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

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QUALITY ASSURANCE DATA ANALYSIS AS A LEADING INDICATOR FOR INFRASTRUCTURE CONDITION PERFORMANCE MANAGEMENT

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FHWA Contact: Matthew R. Corrigan (ORCID: 0000-0002-1230-8462), P.E., Office of Infrastructure Research and Development, 202-493-3365, Matthew.Corrigan@dot.gov.

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INTRODUCTION

The Federal Highway Administration (FHWA) and the transportation community have a longstanding goal to improve the performance and extend the life of transportation infrastructure. The Moving Ahead for Progress in the 21st Century Act emphasizes risk-based and performance-based requirements to plan and program the most efficient use of Federal transportation funds. FHWA issued a draft notice of proposed rulemaking in 2015 and a final ruling in 2017 to establish pavement performance measures, targets, and reporting.⁽¹⁾ The ruling defines targets using the performance metrics cracking (percent), rutting (inch), and international roughness index (IRI) (inches/mile) for flexible pavements. The ruling further defines cracking (percent), faulting (inch), and IRI for rigid pavements.⁽²⁾

State highway agencies (SHAs) establish performance targets and measure progress to assess whether they are meeting their targets; they also recognize that routinely collected condition assessment data are a lagging performance indicator. As advanced pavement design methods, sophisticated construction technologies, and digital data collection become the norm, quality assurance (QA) and construction data serve as leading indicators of pavement performance. Those indicators provide the basis for developing performance-related specifications (PRS) for QA and evaluate the impact of deviations from specifications during construction on long-term performance. Construction-stage data offer an opportunity to enhance an SHA's pavement management system (PMS).

This project evaluated whether QA data and other as-built construction data from four SHA databases have a strong correlation to pavement performance. The project explored different data integration and

statistical procedures required to improve performance prediction at both project and network levels. The goal was to develop practical recommendations and best practices to include these data within the pavement management decision-making framework. These data may provide a foundation to evolve, expand, and improve pavement testing and data processing techniques. As SHAs begin to adopt the framework, they will facilitate and encourage the development of pavement testing and data processing methodologies within each SHA.

Case studies demonstrate how using different types of construction and QA data can improve PMS performance forecasting and validate them as leading indicators of performance. This research yields recommendations and best practices to include SHA QA and construction data within the pavement management decision-making framework.

QA FOR PERFORMANCE PREDICTION WITH CONSTRUCTION DATA

The project team reviewed SHA specifications and published literature related to conventional QA procedures and innovative pavement evaluation technologies. QA data typically are available in either QA databases or SHA records. Many of these parameters—including gradation parameters, hot mix asphalt (HMA) volumetrics, density values (lab and field), layer thicknesses, binder type, portland cement concrete (PCC) strength, aggregate type, and PCC mix design index properties—are directly related to future pavement performance. Field data and mechanistic-empirical models, such as the AASHTOWare® Pavement ME, demonstrate that relationship.⁽³⁾ Table 1 and table 2 summarize QA data from HMA and PCC pavement construction and related performance.

Table 1. Generally established relationships between QA parameter and flexible pavement structural performance.

Conventional QA Parameters	Relationship to 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, S , 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, and HMA thickness.	Indicator of cracking and rutting/permanent deformation potential in HMA pavements.
Mix-design gradation, volumetrics.	

RTFOT = rolling thin film oven test; PAV = pressure aging vessel; G^* = complex shear modulus; δ = phase angle; m = slope of the master curve at 60 s.

Table 2. Generally established relationships between QA parameter and rigid pavement structural performance.

Conventional QA Parameters	Relationship to Performance
w/c ratio, cement content, fly ash replacement levels, air content, aggregate gradation, fineness modulus, unit weight, and aggregate absorption capacity.	Indicator of PCC strength and cracking/faulting potential.
PCC compressive/flexural strength, thickness.	Indicator of cracking and faulting potential.
Aggregate type/CTE.	Indicator of cracking due to thermal 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.

CTE = coefficient of thermal expansion; w/c = water to cementitious materials.

