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Capitalizing on Construction Records to Identify Relationships between Construction and Long-Term Project Performance: Final Report

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TxDOT keeps records of contracted roadway projects in several databases: materials and test records, collected for the quality control / quality assurance program, in the SiteManager (SMGR) database; construction-related information in the Design and Construction Information System (DCIS); and performance measures in the Pavement Analyst (PA) database. The primary objective of this research was to utilize the vast amount of data in these databases to identify relationships between materials and construction records and observed long-term performance of hot-mix asphalt (HMA) pavements.
Materials, construction records, and pavement surface conditions were analyzed using traditional regression analysis and new-generation data analysis tools. A few selected projects were also chosen for site inspection. The data analysis shows that binder content, binder grade, and recycled binder content influence a pavement's performance for a given service life and traffic volume. Site visits of a selected sample of projects showed that some pavements were treated with overlays that were not captured by the DCIS or PA databases.
Two recommendations are made for TxDOT to continue to benefit from the findings of this research project. These are to implement the integrated database into a software platform already available to TxDOT (e.g., Tableau), and to incorporate elements related to maintenance activities into this integrated database.</td></tr>
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Abstract

TxDOT keeps records of contracted roadway projects in several databases: materials and test records, collected for the quality control and quality assurance program, in the SiteManager (SMGR) database; construction-related information in the Design and Construction Information System (DCIS); and performance measures in the Pavement Analyst (PA) database. The primary objective of this research was to utilize the vast amount of data in these databases to identify relationships between materials and construction records and observed long-term performance of hot-mix asphalt pavements.

An internal working data repository was built integrating the SMGR, DCIS, and PA databases. Materials, construction records, and pavement surface conditions were analyzed using traditional regression analysis and new-generation data analysis tools. A few selected projects were also chosen for site inspection. The data analysis shows that binder content, binder grade, and recycled binder content influence a pavement's performance for a given service life and traffic volume. Site visits of a selected sample of projects showed that some pavements were treated with overlays that were not captured by the DCIS or PA databases.

Two recommendations are made for TxDOT to continue to benefit from the findings of this research project, particularly in light of the recent increase in use of relatively newer mixes (e.g., superpave mixes from item 344), which is expected to continue. These are to implement the integrated database into a software platform already available to TxDOT (e.g., Tableau), and to incorporate elements related to maintenance activities into this integrated database.

Executive Summary

The study of the effects of material properties on long-term pavement performance requires a significant amount of time and extensive resources, as pavement performance needs to be measured and documented on a regular basis for years. As part of its quality control and quality assurance (QC/QA) process, TxDOT maintains pavement-related data in several databases: mixture design and QC/QA data in SiteManager (SMGR); construction, bid, and project-related information in the Design and Construction Information System (DCIS); and pavement performance history in the Pavement Analyst (PA) database. Even though a significant amount of information is available in these databases, these data have not been fully utilized to study the effect of material design factors and QC/QA efforts on long-term project performance. The primary objectives of this study are to utilize these databases to identify (i) materials and construction practices that affect the long-term performance of hot-mix asphalt (HMA) pavements; (ii) gaps in the existing data management systems; and (iii) potential modifications or best practices that will lead to TxDOT getting more value for money spent over a pavement's life.

An internal data warehouse was developed, integrating the materials properties collected for QC/QA purposes. Materials data and project location, length, and construction date were collected from TxDOT's SMGR database. Pavement performance, manifested in the form of surface distresses including cracking and rutting, as well as performance measures, such as international roughness index (IRI) and condition score (CS), were collected from the PA database. Several traditional regression analysis tools as well as new computational data analysis tools were used to analyze the results. The effect of materials properties, including the binder content, binder grade, aggregate absorption, mix type, and recycled binder content, on the performance indices such as rutting, cracking, CS, and IRI was studied. Based on the materials information collected from the SMGR database and performance reported in the PA database, thirteen projects from the dense-graded HMA mixture (specification item 341) were selected as a sample for site inspections.

Analysis from this study shows that asphalt content, binder grade, recycled binder content, and aggregate absorption are the notable materials characteristics that influence long-term pavement performance measured in terms of IRI and CS. Limits could be set on these parameters for a given service life and traffic volume for improved pavement performance. More than one standard for the PA data recording system have been found, creating artificial data sparsity. Some of the results from the unified database were consistent with field observations, whereas many surfaces were found with crack sealants, chip seal, or overlays. The discrepancies between the site inspection and PA performance measures indicate that the “well performing” pavement sections were only rated as such because of the maintenance activities that were not captured by this database.

An integrated approach or methodology that incorporates the maintenance activities in addition to the construction and performance information needs to be adopted to obtain an accurate account of the total cost of a pavement section. The researchers recommend that the unified data repository be encoded with a commercial system that is already available to TxDOT for easy visualization, accurate accounting of total dollars spent, and tracking of materials, maintenance, and performance history. They expect that implementation of such a tool will significantly improve current business processes related to construction and material inspection and management of pavements.

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CHAPTER 1. INTRODUCTION AND LITERATURE REVIEW

1.1 INTRODUCTION

To manage materials and construction related information, and performance characteristics for roadway projects, TxDOT maintains several databases: materials and tests related information in the SiteManager database for quality assurance purposes, project related information in the Design and Construction Information System, and long-term performance information in the Pavement Analysts database. The overarching goal of this project is to capitalize on these existing construction records and field performance data to identify systemic factors associated with material specifications, structural design, and construction that can be improved or emphasized to ensure long lasting pavements in the state of Texas. To achieve this goal, the study was performed through the following major tasks

- conducting a comprehensive review of the literature,
- extracting data from different TxDOT databases and develop and internal working data repository,
- analyzing results through site inspections, and
- providing recommendations for implementations.

The report is organized according to the above tasks and objectives.

1.2 EXISTING LITERATURE

The purpose of this part of the study was to synthesize the current knowledge on the utilization and exploration of data by other agencies to achieve similar goals, the data sources retained and populated by the Texas Department of Transportation (TxDOT), and existing data analysis techniques available in the literature that can be used to achieve such goals. The entire report is divided into four sections:

- Synthesis of literature to document the latest developments in the area;
- Exploration of current practices in other state DOTs to understand their practices on capitalizing of construction and quality control/quality assurance (QC/QA) data to improve long-term pavement performance;
- Examination of available data sources at TxDOT to identify the available data and data sources; and
- Identification of viable data analysis techniques and/or tools relevant to the project.

The primary goal of these tasks was to identify the most important data fields influencing the long-term pavement performance and the most viable analysis tool(s) to establish the relationship between them. The scope of this study is restricted to the construction and performance of flexible pavements, and as such information pertaining to the construction of hot mix asphalt (HMA) pavements is presented here.

