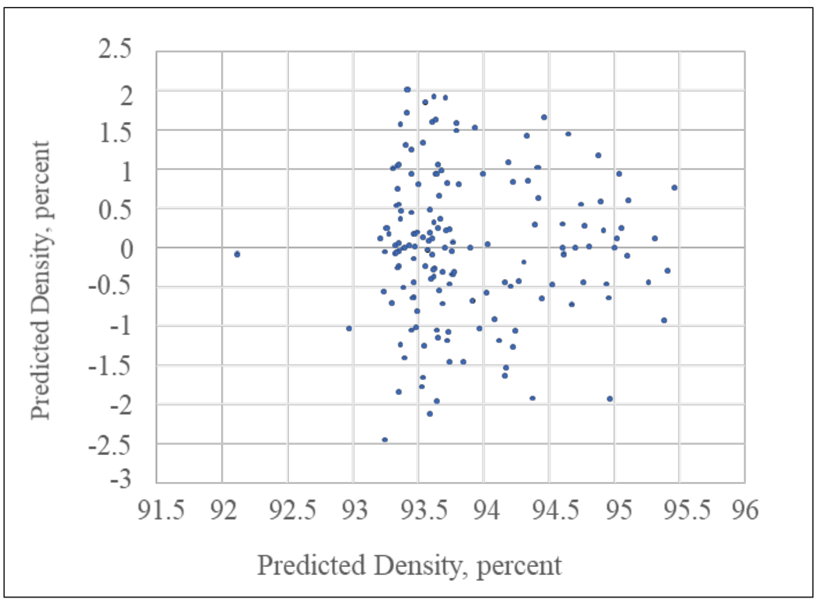
- Variables that have a significant impact on density are project, machine, AMP, and CMV with significance less than 0.1000.
- Variables listed explain approximately 29 percent of variance.
- Project and IC roller represent variance due to differences in HMA specifications and properties and compaction equipment.

Figure 143 and figure 144 show predicted versus measured density and residual versus predicted density. Figure 143 shows a reasonable goodness of fit (R^2 = 0.29), whereas figure 144 shows very insignificant levels of multicollinearity or homoscedasticity.



Source: FHWA.

Figure 143. Graph. Plot of measured versus predicted density.



Source: FHWA.

Figure 144. Graph. Plot of residual (error) versus predicted density.

Summary of Case Study for State 4

Field-measured HMA density, along with other layer types of density, and properties are key test outcomes traditionally used for QA and acceptance of pavement projects. Relationships between HMA density and other pavement properties, such as HMA dynamic modulus and short- and long-term performance, have been established in this and other previous studies.

This case study was conducted to determine whether measurements from new construction technologies, such as IC, can serve as indicators of key material properties, such as density, that are known to have a significant impact on pavement performance. With such established correlations, it would be possible to relate data from IC as an indicator of performance for use in PMS for future pavement performance forecasting. The premise being that, once a relationship is established between say HMA density and future pavement performance, then IC outputs can be incorporated into future pavement performance forecasting models and utilized effectively for PMS.

The outcome of this case study shows that key IC outputs measured during construction (HMA placement and compaction) may be used for future performance forecasting; however, with the current advancements in this technology and the current development of specifications for this technology, it is not possible to guarantee a strong correlation to performance. Future pavement performance data from projects that have utilized IC may provide better insights into the potential for correlation and performance prediction. Therefore, conclusions from the current study are preliminary as more extensive research is required for such model's development. In summary, the results of this case study suggest:

- Relationships between IC outputs and density are complex and cannot be modeled using traditional simple regression procedures.
- Reasonable models can be developed like the one presented in table 135 (which now shows an R^2 of 0.29) once a suitable regression procedure is adopted.

CHAPTER 7. SUMMARY AND CONCLUSIONS

PROJECT SUMMARY

Project Scope and Objectives

The *MAP-21* Act established new performance-based requirements for planning and programming to enable the most efficient use of Federal transportation funds. FHWA issued the NPRM in 2015 and the final ruling in 2017 to establish new requirements for performance management to ensure the most efficient investment of Federal transportation funds and to improve investment decisionmaking.(2) As agencies establish performance targets and measure progress to assess whether they are meeting their established targets, they also recognize that condition assessment data can serve only as a lagging indicator, i.e., distress is measured only after it has manifested to the surface and has started to follow a particular trend. As pavement design and construction technologies become more sophisticated, and as digital data collection and storage are increasingly becoming the norm, there is the potential to relate construction data collected in real time (at the time of construction) to future pavement performance. Thus, agencies are using construction-related data, collected in real time, as measurable factors and leading indicators of future pavement performance trends.

The specific objectives of this project were to:

- Identify construction QA and other as-built pavement-related data that can serve as leading indicators of future pavement performance.
- Develop procedures and processes to utilize these data identified as leading indicators for integration into an agency's PMS. The integration should aim to improve accuracy and reliability of predicted pavement performance.

To fulfill project objectives, research was performed to:

- Identify current (i.e., state of the practice) and innovative (i.e., state of the art) pavement construction and QA testing technologies.
- Establish data collection and storage practices associated with the technologies identified.
- Evaluate the potential for utilizing the identified construction QA data as leading indicators of future pavement performance.
- Determine the feasibility of utilizing potential leading indicators within an agency's PMS to improve prediction capability of pavement performance forecasting models.

The project team used data from four SHAs to conduct detailed statistical correlation and modeling required to determine construction and QA data variables that could serve as leading indicators of performance. The team developed case studies to demonstrate different instances for which different types of construction QA data may be used to improve the performance forecasting component of PMS. The case studies demonstrate that construction QA data can be a leading indicator of performance, and that it is possible to improve PMS performance prediction by incorporating construction QA data into PMS. The main products from this research are practical recommendations and best practices for the inclusion of agency QA and construction data within the pavement management decisionmaking framework.

Research Approach

The research approach involved the following activities:

1. Collecting detailed information on agency practices and performing indepth interviews with agencies of interest to this research.

2. Obtaining QA, construction, and performance data from selected agencies that collect comprehensive data and maintain databases with long-term visions for pavement management that align with the goals of this research. The selection of agencies was based on the following factors:

    a. Maturity of the agency's pavement management program, including performance data collection as per national performance management measures ruling (e.g., the PMS must collect performance measures that characterize smoothness [IRI], load-related cracking, rutting in flexible pavements, and faulting in jointed concrete pavements).

    b. Advancements in the agency's construction QA program (e.g., routine traditional QA testing as well as adoption of innovative QA testing technologies and pavement construction practices).

    c. Assessment of the agency's construction QA and PMS reporting, aggregation, and integration strategies for all forms of data, such as electronic databases, e-documents, or ad hoc reports. This assessment determined the readily available data, the ability to integrate the various data types and formats, and requirements for meaningful statistical analyses.

    d. Awareness and preliminary efforts by the agency to use QA data for purposes beyond construction contracts, such as in PRS, and interest in exploring the value of construction QA and other data types for performance forecasting.

    The later sections of this chapter further discuss in detail the reasons for selection of the agencies and, thus, the parameters available for use in the analyses. As noted, four agencies were selected for data analyses. Because of the project's nonattribution policy, the names of the State agencies are not disclosed in this report.

3. Assembling and processing QA data, construction information, and PMS data from actual agency databases.

4. Assessing feasibility of integrating QA data into the agency's existing PMS using appropriate algorithms and scripts required to relate the wide variety of location referencing systems for the heterogeneous structured and unstructured data assembled.

5. Identifying, through review of past research studies, QA data variables that impact future performance of the as-constructed pavement. These variables have the potential to serve as leading indicators of pavement performance. Note that statistical modeling verified the impact of these variables (see step 6).

6. Conducting statistical correlation, modeling, and ANOVA to determine the feasibility of utilizing construction QA data as a leading indicator of future pavement performance. This activity involved the use of data from three State DOT QA and PMS databases. The statistical analyses included development of:

   a. Pearson's correlation statistics.

   b. General linear models (including the use of the stepwise selection option to identify the QA variables with potential for impacting future pavement performance).

   c. Nonlinear performance models.

   d. ANOVA models to confirm preliminary findings from step 6a and step 6b.

7. Developing case studies that highlight improvements to PMS condition forecasting capacity through utilization of QA data from conventional methods and from innovative test methods/construction technologies. Data from four DOTs were used in the case studies, two of which used data from innovative test methods and construction technologies.

   a. Case study from State 1 DOT demonstrated the added value of using other agency databases such as traffic and climate data.

   b. Case study from State 2 DOT demonstrated the correlation of data generated by innovative technologies (MIT-Scan for rigid pavements and RWD for AC pavements) to performance.

   c. Case study from State 3 DOT demonstrated an example of a practical application of this research for improving pavement management performance prediction models. It involved:

      i. Forecasting performance (structural cracking) using existing PMS performance forecasting models for five pavement families.

      ii. Developing QA data item derived adjustment factors for existing State 3 DOT PMS performance forecasting models.

      iii. Comparing forecasted performance from step 7a and step 7b.

      iv. Assessing the outcome of step 7c and characterizing improvements.

   d. Case study from State 4 DOT demonstrated methods to use data from innovative construction technologies providing spatial coverage of pavement and material characteristics as indirect indicators of performance. Although findings from this case study were marginally successful, the intent was to showcase that data collected from new construction technologies (or QA methods alternatively) with vast spatial coverage may offer correlations to other material QA parameters that may hold a strong correlation to performance.

8. Demonstrating procedures and developing guidelines for the use of QA data to improve pavement performance prediction.

The research was divided into two phases: the first for performing viability studies, and the second to develop revised models, validations, and case studies. The remaining sections of this chapter present project accomplishments and findings.

REVIEW OF QA PRACTICES AND PERFORMANCE PREDICITION CAPABILITIES

QA Parameters Related to Performance Prediction

The project team reviewed State agency QA practices and existing literature pertinent to this research. These reviews produced a list of conventional QA material parameters used by agencies. The parameters are typically directly available in QA databases or in agency records. The most critical data are material and construction parameters that are proven indicators of performance.

Such data include gradation parameters, HMA volumetrics, density values (lab and field), layer thicknesses, binder type, PCC strength, aggregate type, and PCC mix design index properties. The project team also identified generally established relationships for material property and performance; for example, see table 136 for HMA pavements and table 137 for PCC pavements.

Table 136. Generally established relationships between QA parameter and HMA pavement performance.

QA Parameter for HMA Pavements*	Relationship to HMA Pavement Performance
Original $G^*/\sin\delta$ at specified high pavement temperature.	Indicator of permanent deformation potential in HMA pavements.
RTFOT residue $G^*/\sin\delta$ at specified high pavement temperature.	
PAV residue $G^*/\sin\delta$ at specified intermediate pavement temperature.	Indicator of load-associated cracking potential in HMA pavements.
PAV residue creep stiffness at 10°C above the specified low pavement temperature.	Indicator of thermal cracking potential in HMA pavements.
PAV residue *m*-value at 10°C above the specified low pavement temperature.	
Field HMA density, voids, HMA thickness.	Indicator of cracking and rutting/permanent deformation potential in HMA pavements.
Mix design gradation, volumetrics.	

*It can be generally assumed that development of all surface distresses can impact ride quality.

Table 137. Generally established relationships between QA parameter and PCC pavement performance.

QA Parameter for PCC Pavements*	Relationship to PCC Pavement Performance
w/c ratio, cement content, fly ash/SCM replacement levels, air content, aggregate gradation, fineness modulus, unit weight, aggregate absorption capacity.	Indicator of PCC strength and cracking and faulting potential.
PCC compressive/flexural strength, thickness.	Indicator of cracking and faulting potential.
Aggregate type/CTE.	Indicator of cracking due to thermal curling stresses.
Dowel bar diameter and alignment.	Indicator of faulting potential.
Temperature and humidity at time of construction (in construction records).	Directly related to built-in temperature and moisture gradients that affect cracking.

*It can be generally assumed that development of all surface distresses can impact ride quality.

Other Derived Parameters

Past research studies have derived parameters as a function of various material index properties for both HMA and PCC. (See references 10, 11, 14, and 16.) Some of these derived parameters were found to directly correlate to performance based on laboratory test results and M-E models. The upside of these derived parameters is that they are developed as a function of multiple index properties that, in combination, can capture the collective effect of material properties, such as those of binder and aggregates in HMA or cement content and aggregate type in PCC, to offer a direct correlation to performance. The index properties that are significant here are typically available from QA data collection practices. Examples of such derived parameters, discussed in detail in this report, include:

- HMA dynamic modulus, a level 3 input to the M-E pavement design procedure.[16]
- Resistivity correlated to rutting.[10,11] See figure 14.
- Rutting and fatigue resistance models estimating number of allowable load repetitions to failure. See figure 14 through figure 19.
- Permeability correlated to durability, which is not directly predicted in M-E design or measured in traditional PMS data collection activities. See figure 20.
- PCC fatigue and PCC material properties that are direct indicators of performance (in interaction with other site-specific parameters like traffic, climate, and so on). See figure 21 through figure 38.

Using the relationships established in these previous research studies and the approaches adopted in the previous studies for aggregating or clustering QA-type materials data, the project team established the potential for use of data variables in agencies' QA databases, either directly or in combination with other material properties and pavement design variables, to develop cluster parameters for use in predicting future pavement performance.

REVIEW OF STATE PRACTICES, QA, AND PMS DATABASES

The project team conducted detailed phone interviews and onsite visits to collect information from State agencies with various levels of advancements in their QA testing programs and construction quality database systems. The agencies collectively had also achieved significant experience with specifications developed for use in innovative QA testing and modern construction technologies, including 3D construction. Specifications, QA data collection practices (material approval, material certifications, QC, verification, and acceptance), data storage systems, PMS, condition data collection procedures, and performance forecasting models in the PMS were reviewed. Agencies selected for interviews and subject areas of discussion are summarized in table 138.

The information gathered from these agencies covered various aspects of construction and QA practices as well as PMS. The information also included details about location referencing for the different data types and database structures from the standpoint of data integration for the purposes of this project. The outcome was to identify agencies with the most suitable practices and data for use in analyses to satisfy project objectives. The project team selected agencies that have well-established QA and PMS databases, as well as agencies that have an interest in exploring the value of using construction data to improve performance prediction.

Table 138. State agencies interviewed and the subjects discussed.

State	PMS	Construction	QA HMA	QA PCC	QA UB	NDT/Innovations (IC, GPR, MIT-Scan)	3D/CIM
Colorado	●	●	●	●	●	●	●
Maryland	●	●	●	●	●	—	●
Florida	●	●	●	●	●	●	●
Minnesota	●	●	●	●	●	●	
Michigan	●	●	●		●	●	●
Utah	●	●	●	●	●	●	●
Mississippi	●	—	●	—	—	—	—
State 1	●	—	●	—	●	—	—
Oregon	●	—	●	—	—	●	●

—Topic not discussed.