Derived Parameters

Past studies derived engineering and performance parameters to characterize materials as a function of material index properties and mix-design variables.⁽⁴⁻⁸⁾

The derived parameters, based on laboratory test results and mechanistic-empirical models, are directly correlated to performance. The upside of those 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 and mix design, offering a stronger correlation to performance than individual QA material properties. For example, derived parameters include the dynamic modulus of HMA layer (figure 1), which is correlated to flexible pavement cracking and other distresses. The resistivity parameter (figure 2) is correlated to rutting. The creep compliance parameter (figure 3) is correlated to transverse cracking. Permeability (figure 4) is associated with stripping and other material issues. The derived parameters in figure 1 through figure 4 are a function of mix volumetrics, aggregate properties, binder properties, and in-place compaction measurements.

Figure 1. Equation. Estimation of HMA dynamic modulus.⁽⁴⁾

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

Where:

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

δ, α = mix-specific fitting parameters.

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

t_r = time of loading at the reference temperature.

Figure 2. Equation. Resistivity parameter correlated to allowable traffic for rutting.^(6,7)

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

Where:

δ, G_{sb} , and VMA relate to mix volumetrics.

S_a = specific surface of aggregate, a gradation parameter combining effect of three sieve sizes.

Figure 3. Equation. Expression to determine creep compliance.⁽⁴⁾

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

Where:

D_1 and m relate to test temperature, mix volumetrics, and binder properties.

t = response time.

Figure 4. Equation. Estimation of permeability based on mix gradation and volumetrics.⁽⁶⁾

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

Where VTM_{Eff} = the effective air void content, a function of in-place air voids.

For this study, the project team used engineering relationships developed in previous studies and approaches adopted for aggregating or clustering QA materials data, 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 surveyed SHAs during 2015 and 2016 to collect QA and PMS database information and to assess their use for studying performance prediction. The SHAs' QA testing programs varied in practice, ranging from the use of conventional tests to use of innovative testing procedures and intelligent construction technologies. The innovative testing procedures included the use of nondestructive technologies. Those devices provide results over either continuous coverage or larger sampling points in a rapid manner and enable contractors to effectively control the process in certain cases. The team reviewed specifications, QA practices, QA data collection, test data storage systems, PMS, condition data collection procedures, and PMS performance forecasting models. The interviews indicated the following:

- SHAs are not set up to fully automate QA and PMS data integration and thus directly integrate QA data variables into a PMS.

- SHAs acknowledge relationships between QA data variables and future pavement performance with empirical evidence.
- SHAs indicate that QA data can be further used when routinely updating construction specifications as well as in a PMS.
- SHAs expressed interest in bridging the gap between construction QA and PMS activities. The reasons for each SHA's interest may vary.
- SHAs recognize the 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.
- SHAs vary in the extent of QA data maintained, the types of data collected, the extent of electronically accessible data, and the methods of storage. The efforts involved in assembling and integrating databases remain unique to each SHA.
- SHAs recognize that data integration that allows mapping performance to QA data by project or by location requires significant effort.

Based on information obtained about datasets that can potentially be used to establish and validate correlations between QA data and performance, the project team selected data from four SHAs for further analyses and performing case studies. The selection of those SHAs enabled a wide range of analyses of different pavement

types, QA parameters, innovative technologies, supplementary database usage in the SHA, and levels and tiers of analyses.

DATA ANALYSES

The project conducted a preliminary analysis to verify if QA and other construction data can:

- be integrated into PMS databases based on location information.
- include parameters known to affect pavement performance.
- be used to calculate cluster parameters.
- show correlations with future distress and IRI development—thus, the data can serve as leading indicators of future pavement performance.
- be integrated into the SHA's PMS for improved pavement performance forecasting.

The project team completed both network- and project-level analyses of three SHA databases to understand the impact of QA parameters on future pavement performance; the team conducted case studies using further data from those three SHAs and an additional SHA. Table 3 summarizes the performance indicators most viable for long-term prediction, based on available data for flexible and rigid pavements and the case studies used for each State. The team identified the QA parameters showing the strongest correlations to performance and having a significant impact on future

Table 3. Summary of analysis types, performance prediction evaluations, and case studies.

State	Rutting	Faulting	Cracking	IRI	Case Study
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.
2	F, N, Q, A F, P, Q, R, W, 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	Correlate data from nontraditional QA/network-level tests to performance.
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	—	Implement improved prediction model in the DOT's PMS.
4	F, P, Q, IC, A [#]	—	F, P, Q, IC, A [#]	—	Demonstrate methods to "indirectly" link modern technologies to performance.