There have been several studies that utilized data driven models to predict the expected performance of a pavement structure or pavement materials. In fact, the 1993 AASHTO flexible pavement design method was based entirely on an empirical approach that compared the performance of several different pavement structures in a systematic large-scale field experiment. Since then, a few other examples of studies have utilized data-driven approaches to predict pavement or material performance, including studies that were conducted: 1) to develop a pavement performance model using field performance data (Hand et al., 1999); 2) to evaluate the relationship between material and construction variables and pavement performance using back-propagated neural network (BPNN) model (Choi et al., 2004); and 3) in more recent efforts, to use artificial neural network (ANN) to predict Superpave mixture volumetrics (Ozturk and Kutay, 2014). Hand et al. (1999) used linear regression to relate present serviceability index (PSI) with pavement age, traffic, material properties (percent mineral filler), and environmental conditions (maximum average yearly air temperature, minimum average yearly air temperature, total number of wet days per year, number of freeze-thaw cycles), where pavement performance models were developed for mill and overlay (where the surface of asphalt concrete layer is milled before overlay) and overlay rehabilitation treatments (where an overlay of specified thickness is applied for rehabilitation). As part of their study, traffic, climatic, and performance indicators were extracted from the Nevada DOT's PMS database and structural number, material types, and pavement age were obtained from the historical database.

Ozturk and Kutay (2014) used an ANN model to predict volumetric properties of a mix, such as percent of air voids at minimum, design, and maximum number of gyrations and the theoretical maximum specific gravity of the loose mixture. As input parameters they used the gradation of the mix, bulk specific gravity of aggregates (G_{sb}, low and high performance grade (PG) of the binder, binder content ($ac\%$) of the mix and the target number of gyrations at initial (N_{ini}), design (N_{des}) and maximum (N_{max}) for about 1800 Superpave mix designs from HMA pavements constructed between 2008 and 2010 by Nebraska DOT.

Choi et al. (2004) studied pavement sections on which no major rehabilitation was applied from three states: Texas, New Mexico, and Arizona. They compiled 20 different paving projects from the Long-Term Pavement Performance (LTPP) database containing 117 rows and filtered them for the climate Region (Wet No Freeze and Dry No Freeze), Average Daily Truck Traffic (400 - 800), and Functional Class (rural principal arterial of interstate and rural principal arterial of others). They reviewed three types of models: 1) fundamental mixture response variables (FMRV) prediction model (Anderson et al., 1990); 2) singular distress indicator (Roberts et al., 1996); and 3) composite performance indicator (Lee et al., 1993) to select a number of input variables that include percent passing No. 200 sieve, percent air void, asphalt content, cumulative ESAL, structural number, and total asphalt layer thickness. Among these variables, they studied the effect of percent passing No. 200 sieve, percent air void, asphalt content, and total asphalt layer thickness on pavement performance measured in terms of international roughness index (IRI) using a BPNN algorithm and showed that the selected attributes have significant influence on IRI.

Another study on the LTPP data by Chen et al. (2016) analyzed various types of pavement distresses and influence factors, such as age, layer thickness, material type, weather and traffic data to estimate distress condition index using a compound statistical approach that employs multiple regression analysis.

Schmitt and others developed a database template for the Wisconsin DOT to perform pavement performance analysis using the design, construction, and performance data for HMA pavements (Schmitt et al., 2007). They also investigated several statistical methods, including analysis of variance (ANOVA), comparison of means, and regression models, in establishing relationships between the design, construction, and performance data (Schmitt et al., 2007, 2006).

1.3 CURRENT PRACTICES BY OTHER DOTS TO LEVERAGE CONSTRUCTION AND PAVEMENT PERFORMANCE DATA

Efforts by several DOTs in capitalizing construction records for long-term pavement performance are summarized in this section. Hand et al. (1999) used linear regression and Nevada DOT's pavement management system (PMS) database to relate present serviceability index (PSI) to pavement age, traffic, materials properties, and environmental condition. Yang and colleagues used artificial neural networks (ANNs) to develop a pavement performance model for the PMS used by the Florida Department of Transportation (FDOT) (Yang et al., 2003), where FDOT's pavement condition data, such as age, crack index, rut index, ride index, and maintenance cycle, were employed to train and test the ANN model.

Schmitt and others developed a database template for the Wisconsin DOT to perform pavement performance analysis using the design, construction, and performance data for HMA pavements (Schmitt et al., 2007). They also investigated several statistical methods, including analysis of variance (ANOVA), comparison of means, and regression models, in establishing relationships between the design, construction, and performance data (Schmitt et al., 2007, 2006).

In addition to reviewing existing literature on this topic, the research team also contacted subject matter experts of several state DOTs in the U.S. and researchers from different states, including California Department of Transportation (CalTrans), Louisiana Department of Transportation and Development (LaDOTD), and University of Maryland. CalTrans utilized data analysis techniques to track commonly used rehabilitation and maintenance strategies, their application frequency, and the associated cost for both the flexible and rigid pavements. LaDOTD, on the other hand has a PMS database but not a comprehensive system of logging construction records. Based on the information collected, from these state DOTs, none of them have reported any extensive / in-depth studies that identify relationships between the construction records and long term pavement performance.

1.4 TXDOT DATABASES

The use of multiple TxDOT databases is critical to achieve the stated goals of this study. These databases will be used to extract project-related information to investigate the impact of materials and construction practices on the long-term performance of asphalt mixtures and flexible pavements. A thorough understanding of these databases is necessary to connect relevant information that exists in different databases and draw meaningful conclusions in the support of the overall goal of this study. The following sections describe these databases.

1.4.1 SiteManager

The TxDOT SiteManager database is a comprehensive record of material, design, and construction quality control and assurance (QCQA) information collected on all contracted (both construction and maintenance) projects constructed by TxDOT. This database is composed primarily of the HMA information collected from projects that include specification Items 340/341 dense-graded, 342 permeable friction course (PFC), 344 performance designed (e.g., Superpave), 346 stone matrix asphalt, 347 thin overlay mixes (TOM), and 348 thin bonded wearing courses, and those constructed under special specifications including crack attenuating mixtures. The database traditionally comprised HMA items per the TxDOT 2004 book and was recently updated to include 2014 specification items. A distinction is made between mix design information and QCQA data collected during construction. These information types are collected from separate templates, and indeed, it is possible that the same mix design could be used on multiple different projects. The database includes a referencing system that allows linking of different database tables within SiteManager. It is this referencing system that can be used to extract material and design information for an HMA project and ultimately link it to performance information.

1.4.1.1 Mix design

Pertinent HMA material and mix design information in SiteManager is updated from mix design templates, previously for 2004 (TX2MIXDE4), now for 2014 (TX2MIXDE14) specification items. The mix design template is essentially an Excel-based spreadsheet application that is completed by the HMA contractor/supplier that must be approved by TxDOT. It serves to establish the job-mix formula for the HMA project in terms of design gradation and asphalt binder content.

1.4.1.2 Quality control and quality assurance (QCQA)

QCQA data collected during construction on HMA projects is input into a separate Excel template, previously TX2QCQA04 for 2004 specification items and currently TX2QCQA14 for 2014 specification items. Data in these templates are collected by both TxDOT and contractors on a sub-lot basis. Each template represents data collected on a lot comprising four sub-lots. The QCQA templates are used to calculate the contractor's payment for the lot, which for some specification items is multiplied by a pay factor; this pay factor is a function of the production quality controlled via lab-compacted density of the mix and the placement quality controlled via the air void content of the compacted mat. Contractors can receive a bonus for high quality construction. It is important to emphasize that this bonus ensures that the approved mix design is replicated in the field during construction. The question remains, however, whether this translates to improved performance and extended service life. This is because current quality measures only ensure that a laboratory mix design is replicated in the field as intended, but the laboratory mix design itself may be inherently prone to poor long-term performance due to gaps in the design method or practices.