Summary of Agency Practices Leading to Selection of Data for Analyses

State agency surveys were conducted in 2015–2016 with the aim to collect information about agency QA and PMS databases and to assess their use for performance prediction under this study. The surveys provided the following conclusions:

- Agencies are not set up to fully automate QA and PMS data integration and thus directly integrate QA data variables into a PMS.

- Agencies empirically acknowledge relationships between QA data variables and future pavement performance.

- Agencies indicate that QA data can be further used when routinely updating construction specifications as well as in a PMS.

- Agencies have, to a high degree, an interest in bridging the gap between the construction QA and PMS activities. The reasons for each agency's interest in cross-linking these databases may vary.

- States recognize that there is an increased scope for facilitating the integration process by using the enhancements in as-built data collection that are largely enabled by automation in construction technologies. Current practice does not permit the use of as-built records.

- The extent of QA data available, the types of data collected, the extent of data accessible electronically, and the methods of storage vary across agencies. The efforts involved in assembling and integrating databases remain unique to each agency.

- Data integration that allows mapping performance to QA data by project or by location requires significant effort.

It was with the understanding of these conclusions that the project team selected State agencies to obtain data for the analyses under this project. In addition, knowledge of specific details of databases in each agency was a factor in selecting agency databases for use in this study.

Identification of State Agencies for Data Analyses and Case Studies

Based on State agency interviews and information obtained about datasets that can be potentially used to establish and validate correlations between QA data and performance, the project team selected data from four agencies. The selection of these agencies enabled a wide range of analyses covering different pavement types, QA parameters, innovative technologies, and levels and tiers of analyses. The following factors were considered when selecting the State agencies:

- Ability to include different QA material parameters in the analyses with the data. Data from multiple States highlighted the similarities and differences in the outcomes from one State to another.

- Ability to perform both network and project-level analyses.

- Historical condition data over an adequate period for performance forecasting.

- Agency's general vision for improving PMS and a desire to use QA data for forecasting.

- Maturity and advancements in the construction quality database system.

- Extent of data maintained in electronic format, to an extent, instead of using paper records.

- Data from evolving QA and construction technologies.

- Suitable location referencing formats across different databases, and the ability to identify data for a given project segment within each database.

- General efforts of the State DOT that aligned with project goals.

- Willingness to assist the project team.

Individual State agencies were selected for analyses for the following specific reasons:

- State 1:
    - Maintained comprehensive and well-organized data in both the QA and PMS databases.

    - Organized the QA data by lots and assigned data by specific paving dates.

    - Accessed traffic and climate data from other national databases to develop a case study demonstrating the added value of integrating other agency databases.

- State 2:
    - Analyzed both PCC and HMA projects.

    - Made QA data and PMS data available, with the ability to match the location referenced at both the network and project levels, and, therefore, the ability to perform a project-level case study.

    - Provided the ability to consider at least two innovative technologies: in this case, the MIT-Scan for PCC pavements and a continuous deflection monitoring device/RWD for HMA pavements.

- State 3:
    - Maintained comprehensive and well-organized data in both the QA and PMS databases.

    - Was already interested in pursuing the use of construction data for structural and functional performance measures. The agency's main interest was utilizing aggregate properties, AC properties for the prediction of cracking, and rutting in HMA.

- State 4:
    - Used IC data from three construction projects with corresponding QA in-field HMA density data and QA material mix design data, which enabled a project-level case study. Note: these data were used only for a case study.

Table 31 and table 33 present summaries of the analyses performed utilizing data from these States for flexible and rigid pavement, respectively. Note the general unavailability of data related to 3D designs and as-constructed plans. This obstacle was mostly due to the limited maturity in the use of these technologies and agencies not having developed clear policies for ownership, collection, and archiving of 3D plans. Thus, because of the lack of 3D data from as-built projects, the project team did not include case studies with data collected from 3D technologies for this project. The data, however, exist. A clear policy on data management of as-built designs will make them available for future analyses.

DATA ANALYSES

The project team conducted preliminary and detailed data analyses to verify the following:

- QA data and other construction data collected at the time of construction can be integrated into PMS databases and structures.
- QA data and other construction data collected at the time of construction are detailed enough to be used to compute clusters and parameters known to impact future pavement performance.
- QA data and other construction data collected at the time of construction impact future distress and IRI development and progression, and thus the data can serve as leading indicators of future pavement performance.
- QA data and other construction parameters can be integrated into the agency's PMS and used for improved pavement performance forecasting.

The project team used data from the three State databases—States 1, 2, and 3—to perform a variety of analyses that would offer a broad understanding of the impact of QA parameters on future pavement performance and thus serve as a leading indicator. The project team completed both network-level and project-level analyses. However, the team focused on identifying the QA parameters that showed the strongest correlations with performance and had a significant impact on future performance. Models that aligned with laboratory and field observations in past research studies were developed and tested the individual QA data items and clusters for significance.

Table 73 shows a summary of the various performance indicators that were most viable for long-term prediction based on the available data for flexible and rigid pavements. This summary also indicates whether the performance prediction was done at the network or project level. The table also displays the type of QA and construction parameters that were used to predict performance.

As also shown in table 139 and table 140, the case studies used data from States 1, 2, 3, and 4. These case studies addressed different aspects of applying the results of this research.

Table 139. Summary of performance prediction evaluations and case studies included in the report.

State	Performance Indicator			Case Study
	Rutting	Faulting	Cracking	
State 1	F, N, Q, A F, N, Q, V F, N, Q, D, A F, N, Q, D, V F, N, Q, D, A, T, C#	—	F, N, Q, A F, N, Q, V F, N, Q, D, A F, N, Q, D, V F, N, Q, D, A, T, C#	Benefit of adding traffic and climate data.
State 2	F, N, Q, A F, P, Q, RW, A#	R, N, Q, A R, P, Q, M, A#	F, N, Q, A R, N, Q, A F, P, Q, RW, A#	Data from nontraditional QA/network-level tests correlated to performance.
State 3+	F, N, Q, A F, N, Q, D, A F, N, Q, A	—	F, N, Q, A F, N, Q, D, A F, N, Q, A	Implementation of improved prediction model in the DOT's PMS.
State 4	F, P, Q, IC, A#	—	F, P, Q, IC, A#	Demonstration of methods to "indirectly" link modern technologies to performance.

—No data.
#In case study.
+State has functional and structural cracking in pavement management database.
Pavement type: F = flexible, R = rigid; analysis level: N = network level, P = project level; data types: Q = traditional QA data, D = QA-derived parameters, M = MIT-Scan, RW = RWD, IC = IC data, T = traffic, C = climate; data used: A = averages, V = COV/variability.

Table 140. Summary of analysis type and case studies included in the report.

State	Analysis Type: IRI	Case Study
State 1	—	Benefit of adding traffic and climate data.
State 2	F, N, Q, A R, N, Q, A	Data from nontraditional QA/network-level tests correlated to performance.
State 3+	—	Implementation of improved prediction model in the DOT's PMS.
State 4#	—	Demonstration of methods to "indirectly" link modern technologies to performance.

—No data.
#In case study.
+State has functional and structural cracking in pavement management database.

Challenges in Data Analyses

Several challenges, both anticipated and unanticipated, were encountered and overcome. The challenges are summarized as follows:

- QA data within an agency are stored in multiple unstructured and disconnected databases that are maintained by different departments and personnel. The data are not necessarily consistent in format or location referencing fields.

- Significant effort may be required to assemble (not integrate) data from different stages of the project, including material certification, mix design approvals, QC, and acceptance. The data are also archived for different periods.

- Electronic data in some cases, especially related to projects over a decade old, have been converted to hardcopies and original electronic records that are not traceable. The project team used scanned PDF reports to obtain the necessary data in such cases.

- Study data received by the project team were, in some cases, not in the format or level of detail required for use in performance forecasting. This situation was a result of less stringent requirements by the State DOT in the data entry procedures, which permitted incomplete data entries. Such incomplete datasets were not used for analyses.

- Various QA data items were aggregated at different levels: from the whole project, i.e., several miles to 0.1- to 1-mi sections, to specific locations within a project. The level of aggregation has a significant impact on the ability to use the data for performance forecasting and the accuracy and improvements in performance forecasting due to the inclusion of QA type data.

- Multiple databases, beyond construction QA and PMS, were integrated to correlate QA and PMS data to link the referenced project and location. The project team recognized how this procedure, and the complexity associated with it, varied between agencies. Coordinating basic data collection and reporting standards within agencies is needed to improve the feasibility of integrating the various datasets.

Procedures for Statistical Analyses

The statistical procedures include, as discussed in detail in chapter 6, the following steps:

1. Review assembled PMS and QA test databases for accuracy and reasonableness and then estimate computed parameters that can be derived from QA test data.

2. Use time-series (historical) PMS distress (cracking, rutting, faulting, IRI) data to develop simple linear regression models for forecasting future pavement performance (e.g., distress and IRI).

3. Estimate for each PMS section the baseline distress level, which is the distress measured and forecast at the end of a given service life, about 10 or 15 yr.

4. Perform statistical analysis, which involves the following:

    a. Identify preliminary Pearson's correlations between distress/IRI and QA test data.

    b. Develop general linear models relating distress, IRI, and QA test data using GLM and stepwise regression statistical techniques. The overall model acceptance was determined based on the values and criteria due to various diagnostic statistics, including overall model's *p*-value, Mallows coefficient, C_p, PRESS statistic, and coefficient of determination R^2. For QA data variables to be included in a specific individual model, selection and acceptance were due to the data variables' significance level and VIF. A significance level of 15 percent and VIF less than 10 percent were used.

    c. Formulate the final model and assess the model's independent QA test data variables' significance and sensitivity to the given distress. A robust model was selected in this step with a significant validation of material behavior. The final model was selected based on several factors, including diagnostic statistics (R^2, RMSE, COV, VIF, and *p*-value) and evaluation of the models' reasonableness.

Based on the steps listed previously, the variables that were identified as having a strong correlation with distress and IRI are tabulated in table 141 to table 143 for HMA, and table 144 for PCC pavements. The set of significant variables included in the final model, i.e., parameters with a *p*-value less than 15 percent, are tabulated in table 145 for HMA and table 146 for PCC. The models and the coefficients for each parameter are discussed in chapter 6.

Table 141. Summary of HMA QA data items categorized as "strong" based on computed Pearson's correlation statistic (*r*) for cracking.

QA Variables	State 1	State 2	State 3*
HMA core thickness	—	—	Yes**
Large coarse aggregate sizes (≥1.0 inch)	—	—	Yes*
Intermediate coarse aggregate sizes (≤1.0 inch and greater than No. 40)	Yes	—	Yes*
Fine aggregate sizes (less than or equal to No. 40)	Yes	—	Yes*
Percent AC binder content	Yes	—	—
HMA bulk density	—	—	—
HMA lab air voids	—	—	
HMA VMA	Yes	—	Yes*
HMA VFA	Yes	—	Yes***
HMA VTM	—	—	Yes*
Computed E^*	—	—	Yes***
SA1	—	—	Yes***
$\lvert G^* \rvert \sin \delta$	—	—	Yes***
DSR G^* (ORIG)	—	—	Yes***
DSR δ (ORIG)	—	—	Yes***
G_{sb}	—	—	Yes**
G_{mm}	—	—	Yes**
G_{mb}	—	—	Yes**
TSR	—	—	Yes*

—No data.
*Structural and functional.
**Functional only.
***Structural only.

Table 142. Summary of HMA QA data items categorized as "strong" based on computed Pearson's correlation statistic (*r*) for rutting.

QA Variables	State 1	State 2	State 3
HMA core thickness	—	—	—
Large coarse aggregate sizes (≥1.0 inch)	—	—	Yes
Intermediate coarse aggregate sizes (≤1.0 inch and greater than No. 40)	—	—	—
Fine aggregate sizes (less than or equal to No. 40)	Yes	—	—
Percent AC binder content	—	Yes#	—
HMA bulk density	—	—	Yes
HMA lab air voids	Yes	Yes#	Yes
HMA VMA	—	—	—
HMA VFA	—	—	—
HMA VTM	—	—	—
Computed E^*	—	—	—
SA1	—	—	—
$\|G^*\|\sin\delta$	—	—	—
DSR G^* (ORIG)	—	—	—
DSR δ (ORIG)	—	—	Yes
G_{sb}	—	—	—
G_{mm}	—	—	—
G_{mb}	—	—	—
TSR	—	—	—

—No data.
#Bottom layer and top layer/lift.

Table 143. Summary of HMA QA data items categorized as "strong" based on computed Pearson's correlation statistic (*r*) for IRI.

QA Variables	State 1	State 2	State 3
HMA core thickness	—	—	—
Large coarse aggregate sizes (≥1.0 inch)	—	—	—
Intermediate coarse aggregate sizes (≤1.0 inch and greater than No. 40)	—	—	—
Fine aggregate sizes (less than or equal to No. 40)	—	—	—
Percent AC binder content	—	Yes	—
HMA bulk density	—	—	—
HMA lab air voids	—	Yes[#]	—
HMA VMA	—	—	—
HMA VFA	—	—	—
HMA VTM	—	—	—
Computed E^*	—	—	—
SA1	—	—	—
$\|G^*\|\sin\delta$	—	—	—
DSR G^* (ORIG)	—	—	—
DSR δ (ORIG)	—	—	—
G_{sb}	—	—	—
G_{mm}	—	—	—
G_{mb}	—	—	—
TSR	—	—	—

—No data.
[#]Bottom layer and top layer/lift.

Table 144. Summary of PCC QA data items categorized as "strong" based on computed Pearson's correlation statistic (*r*) for cracking and faulting.

QA Variables	State 1 Cracking	State 2 Cracking	State 3 Cracking	State 1 Faulting	State 2 Faulting	State 3 Faulting
PCC fly ash content		Yes			Yes	
PCC coarse aggregate content		—			Yes	
PCC sand content		Yes			Yes	
PCC cement content		Yes			—	
w/c ratio		—			Yes	
Additive (WRA) amount		Yes			Yes	
PCC water content		—			Yes	
PCC air content		—			Yes	
PCC unit weight		—			—	
PCC yield strength	N/A	—	N/A	N/A	Yes	N/A
Coarse aggregate specific gravity		—			Yes	
Coarse aggregate absorptivity		Yes			Yes	
Coarse aggregate LA abrasion		—			Yes	
Intermediate aggregate LA abrasion		Yes			—	
Fineness modulus		—			Yes	
Fine aggregate absorptivity		—			Yes	

—No data.