—No data.

= in case study; + = State has functional and structural cracking in pavement management database; A = averages; C = climate data; D = QA derived parameters; DOT = department of transportation; F = flexible pavement type; IC = intelligent compaction data; M = MIT-SCAN; N = network-level analysis; P = project-level analysis; Q = traditional; QA data; R = rigid pavement type; RW = rolling weight deflectometer; T = traffic data; V = coefficient of variation.

performance. The analysis included models aligned with laboratory and field observations in past research studies using QA data items as individual variables and in data clusters.

SHAs need to overcome challenges posed by integrating multiple years of linked data across multiple databases. QA data within an SHA are stored in various unstructured and disconnected databases that are maintained by different departments and personnel. Assembling data from various stages of a project may require significant effort. The data are also archived for different periods. Some electronic data related to projects over a decade old have been converted to hard copies. The various QA data items were aggregated at different levels—from the whole project to specific locations within a project. The level of aggregation has a significant impact on the ability to use the data for performance forecasting. In addition to construction QA and PMS, databases were incorporated into integration procedures that correlate QA and PMS data with their referenced project and location linked.

The statistical procedures adopted included the following steps:

1. Review of data.
2. Development of simple linear regression models for forecasting future performance.
3. Statistical analysis of data to first, identify correlations between given distress and QA test data; second, develop a general linear model (GLM) for each model; and third, formulate the final model.

The set of significant variables (i.e., parameters with a *p*-value less than 15 percent) are tabulated in table 4 and table 5 for HMA and PCC pavements respectively. The values are based on the steps listed above and the variables that were identified as having a strong correlation with pavement distress and IRI. The final research report describes the statistical models and provides the statistics associated with each model.⁽⁹⁾

Table 4. 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 <i>E</i> *	<0.0001	—	—	0.0005	—	—	—	—	—
Mix type (neat/RAP)	—	—	0.1222	—	—	—	—	—	—
PG binder	—	—	0.1222	—	—	0.0169	—	—	—
Traveling speed deflection, <i>d</i>	—	<0.0001	—	—	<0.0001	—	—	<0.0001	—

—No data.

*E** = dynamic modulus of HMA; RAP = reclaimed asphalt pavement.

Table 5. 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	—	<.0001
Sand equivalent	—	<.0001
PCC 7-d compressive strength	—	0.0075
MIT-SCAN (misalignment parameter, S)	—	<.0001

JPCP = joint plain concrete pavement.

Evaluation of Derived Parameters as Indicators of Performance

The statistical analyses performed using the derived parameters as model inputs significantly improved performance predictions. Table 6 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. Based on goodness of fit, the following models improved in many cases: average cracking (remained the same), average rutting, and coefficient of variation (COV) of rutting in State 1; and structural cracking in State 3. The functional cracking model did not improve; derived parameters capture the material parameters affecting the structural cracking mechanism.

Table 6. Summary of goodness of fit using QA data and 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 project team considered a wide range of QA data elements during the statistical analyses. The case studies addressed additional considerations required for an SHA to integrate construction data with PMS. An SHA may decide to include other databases or select nontraditional QA tests and network-level tests and incorporate select parameters into its PMS.

Case Study with State 1 DOT—Using Traffic and Climate Data

State 1 DOT analyses predicted cracking and rutting performance using gradation, mix volumetrics, in-place density, and AASHTOWare Pavement ME level 3-computed dynamic modulus parameters as significant independent variables. The traditional PMS model in an SHA PMS uses only age as a variable. This case study demonstrated the value of integrating other SHA data. State 1 analysis was extended to consider the impact of traffic and climate in addition to conventional QA and construction data, using the model form shown in figure 5 for cracking. The revised model statistics resulted in a 45-percent increase in R^2 , a 17 percent decrease in COV, and an 18-percent decrease in standard error.

Figure 5. Equation. Modified version of PMS cracking prediction model form.

$$CRK = a_0 + \sum_{n=1}^N a_n AGE^n + \sum_{k=1}^K a_k QA^k + \sum_{j=1}^J a_j CLIM^j + Others$$

Where:

$\alpha_0, \alpha_n, \alpha_k, \alpha_i$ = regression coefficients.