For QC/QA purposes, laboratory testing of asphalt mix samples is performed for both production and placement on a lot-by-lot basis. Each lot contains four sublots and samples are taken randomly from each sublot for laboratory testing. Both TxDOT personnel and contractors record QC/QA information in Excel based spreadsheet templates. Data logged in the spreadsheet are then uploaded into the SMGR database server. This database contains two tables: 1) CCSJ table and 2) QC/QA table. A summary of these two SMGR tables and the corresponding data fields is presented in Table 1.1.

The CCSJ table of the SMGR database contains data fields required for identifying a project, its executed items, and identification numbers for all the samples collected as part of the QC/QA. The CONT_ID is a unique identification number for an individual contract whereas PRJ_NBR indicates the corresponding project. Each contract assigned to any individual contractor may consist of more than one project. Hence, a project can be uniquely identified by a combination of the CONT_ID and PRJ_NBR.

Table 1.1. Typical SiteManager database contents (Buddhavarapu et al., 2014; Texas Department of Transportation, 2005).

	Field	Description
CCSJ Table	CONT_ID	Control section job number
	PRJ_NBR	Project control number
	LN_ITM_NBR	Line item number
	SMPL_ID	Sample identification number
QC/QA table	SMPL_ID	Sample identification number
	TST_METH	Test method applied
	SMPL_TST_NBR	sample test number
	FLD_NBR	Field reference number
	FLD_VAL	Field value

1.4.1.3 Performance test for HMA mixtures

All TxDOT designated test data required for HMA QC/QA are recorded in the SMGR database system. All TxDOT data relevant to the mix designs used in flexible pavements are also recorded in the SMGR database. The mix design and QC/QA data contain information from different laboratory test methods that are relevant to the expected performance of the asphalt mixtures. Some of these tests related to this project include indirect tensile strength test (TX226) to determine tensile strength, Hamburg wheel-tracking test (TX242) to determine rutting susceptibility, Cantabro loss (TX245) to determine durability of the porous friction course, and overlay test (TX248) to determine cracking resistance. The test results associated with a mix design that is used as the basis for any given QC/QA sample can be extracted from the SMGR database using their corresponding test methods (TST_METH) provided in parentheses. These test results are more relevant for the purposes of this study because these methods and concomitant metrics are being used as an indicator for long-term performance of the pavements. This study offers the opportunity to validate the efficacy of these indicators based on actual long-term performance of pavements across the state of Texas.

QC/QA table consists of the data fields necessary for storing information collected during construction. SMPL_ID data field provides the key for connecting this table with the previously described CCSJ table. Based on the construction year, multiple templates are used for collecting QC/QA information, which are indicated by the TST_METH data fields. In addition, FLD_NBR presents each individual cell for a specific spreadsheet template, and FLD_VAL identifies the input value entered either by TxDOT personnel or the contractor into the specified FLD_NBR cell. Thus, TST_METH, FLD_NBR, and FLD_VAL are required to specify a unique cell value from a specific QC/QA table. SMPL_TST_NBR indicates the lot number; which distinguishes the QC/QA information of any two samples from dissimilar lots (Buddhavarapu et al., 2014).

1.4.2 Pavement Analyst (PA)

To monitor the condition of roads in Texas, TxDOT annually collects distress data on the entire roadway network. The data for HMA or flexible pavements include annual automated and visual assessments of rutting, cracking, and roughness. The Pavement Analyst (formerly known as the Pavement Performance Information System) database also includes friction measurements covering the network on a biennial basis. This is a comprehensive database with historical data of roadway performance. In addition to performance measures, PA also provides a breakdown of the traffic on the road sections for which performance is reported in terms of 18-kip axles, which is a surrogate measure of equivalent standard axle loads and average annual daily traffic. A number of selected data fields captured by PA database are presented in Table 1.2.

PA reports performance measures along the roadway in roughly 0.5-mile segments defining data collection sections (Texas Department of Transportation, 2016). The location of these PA sections on the TxDOT network is by reference marker or specifically Texas reference marker (TRM). Every performance measure in PA is accompanied with a beginning and ending reference marker and associated displacements from these reference markers.

Table 1.2. A few selected data fields of PA database related to the project (Texas Department of Transportation, 2003).

PA data collection	Annual average daily traffic 18-kip equivalent single axel load (ESAL) Fiscal year Beginning and Ending reference marker numbers
PA condition summary	Fiscal year Beginning and Ending reference marker numbers Signed highway roadbed ID Distress score Condition score Ride score Left and right IRI Rut depth Alligator cracking Block cracking Transverse cracking Patching

About 39 different fields are recorded by the PA data collection section table that describe the section characteristics. These characteristics include section location information such as district, county, and route number. Traffic information such as 18-kip equivalent single axel load (ESAL) value, annual average daily traffic (AADT), maintenance cost, and pavement type are some of the noteworthy data fields. The number of 18-kip ESAL values is represented using the CURRENT-18KIP-MEAS data field. AADT is the average daily estimate of the number of vehicles on all the lanes in a single direction for divided facilities and includes traffic on all the lanes in both directions for frontage and undivided roads (Buddhavarapu et al., 2014; Texas Department of Transportation, 2003). AADT-CURRENT data field reports the maximum AADT value published for a given stretch of test section.

PA condition summary table captures 47 different fields related to the performance of the test section in terms of specific distresses (Buddhavarapu et al., 2014). Some of data fields relevant to this project are listed in Table 1.2. Definition from the TxDOT's PA data dictionary of these data fields are given below (Texas Department of Transportation, 2003).

Fiscal year records the year in which the data were collected. Signed highway roadbed ID comprises of route name, route number, and road bed constituting a highway section. Beginning and ending reference marker numbers are the nearest Texas Reference Markers (TRMs) for beginning and ending of the section, respectively (Buddhavarapu et al., 2014; Texas Department of Transportation, 2003). Both the fiscal year and location information such as beginning and ending reference markers are common to both the data collection table and condition summary table, and hence can be used as primary keys to link fields from these tables.