Table 145. Summary of HMA QA data variables included and associated *p*-values in cracking, rutting, and IRI prediction models.

HMA QA Variables	State 1 HMA Cracking	State 2 HMA Cracking	State 3 HMA Cracking	State 1 Rutting	State 2 Rutting	State 3 Rutting	State 1 IRI	State 2 IRI	State 3 IRI
Percent passing ¾-inch sieve	0.0254	—	<0.0001	0.0925	—	0.0022	—	—	—
Percent passing No. 4 sieve	<0.0001	—	—	—	—	—	—	—	—
HMA percent passing No. 40 sieve	—	—	—	0.0272	—	—	—	—	—
HMA percent asphalt binder	—	—	—	0.0144	<0.0001	—	—	0.0299	—
HMA bulk density	0.0008	—	—	—	—	—	—		—
HMA lab air voids	—	—	0.0001	0.0261		0.0318	—	0.1172	—
HMA in-place air voids	0.0018	—	—	0.0313	—	—	—	—	—
Computed HMA E^*	<0.0001	—	—	0.0005	—	—	—	—	—
Mix type (Neat/RAP)	—	—	0.1222	—	—	—	—	—	—
Binder PG Grade	—	—	0.1222	—	—	0.0169	—	—	—
RWD maximum deflection, *d*	—	<0.0001	—	—	<0.0001	—	—	<0.0001	—

—No data.

Table 146. Summary of PCC QA data variables included and associated *p*-values in cracking and faulting models.

PCC QA Variables	JPCP Cracking (Fatigue)	Faulting
w/c ratio	0.0009	—
PCC unit weight	0.0002	—
Coarse aggregate absorptivity	—	<0.0001
Sand equivalent	—	<0.0001
PCC 7-d compressive strength	—	0.0075
MIT-Scan (misalignment parameter, *S*)	—	<0.0001

—No data.

Evaluation of Derived Parameters as Indicators of Performance

Results presented in table 129 through table 135 represent preliminary analyses to determine the improvements that can be expected with the inclusion of the derived parameters.

QA data from State 1 and State 3 to calculate derived parameters are discussed in detail in chapter 2 and summarized earlier in this chapter. The results of the statistical analyses performed using the derived parameters as model inputs were found to significantly improve performance prediction. Table 147 summarizes the R^2 obtained for the prediction models based on the conventional QA parameters directly obtained from State QA databases and for the models developed using the derived parameters. It is clear, at least based on goodness of fit, that the models were improved in many cases: for average cracking (remained the same), average rutting, and COV of rutting in State 1; for structural cracking in State 3. The lack of improvement in functional cracking is not a concern because the derived parameters capture the material parameters that affect the mechanism of structural cracking.

Table 147. Summary of goodness of fit using QA data and using derived parameters.

State	Model	R^2 for Models with Conventional QA Data	R^2 for Models with Derived Parameters
State 1	Average cracking	42	42
	COV cracking	40	59
	Average rutting	27	46
	COV rutting	26	25
State 3	Functional cracking	21	13
	Structural cracking	36	45
	Rutting	19	14

Case Studies

The statistical analyses, performed using data from three State databases with different QA data elements, covered a wide range of performance models. However, for an agency to adopt this study's approach for improving performance predictions of the PMS models, additional considerations are required. This process may involve an agency deciding to include other databases, or selecting nontraditional QA tests and network-level tests, or simply using an optimal approach of incorporating select parameters into PMS models. The project team developed four case studies that covered different aspects of applying this research for practice. The following case studies analyzed data from each State and display the associated results.

Case Study with State 1 DOT—Using Traffic and Climate Data

State 1 analyses identified gradation, mix volumetrics, in-place density, and AASHTOWare Pavement ME level 3 computed dynamic modulus parameters as the independent variables as inputs to the cracking and rutting performance (table 89). The traditional PMS model in an agency's PMS uses only age as a variable. This case study incorporated data from additional databases to estimate traffic and climate data in addition to conventional QA and PMS data. By integrating the four data sources, the model was significantly improved. The model statistics for the equations, presented in table 148, shows the significant improvement to the performance prediction model by incorporating data from other QA and other databases, such as traffic and climate. It resulted in a 45 percent increase in R^2, 17 percent decrease in COV, and an 18 percent decrease in SEE. Figure 123 shows a plot of measured and predicted cracking versus age for model age as a variable, whereas figure 124 shows the same for predictive model in using age, climate, traffic, and QA variables. A review of the plots presented shows the superior predictive capacity of the model using age, QA, traffic, and climate parameters.

Table 148. Model statistics for example PMS cracking prediction models using age and additional QA parameters.

Model	*N*	R^2	COV	RMSE (Percent)
Model using age (figure 121)	1,589	0.38	96.3	2.86
Model using age and QA parameters (figure 122)	1,393	0.55	80.9	2.35

Case Study with State 2 DOT—Using Advanced Test Methods

Data from State 2 DOT were used to evaluate, at a project level, the correlation of data from structural condition monitoring (not traditional QA) to HMA performance as well as data from MIT-Scan-based *S* testing to joint faulting within 10 yr after construction. This case study highlights the ability to utilize data from nonconventional QA test methods as indicators of performance.

A rehabilitation project considered on a SH in State 2 DOT showed high levels of pre-overlay distress along the entire segment (figure 126 to figure 128). The pavement was overlaid with traditional overlay and mill-and-fill strategies using two HMA mix designs. Location referencing on the project was not provided for the mixes; therefore, it was not clear from QA data the specific locations of the two mixes on the project. RWD test data soon after construction showed higher deflections and lower structural capacity on one segment of the rehabilitation project (figure 129 to figure 131), which correlated to post-overlay performance. A statistical analysis showed the following:

- RWD-measured pavement deflection had a significant impact on all three performance measures (cracking, rutting, and IRI).
- Pavement sections with measured maximum deflection less than 15 mils exhibited the least amount of distress.
- Pavement sections with measured maximum deflection greater than 25 mils exhibited the highest amount of distress.
- Fatigue cracking had the highest R^2 with RWD deflections (40 percent). For rutting and IRI, R^2 was 15 to 18 percent.

A second case study with data from State 2 DOT utilized *S* measured using the MIT-Scan at the time of construction and correlated it with performance 6 yr postconstruction. A nonlinear model, as shown in figure 135 and figure 136, illustrates that the measure of dowel alignment is potentially a leading indicator of faulting development. Using this parameter might help an agency in developing future faulting prediction models. It is recognized that a relatively small subset of existing QA data from an agency would include data from this technology; however, agencies should consider making such data available for future projects.

Case Study with State 3 DOT—Incorporating Performance Predictions Into PMS

This case study demonstrated the ultimate application of the results from this study, i.e., developing QA data-based performance prediction models for an agency's PMS. This case study showed, using performance forecasting curves for seven pavement families, methods to incorporate data items identified as having a significant impact on pavement performance. The example was developed using data from State 3 DOT PMS and QA data tables, and it uses existing State 3 DOT performance forecasting models as well as performance predictions within this study developed for structural cracking. The methodology presented in this case study involves the following steps:

1. Identify the pavement type of interest and the performance criteria, which in this case study was the flexible pavement SCI.
2. Determine which QA data items that impact performance can be utilized as leading indicators of performance. Statistical analyses showed that the parameters, lab air voids, HMA type, PG grade of the binder, and the percent passing the 19-mm sieve were used in the model, as shown in table 145 and table 133.
3. Determine existing (State 3 DOT) PMS performance forecasting models for the identified pavement types of interest, which are shown in figure 138 and figure 139.

4. Develop correction factors for the performance forecasting models identified in step 3 using the QA data items identified as leading indicators and adjust/correct existing PMS model outputs as needed. The correction factor developed is shown in figure 140.

5. Evaluate predictions of performance with correction factors and characterize improvements in goodness of fit and bias. The case study showed that the bias in the existing models was remedied significantly using the construction QA parameters, as shown in the statistics for the prediction shown in figure 141.

Case Study with State 4 DOT—Utilizing Data From Innovative Technologies as Leading Indicators of Performance

This case study was performed using State 4 data to examine the value of incorporating results from an innovative technology—IC in this case study—to improve pavement management performance models. At the time of this study, IC specifications were being used by States to record coverage and number of passes, which is worthy of recommending IC data for future use in asset management and for purposes of evaluation of anomalies in pavement condition data. It has also been found that the consistency in IC outputs in relation to in situ material properties is machine dependent. The intent of this case study was to determine the extent to which IC data correlate to traditional QA parameters. Success in establishing this correlation provides the opportunity to use IC data as an indirect measure of QA and, therefore, an opportunity to relate them to performance.

The analyses performed with the assembled datasets to establish a correlation between field density and IC outputs involved the following steps:

1. Identifying projects that have suitable data. In this case study, IC data from three construction projects were used. The data provide compaction history for the "entire" pavement, layer by layer and lift by lift. The corresponding survey grade GPS tracking and temperature measurements from IR sensors were also available. Other QA data included field density and lab aggregate, binder, and HMA test data.

2. Assembling data for multiple regression analysis. From all three projects identified for the analyses, over 16 million IC readings were collected. A summary of the data assembled are presented in table 45 and table 46 for IC and field QA data, respectively. Table 60 and table 61 showing summaries of IC and conventional field testing data, respectively. Figure 104 and figure 105 present heatmaps of the spatial temperature data.

3. Performing regression analysis. Multivariate regression analysis was conducted to identify IC outputs that significantly impact field-measured HMA density and evaluate the feasibility of modeling/predicting field-measured HMA density. The regression model adopted related field-measured density with interaction of "project," "compaction equipment," and key IC outputs "CMV" and "amplitude" (figure 142 and table 135).

Overall this case study demonstrated that key IC outputs measured during construction (HMA placement and compaction) may be used for future performance forecasting; however, with the current advancements in this technology and the current development of specifications for this technology, it is not possible to guarantee a strong correlation to performance. Future pavement performance data from projects that have utilized IC may provide better insights into the potential for correlation and performance prediction. Therefore, conclusions from the current study are preliminary, as more extensive research is required for the model's development.

CONCLUSIONS

The research showed promising results supporting the use of QA and construction data as leading indicators of performance prediction. The following conclusions can be made from this study:

- It is evident that no State is set up to directly correlate QA data with PMS condition data based on the review of State practices.
- There exists among State agencies a high degree of interest in complementing PMS models with construction and QA data due to increased knowledge of the impact of several material properties with performance. The adoption of M-E design procedures by States, combined with FHWA efforts to implement PRS, have urged agencies to consider systematic collection of QA data more seriously. Furthermore, agencies also recognize this process as a necessary step to streamline their QA procedures and improve their specifications.
- There is an increased scope for facilitating the integration process by the enhancements in as-built data collection largely enabled by automation in construction technologies (LiDAR, GNSS, AMG, sUAS, IC, and so on) combined with mobile technologies and tagging features in QA test devices.
    - These emergent technologies are promising for enhancing the construction data integration procedures. However, the current state of practice does not permit the use of as-constructed data because States do not currently require contractors to submit as-built records.
- None of the agencies have matured their ideas to a formal, well-established, and automated process to integrate QA and performance.
- The extent and types of material property data available in databases varies between States. Thus, the development of prediction models will be unique to each agency. Individual analyses will be required for each distress type to identify significant variables and to develop performance models.
- The integration of QA databases requires significant effort and will require a customized effort for each State agency.
- Statistical models can be developed for the prediction of all distress types identified in the NPRM. The following QA properties were found to be significant for each distress type:
    - Flexible pavement cracking—HMA aggregate gradation, binder type, air voids, density, modulus, or mix type (Neat/RAP).

    - Flexible pavement rutting—HMA aggregate gradation, binder content, air voids, and modulus.
    - Flexible pavement IRI—HMA binder content and air voids (model minimally analyzed).
    - Rigid pavement cracking—PCC mix design index properties such as w/c ratio materials content and unit weight.
    - Rigid pavement faulting—PCC mix design index properties such as coarse aggregate absorptivity, sand equivalence, and PCC 7-d compressive strength.
- Innovative technologies used in QC, construction, and pavement evaluation have a potential to predict long-term performance if:
    - MIT-Scan (misalignment parameter, *S*) was highly correlated to joint faulting developed within 2–4 yr after construction.
    - Deflections measured from a continuous deflection monitoring technology, such as the RWD, were correlated to cracking, faulting, and IRI measured within 5 yr after construction.

Findings of this study are convincingly promising and suggest the following:

- QA parameters can be correlated to performance measures that have been identified in the NPRM.
- QA data can be integrated into a State PMS to improve distress prediction models.
- Agencies with the right tools are interested in exploring the use of QA data to improve PMS pavement performance forecasting accuracy.
- Agencies could use the integrated QA and PMS databases to improve construction specifications and other performance measures outside of the NPRM, such as pavement friction or JPCP joint spalling.

CHAPTER 8. GUIDELINES FOR UTILIZING QA DATA AS LEADING INDICATORS IN PMS

This chapter provides practical guidelines and recommendations for agencies that consider the integration of QA test data and other construction data identified as leading indicators of pavement performance in its PMS. The guidelines are based on the results of the present study and its success in establishing correlations between QA data collected at the time of construction and future pavement performance. These recommendations are intended to encourage States to be proactive in collecting and storing construction and QA data beyond the construction contract period and to make data accessible for advanced performance forecasting modeling and analyses that support pavement management decisionmaking.

BASIS FOR DEVELOPMENT OF GUIDELINES

The following factors shaped the development of these guidelines:

- States have made, and continue to make, great strides toward adopting digital data collection techniques, closing the gap between construction, performance, and asset management. Efforts by States to implement M-E design methods and PRS for construction have triggered the setup of comprehensive laboratory and field-testing programs to collect material test data directly related to pavement performance. Agencies are increasingly developing material libraries and are streamlining efforts to manage project- and network-level data for design, QA, M&R, and pavement management.

- QA and construction data used as leading indicators of performance can and should leverage the momentum of these ongoing efforts and, to all intents and purposes, support a very critical program of a highway agency—its PMS. As such, adopting these guidelines should not be viewed as an attempt to implement a major programmatic change to an agency's operation or management. Rather, the guidelines should be perceived as part of the natural progression toward the adoption and use of new technologies to implement better processes that are already in use by agencies. The guidelines will, however, require a committed effort by an agency to engage different departments and divisions to collaborate and then adopt the new technologies. The guidelines will better enable agencies to share data and other information for more efficient data collection and data interoperability.