AGE = pavement age in years.

CLIM = climate-related variables.

CRK = alligator fatigue cracking.

QA = QA variables.

Others = other variables, such as layer thickness.

Case Studies with State 2 DOT—Using Advanced Test Methods

Data from State 2 DOT were used to evaluate the correlation of a traveling speed deflection testing device—the rolling weight deflectometer-(RWD) based structural condition monitoring data—to HMA performance, as well as data from MIT-SCAN-based dowel misalignment testing to joint faulting within 10 yr of construction.

A rehabilitation project from 2008 on a State highway in State 2 showed high levels of preoverlay distress along the entire segment. RWD test data soon after construction showed higher deflections and lower structural capacity on one segment of the rehabilitation project. Postoverlay fatigue, rutting, and IRI were higher from 2008 to 2013 in this segment, correlating with a measurement from an innovative technology to field performance. After a second overlay in this segment in 2013, the distresses reported were uniform and low along the entire project. Statistical analysis used the model form in figure 6.

Figure 6. Equation. Model form to estimate distress or IRI.

$$\text{Distress or IRI} = \beta_0 + \beta_1 * \delta$$

Where:

Distress or IRI = fatigue cracking or rutting or IRI.

δ = maximum deflection class (<15 mils = low; >15 = high).

β_0, β_1 = regression coefficients.

A second case study with data from eight projects correlated dowel misalignment at the time of construction with performance 6 yr after construction, using the MIT-SCAN. A nonlinear model illustrated the measure of dowel alignment as a potential leading indicator of faulting development. The model form is presented in figure 7.

Figure 7. Equation. Faulting as a function of dowel misalignment.

$$\text{Fault} = \alpha S^\beta$$

Where:

Fault = average transverse joint faulting, inches.

S = dowel misalignment, mils.

α, β = regression coefficients.

Case Study with State 3 DOT—Incorporating Performance Predictions into PMS

This case study demonstrated the ultimate application of the QA data-based performance predictions to PMS data. The study used performance forecasting curves for seven pavement families and demonstrated methods to incorporate data items identified as having a significant impact on pavement performance. The methodology in this case study followed these steps:

1. Identify the pavement type of interest and the performance criteria and determine existing PMS performance forecasting models for the identified pavement types of interest.
2. Determine which QA data items that affect performance can be used as leading indicators of performance.
3. Develop correction factors for the performance forecasting models, using the QA data items identified as leading indicators, and adjust PMS model outputs as needed.
4. 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.

This case study examined the forecasting models for structural cracking index based on QA data, laboratory air voids, HMA binder type, and percent passing $\frac{3}{4}$ -inch sieve, and these variables were deemed significant. The R^2 of the PMS model was 21.9 percent and showed significant bias in predictions based on hypothesis testing that slope = 0. An adjustment factor was developed as a function of binder type, air voids, and percent passing $\frac{3}{4}$ -inch sieve. The revised forecasting model reported R^2 was 50.0 percent and eliminated bias in the predictions.

Case Study with State 4 DOT—Incorporating Data from Intelligent Construction

This case study determined 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. When a relationship is established between HMA density and future pavement performance, then perhaps IC outputs can be incorporated into future pavement performance forecasting models and used effectively for PMS. The results from this case study were inconclusive.

CONCLUSIONS

The research showed promising results supporting the use of QA and construction data as leading indicators of performance prediction. The following are key conclusions:

1. Based on the review of SHA practices, States are not set up to directly correlate QA data with PMS condition data; however, an interest exists within SHAs to complement PMS activities with information from construction.
2. The enhancements in as-built data collection, largely enabled by automation in construction technologies, provide increased scope for facilitating the integration process.
3. The extent and types of material property data in databases vary among SHAs; each SHA uses unique prediction models. Individual analyses were required for each distress type to identify significant variables and develop performance models. Integration of QA databases requires significant effort and a customized effort for each SHA.
4. Statistical models can be developed for the prediction of all distress types identified in the FHWA ruling.⁽²⁾ The following QA data, listed by distress type, were found to be significant:
 - a. Flexible pavement cracking—HMA aggregate gradation, binder type, air voids, density, modulus, or mix type (neat/RAP).
 - b. Flexible pavement rutting—HMA aggregate gradation, binder content, air voids, and modulus.
 - c. Flexible pavement IRI—HMA binder content and air voids (model minimally analyzed).
 - d. Rigid pavement cracking—PCC mix-design index properties, such as w/c materials content, and unit weight.

e. Rigid pavement faulting—PCC mix-design index properties, such as coarse aggregate absorptivity, sand equivalence, and PCC 7-d compressive strength.