Distress score represents the extent of surface distress (such as cracking, patching, rutting, etc) on the data collection section. It is calculated by multiplying utility values for each distress evaluated on a pavement type and varies between 0 (most distressed) and 100 (least distressed). The utility value represents the value of service provided by the damaged pavement section. This value varies from 0.0000 (worst) to 1.0000 (best). Ride score describes the overall ride quality of the data collection section and varies between 0.1 (roughest) to 5.0 (smoothest). Condition score defines the overall condition of the data collection section. It includes both the surface distress and ride quality and ranges from 1 (worst) to 100 (best). Condition score is a function of distress score and the ride score and expressed as

$$\mathrm{CS} = \mathrm{DS} \times \mathrm{U} \tag{1.1}$$

where: CS = condition score; DS = distress score; U = ride quality utility factor computed based on three traffic classes determined by a product of ADT and speed limit

$$\mathrm{U} = 1.0 - \alpha \mathrm{e}^{-\left((\rho/L_i)^{\beta}\right)} \tag{1.2}$$

where: α = horizontal asymptote factor that controls the maximum amount of utility that can be lost; β = slope factor that controls how steeply utility is lost in the middle of a curve; ρ = prolongation factor that controls how long the utility curve will last above a certain value; L_i = normalized ride quality, based on the percentage of ride quality lost.

For low traffic $((\mathrm{ADT} \times \text{speed limit}) <= 27,500)$

$$\begin{aligned} &L_i = 0, \text{ when ride score} >= 2.5 \text{ and} \\ &L_i = 100 \times ((2.5 - \text{ride score})/2.5), \text{ when ride score} < 2.5 \end{aligned} \tag{1.3}$$

For medium traffic ((ADT $\times$ speed limit) between 27,500 and 165,00)

$$\begin{aligned} L_i &= 0\text{, when ride score} >= 3.0 \text{ and} \\ L_i &= 100 \times ((3.0 - \text{ride score})/3.0)\text{, when ride score} < 3.0 \end{aligned} \tag{1.4}$$

For high traffic ((ADT $\times$ speed limit) $> 165,000$)

$$\begin{aligned} L_i &= 0\text{, when ride score} >= 3.5 \text{ and} \\ L_i &= 100 \times ((3.5 - \text{ride score})/3.5)\text{, when ride score} < 3.5 \end{aligned} \tag{1.5}$$

For $L_i = 0$, U is set 1.0. Left and right IRI describe the average IRI value on the left and right wheel paths, respectively. Rutting is categorized in four categories - shallow, deep, severe, and failure - depending on the rut depth and is reported as the average percentage of individual categories for all measured data. Shallow rut represents the percentage of the shallow rutting (ranges between $0.25 - 0.49$ inches) in a given data collection test section. Similarly, deep and severe ruts represents the percentage of the deep (between $0.50 - 0.99$ inches) and severe (from 1.00 to 1.99 inches) rutting in a given data collection test section (Texas Department of Transportation, 2003, 2016). When rut depth exceeds 2.00 inches, it is deemed failure. The pavement is considered to fail when rut depth exceeds 2.00 inches. Block cracking is reported as the percentage of lane area with block cracking in the measured lane of the data collected section and ranges from 0 to 100%. Alligator cracking is indicated as the percentage of the rated lane's total wheel path area that is covered with alligator cracking. It is also reported between 0 and 100%. Transverse cracking is defined as the number of transverse cracks per station in the rated lane of the data collection section. The reported vales range from 0 to 99 per station, where each station is 100 ft long. Patching defines the percentage of lane area with patching in the rated lane of the data collection section (Texas Department of Transportation, 2003, 2016).

1.4.3 Design and Construction Information System (DCIS)

To investigate the influence of material properties on pavement performance, it is necessary to link the SiteManager and PA databases. The TxDOT DCIS database provides this link. The DCIS database provides a listing of all contracted projects constructed by TxDOT. This is an administration tool used to track the progress and payments made on projects and to track change orders. It also provides location information that can be used to link SiteManager data with performance information in the PA. All contracted projects in DCIS are given a unique identifier, called the control-section-job or CSJ number. This CSJ number is also used to identify projects in SiteManager. DCIS furthermore reports the reference marker extents of projects that allows locating the extents of the project within the PA database. The DCIS database comprises five tables: 1) Bid, 2) Project, 3) Proposal, 4) Item List, and 5) Districts and County (Buddhavarapu et al., 2014). A summary of the first four tables and the corresponding data fields is presented in Table 1.3. A brief description of each data field is provided below. Bid table logs CONTID, a unique number to identify each construction contract approved by TxDOT. VENDOR identifies the contractor involved with the assigned contract. The ITEM field records the item numbers specified by the TxDOT specifications. CONTID and ITEM are two primary data keys that provide meaningful connections between different tables, and important information can be extracted using these primary keys. In addition to these fields, the planned quantities and the offered bid prices for each individual construction item are also recorded by the bid table (Buddhavarapu et al., 2014).

Project-specific information such as description of the project and its location information, including county; district; route name; and beginning, mid, and ending stations are stored in the project table. The change in specifications over time is recorded by the ISPECYR data field and can be linked with the item number (ITEM) in the bid table using CONTID. Proposal table reports information related to all TXDOT proposals. Description of the Counties and Districts that are represented by number, can be obtained from the District and County tables (Buddhavarapu et al., 2014).

Item table captures the description and the specification year for each item and uses IDESCR field to describe those items listed within a given project. Lastly, the quantity of each item is recorded by IUNITS field.

1.4.4 Compass database system or Maintenance Management Information System (MMIS)

SMGR only manages contracted projects. In-house maintenance and rehabilitation projects undertaken by TxDOT crews are managed with the Compass database system (previously the Maintenance Management Information System (MMIS)). Calculating the service life of a pavement is not trivial. TxDOT does not allow its pavements to deteriorate to failure; cracks are filled and potholes are patched as soon as these are apparent. Thus, attempts to correlate material or pavement design information to performance score of the pavement can result in inaccurate conclusions because the performance score is controlled via routine maintenance efforts. Therefore in many cases the pavement performance score can provide misleading results. In such cases, the extent of maintenance activity that a specific pavement section required after construction can serve as a good surrogate for pavement performance. However, even this parameter must be used with caution. For example, some TxDOT districts apply rehabilitation on a regular basis, wherein a seal coat or HMA surface layer will be overlaid every 7 years, regardless of the condition of the surface. Attempts to track the service life of some pavements is not always possible since a section of roadway that was originally contracted under DCIS could well be maintained by in-house crews at a later stage.

Table 1.3. Tables and fields of DCIS database system (Buddhavarapu et al., 2014).

Table name	Field	Description
Bid	CONTID	Project number (control-section-job (CSJ))
	VENDOR	Vendor number
	ITEM	TxDOT specification number
	BTUPRICE	Pricing per unit quantity
	BTOQTY	Unit quantity
Project	CONTID	Project number (CSJ)
	PJDESC1	Project description
	ISPECYR	Specification year
	COUNTY	Project county nunber
	PJDISTR	Project district nuber
	PJROADNM	Road (route) name
	PJBTERMI	Begining termini
	PJETERMI	Ending termini
	PJBSTATN	Begining station
	PJESTATN	Ending station
	PJLENGTH	Project length
	PJXCOORD	Longitude of midpoint
	PJYCOORD	Latitude of midpoint
Proposals	CONTID	Project number (CSJ)
	ISPECYR	Specification year
	CNDISTR	Primary district
	COUNTY	County number
	CNRDSYS	Road system
	CNROUTE	Route
	CNDTLET	Letting date
	CNDTSTRT	Estimated starting date
	CNDTCPE	Estimated completion date
	VENDOR	Contracted vendor
	UNITSYS	Measurement system (English or metric)
Item list	ITEM	Item number
	ISPECYR	Specification year
	IDESCR	Item description
	IUNITS	Quantity unit

1.5 EXISTING DATA ANALYSIS TOOLS

1.5.1 Traditional statistical methods

Several statistical methods, including analysis of variance (ANOVA), comparison of means, and regression models, are effective in establishing relationships between the design, construction, and performance data (Schmitt et al., 2007, 2006). A summary of some common statistical tools with specific applications are briefly described in this section.