- All agencies collect QA data and pavement condition data. The extent of data collection and their use—specifications governing QA, stages of data collection (material approval, material certifications, QC, verification, and acceptance), the types of data collected, the format of data collection (electronic to paper records), data storage and archiving procedures (number of years of data available), and data accessibility—vary between agencies. The efforts involved in assembling and integrating databases will remain unique to each agency. Therefore, the guidelines presented are a set of unified and generalized recommendations: they do not attempt to describe the specifics of the procedures required to integrate QA and construction data into PMS for improved performance prediction. However, they highlight the major steps involved and identify data to be organized and the technologies readily available for doing so.

- This effort will involve assembling and integrating various construction, performance, and supplemental datasets, correlating QA data with performance data, identifying the parameters of interest, and developing prediction models, as discussed previously. To undertake these statistical analyses, an agency must assemble performance data over a significant period to capture the impact of construction and design parameters on performance. Data should be amenable to showing performance trends for all categories of pavements and distress types, including smoothness. Performance data used under this study spanned at least 10 yr.

- The recommendations do not identify the specific QA and construction parameters that will be significant for an agency to develop performance prediction models. The outcome of the statistical modeling will depend on the QA parameters available in an agency's database, the accuracy and sampling rates, the existing referencing systems across different agency databases and thus ability to integrate with PMS, variability in as-constructed design features and material properties within the local area and project, and the specifications used within the agency to control quality during construction. In other words, a detailed analysis is required by each agency to identify the parameters most critical for its needs.

- Agencies across the Nation are at various levels of advancements with their QA testing programs and construction quality database systems. This finding ranges from agencies performing traditional QA tests for acceptance and maintaining electronic/paper records to agencies using innovative QA testing with geotagging and modern construction technologies with spatially mapped 3D construction data. Most agencies are in the process of transitioning to higher forms of data collection, i.e., agencies are making headway collecting data digitally and then storing construction and QA records with location referencing protocols. The guidelines address all tiers of QA and construction programs. The guidelines support agencies that will gradually scale up their QA and construction programs.

  QA and construction data are categorized under three tiers (also see table 149):

  - Tier 1: traditional construction and QA test methods. Data from these tests "currently" exist in State agency records, and they can be correlated to existing performance data. These tests have been used for at least 15 yr. An example of tier 1 test data would be thickness or density measured from field cores at specific locations. These data might not exist in an electronic format now, or they might exist in multiple formats, making data access and data integration a challenge for performance modeling. However, most agencies do not need to make changes to their current construction specifications or adopt new technologies to begin using tier 1 data for performance prediction. Instead, States should direct their efforts toward ensuring that, in the future, such data are collected and stored in a manner that makes them easily accessible and appropriately referenced for immediate and future use.

- Tier 2: innovative construction or QA test methods. These data include test results from most of the NDE-based test devices and construction technologies that have been in use over the last 7–10 yr. These test methods have mostly been standardized with formal test standards, and some agencies have specifications, while others might soon adopt the methods. It might be possible, although with limited project-level datasets, to correlate these data to performance. However, it is expected that, over the next 5–7 yr, data from tier 2 tests can be associated with performance data to result in analyses covering a 10- to 15-yr duration. An example of tier 2 test data would be GPR thickness measured with a higher sampling rate along the project, IR temperature data that may be correlated to density, or JPCP dowel alignment measured using MIT-Scan. Agencies must review current tier 2 data collection and storage protocols to ensure that the collection is being completed in a manner that will make data usable and readily available within the agency. Failure to do so may result in accumulation of vast amounts of legacy data that can be used in the future only with added costs.

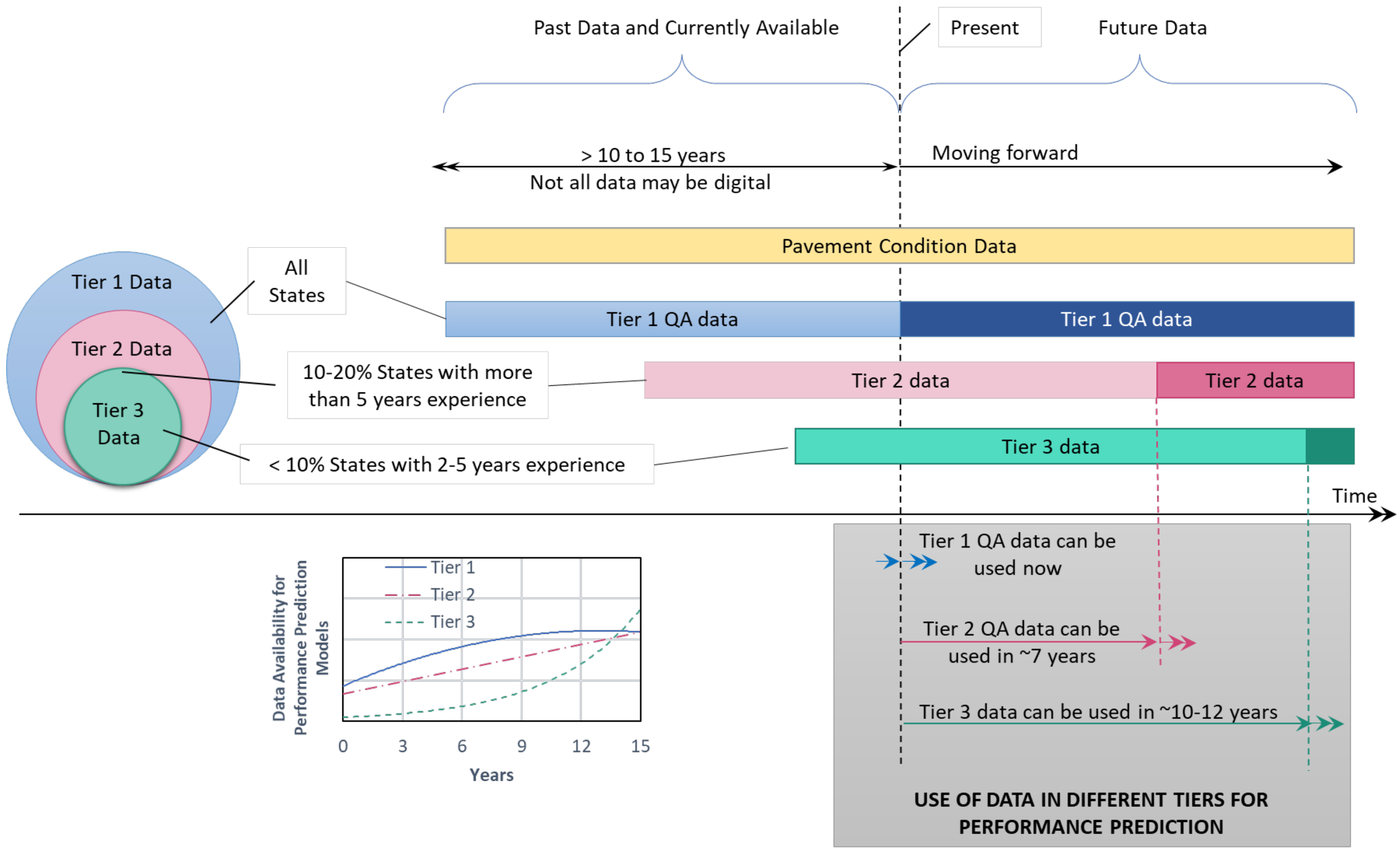
- Tier 3: emerging construction technologies and test methods. These data belong to technologies launching the digital revolution in the industry today. They are technologies and test methods considered promising for routine use and are being adopted rapidly by many agencies. There are likely no performance data at this stage, and agencies have not fully established formal processes (or contract language) to be able to obtain data from construction. However, construction and QA testing indicate that agencies will generate parameters that can potentially be correlated either directly to pavement performance or to proven indicators of performance. Note that, currently, there is no strong evidence of the use of such data to correlate to performance. Again, it is never too early for agencies to begin reviewing tier 3 data collection and storage protocols to ensure that these tasks are performed in a manner that will make them usable and readily available within the agency. Rather, delays in data collection efforts may result in accumulation of vast amounts of legacy data that can be used in the future only with added costs.

A summary of the current status of available data and the projected data available under all three tiers for performance prediction is illustrated in figure 145.

Table 149. Tiered QA and construction data.

Data Tier	Examples of QA and Construction Data Under Each Tier	Sources and File Formats
Tier 1 (Traditional QA Test Data)	• HMA: density, AC content, voids, gradation, lift thickness, derived parameters. • PCC: compressive strength, flexural strength, air content, w/c ratio, SCM content, PCC thickness, CTE. • Aggregate: gradation, moisture content. • Subgrade: M_r, moisture content, fines content • Pavement: initial IRI.	• Databases (ACCDB). • Spreadsheets (XLSX, CSV). • Documents (PDF, TEXT).
Tier 2 (Innovative QA Test Methods and Construction Technologies in Recent Use)	• GPR thickness measurement, nonnuclear density, modulus from seismic testing.	• Hierarchical data format files, spreadsheets, databases.
	• MIT-Scan for dowel alignment and effective dowel diameter. • IC, IR, in-place paving temperature. • RWD/FWD from pavement evaluation.	
Tier 3 (Emerging QA and Construction Technologies)	• 3D construction break lines and 3D construction surfaces. • AMPT S_{app}.	• CADD data: DWG, DXF, DGN, LandXML, TXT. • XYZ LiDAR Data: LAS, E57. • Spreadsheets. • Databases.

AMPT = asphalt mixture performance tester; S_{app} = fatigue index parameter.



Source: FHWA.

Figure 145. Illustration. The three tiers of QA data for pavement performance prediction.

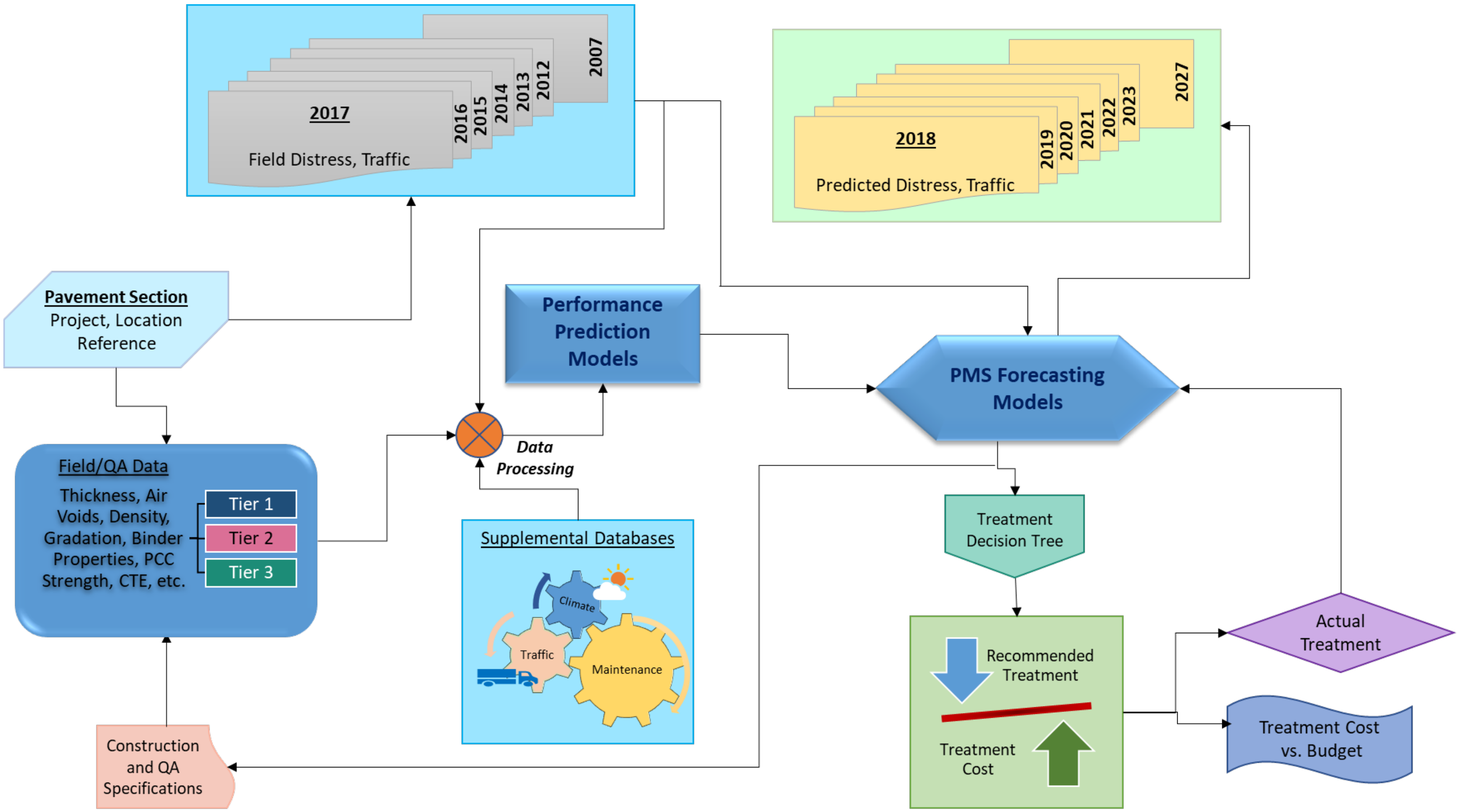
Agencies empirically acknowledge relationships between QA data variables and future pavement performance. None of the agencies studied has matured its ideas to a formal, well-established, and automated process to integrate QA, construction, and PMS databases. Initial efforts to locate, assemble, conflate, and model existing data are expected to be intense. Data integration that allows aligning spatial reference systems from PMS and construction QA databases by project or by location requires significant effort. Next, efforts to restructure collection of future QA and construction data compatible with pavement management are expected to be moderate. However, on successfully establishing the system, absorbing future data and updating models will be an automated process and may require relatively less effort.

States recognize that there is an increased scope for facilitating the integration process by the enhancements in as-built data collections that are largely enabled by automation in construction technologies (LiDAR, GNSS, AMG, sUAS, IC, and so on) combined with mobile technologies and tagging features in QA test devices. These emergent technologies are promising for enhancing the construction data integration procedures. The current research shows that the variable of interest is the layer or lift thickness parameter that has a time reference (i.e., day and time of paving) and a location reference (i.e., geospatial coordinates). However, the current state of practice does not permit the use of as-constructed data, because States do not currently require contractors to submit as-built records. Agencies must consider requesting as-built models to enable the use of data from 3D construction for this specific application in pavement management.