6. Innovative technologies used in quality control, construction, and pavement evaluation have the potential to predict long-term performance.
7. The findings of this study are promising and suggest that QA data can be integrated into a State PMS to improve distress prediction models.

GUIDELINES FOR USING QA DATA AS LEADING INDICATORS IN PMS

The following factors shaped the development of these guidelines:

- States have made progress toward adopting digital data collection, narrowing the gap between construction, performance, and asset management. Efforts by States to implement AASHTOWare Pavement ME and PRS for construction provide the impetus for SHAs to set up comprehensive laboratory and field-testing programs to collect material test data directly related to pavement performance.
- QA and construction data as leading indicators of performance can and should gain momentum through these efforts and support pavement management. Guidelines should be part of the progression toward the use of recent technologies to improve existing processes.
- SHAs all collect QA and pavement condition data. Data collection and use vary among SHAs. Guidelines are a set of unified and generalized recommendations.
- Recommendations do not identify the specific QA and construction parameters that will be significant for an SHA to develop performance prediction models; rather, the recommendations can inform guidelines for statistical modeling of data available to the SHA.
- SHAs are at various levels of advancement with their QA testing programs and construction quality database systems. The guidelines address all tiers of QA and construction programs. The guidelines support SHAs that will gradually scale up their QA and construction programs. QA and construction data are categorized under three tiers, shown in table 7.

Table 7. Tiered QA and construction data.

Data Tier	Examples of QA and Construction Data Under Each Tier	Sources, File Formats/Extensions
Tier I (traditional QA test data).	• HMA: density, AC content, voids, gradation, lift thickness, and other derived parameters. • PCC: compressive strength flexural strength, air content, w/c ratio, SCM content, PCC thickness, CTE. • Aggregate: gradation, moisture content, Subgrade resilient modulus, moisture content, fines content. • Pavement: initial IRI • 0.0009	Databases (ACCDB). Spreadsheets (XLSX, CSV). Documents (PDF, TEXT).
Tier II (innovative QA test methods and construction technologies in recent use).	GPR-measured thickness, density measured with a nonnuclear gauge, modulus from nondestructive tests. Magnetic tomography-based scanning for dowel alignment and effective diameter. IC, infrared in-place paving temperature, RWD/FWD from pavement evaluation.	Hierarchical Data Format files, spreadsheets, and databases.
Tier III (emerging QA and construction technologies).	3D construction break lines and 3D construction surfaces, AMPT S_{app} .	CAD data with the following file extensions: DWG, DXF, DGN, LandXML, and TXT. LiDAR data with the following file extensions: LAS, E57. Spreadsheets and databases.

AC = asphalt concrete; AMPT = asphalt mixture performance tester; FWD = falling weight deflectometer; GPR = ground-penetrating radar; S_{app} = fatigue index parameter; SCM = supplementary cementitious materials; 3D = three dimensional; CAD = computer-aided design; LiDAR = light detection and ranging.

GUIDELINES FOR INTEGRATING QA AND CONSTRUCTION DATA INTO PMS

Figure 8 illustrates a framework for integrating QA and construction data with PMS. The guidelines are divided into three parts: recommendations for data collection; recommendations for data processing, conflation, and integration; and recommendations for performance prediction and integration into PMS.

Recommendations for Data Collection

SHA practices in QA and construction data collection have evolved over the years. The data collection recommendations cover best practices for handling legacy data and data from future projects (i.e., the testing parameters) as well as the considerations for integrating data into PMS.