1.5.1.1 Sample size determination

To conduct meaningful statistical analysis, there is a required minimum sample size which can be calculated by the following two equations Schmitt et al. (2007):

$$n = \left(\frac{t(s)}{PREC}\right)^2 \text{ for } n < 30 \tag{1.6}$$

$$n = \left(\frac{z(\sigma)}{PREC}\right)^2 \text{ for } n > 30 \tag{1.7}$$

where: n = required sample size; t = standard sample variate with significance level α for a one-sided test or $\alpha/2$ for a two-sided test; s = sample standard deviation; $PREC$ = desired level of precision; z = standard normal variates with significance level α for a one-sided test or $\alpha/2$ for a two-sided test; σ = assumed known or reasonably well known standard deviation.

The decision of which equation to use depends on whether the population parameters, e.g., population mean and population standard deviation, are unknown. However, the population parameters are rarely known. Therefore, the most commonly used equation is for the case that the population parameters are unknown and uses the sample parameters in the equation. When the sample size is small, it is important to apply this method before conducting other statistical analysis. Otherwise, it is possible that the results of other statistical analysis are not statistically meaningful.

1.5.1.2 Confidence interval

Because of the variability of the variables, the estimated value is the mean of possible true values. The true value of that variable can fall into the range of values with a certain confidence, and this range of value is the confidence interval which is calculated by the chosen confidence, variability of that variable, and sample size.

The confidence interval provides information about the range of the estimated value based on a selected level of confidence, i.e., 95% confidence interval means that there is a 95% certainty that the interval contains the true value. Therefore, when a value is estimated, the confidence interval of that value can deliver more information for further analysis or decision-making.

1.5.1.3 Comparison of means

t-test is commonly used to compare sample means. For example, if the performances of two pavement sections need to be compared, a t-test can be conducted with the null hypothesis being that the two means are equal. Whether or not to reject the null hypothesis depends on the chosen confidence level, the variabilities of the two samples, and the sample sizes.

Though t-test is used for comparing the sample means, it cannot recognize the factors that cause the difference. To examine whether a factor contributes to the difference in results, other models, for example, analysis of variance or regression analysis, should be employed.

1.5.1.4 Analysis of variance (ANOVA)

For categorical variables, ANOVA can test whether different categories or features of data cause statistically significant differences in the results. For instance, ANOVA can be used to detect whether factors such as pavement service life, region, mix type, and binder grade affect the long term pavement performance.

Chatti et al. (2005) summarized several remedial measures if the data depart from the assumptions for conducting ANOVA. One way to remedy the non-constancy of the error variance is to transform (e.g. log or square root) the response or dependent variable. Weighted least squares may also be used if the error term is normally distributed but the error variance is not constant.

Aside from the limitations of these assumptions, ANOVA is only applicable when the explanatory variables are categorical. In order to determine the effects of the continuous explanatory variables on the dependence variable, regression analysis may prove beneficial.

1.5.1.5 Regression analysis

Regression analysis and stepwise regression are commonly used to identify promising combinations of variables that impact the performance of the pavement (Khazanovich et al., 1998). The adjusted R-square and F-test may be used to indicate the effectiveness of a regression model. The adjusted R-square shows the amount of variability in the dependent variable explained by the model, and F-test is used to test whether the regression model is statistically significant.

Similar to ANOVA, there are underlining assumptions for a regression model to be meaningful. Therefore, it is necessary to check those assumptions (Fahrmeir et al., 2013; Kutner et al., 2005). These assumptions include the mean of residuals being zero, that the variance of the residuals being a constant, the independent residuals, and the linearity of the regression function. These assumptions should be checked either by visually inspect the residual plot or perform related tests.

Regression models are easy to use and interpret (particularly for linear regression model), making them the most commonly applied technique by many agencies. However, linear regression models assume a linear relationship between dependent variables and explanatory variables. Such linear relationship does not always exist for pavement performance (Ford et al., 2012). Therefore, the predictive reliability of linear regression models in pavement performance is limited. Other methods should be sought when R-square or F-test indicate poor efficacy of the model.

1.5.2 New generation data analytic tools

Due to the evolution in computing speeds, a new generation analytical tools is becoming popular in establishing predictive relationships between observed performance and performance tests and construction records (Choi et al., 2004; Karlaftis and Badr, 2015; Mazari and Rodriguez, 2016; Ozturk and Kutay, 2014; Yang et al., 2003). Below a few selected advanced data analytic tools are summarized.

1.5.2.1 Neural network

Artificial Neural Networks (ANNs) are mathematical models inspired by simulation of biological nervous systems. One of the most popular neural networks is the multi-layer perceptron (MLP). MLP includes an input layer (which consists of independent variables), a hidden layer (a number of hidden variables), and an output layer which contains the target values. These variables are interconnected with several weighted links. The best solution of the network is found by forward feeding the initial solutions, back-propagating the errors throughout the entire network and adjusting the connection weights (Mazari and Rodriguez, 2016).

Yang and others used pavement condition data, including age, maintenance cycle, crack index, rut index, and ride index, to train and test ANNs for predicting pavement performance (Yang et al., 2003). Another genetically optimized ANN study applied design, traffic, weather data, and rehabilitation strategies from the LTPP database to identify factors affecting the performance of rehabilitated pavement cracks (Karlaftis and Badr, 2015).

Choi et al. (2004) compared the accuracy of a multiple linear regression (MLR) model and a neural network in predicting the pavement serviceability rating of pavement sections, and found that neural network is more effective because of the complex and nonlinear relationships between the selected variables and pavement performance (Choi et al., 2004). Similarly, (Yang et al., 2003) compared mean square error (MSE) and goodness of fit between the results of neural network and autoregressive models (AR), and came to the same conclusion that neural network has higher accuracy and better goodness of fit. However, in order to produce accurate results, the neural network should be trained with a large dataset. As a result, with limited data, regression models are a better choice. Also, regression models are superior to neural network in terms of simplicity in interpretation. Since the regression models are in the form of equations, how an explanatory variable will impact the results can be easily identified.On the contrary, it is a challenge to interpret a black box model like the neural network.

1.5.2.2 Fuzzy regression

To deal with linguistic visual inspection data and uncertainties involved during inspection, fuzzy regression models are developed by combining conventional regression analysis and fuzzy theory (Pan et al., 2009, 2011). In conventional regression models, the coefficients of explanatory variables are crispy values (precise values). However, in fuzzy regression models, the dependent variables and the coefficients are fuzzy numbers.