Finally, these guidelines should urge agencies toward a change in mindset in collecting and storing construction and QA data at all levels—for material approval, material certification, job mix formula approvals, QC, acceptance, and inspection checklists. The forethought that these data can and will be used for pavement management performance forecasting should be one of the key factors driving all design, construction, and QA data collection practices. These practices include accuracy and precision in recorded data; location referencing; and identification of highway and route numbers, project, layer, and lift information. These data also serve as an implied assertion to the fact that the quality of materials and construction has far-reaching outcomes, well beyond determining pay factors for construction contracts. It will perhaps require establishing a new “culture” in QA and construction data collection and storage.

GUIDELINES FOR INTEGRATING QA AND CONSTRUCTION DATA INTO PMS

Figure 146 illustrates a high-level overview for incorporating QA data into pavement management forecasting models. The diagram highlights the overall vision for combining data from the time of construction with other supplemental databases (for example, databases with traffic, climate, and maintenance information) to develop performance prediction models that may be used to further enhance or replace pavement management forecasting models and support investment decisions. These newly generated models are expected to forecast pavement distress more accurately than current methods do, which mostly forecast future distress based on trends identified in past distress data alone or augmented with as-designed pavement data. This schematic also highlights that the end use of construction and QA data is well beyond construction; these data extend into managing the pavement network.



Source: FHWA.

Figure 146. Illustration. Proposed integration of QA and construction data as leading indicators of performance for PMS.

The guidelines are divided into three parts:

- Recommendations for data collection.
- Recommendations for data processing, conflation, and integration.
- Recommendations for performance prediction and integration into PMS.

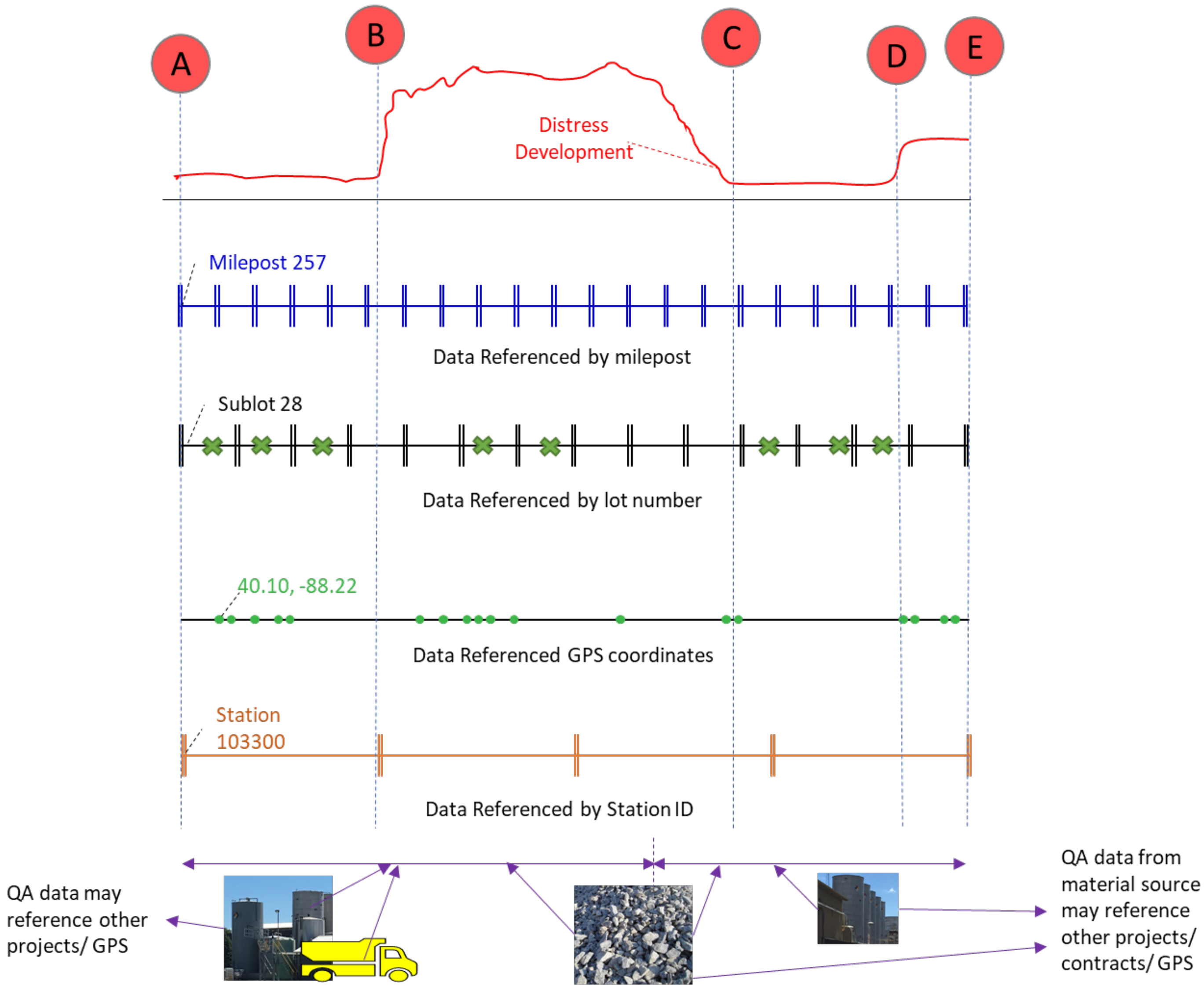
Recommendations for Data Collection

Data Collected to Date in an Agency and Their Use—Legacy Data

Several years ago, as agencies transitioned from manual to electronic data collection procedures, databases were designed and developed within agencies, generally for each individual material type. The features and capabilities of each of these databases reflect the needs of the agency as well as the computing/data-sharing technologies that existed at the time they were developed. Most often, these databases stored test results using limited referencing parameters and provided project or contract information, route numbers, lot number, test date, and stationing. These databases were also capable of producing ad hoc reports replicating the manual data entry processes that they then replaced. Future-generation databases added features and data elements, but none was necessarily designed with the vision of integrating QA and performance data. Linking databases using spatial mapping has been a challenge (figure 147), and such efforts were mostly exploratory or for research needs. They had to adopt other means to combine QA and performance data by project or contract (for example, integrating using a third database to identify common referencing data elements).

In general, legacy data (i.e., past data) are not amenable for integrating QA and performance databases by test location or at a project level. As an example, a pavement construction contract completed within the bounds of a given construction stationing, using materials potentially from multiple sources, with QC and acceptance test results from different lots may exhibit variability in performance when condition data are monitored at different MPs (figure 147). In the absence of suitable data collection methods providing relative mapping across the different referencing systems, as is the case with agency legacy data, good, fair, and bad performance along the project may not be directly correlated to corresponding QA test results or material sources. The average performance of the section (between points A and E) may be correlated to the average values of each QA variable along the entire project, resulting in performance modeling at a network level. This approach might not fully capitalize on the value of the available QA data, because it does not correlate corresponding data for each segment to predict different performance levels in segments AB (good), BC (poor), CD (good), and DE (fair) at a project level.

Because agencies cannot augment existing data to higher levels of data operability, they must consider alternatives to best utilize all data available and conflate QA performance datasets for immediate use in performance forecasting. However, agencies must try to overcome such limitations for modeling to establish systematic data collection for future data generated.



Source: FHWA.

Figure 147. Illustration. Referencing using different geospatial systems, GPS, station ID, lot number, or MP.

Recommendations for QA Data Collection—Future Projects

The key recommendation from this research for future data collection is that every QA or construction data record must possess a global location referencing system. The GPS location referenced must be accurate enough to enable identification of the specific location within a few inches, and every location on the project must be mapped to the associated construction data and QA data—field measured, lab measured, material approvals, and source certification. Compelling a common GPS referencing system is a fundamental requirement to enable direct correlation between construction and performance and to extend these performance prediction capabilities to pavement management and asset management functions. It is recommended that all data collected at the time of construction or pavement evaluation be mapped to a physical location on the highway, resulting in the following:

- Every QA data record shall be associated with a finite and a geospatially specifiable physical field location. This location may represent a single point, an area, a lot, an entire project, or a set of projects. For example, the density of a core taken from the field shall be referenced with GPS coordinates of the core location. This measurement shall be applicable for the core location and the boundaries of the lot. Likewise, material certification or mix gradation shall be applicable to the project segment using the mix, as defined by the GPS coordinates. Furthermore, the binder certification data shall be associated with the projects (or project segments) that use the given binder. This action will be easily supported by some of the newer QA testing and construction technologies that have the capability for geotagging, thus providing the GPS coordinates for the test location.

- Every field location (i.e., on the project) shall be associated with QA and construction data corresponding to the materials and construction methods used in that location.

The second recommendation is to align collection of QA data with PMS data. This action may require equally distributed test sample locations within the construction project area so as to obtain QA data for each pavement management section. The goal here is to ensure changes in QA data (i.e., leading indicators of performance) are captured within each PMS section and thus future observed performance and current forecasts of performance. Figure 147, as an example, shows the number of test results represented by lots in segments AB and CD exceed the number of tests in BC, where the pavement shows poor performance. Such datasets in which changes in performance are not supported by adequate QA data will result in analyses using project averages that negatively affect PMS reliability.

Note that, when adopting these recommendations for QA data collection practices, an agency may continue to use the testing and sampling program in existing specifications or adopt new test methods in the future. It is not within the scope of this project to suggest an optimum number of QA tests and the specific tests to be adopted. However, most agencies do already have detailed procedures, such as material sampling and testing, to provide representative characterization of a given pavement section. Agencies such as the FHWA, NCHRP, and AASHTO also have available similar protocols and standards. Current protocols may be modified and adapted to make them compatible with the goals of utilizing QA data as leading indicators of pavement performance within PMS.

In summary, regardless of the databases used, it is imperative that agencies have a means of tracking the specific location of each test data recorded as well as have a means to track all data associated with each location on the project. It is also necessary to align QA data with performance data collected (i.e., for each pavement management section) to develop robust prediction tools and to capture the sensitivity of each QA parameter to performance. These data collection measures are essential to the long-term use of QA and construction data for PMS or asset management.

Recommendations for QA Data Elements to Be Collected for Future Projects

Table 150 provides a summary of QA test parameters that shall be considered by an agency for use in establishing QA test specifications from the standpoint of performance prediction for pavement management. Research, including work reported in the earlier chapters of this report, demonstrates that several of these test specifications may produce data that might serve as leading indicators of pavement future performance. However, the project team is not certain which of these variables can significantly affect performance for a given agency at the local level. Additional data analyses using agency databases will be necessary to ascertain the critical parameters with strong correlations to future performance.

Table 150. Recommended AASHTO/ASTM test standards for determining potential QA test data (includes material approval, QC, and acceptance testing).

Material Type	Test Property	National Test Standard
Asphalt mix (lab testing)	Nominal maximum aggregate size and gradation.	AASHTO M 323[38] AASHTO M 325[39]
	Type and percentage of recycled asphalt binder.	
	Bulk specific gravity of the combined aggregate.	
	Effective specific gravity of the aggregate.	
	Bulk specific gravity of the binder.	
	Design compaction level.	
	Design binder content.	
	Design air void content.	
	Design VMA.	
	Design VFA.	
	FAA.	
	Coarse aggregate crushed faces.	
	Fine aggregate sand equivalent.	
	Coarse aggregate flat and elongated particles.	
	Filler-to-effective asphalt ratio.	
	Moisture sensitivity.	

Material Type	Test Property	National Test Standard
Asphalt mix (loose mix and field cores testing)	Asphalt content.	AASHTO T 308[40]
	Laboratory density.	AASHTO T 312[42]
	In-place compaction. Nuclear gauge/nonnuclear gauge.	AASHTO T 166[41]
	Thickness.	ASTM D 3549[111]
	Air voids/unit weight.	AASHTO T 166[41], AASHTO T 331[112], AASHTO T 269[113]
	Tensile strength.	AASHTO T 283[114]
	Dynamic modulus (E^*).	AASHTO T 342[115] or AASHTO T 378[116]
	Low-temperature creep compliance and strength.	AASHTO T 322[117]
	Rutting resistance.	AASHTO T 378[116], or AASHTO T 324[118], or AASHTO T 340[119]
	Fatigue cracking resistance.	AASHTO T 321[120] or AASHTO TP 107[121]
AC binder or blend of virgin and recycled binder in mixtures containing RAP and/or RAS	Performance grade of the binder.	AASHTO M 320[27] or AASHTO M 332[122]
	Asphalt binder complex G^* and δ.	AASHTO T 315[123], AASHTO M 320[27]
	Nonrecoverable compliance (J_{NR}) and percent recovery (R%).	AASHTO T 350[124]
	Creep stiffness, *m*-value, and the delta Tc parameter, ΔT_C.	AASHTO T 313[125]
	Viscosity-temperature relationship.	AASHTO T 316[126]
AC aggregates	Toughness and abrasion resistance.	AASHTO T 96[29]
	Durability and soundness.	AASHTO T 104[31]
	Clay content.	AASHTO T 90[32] or AASHTO T 176[33]
	Gradation.	AASHTO T 27[34] and AASHTO T 11[35]
	Aggregate flat and elongated.	ASTM D 4791[127]
	Coase aggregate angularity.	ASTM D 5821[128]
	FAA.	AASHTO T 304[129]
	Specific gravity.	AASHTO T 84[36] and AASHTO T 85[37]

Material Type	Test Property	National Test Standard
Hardened PCC	Flexural strength.	AASHTO T 97[55]
	Compressive strength.	AASHTO T 22[54]
	Indirect tensile strength.	AASHTO T 198[57]
	Modulus of elasticity and Poisson's ratio.	ASTM C 469[55]
	CTE.	AASHTO T 336[58]
	PCC air content.	AASHTO T 152[130]
	PCC thickness. Core measurements, GPR.	
	Shrinkage (ultimate shrinkage and time to achieve 50 percent of ultimate).	AASHTO T 160[58]
	Unit weight.	AASHTO T 121[49]
	Length change due to concrete shrinkage.	AASHTO T 160
Cementitious materials	Cement type.	ASTM C 150[44]
	Fly ash class.	ASTM C 618[45]
PCC aggregates	Fine aggregates (gradation, sand equivalency, fineness modulus, specific gravity, potential for ASR).	AASHTO M 6[44], AASHTO T 11[35], AASHTO T 176[33], AASHTO T 27[34], AASHTO T 84[36], ASTM C 1260[47]
	Coarse aggregates (gradation, nominal aggregate size, abrasion, specific gravity).	AASHTO M 80[47], AASHTO T 27[34], AASHTO T 96[29], AASHTO T 85[55]
Fresh PCC	Unit weight air content.	AASHTO T 121[49] AASHTO T 196[50]
	w/c ratio. Mix design.	Obtained from mix design information
	Slump.	AASHTO T 119[51]
	Bleeding.	ASTM C 232[52]
	Initial and final set time.	ASTM C 403[53]
PCC durability	Parameters of air void system in hardened concrete.	ASTM C 457[60]
	Rapid freeze-thaw resistance.	ASTM C 666[61]
	Scaling resistance.	ASTM C 672[62]
Pavement QA	Ride quality.	AASHTO R 54[43]
	PCC joint effective dowel diameter (based on dowel alignment).	Agency specifications for measuring *S*
	TSDD.	Not available
	FWD.	AASHTO T 256[131]
	IC.	Agency specifications
	AC layer in situ temperature using IR.	Agency specifications

—No data.