Recommendations for Data Collected to Date in an SHA and Its Use—Legacy Data

Several years ago, as SHAs transitioned from manual to electronic data collection procedures, they designed and developed databases for each material type. Those databases stored test results using limited referencing parameters, and they provided project or contract information, route number(s), lot number, test date, and stationing. Linking databases using spatial mapping was a challenge; such efforts were mostly exploratory

or for research needs. SHAs adopted alternatives to linking databases to combine QA and performance data by project or contract. Generally, legacy data are not amenable for integrating QA and performance databases by test location or at a project level. In the absence of suitable data collection methods, providing relative mapping across different referencing systems may be a challenge. Because SHAs cannot augment existing data to higher levels of data operability, they must consider alternatives to best use all data available and conflate QA performance datasets for immediate use in performance forecasting.

Recommendations for QA Data Collection on Future Projects—Future Data

This research provided two recommendations. First, for future data collection, every QA or construction data record must possess a global location referencing system. The Global Position System (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 data to enable direct correlation. All data collected at the time of construction or pavement evaluation must be mapped to a physical location on the highway; this practice associates every QA data record to a finite and a geospatially specific physical field location.

The second recommendation is to align collection of QA data with PMS data. This recommendation may require equally distributing test sample locations within the construction project area to obtain QA data for each pavement management section. 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. When adopting these recommendations for QA data collection practices, an SHA can continue to use the testing and sampling program in existing specifications and then adopt new test methods in the future.

Recommendations for QA Data Elements to Be Collected for Future Projects

An SHA must consider an extensive number of QA test parameters when establishing QA test specifications that predict pavement management performance. See the full report, *Quality Assurance Data Analysis as a Leading Indicator for Infrastructure Condition Performance Management*, for a complete list of the test properties and associated national test standards for each material type studied.⁽⁹⁾

3D Construction Data Integration for PMS

Performance Prediction

This research determined that the key parameter of interest from 3D construction data is the thickness parameter measured with full project coverage. These data may supplement the thickness that is measured in the field using traditional, location-based core

test data. Contractors have been increasingly using automated machine guidance construction equipment for grading, trimming, and paving that accepts either 3D construction surfaces or 3D break lines to represent the pavement crown and edges. LiDAR data may provide a more accurate representation of each pavement structure layer.

Recommendations for Data Processing, Conflation, and Integration

The project team intends the recommendations in the report to provide SHAs with the information required for making informed decisions regarding data processing, assembly, and integration, internal or external to their current QA databases and PMS programs.