As a regression model, fuzzy regression models are represented as equations, which make it easy to identify variables affecting pavement performance. The fuzzy dependent variable can account for uncertainties in pavement inspection and deterioration. Furthermore, the fuzzy regression analysis is computationally efficient and easy to implement.

1.5.2.3 Neuro-fuzzy model

The neuro-fuzzy model is characterized by the reasoning process of the IF-THEN fuzzy rules led by multilayer neural networks (Bianchini and Bandini, 2010). Bianchini and Bandini (2010) reported that the performance of the neuro-fuzzy model is better than the classical linear regression model, as demonstrated by both the R^2 value and the square root of *mse* (mean square error).

As mentioned previously, fuzzy rules can take uncertainty and linguistic expression into consideration, and neural networks are capable of providing prediction with high accuracy. When combined together, fuzzy rules can overcome the disadvantage of neural networks (such as difficulty of introducing prior knowledge) by defining fuzzy IF-THEN rules, which is a problem-specific prior knowledge. The fuzzy rules defined in the neuro-fuzzy model reveal the impact of each explanatory variable to the dependent variable.

In another paper, adaptive neural-based fuzzy inference system (ANFIS) was used to predict pavement performance by the stipulated input-output pairs (Terzi, 2013). ANFIS combines the back-propagation gradient descent error digestion and a least square method to identify a set of parameters for fuzzy IF-THEN rules, which are used for generating the input-output pairs (Jang, 1993). In other words, a neural network is used to tune the parameters of a fuzzy inference system with an objective to minimizing the difference in actual outputs and desired outputs.

According to Al-Hmouz et al. (2012), ANFIS, provides fast and accurate learning, is easy to implement, and holds strong generalization abilities. Depending on the algorithm and dataset, ANFIS may outperform neural network. It is, therefore, suggested to compare the performances of selected algorithms before choosing the suitable algorithm for a given dataset.

1.5.2.4 Gene expression programming (GEP)

Gene Expression Programming (GEP), as a specified form of genetic programming (GP), is able to produce a practical solution for predictive models (Mazari and Rodriguez, 2016). GEP, composed of a population of mathematical solutions, evolves individual solution and selects the best solution through an optimization process. Therefore, the final result of the GEP is a mathematical solution, which is an explicit function. This feature overcomes the black box dilemma i.e. lack of interpretation associated with the neural network algorithms.

To further improve the GEP performance, Mazari and Rodriguez (2016) combined it with a neural network model and proved that the GEP-ANN model has the highest accuracy among other methods (pure GEP, pure ANN and ANFIS) for the selected attributes and dataset used in their work.

1.6 SUMMARY

A comprehensive literature review has been performed to identify the most important data fields influencing the long term pavement performance and the most viable analysis tool(s) to establish the relationship between them. Efforts by other states, including California, Nevada and Wisconsin, in capitalizing on construction records for long term pavement performance have been surveyed and summarized. A selected number of materials and construction parameters that are used by the existing predictive models are environmental condition, pavement age, traffic, ESAL, total asphalt layer thickness, maintenance cycle, % passing No. 200 sieve, asphalt content, and percent air void. A few performance attributes, related to this work and adopted previously for performance modeling, include IRI, crack index, rut index, ride index, and service life. Apart from the traditional statistical methods, such as analysis of variance (ANOVA), comparison of means, and regression analysis, a new generation of data analysis tools, that use large data to decipher complex relationships among independent variables, gained credibility in developing predictive models in recent years. Neural network, fuzzy regression, neuro-fuzzy model, and gene expression programming are notably popular data analysis tools that can be capitalized on for predicting pavement performance, as pavement performance is a complex function of multiple construction, geographical, and material variables.

CHAPTER 2. DATA EXTRACTION AND INTEGRATION

2.1 INTRODUCTION

The previous chapter presented literature on existing studies linking hot mix asphalt pavement materials and construction parameters with long-term pavement performance data. As part of this work, efforts by other states and national research agencies were summarized to identify the most relevant materials and construction parameters indicative of the long-term pavement performance and the available analytical, statistical, and data mining tools to establish the relationship between them. A comprehensive description of TxDOT's existing database systems, namely SMGR, DCIS, and PA, and data collection process were also presented. This chapter provides a brief description of data extracted from these databases to build an in-house data repository. This data repository contains data pertaining to the construction of the hot mix asphalt pavements from the SMGR and DCIS databases and performance indices of flexible pavements from the PA database. The primary objective of this section is to furnish a framework for data integration that links the materials and construction parameters to the pavement performance and serves as a foundation for future analyses.

2.2 IN-HOUSE DATA REPOSITORY AND ITS COMPONENTS

TxDOT databases contain as-produced mixture properties and as-constructed pavement quality information in the SMGR database; project location, bid, and letting related information in the DCIS database; and performance related information including ride quality, structural adequacy, and skid resistance in the PA database. These databases include information related to the flexible pavement, continuously reinforced concrete pavements, jointed concrete pavement, and many other components of the state maintained highway system. For the current study, in order to facilitate efficient data query and analyses, an internal consolidated data repository was developed that comprises HMA materials and construction related information and flexible pavement performance data. The data items extracted from these databases are summarized in Table 2.1.

Table 2.1. Typical data items extracted from different database systems

Data Source	Data Item
SMGR	The following data have been extracted for all specification items (including but not limited to item 340, 341, 342, 344, 346, 347, and 348) in the 2004 and 2014 specification books as well as items for special specifications to cover HMA mixtures used by the Receiving Agency. • Material-related information: Aggregate type, aggregate gradation, binder and additives used in the mix. • Volumetric properties: Mixture density and related properties as calculated based on the specific gravities of the materials and maximum theoretical density of the mix such as voids in the mineral aggregate (VMA). • Laboratory test data: Results pertaining to Hamburg Wheel Tracking Test, Overlay Tester (where available), and Indirect Tensile Strength. • Construction cost: Information related to quantities, unit costs, and total payment.
DCIS	Project related information, such as, • size of HMA projects in terms of number of lots paved, tonnage, and lane-miles covered, • data collection location information in terms of offset to and from the beginning of the highway, and • letting and budget related information.
PA	Entire performance data records for pavements with service life of at least 5 years or more, including • condition score and each individual component of the condition score (such as distress score, ride score, rut depth, cracking, and roughness), international roughness index, • route and roadbed type, • traffic in terms of 18-kip equivalent single axle load (ESAL), average annual daily traffic (AADT), and maximum speed.

2.2.1 Data extraction

Data tables extracted from the SMGR, DCIS, and PA databases are listed in Tables 2.2. The internal database has two schemas - the PUBLIC schema consists of the materials and construction related information stored in the SMGR and DCIS databases, and PMIS schema comprises information related to data collection section and pavement performance measures of flexible pavements. Some typical data items stored in the PUBLIC schema are provided in Table 2.3. A brief description of these data items are also presented. The CZONE table lists county numbers and climatic zone, and the TEXAS table contains names and numbers of counties and districts. These two tables can be simultaneously used to find the broad category of the climatic zone in which each district lies: wet-cold, wet-warm, dry-cold, and dry-warm. The DCIS_PRJ_INFO_VW table is a copy of the part of the DCIS database stored in the SMGR table. This table provides project location in the form of beginning mile point, ending mile point, offset from the beginning of the highway, county, and district; project length; and letting date among other project related information. The location information are also stored in the T_CONT_PRJ table. Data related to the specification items involved in the project, such as item code, unit price, bid quantity, and change order are included in the T_CONT_ITM table.