This research also recommends the collection of data from other performance-based tests that produce parameters used in correlations developed for performance prediction. FHWA has led efforts in the past decade to develop new and improved pavement performance forecasting models for both asphalt and concrete pavements for use in developing PRS. The PRS relationships were developed based on extensive work done under NCHRP Project 1-37A and research conducted at University of Maryland, Arizona State University, and North Carolina State University. Agencies can utilize some of these relationships when developing and enhancing their own local models.

Significant research has focused on developing advanced material characterization models and associated calibration and testing procedures to support performance prediction models for permanent deformation, fatigue cracking, thermal cracking, and reflection cracking distresses in HMA pavements. The AMPT can be incorporated into both mix design and structural design to estimate performance of the pavement constructed with the HMA mix.

AMPT testing currently determines the S_{app} parameter to estimate as-built fatigue performance. FHWA is researching the development of an equivalent parameter to estimate as-built rutting performance. FHWA has major ongoing efforts, through shadow projects being performed in several States, for the incorporation of AMPT performance tests of the mix design into PRS models for asphalt pavements. Additional data are expected to provide the validation and field data for calibration. The underlying concept of acknowledging the mix volumetrics-to-performance relationships through the AMPT is of immense relevance to the recommendations provided in this chapter. This project recommends that, as AMPT procedures are developed, these data need to be stored and evaluated for use in future pavement performance prediction models to be integrated with PMS.

3D Construction Data Integration for PMS Performance Prediction

This research has determined that the key parameter of interest from 3D construction data is the thickness parameter measured with full project coverage. These data will supplement the thickness measured in field using traditional location-based core test data. The guidance for incorporating this parameter is provided with limited details because of the lack of formal standards existing now and the lack of procedures to obtain as-built data. The recommendations are rather abstract without a research validation under this study. However, the project team does recognize the potential to collect thickness data and its value in PMS.

Contractors have been increasingly using AMG construction equipment for grading, trimming, and paving that accepts either 3D construction surfaces or 3D break lines that represent the crown and the edges of pavement. The 3D surface data are a mesh or triangulated irregular network of the pavement layer made from individual grid points (x, y, and z geospatial coordinates), as shown in figure 148. The x and y coordinates denote northing and easting horizontal location, whereas the z coordinate represents the elevation of the point. The 3D break lines are a series of (x,y,z) points that create a line string used for paving equipment. However, the pavement surface may be created from those 3D break lines. The 3D data used for construction come from the geospatially correct model created during the design phase. If the design surface varies from the actual as-built pavement surface, the contractor may be able to provide an as-built file for each layer. Alternatively, these surfaces may be obtained by scanning each pavement layer each day using a terrestrial LiDAR scanner. LiDAR data may be a more accurate representation of each layer of the pavement structure.

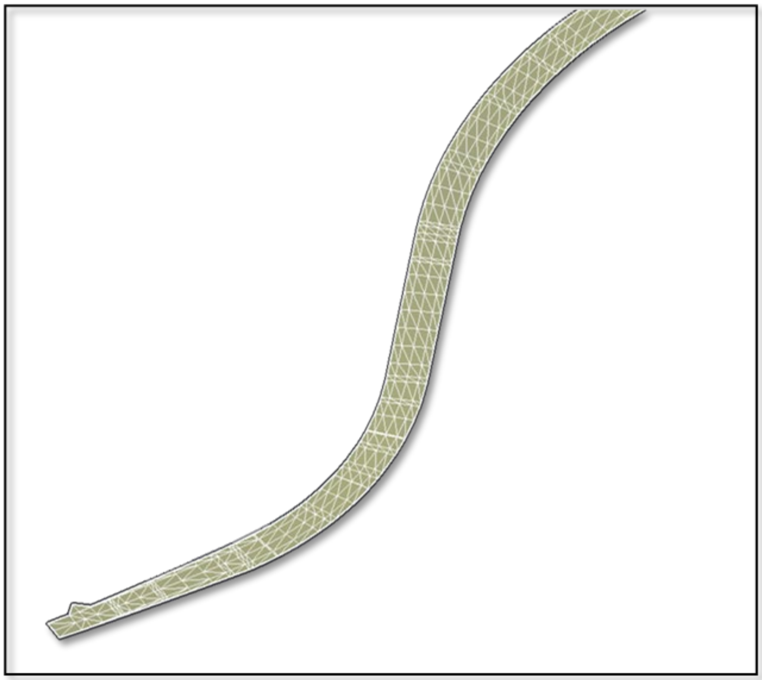


Figure 148. Image. Example of a 3D construction surface.

After the surfaces have been obtained, the data must be processed using 3D design or construction software packages that offer tools to analyze the surfaces to compute the minimum thickness of the mesh. Most GIS software programs offer the needed functionality.

The agency may request the as-built surfaces of each of the modeled pavement layers used from the contractor. The file format in which pavement surface data are received will be dependent on the equipment and software the contractor uses. It is important to consider which file format to obtain to ensure the agency sets up procedures to process the data to obtain the minimum thickness. Thus, the agency may request the surfaces constructed per day of operation in the desired format to calculate average thickness per lot (or for a select sampling area) of roadway paved. It is important to note that the surfaces can be associated with the horizontal alignment of the roadway to determine station values for beginning and stopping points for the daily operation.

Recommendations for Data Processing, Conflation, and Integration

The recommendations provided here are not intended to necessarily modify existing QA or PMS programs, but rather to provide agencies with the information that is required for making informed decisions regarding data processing, assembly, and integration within or external to their current QA databases and PMS programs. The key considerations for data integration before statistical modeling can be performed are discussed as follows.

Data Conversion and Ingestion

One of largest challenges expected when incorporating QA and construction data-based performance models into PMS is the data conversion process. As shown in table 149, the various data at each tier are available in several electronic formats and hardcopies. The data will need to be extracted from the files and spatially aligned with the baseline roadway data. The details of this process will be largely dictated by the formats of the agencies' legacy data and future data collection methodologies. Regardless of the existing datasets and the PMS section attributes, the data integration and statistical analyses system developed will expect data to be in a particular format for data ingestion. Custom tools and scripts may need to be developed to preprocess the existing files and then convert them to a format compatible with the data assembled from the PMS. The following sections describe some of the common challenges encountered when preprocessing and converting data for use with a PMS.

Geospatial Alignment

As construction and QA data may be referenced by lot, station, or a GPS coordinate, the data will need to be converted and synthesized in a format in which the data are geospatially aligned. This conversion is necessary because different types of data may have different spatial references, resolutions, and accuracies; for example, thickness data may be available by lot number, whereas gradation data may only be available for a project or within certain station limits.

A spatial join or data conflation may be performed at any level of granularity by upsampling or downsampling data. The process of upsampling data, i.e., converting low-granularity data to a higher granularity, will involve assigning a whole or interpolated value to the finer grain data. The process of downsampling, i.e., converting higher granularity data to a lower granularity, will involve selecting a representative value (e.g., mean value) and then assigning it to the coarser dataset. As spatial references might not perfectly overlap (figure 147), an interpolated value may be needed in either case of upsampling or downsampling.

3D construction data are available only in GPS coordinates that can be tied only to a station ID by using the horizontal alignment of the roadway. Currently available GIS software, such as ArcGIS or QGIS, have the capabilities to spatially join different data sources that are georeferenced. However, custom tools or scripts may need to be developed to perform a spatial alignment for more complex data.

Discrete Versus Continuous Data

Due to the nature of the how measurements are taken (e.g., a continuous scanner of a section versus core samples every 100 ft), agencies will need to develop processes to bin the data as needed into the baseline data. Binning for continuous data will usually involve selecting a representative sample for each bin (e.g., median or mean value). Binning for discrete data may involve selecting a representative sample (if there are multiple samples available for each bin) or interpolating discrete values between bins (if no data are available for a specific bin).

File Formats

As each type of data may be in various formats related to the tools or techniques with which the data were gathered, agencies will need to use conversion tools or processes to parse the relevant data or metadata available. These conversion tools may be available open source or commercially or may need to be developed in house by the agencies to absorb data. If the file formats are proprietary and cannot be parsed using available tools or documentation, software with proprietary formats will typically have the capability to export the file to some common interchange file format; however, this format will typically be a lossy (typically metadata) conversion.

Data Inference

Under certain circumstances, the data may not be explicitly available but can be inferred from available construction information. For example, material certification data may be inferred from the supplier; these data may be applicable per site or project, or for many projects. Agencies need to set procedures to use data from different functions of the QA program, if these data are not already stored in the construction and QA databases.

Geospatial Referencing

For data referenced by GPS, a conversion may be necessary to ensure all datasets share the same GPS format and coordinate system. A GPS format conversion is necessary if two datasets share the same map projection but have different GPS formats. For example, one dataset may be in decimal degrees (DD) format, and the other dataset may be in degrees-seconds-minutes format. Off-the-shelf software and libraries can perform simple conversions.

If two datasets do not share the same geographic coordinate system, a map reprojection will be necessary so that all datasets are referenced to the same geodetic datum. For example, the world geodetic system (WGS) 1984 datum and the projection of universal transverse mercator (UTM) are not compatible, although UTM projected coordinates are referenced to WGS 1984 datum. WGS 1984 uses latitude and longitude for geospatial referencing, whereas UTM uses easting and northing coordinates.

Recommendations for Performance Prediction

The statistical procedures include, as discussed in detail in chapter 6, the following steps:

1. Review assembled integrated PMS and QA test databases for accuracy and reasonableness and then estimate derived parameters from QA test data.

2. Review and assemble supplemental databases such as climate and traffic. The agency needs to determine the specific climate and traffic parameters that will best explain performance characteristics and trends for each distress type.

3. Use time-series (historical) PMS distress (cracking, rutting, faulting, IRI) data to develop simple linear regression models for forecasting future pavement performance (i.e., distress and IRI).

4. Estimate for each PMS section the baseline distress levels, which is the distress measured and forecast at the end of a given service life, about 10–15 yr.

5. Perform statistical analysis, which involves the following:

   a. Identify preliminary Pearson's correlations between distress, IRI, and QA test data.

   b. Develop GLMs relating distress, IRI, and QA test data using GLM and stepwise regression statistical techniques. The overall model acceptance should be determined based on the values and criteria of various diagnostic statistics, including overall model's *p*-value, Mallows coefficient, C_p, PRESS statistic, and coefficient of determination R^2. For QA data variables to be included in a specific individual model, selection and acceptance should be based on the significant of the variables and VIF to eliminate multicollinearity. The recommendation is to use significance level of less than 15 percent and VIF less than 10 percent.

   c. Formulate the final model and assess the model's independent QA test data variables' significance and sensitivity to the given distress. A robust model needs to be selected in this step with a significant validation of material behavior. The final model selected should be based on several factors, including diagnostic statistics (R^2, RMSE, COV, VIF, *p*-value) and evaluation of the model's reasonableness.

6. Using this model and the parameters determined as significant to predict performance, develop suitable adjustment factors to the PMS models.

SUMMARY

Federal and State DOTs have achieved significant progress in incorporating advanced location, sensor-based, and imaging technologies in pavement construction and QA testing technologies. The experimental or regular use of these technologies has resulted in the availability of considerable amounts of data that characterize and describe all aspects of the pavement, such as design, materials properties, and condition.

Development of new and improved technologies, such as 4G and 5G mobile networks, cloud-based computing and storage, machine learning, and artificial intelligence, is increasingly making it easier and possible to collect vast amounts of data and analyze it in real time or shortly thereafter.

Thus, new technologies are available to ensure collection of traditional and state-of-the-art QA data, as well as incorporation of these data into an existing agency PMS to enhance performance forecasting. Doing so, however, will require agencies to perform a comprehensive review of current data collection practices (type, referencing system, frequency, reporting standards, and so on) and align these practices with future use. Agencies will also be required to review data storage capabilities, as data storage from existing and new technologies requires several terabytes of storage space annually, and this storage may not be readily available. Finally, analysis of the processing and analyzing of several terabytes of data will require computing capacity that might be beyond what is currently available to agencies. The use of new cloud-based computing methodologies may be a feasible and cost-effective way of overcoming such hurdles.

By carefully considering all the issues presented in these guidelines, agencies may be better prepared for identifying and incorporating QA-related pavement performance leading indicators into their PMS. It must be noted that new technologies and improvements to current test systems are ongoing processes. Thus, new data collection, processing, storage, integration, and analyses systems must be developed in a manner that ensures flexibility and adaptation to future changes in technologies.

ACKNOWLEDGMENTS

The research team thanks several highway agencies and organizations for providing detailed information about their agency practices. These agencies provided specific data and documents that helped the team assess the scope of analyses possible and to develop the case study analyses.

- Arizona DOT.
- Colorado DOT.
- Florida DOT.
- MDSHA.
- Michigan DOT.
- Minnesota DOT.
- Mississippi DOT.
- Oregon DOT.
- Utah DOT.

REFERENCES

1. Govinfo. 2012. "Moving Ahead for Progress in the 21st Century (MAP-21) Act, H.R. 4348" (web page). https://www.govinfo.gov/content/pkg/BILLS-112hr4348enr/pdf/BILLS-112hr4348enr.pdf, last accessed July 1, 2020.

2. Department of Transportation, Federal Highway Administration. 2017. "National Performance Management Measures; Assessing Pavement Condition for the National Highway Performance Program and Bridge Condition for the National Highway Performance Program, 23 CFR Part 490, Federal Register, Vol. 82, No. 11" (web page). https://www.govinfo.gov/content/pkg/FR-2017-01-18/pdf/2017-00550.pdf, last accessed January 21, 2020.

3. Burati, J. L., R. M. Weed, C. S. Hughes, and H. S. Hill. 2003. *Optimal Procedures for Quality Assurance Specifications*. Report No. FHWA-RD-02-095. Washington, DC: Federal Highway Administration.