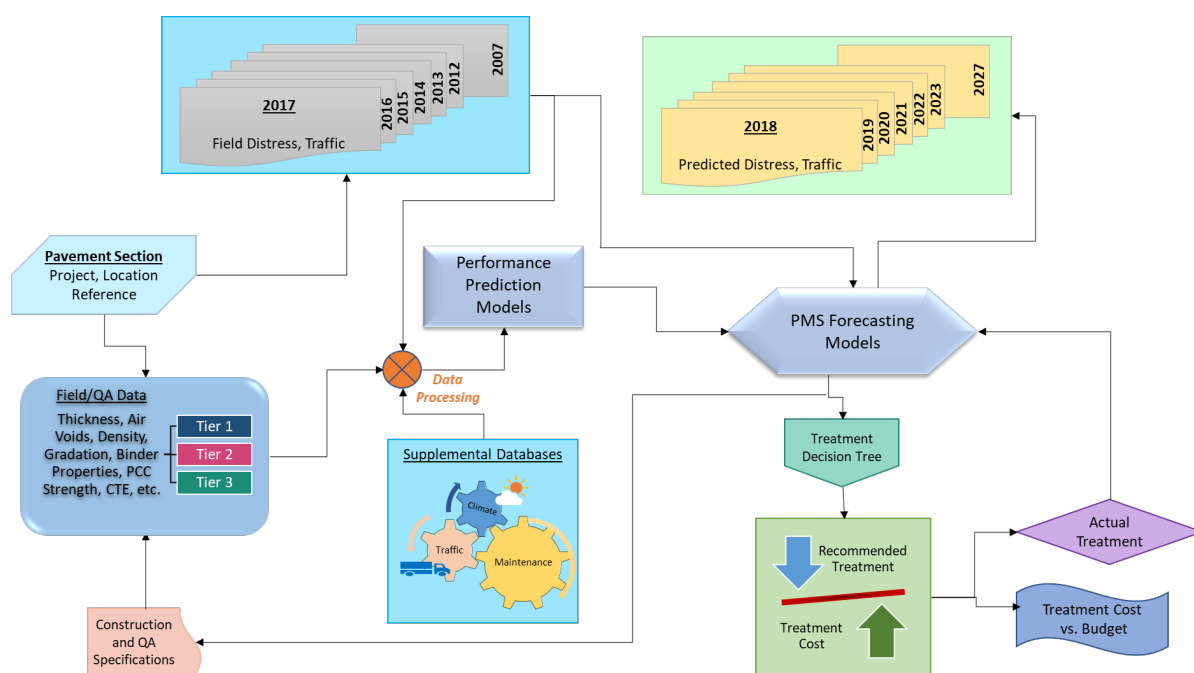
Data Conversion and Ingestion

The data conversion process is one of greatest challenges expected when incorporating QA and construction data-based performance models into PMS. The various data at each tier are available in many electronic formats as well as in hard copies. The data must be extracted from the files and then spatially aligned with the baseline roadway data.

Geospatial Alignment

Refer to construction and QA data by lot, station, or by GPS coordinate and then synthesize the data in a format in which they are geospatially aligned. Perform a spatial join or data conflation at any level of granularity by up-sampling or down-sampling data. 3D construction

Figure 8. Illustration. Proposed integration of QA and construction data as leading indicators of performance for PMS.



Source: FHWA.

data are available only in GPS coordinates that can be tied only to a station identification by using the horizontal alignment of the roadway. Currently available geographic information system software can spatially join different data sources that are georeferenced; however, custom tools or scripts will be needed for spatial alignment of complex data.

Geospatial Referencing

For data referenced by GPS, convert datasets where necessary to ensure that data share the same GPS format and coordinate system. For example, convert the GPS format if two datasets share the same map projection but have different GPS formats.

Discrete vs. Continuous Data

Because of the way SHAs take measurements, develop processes to bin the data as needed into the baseline data. Binning for continuous data usually involves selecting a representative sample for each bin. Binning for discrete data may involve selecting a representative sample or interpolating discrete values between bins.

File Formats

When data are in various formats related to the collection tools or techniques, use conversion tools or processes to parse the relevant data or available metadata. Those conversion tools may be available from an open-source or commercial product, or the SHAs may develop the tools in house. If a data file format is proprietary and cannot be parsed using available tools or documentation, use the software to export the file from the proprietary format to some common interchange file format.

Data Inference

Under certain circumstances, the data may not be explicitly available but can be inferred from available construction information. Select procedures to use data from different functions of the QA program if those data are not already stored in the construction and QA databases.

Recommendations for Performance Prediction

The statistical procedures include the following steps:

1. Review assembled and integrated PMS and QA test databases to ensure that they are accurate and reasonable and then estimate derived parameters from QA test data.

2. Review and assemble supplemental databases, such as climate, traffic, and groundwater depth. The SHA must determine the specific climate and traffic parameters that will best explain performance characteristics and trends for each distress type.
3. Develop simple linear regression models for forecasting future pavement performance using time-series (historical) and PMS distress (cracking, rutting, faulting, IRI) data.
4. Estimate for each PMS section the baseline distress level, the distress measured and forecast at the end of a given pavement service life, about 10 to 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 general linear models relating distress or IRI, and QA test data using GLM and stepwise regression statistical techniques. Determine the overall model acceptance based on the values and criteria of various diagnostic statistics, including the overall model's p -value; the Mallows coefficient, $C(p)$; the predicted residual error sum of squares the predicted residual error sum of squares (commonly referred to as the PRESS statistic); and the coefficient of determination, R^2 . Include QA data variables for a specific individual model, selection, and acceptance based on the data variables' significance level and variance inflation factor (VIF). The project team recommends using a significance level of less than 15 percent and VIF less than 10 percent.
 - c. Formulate the final model and then assess the model's independent QA test data variables' significance and sensitivity to the given distress. Select a robust model in this step with a significant validation of material behavior. Select the final model based on several factors, including diagnostic statistics (R^2 , root mean squared error/standard error, COV, VIF, and p -value) and the evaluation of the model's reasonableness.
6. Develop suitable adjustment factors to the PMS models using this model and the parameters determined as significant to predict performance.

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