Table 2.2. Schemas and relations of the in-house working data repository

Schema	Table
PUBLIC	CZONE TEXAS DCIS_PROJ_INFO_VW T_CONT T_CONT_ITM T_CONT_PRJ T_CONT_SMPL T_ITM_MSTR T_SMPL T_SMPL_TST T_VEND TX_TST_RSLT_VAL
PMIS	PMIS

The as-produced mixture properties and as-constructed pavement quality data are collected as part of the QC/QA to the TX_TST_RSLT_VAL table. Some of the noteworthy QC/QA data that are collected on a daily basis are maximum specific gravity, laboratory molded density, in-place air voids, binder grade and content, aggregate gradation, recycled materials, and mixture properties evaluated by the indirect tensile strength, overlay test, and Hamburg wheel tracking test. This information is collected through the TX2QCQA14 test method - formerly TX2QCQA04 for specification year 2004. In addition, data regarding the materials sources, properties, and proportions such as aggregate and binder sources and producers, recycled material sources, material durability and strength are collected via the TX2MIXDE14 test method. These data are captured in the fld_val column, and they are referenced by the corresponding fld_nbr column.

Table 2.3. Selected tables and fields of the PUBLIC schema.

Table	Field	Description
CZONE	cnty	County number
	zone	Climate zone number
TEXAS	conty_nbr	County number
	cnty_nm	County name
	dist_nbr	District number
	dist_nm	District name
	dist_abn	District abbreviation
DCIS_PRJ_INFO_VW	control_section_job	Project number (CSJ)
	proj_nbr	Project number (CSJ)
	district_number	District number
	county_number	County number
	proj_length	Length of the project
	layman_description1	Layman description
	beg_mile_point	Begining mile point
	end_sta_nbr	Ending mile point
	actual_let_date	Actual letting date
	to_distance_from_origin	The beginning distance from origin

Table 2.3 continued

Table	Field	Description
	from_distance_from_origin	The ending distance from origin
T_CONT_ITM	cont_id	Contract ID
	proj_nbr	Project number (CSJ)
	ln_item_nbr	Line item number
	itm_cd	Item code
	unt_pric	Unit price
	spec_yr	Specification year
	bid_qty	Bid quantity
	net_c_o_qty	Net change order quantity
T_CONT_PRJ	cont_id	Contract ID
	proj_nbr	Project number (CSJ)
	road_nm	Road (route) name
	beg_sta_nbr	Beginning of the work
	end_sta_nbr	Ending of the work
	lat	Midpoint latitude of the job
	longtd	Midpoint longitude of the job
T_CONT_SMPL	cont_id	Contract ID
	proj_nbr	Project number (CSJ)
	ln_item_nbr	Line item number
	smpl_id	Sample ID
T_CONT_STREQ_MATL	cont_id	Contract ID
	proj_nbr	Project number (CSJ)
	ln_item_nbr	Line item number
	matl_cd	Material code or identifier
T_SMPL_TST	smpl_id	Smple ID
	tst_meth	Test method
	smpl_tst_nbr	Sample test number

Table 2.3 continued

Table	Field	Description
	actl_cmpl_dt	Actual completion date
TX_TST_RSLT_VAL	smpl_id	Smple ID
	tst_meth	Test method
	smpl_tst_nbr	Sample test number
	fld_nbr	Field number
	fld_val	Field value

Table 2.4 lists the performance indices extracted from the PA database. The PMIS table in the in-house PMIS schema contains the data collection section information including county, route, and distance to the beginning and ending of the data collection section from the beginning of the highway. Furthermore, it contains information related to the annual average daily traffic (AADT), maximum legal speed limit, and the current 18-kip equivalent single axle load (ESAL) value. In addition to the data collection section information, this table provides international roughness index (IRI), condition scores (CS), and distress scores (DS). Pavement distresses are manifested in the form of 1) rutting; 2) block, alligator, transverse and longitudinal cracking; 3) patching; 4) raveling; and 5) flushing. These types of distresses are measured to calculate DS, which is further combined with the ride score (RS) and vehicle speed to quantify CS for the data collection section. Information regarding these individual distresses is also stored in this table.

Table 2.4. Selected fields of the PMIS table.

Field	Description
eff_year	The year pavement condition data are collected
route_name	Route name
tx_county_nbr	County number
offset_from	The beginning distance from origin
offset_to	The ending distance from origin
tx_visual_lane_code	The lane of the data collection section for which the visual distress was collected

Continued on next page

Table 2.4 continued

Field	Description
tx_distress_score	The overall amount of surface distress on the data collection section
tx_condition_score	The overall condition of the data collection section in terms of surface distress and ride quality
tx_ride_score	The overall ride quality of the data collection section
tx_acp_patching_pct	The percentage of lane area with patching in the rated lane of the data collection section
tx_acp_failure_qty	The number of visually observed failures in the rated lane of the data collection section
tx_acp_block_cracking_pct	The percentage of lane area with block cracking in the measured lane of the data collection section
tx_acp_alligator_cracking_pct	The percentage of wheel path length with alligator cracking in the measures lane of data collection section
tx_acp_longitude_cracking_pct	The length in feet per station of visually observed longitudinal cracking on the segment in the rated lane of the data collection section
tx_acp_transverse_cracking_qty	The number of visually observed transverse cracks per station in the measures lane of the data collection section
tx_acp_raveling_code	The area of pavement raveled
tx_acp_flushing_code	The area of pavement flushed
tx_acp_rut_auto_shallow_av_pct	The average percentage of shallow rutting for all data measured by automated equipment in the data collection section
tx_acp_rut_auto_deep_avg_pct	The average percentage of deep rutting for all data measured by automated equipment in the data collection section

Continued on next page

Table 2.4 continued

Field	Description
tx_acp_rut_auto_severe_avg_pct	The average percentage of severe rutting for all data measured by automated equipment in the data collection section
tx_acp_rut_auto_failure_av_pct	The average percentage of failure rutting for all data measured by automated equipment in the data collection section
tx_acp_rut_lft_wp_dpth_meas	The average depth of rutting measured in the left wheelpath
tx_acp_rut_rit_wp_dpth_meas	The average depth of rutting measured in the right wheelpath
tx_acp_rut_avg_wp_depth_meas	The average rut depth of the left and right wheelpaths
tx_iri_left_score	The average international roughness index in inches per mile for the left wheelpath
tx_iri_right_score	The average international roughness index in inches per mile for the right wheelpath
tx_iri_average_score	The average international roughness index in inches per mile for the lefth and right wheelpaths
tx_pmis_highway_system	The broad category of highways used in PA
tx_current_18kip_meas	Current 18-kip ESAL value obtained for the data collection section
tx_aadt_current	The published average daily estimate of vehicles for all lanes of traffic on a particular highway over the length of a traffic section
tx_growth_factor_adt_pct	The growth factor for traffic ADT for the data collection section
tx_truck_aadt_pct	The percentage of the current annual average daily traffic classified as trucks
tx_speed_limit_max	The maximum legal speed limit in miles per hour
tx_number_thru_lanes	The total number of thru-lanes in a a roadbed for a data collection section