4. Hughes, C. S. 2005. *State Quality Assurance Programs, A Synthesis of Highway Practice*. NCHRP Synthesis 346. Washington, DC: National Cooperative Highway Research Program.

5. Burati, J. L., R. M. Weed, C. S. Hughes, and H. S. Hill. 2004. *Evaluation of Procedures for Quality Assurance Specifications*. Report No. FHWA-HRT-04-046. Washington, DC: Federal Highway Administration.

6. Rao, C., M. I. Darter, A. Smit, J. Mallela, K. L. Smith, H. L. Von Quintus, and J. Grove. 2006. *Advanced Quality Systems: Guidelines for Establishing and Maintaining Construction Quality Databases.* Report No. DTFH61-05-D-00027. Washington, DC: Federal Highway Administration.

7. Rao, C., A. Smit, and M. I. Darter. 2009. *Case Studies in Analyzing Construction Quality Databases*. Report No. DTFH61-05-D-00027. Washington, DC: Federal Highway Administration.

8. Khandal, P. S., and F. Parker. 1998. *Aggregate Tests Related to Asphalt Concrete Performance in Pavement*. NCHRP Report No. 405. Washington, DC: Transportation Research Board.

9. Christensen, D. W., T. Pellinen, and R. F. Bonaquist. 2003. "Hirsch Model for Estimating the Modulus of Asphalt Concrete." *Journal of the Association of Asphalt Paving Technologists* 72: 97–121.

10. Christensen, D. W., and R. F. Bonaquist. 2006. *Volumetric Requirements for Superpave Mix Design*. NCHRP Report No. 567. Washington, DC: Transportation Research Board.

11. Christensen, D. W. 2008. *Airfield Asphalt Pavement Technology Program Project 04-02: PG Binder Grade Selection for Airfield Pavement*. Kearneysville, WV: Advanced Asphalt Technologies.

12. Von Quintus, H. L., and B. Killingsworth. 1998. *Analyses Relating to Pavement Material Characteristics and Their Effects on Pavement Performance*. Report No. FHWA-RD-97-085. Washington, DC: Federal Highway Administration.

13. Masten, M. 2016. "*Performance Mixes and MnDOT Specification Report*" Presented at the *Aggregate and Ready Mix Association of Minnesota 2016 Convention*. Minneapolis, MN.

14. Rao, C., L. Titus-Glover, B. Bhattacharya, M. I. Darter, M. Stanley, and H. L. Von Quintus. 2012. *Estimation of Key PCC, Base, Subbase, and Pavement Engineering Properties from Routine Tests and Physical Characteristics.* Report No. FHWA-HRT-12-030. Washington, DC: Federal Highway Administration.

15. Von Quintus, H. L., and C. Rao. 2009. *NDT Technology for Quality Assurance of HMA Pavement Construction*. Report No. NCHRP 626. Washington, DC: Transportation Research Board.

16. Applied Research Associates, Inc. 2004. *Development of the 2002 Guide for the Design of New and Rehabilitated Pavement Structures*: *Phase II*. Report No. NCHRP Project 1-37A. Washington, DC: Transportation Research Board.

17. Applied Research Associates, Inc. 2006. *Changes to the Mechanistic-Empirical Pavement Design Guide Software Through Version 0.900*. NCHRP Project 1-40D Research Results Digest. Washington, DC: Transportation Research Board.

18. Applied Research Associates, Inc. 2011. *Recalibration of DARWin-ME Rigid Pavement National Models Based on Corrected CTE Values*. Final Report Project NCHRP 20-07/Task 288. Washington, DC: Transportation Research Board.

19. AASHTO. 2015. *Mechanistic-Empirical Pavement Design Guide: A Manual of Practice*, 2nd ed. Washington, DC: American Association of State Highway and Transportation Officials.

20. Lytton, R. L., F. L. Tsai, S. Lee, R. Luo, S. Hu, and F. Zhou. 2010. *Models for Predicting Reflection Cracking of Hot-Mix Asphalt Overlays*. Report No. NCHRP 669. Washington, DC: Transportation Research Board.

21. Von Quintus, H. L., J. Mallela, R. Bonaquist, C. W. Schwartz, and R. L. Carvalho. 2012. *Calibration of Rutting Models for Structural and Mix Design*. Report No. NCHRP 719. Washington, DC: Transportation Research Board.

22. Applied Research Associates, Inc. 2012. *PaveSpec 4.0*, *Implementation of Jointed Plain Concrete Pavement Performance Related Specification by State Highway Agencies*.

Report No. FHWA DTFH61-08-C-00029. Washington, DC: Federal Highway Administration.

23. Ruiz, J. M., S. Garber, and J. Dick. 2015. *Computer-Based Guidelines for Concrete Pavements*, *HIPERPAV III®, version 3.3 User's Manual*. Report No. FHWA-HRT-14-087. Washington, DC: Federal Highway Administration.

24. FHWA. 2019. "Quality Assurance Procedures for Construction, Federal Highway Administration, CFR Title 23, Part 637, Subpart B, Federal Register" (web page). https://www.govinfo.gov/content/pkg/CFR-2019-title23-vol1/pdf/CFR-2019-title23-vol1-part637.pdf, last accessed in February 2020.

25. Asphalt Institute. 2016. "US State Binder Specification" (web page). http://www.asphaltinstitute.org/engineering/specification-databases/us-state-binder-specifications/, last accessed April 28, 2016.

26. AASHTO. 2001. *Standard Practice for Certifying Suppliers of Performance-Graded Asphalt Binders*. AASHTO R 26. Washington, DC: American Association of State Highway and Transportation Officials.

27. AASHTO. 2017. *Standard Specification for Performance-Graded Asphalt Binder*. AASHTO M 320. Washington, DC: American Association of State Highway and Transportation Officials.

28. Roberts, F. L., P. S. Khandal, E. R. Brown, D. Y. Lee, and T. W. Kennedy. 1996. *Hot Mix Asphalt Materials, Mixture Design, and Construction*. Lanham, MD: NAPA Research and Education Foundation.

29. AASHTO. 2002. *Standard Method of Test for Resistance to Degradation of Small-Size Coarse Aggregates by Abrasion and Impact in the Los Angeles Machine.* AASHTO T 96. Washington, DC: American Association of State Highway and Transportation Officials.

30. AASHTO. 2009. *Standard Method of Test for Determining the Percentage of Fracture in Coarse Aggregates*. AASHTO T 335. Washington, DC: American Association of State Highway and Transportation Officials.

31. AASHTO. 1999. *Standard Method for Test for Soundness of Aggregate by Use of Sodium Sulfate or Magnesium Sulfate*. AASHTO T 104. Washington, DC: American Association of State Highway and Transportation Officials.

32. AASHTO. 2016. *Standard Method of Test for Determining the Plastic Limit and Plasticity Index of Soils.* AASHTO T 90. Washington, DC: American Association of State Highway and Transportation Officials.

33. AASHTO. 2017. *Method of Test for Plastic Fines in Graded Aggregate and Soils by Use of the Sand Equivalent Method*. AASHTO T 176. Washington, DC: American Association of State Highway and Transportation Officials.

34. AASHTO. 2014. *Standard Method of Test for Sieve Analysis of Fine and Coarse Aggregates*. AASHTO T 27. Washington, DC: American Association of State Highway and Transportation Officials.

35. AASHTO. 2005. *Standard Method for Test for Materials Finer than 75-μ (No. 200) Sieve in Mineral Aggregates*. AASHTO T 11. Washington, DC: American Association of State Highway and Transportation Officials.

36. AASHTO. 2013. *Standard Method of Test for Specific Gravity and Absorption of Fine Aggregate*. AASHTO T 84. Washington, DC: American Association of State Highway and Transportation Officials.

37. AASHTO. 2014. *Standard Method of Test for Specific Gravity and Absorption of Coarse Aggregate.* AASHTO T 85. Washington, DC: American Association of State Highway and Transportation Officials.

38. AASHTO. 2017. *Standard Specification for Superpave Volumetric Mix Design*. AASHTO M 323. Washington, DC: American Association of State Highway and Transportation Officials.

39. AASHTO. 2017. *Standard Specification for Stone Matrix Asphalt*. AASHTO M 325. Washington, DC: American Association of State Highway and Transportation Officials.

40. AASHTO. 2018. *Standard Method of Test for Determining the Asphalt Binder Content of Hot Mix Asphalt (HMA) by the Ignition Method.* AASHTO T 308. Washington, DC: American Association of State Highway and Transportation Officials.

41. AASHTO. 2016. *Standard Method of Test for Bulk Specific Gravity (Gmb) of Compacted Hot Mix Asphalt (HMA) Using Saturated Surface-Dry Specimens.* AASHTO T 166. Washington, DC: American Association of State Highway and Transportation Officials.

42. AASHTO. 2019. *Standard Method of Test for Preparing and Determining the Density of Asphalt Mixture Specimens by Means of the Superpave Gyratory Compactor.* AASHTO T 312. Washington, DC: American Association of State Highway and Transportation Officials.

43. AASHTO. 2014. *Standard Specification for Accepting Pavement Ride Quality When Measured Using Internal Profiling Systems*. AASHTO R 54. Washington, DC: American Association of State Highway and Transportation Officials.

44. ASTM. 2020. *Standard Specification for Portland Cement.* ASTM C150-20. West Conshohocken, PA: ASTM International.

45. ASTM. 2019. *Standard Specification for Coal Fly Ash and Raw or Calcinated Natural Pozzolan for Use in Concrete.* ASTM C618-19. West Conshohocken, PA: ASTM International.

46. AASHTO. 2013. *Standard Specification for Fine Aggregate for Hydraulic Cement Concrete*. AASHTO M 6. Washington, DC: American Association of State Highway and Transportation Officials.

47. ASTM. 2014. *Standard Test Method for Potential Alkali Reactivity of Aggregates (Mortar-Bar Method).* ASTM C1260-14. West Conshohocken, PA: ASTM International.

48. AASHTO. 2013. *Standard Specification for Coarse Aggregate for Hydraulic Cement Concrete*. AASHTO M 80. Washington, DC: American Association of State Highway and Transportation Officials.

49. AASHTO. 2019. *Standard Method of Test for Density (Unit Weight), Yield, and Air Content (Gravimetric) of Concrete*. AASHTO T 121. Washington, DC: American Association of State Highway and Transportation Officials.

50. AASHTO. 2011. *Standard Method of Test for Air Content of Freshly Mixed Concrete by the Volumetric Method*. AASHTO T 196. Washington, DC: American Association of State Highway and Transportation Officials.

51. AASHTO. 2018. *Standard Method of Test for Slump of Hydraulic Cement Concrete*. AASHTO T 119. Washington, DC: American Association of State Highway and Transportation Officials.

52. ASTM. 2019. *Standard Test Method for Bleeding Concrete.* ASTM C232-14. West Conshohocken, PA: ASTM International.

53. ASTM. 2016. *Standard Test Method for Time of Setting of Concrete Mixtures by Penetration Resistance.* ASTM C403-16. West Conshohocken, PA: ASTM International.

54. AASHTO. 2017. *Standard Method of Test for Compressive Strength of Cylindrical Concrete Specimens.* AASHTO T 22. Washington, DC: American Association of State Highway and Transportation Officials.

55. AASHTO. 2018. *Standard Method of Test for Flexural Strength of Concrete (Using Simple Beam with Third-Point Loading).* AASHTO T 97. Washington, DC: American Association of State Highway and Transportation Officials.

56. ASTM. 2014. *Standard Test Method for Static Modulus of Elasticity and Poisson's Ratio of Concrete in Compression.* ASTM C469-14. West Conshohocken, PA: ASTM International.

57. AASHTO. 2015. *Standard Test Method for Splitting Tensile Strength of Cylindrical Concrete Specimens.* AASHTO T 198. Washington, DC: American Association of State Highway and Transportation Officials.

58. AASHTO. 2015. *AASHTO T 336 Standard Method of Test for Coefficient of Thermal Expansion of Hydraulic Cement Concrete*. Washington, DC: American Association of State Highway and Transportation Officials.

59. AASHTO. 2017. *AASHTO T 160 Standard Method of Test for Length Change of Hardened Hydraulic Cement Mortar and Concrete*. Washington, DC: American Association of State Highway and Transportation Officials.

60. ASTM. 2016. *Standard Test Method for Microscopical Determination of Parameters of the Air-Void System in Hardened Concrete.* ASTM C457-16. West Conshohocken, PA: ASTM International.

61. ASTM. 2015. *Standard Test Method for Resistance of Concrete to Rapid Freezing and Thawing.* ASTM C666-15. West Conshohocken, PA: ASTM International.

62. ASTM. 2012. *Standard Test Method Scaling Resistance of Concrete Surfaces Exposed to Deicing Chemicals.* ASTM C672-12. West Conshohocken, PA: ASTM International.

63. AASHTO. 2015. *Standard Method of Test for Electrical Indication of Concrete's Ability to Resist Chloride Ion Penetration*. AASHTO T 277. Washington, DC: American Association of State Highway and Transportation Officials.

64. Far, M., B. Underwood, S. Ranjithan, Y. Kim, and N. Jackson. 2009. *Application of Artificial Neural Networks for Estimating Dynamic Modulus of Asphalt Concrete*. Transportation Research Record No. 2127, Washington, DC: Transportation Research Board.

65. Bonaquist, R. 2011. *Effect of Recovered Binders from Recycled Shingles and Increased RAP Percentages on Resultant Binder PG*. Report No. WHRP 11-13. Madison, WI: Wisconsin Department of Transportation. http://wisconsindot.gov/documents2/research/final-reports-proj-briefs/WisDOT-WHRP-project-0092-10-06-final-report.pdf, last accessed April 1, 2016.

66. Asphalt Institute. 1982. *Research and Development of the Asphalt Institute's Thickness Design Manual (MS-1)*, 9th ed. Research Report 82-2. Lexington, KY: Asphalt Institute.

67. Elliott, R. P., and M. R. Thompson. 1985. *Mechanistic Design Concepts for Conventional Flexible Pavements*. Report No. FHWA-IL-UI-208. https://apps.ict.illinois.edu/projects/getfile.asp?id=2866, last accessed April 29, 2016.

68. Christensen, D. 1998. "Analysis of Creep Data from Indirect Tension Test on Asphalt Concrete." *Journal of the Association of Asphalt Paving Technologists* 67: 458–492.

69. Titus-Glover, L., J. Mallela, J. Jiang, M. E. Ayres, and H. I. Shami. 2001. *Assessment of Selected LTPP Material Data Tables and Development of Representative Test Tables.* Report No. FHWA-RD-02-001. Washington, DC: Federal Highway Administration.

70. Wood, S. L. 1992. *Evaluation of the Long-Term Properties of Concrete*. Research and Development Bulletin RD102T. Skokie, IL: Portland Cement Association.

71. American Concrete Institute. 2005. *Building Code Requirements for Structural Concrete and Commentary*. ACI 318-05. Farmington Hills, MI: American Concrete Institute.

72. Bažant, Z. P., S. Baweja. 2000. "Creep and Shrinkage Prediction Model for Analysis and Design of Concrete Structures: Model B3." Presented at the *Adam Neville Symposium: Creep and Shrinkage—Structural Design Effects*, ACI SP–194, ed. A. Al-Manaseer. Farmington Hills, MI: American Concrete Institute.

73. Wimsatt, A. J., T. Scullion, E. Fernando, S. Hurlebaus, R. Lytton, and D. Zollinger. 2009. *A Plan for Developing High-Speed, Nondestructive Testing Procedures for Both Design Evaluation and Construction Inspection*. Report No. SHRP 2-R06. Washington, DC: Transportation Research Board.

74. Zofka, A., M. Chrysochoou, I. Yut, C. Johnston, M. Shaw, S. Sun, J. Mahoney, S. Farquharson, and M. Donahue. 2013. *Evaluating Applications of Field Spectroscopy Devices to Fingerprint Commonly Used Construction Materials*. Report No. SHRP 2-R06B. Washington, DC: Transportation Research Board.

75. Sebesta, S., T. Saarenketo, and T. Scullion. 2013. *Using Infrared and High-Speed Ground-Penetrating Radar for Uniformity Measurements on New HMA Layers*. Report No. SHRP2-R06C. Washington, DC: Transportation Research Board.

76. Flintsch, G., B. Ferne, B. Diefenderfer, S. Katicha, J. Bryce, S. Nell, and T. Clark. 2013. *Assessment of Continuous Pavement Deflection Measuring Technologies.* Report No. SHRP 2-R06F. Washington, DC: Transportation Research Board.

77. Heitzman, M., K. Maser, N. H. Tran, R. Brown, H. Bell, S. Holland, H. Ceylan, K. Belli, and D. Hiltunen. 2013. *Nondestructive Testing to Identify Delaminations Between HMA Layers*, Vol. 1. Report No. SHRP 2-R06D. Washington, DC: Transportation Research Board.

78. Schwartz, C. W., J. S. Khan, G. H. Pfeiffer, and E. Mustafa. 2014. *Radio Frequency Identification Applications in Pavements*. Report No. FHWA-HRT-14-061. Washington, DC: Federal Highway Administration.

79. White, D., and T. Cackler. 2007. *Field Validation of Intelligent Compaction Monitoring for Unbound Materials and HMA*. Report No. MN/RC-2007-10. St. Paul, MN: Minnesota Department of Transportation.

80. Von Quintus, H. L., C. Rao, H. Titi, B. Bhattacharya, and R. English. 2010. *Evaluation of Intelligent Compaction Technology for Densification of Roadway Subgrades and Structural Layers*. Report No. WisDOT SPR# 0092-08-07. Madison, WI: Wisconsin Department of Transportation.

81. Mooney, M. A., R. V. Rinehart, N. W. Facas, O. M. Musimbi, D. J. White, and P. K. R. Vennapusa. 2010. *Intelligent Soil Compaction Systems.* NCHRP Report 676. Washington, DC: National Cooperative Highway Research Program, National Research Council.

82. Chang, G., Q. Xu, J. Rutledge, and S. Garber. 2014. *A Study on Intelligent Compaction and In-Place Asphalt Density.* Report No. FHWA-HIF-14-017. Washington, DC: Federal Highway Administration.

83. Rada, G. R., S. Nazarian, B. A. Visintine, R. Siddharthan, and S. Thyagarajan. 2015. *Pavement Structural Evaluation at the Network Level.* Report No. FHWA-HRT-15-074. Washington, DC: Federal Highway Administration.

84. Yamaura, J., G. White, S. Katara, K. Willoughby, R. Garcia, and M. Beer. 2015. *Project Inspection Using Mobile Technology—Phase II: Assessing the Impacts of Mobile Technology on Project Inspection*. Report No. WA-RD 840.2. Olympia, WA: Washington State Department of Transportation.

85. Darter, S. C., F. Maier, and J. Q. Struthers. 2015. *Final Report: Webinars and Workshops for 3D Engineered Models for Construction*. Washington, DC: Federal Highway Administration.

86. Darter, S., and F. Maier. 2015. *Final Report for Iowa DOT 3D Engineered Models for Construction Workshop*. Washington, DC: Federal Highway Administration.

87. Maier, F., L. E. Chummers, A. Mitchell, and T. Kim. 2017. *Utilizing 3D Digital Design Data in Highway Construction*. Report No. FHWA-HIF-17-031. Washington, DC: Federal Highway Administration.

88. Nasr, E., T. Shehab, and A. Vlad. 2013. “Tracking Systems in Construction: Applications and Comparisons.” Presented at the *49th ASC Annual International Conference Proceedings*. Long Beach, CA: Associated Schools of Construction.

89. AASHTO. 2008. *Guide Specifications for Highway Construction*. Washington, DC: American Association of State Highway and Transportation Officials.

90. Perera, R., S. D. Kohn, and S. Tayabji. 2005. *Achieving a High Level of Smoothness in Concrete Pavements Without Sacrificing Long-Term Performance*. Report No. FHWA-HRT-05-068. Washington, DC: Federal Highway Administration.

91. Belcher, D. 2016. *IT Support and User Training.* Detroit, MI: Michigan Department of Transportation.

92. Flintsch, G., and K. K. McGhee. 2009. *Quality Management of Pavement Condition Data Collection—Synthesis of Highway Practice*. NCHRP Synthesis Report 401. Washington, DC: Transportation Research Board.

93. Miller, J. S., and W. Y. Bellinger. 2014. *Distress Identification Manual for the Long-Term Pavement Performance Program*. Report No. FHWA-HRT-13-092. Washington, DC: Federal Highway Administration.

94. Hudson, W. R., C. L. Monismith, C. E. Dougan, and W. Visser. 2003. "Use of PMS Data for Performance Monitoring with SuperPave as an Example." Presented at the *82nd Annual Meeting of the Transportation Research Board*. Washington, DC: Transportation Research Board.

95. Hughes, C. 1996. *Variability in Highway Pavement Construction.* NCHRP Synthesis Report 232. Washington, DC: Transportation Research Board.

96. Darter, M. I., and S. Rao. 2009. *Impact of Materials and Construction Variability on the Performance of Pavements*. FHWA Report No. DTFH61-05-D-00027, Washington, DC: Federal Highway Administration.

97. Rao, S. P., K. L. Smith, and M. I. Darter. 2007. *Development and Implementation of a Performance-Related Specification for a Jointed Plain Concrete Pavement*. Report No. WI/SPR-01-06. Madison, WI: Wisconsin Department of Transportation.

98. Minnesota Department of Transportation. 2011. *Data Business Plan.* St. Paul, MN: Minnesota Department of Transportation.

99. Blackburn, A. 2015. *Update on Information Technology Strategic Plan.* Tallahassee, FL: Florida Department of Transportation.

100. State of California Department of Transportation. 2011. *Transportation System Data Business Plan.* Sacramento, CA: State of California Department of Transportation.

101. Jahren, C. 2014. "Scan 13-02 Advances in Civil Integrated Management." Presented at the *56th Annual International Highway Engineering Exchange Program, New Orleans, LA*. IHEEP. http://www.heep.org/conference/archive/2014/files/presentations/advances_in_cim.pdf, last accessed October 5, 2016.

102. Goodrum, P. 2015. *Developing a Guidebook for Implementing CIM in Departments of Transportation*. Little Rock, AK: AASHTO Subcommittee on Construction.

103. Hamski, T. 2016. *Iowa DOT's Journey to Enterprise Data.* Saratoga Springs, NY: Federal Highway Administration.

104. Montana Department of Transportation. 2016. *MDT Civil Integrated Management Implementation Plan*. Helena, MT: Montana Department of Transportation.

105. Utah Department of Transportation. 2016. *UDOT Intelligent Design & Construction Mid to Long Term Plan Update—Spring 2016*. Salt Lake City, UT: Utah Department of Transportation.

106. Burns, S. 2016. *Integrated Transportation Solutions*. Lansing, MI: Federal Highway Administration.

107. Hill, C. 2016. "PennDOT develops construction inspection app that will save agency $28 million over 2 years." *Better Roads* (September 19, 2016). http://www.equipmentworld.com/penndot-develops-construction-inspection-app-that-will-save-agency-28-million-over-2-years/?utm_source=daily&utm_medium=email&utm_content=09-20-2016&utm_campaign=Equipment%20World&ust_id=%5B-MD5-%5D, last accessed October 5, 2016.

108. Pennsylvania Department of Transportation. 2015. *Mobile Highway Construction App Improving State Operations*. Harrisburg, PA: Pennsylvania Department of Transportation.

109. Miles, L. 2016. *Construction Administration Management Tools.* Detroit, MI: Michigan Department of Transportation.

110. Al-Qadi, I. L., Q. Aurangzeb, and S. H. Carpenter. 2012. *Impact of High RAP Content on 1 Structural and Performance Properties of Asphalt Mixtures*. Report No. FHWA-ICT-12-2 002. Rantoul, IL: Illinois Center for Transportation.

111. ASTM. 2018. *Standard Test Method for Thickness or Height of Compacted Asphalt Mixture Specimens.* ASTM D 3549-18. West Conshohocken, PA: ASTM International.

112. AASHTO. 2013. *Standard Method of Test for Bulk Specific Gravity (Gmb) and Density of Compacted Hot Mix Asphalt (HMA) Using Automatic Vacuum Sealing Method.* AASHTO T 331. Washington, DC: American Association of State Highway and Transportation Officials.

113. AASHTO. 2014. *Standard Method of Test for Percent Air Voids in Compacted Dense and Open Asphalt Mixtures.* AASHTO T 269. Washington, DC: American Association of State Highway and Transportation Officials.

114. AASHTO. 2014. *Standard Method of Test for Resistance of Compacted Asphalt Mixtures to Moisture-Induced Damage*. AASHTO T 283. Washington, DC: American Association of State Highway and Transportation Officials.

115. AASHTO. 2011. *Standard Method of Test for Determining Dynamic Modulus of Hot Mix Asphalt (HMA) Using the Indirect Tensile Test Device.* AASHTO T 342. Washington, DC: American Association of State Highway and Transportation Officials.

116. AASHTO. 2017. *Standard Method of Test for Determining the Dynamic Modulus and Flow Number for Asphalt Mixtures Using the Asphalt Mixture Performance Tester (AMPT).* AASHTO T 378. Washington, DC: American Association of State Highway and Transportation Officials.

117. AASHTO. 2007. *Standard Method of Test for Determining the Creep Compliance and Strength of Hot Mix Asphalt (HMA) Using the Indirect Tensile Test Device.* AASHTO T 322. Washington, DC: American Association of State Highway and Transportation Officials.

118. AASHTO. 2019. *Standard Method of Test for Hamburg Wheel-Track Testing of Compacted Asphalt Mixtures.* AASHTO T 324. Washington, DC: American Association of State Highway and Transportation Officials.

119. AASHTO. 2010. *Standard Method of Test for Determining Rutting Susceptibility of Hot Mix Asphalt (HMA) Using the Asphalt Pavement Analyzer (APA).* AASHTO T 340. Washington, DC: American Association of State Highway and Transportation Officials.

120. AASHTO. 2017. *Standard Method of Test for Determining the Fatigue Life of Compacted Asphalt Mixtures Subjected to Repeated Flexural Bending.* AASHTO T 321. Washington, DC: American Association of State Highway and Transportation Officials.

121. AASHTO. 2018. *Standard Method of Test for Determining the Damage Characteristic Curve and Failure Criterion Using the Asphalt Mixture Performance Tester (AMPT) Cyclic Fatigue Test.* AASHTO TP 107. Washington, DC: American Association of State Highway and Transportation Officials.

122. AASHTO. 2018. *Standard Specification for Performance-Graded Asphalt Binder Using Multiple Stress Creep Recovery (MSCR) Test.* AASHTO M 332. Washington, DC: American Association of State Highway and Transportation Officials.

123. AASHTO. 2019. *Standard Method of Test for Determining the Rheological Properties of Asphalt Binder Using a Dynamic Shear Rheometer (DSR).* AASHTO T 315. Washington, DC: American Association of State Highway and Transportation Officials.

124. AASHTO. 2019. *Standard Method of Test for Multiple Stress Creep Recovery (MSCR) Test of Asphalt Binder Using a Dynamic Shear Rheometer (DSR).* AASHTO T 350. Washington, DC: American Association of State Highway and Transportation Officials.

125. AASHTO. 2019. *Standard Method of Test for Determining the Flexural Creep Stiffness of Asphalt Binder Using the Bending Beam Rheometer (BBR).* AASHTO T 313. Washington, DC: American Association of State Highway and Transportation Officials.

126. AASHTO. 2019. *Standard Method of Test for Viscosity Determination of Asphalt Binder Using Rotational Viscometer.* AASHTO T 316. Washington, DC: American Association of State Highway and Transportation Officials.

127. ASTM. 2019. *Standard Test Method for Flat Particles, Elongated Particles, or Flat and Elongated Particles in Coarse Aggregate.* ASTM D4791-19. West Conshohocken, PA: ASTM International.

128. ASTM. 2013. *Standard Test Method for Determining the Percentage of Fractured Particles in Coarse Aggregate.* ASTM D5821-13. West Conshohocken, PA: ASTM International.

129. AASHTO. 2017. *Standard Method of Test for Uncompacted Void Content of Fine Aggregate.* AASHTO T 304. Washington, DC: American Association of State Highway and Transportation Officials.

130. AASHTO. 2019. *Standard Method of Test for Air Content of Freshly Mixed Concrete by the Pressure Method.* AASHTO T 152. Washington, DC: American Association of State Highway and Transportation Officials.

131. AASHTO. 2019. *Standard Method of Test for Pavement Deflection Measurements.* AASHTO T 256. Washington, DC: American Association of State Highway and Transportation Officials.

Recommended Citation: Federal Highway Administration, *Quality Assurance Data Analysis as a Leading Indicator for Infrastructure Condition Performance Management* (Washington, DC: 2022) https://doi.org/10.21949/1521712.

HRDI-20/04-22(WEB)E