Continued on next page

Table 2.4 continued

Field	Description
tx_totl_surf_rdway_width_meas	The total width in feet of paved surface including all travel lanes and paved shoulders

2.2.2 Data integration

Data from the SMGR, DCIS, and PA databases are linked to each other using the common primary keys to form an integrated database for the research team's internal use. Figure 2.1 highlights the primary fields that are shared by different tables and can be used to link them. QC/QA and mixture design information acquired on a daily basis for an individual lot is identified by the smpl_id. However, smpl_id is not unique to a lot and needs to be accompanied by the tst_meth and smpl_tst_nbr to connect different fields from the fld_val column corresponding to the reference fld_nbrs. The T_CONT_SMPL and T_SMPL_TST tables can be linked to find all lots that are being paved under a specific project. Route, location, and county information for a specific lot can be obtained by simultaneously connecting the DCIS_PRJ_INFO_VW, T_CONT_PRJ, and T_CONT_SMPL tables. Similarly, climatic zone for a project can be obtained by linking CZONE , TEXAS, and DCIS_PRJ_INFO_VW tables together. A part of a sample SQL query providing such links is presented in Figure 2.2.

The PMIS and DCIS_PRJ_INFO_VW tables can be connected by the offset distances to the data collection section from the highway origin (DFOs). The beginning distance from origin (Beginning DFO) locates the beginning of the data collection section. This information is recorded as offset_from in the PMIS table and identifies the beginning of the data collection section from the beginning of the highway. The offset_to field measures the distance to the end of the data collection section from the beginning of the highway. Offset_from and offset_to are equivalent to from_distance_from_origin and to_distance_from_origin in the DCIS_PRJ_INFO_VW table, respectively. Thus these fields can be served as the key to linking project related information in the DCIS database to pavement performance measures in the PA database. The location markers identified by from_distance_to_origin and to_distance_to_origin have been incorporated in the DCIS table a few years ago, and these fields may be empty prior to implementing them. For cases where these fields are missing, the offset_from and offset_to items can be generated from the project number, route, and beginning and ending mile points information.

Linking the PMIS table with the DCIS_PRJ_INFO_VW provides the project level performance information. However, lot level performance parameters may not be feasible to find as the exact location of a lot in a specific project is not known. In order to mitigate this, all the lot level QC/QA and mixture design data were averaged over the project to obtain the project level QC/QA and design information. Likewise, project level performance indices were obtained by averaging the performance measures over a project length for a specific year. These two pieces of information were then linked to provide an integrated table that connected the project level materials and construction information with the project level performance measures.

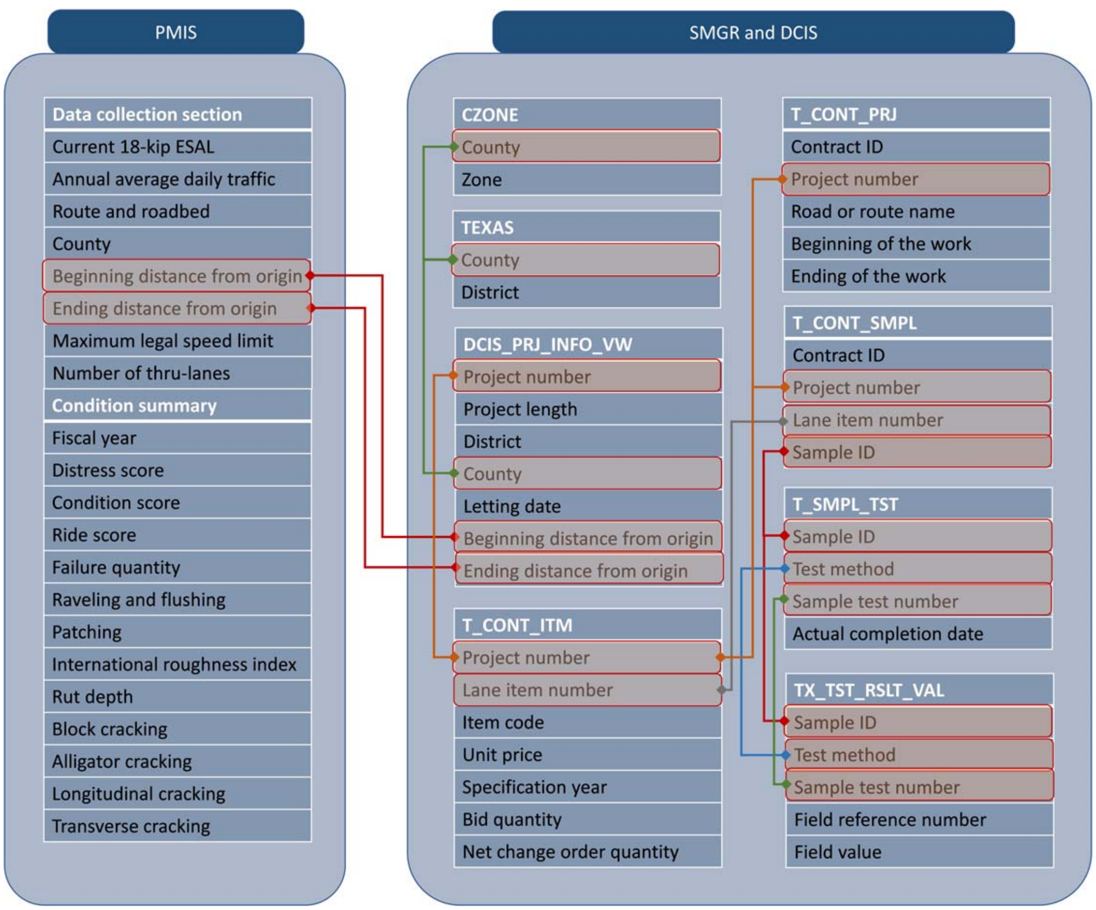


Figure 2.1. The in-house data repository with tables and data fields relevant to this work. The common primary keys that can be used to integrate different tables from different sources are highlighted.

```sql
create or replace view z1_itm344_prj_dist_smpl_meth_tstnbr_nbrlots_offset as

with  prj_itm_smpl as

(
  select t1.prj_nbr
  , t1.ln_itm_nbr
  , substr(t1.itm_cd,2,3) as item
  , t2.smpl_id
       from public.t_cont_itm as t1
  left join public.t_cont_smpl as t2
  on t1.prj_nbr=t2.prj_nbr and t1.ln_itm_nbr=t2.ln_itm_nbr
  where substr(t1.itm_cd,1,4)='0344'::text -->>    (does not work if you put 344)
)

, prj_nbr_lots as

(
  select item
  , prj_nbr
  , count(*) as nbr_lots
  from prj_itm_smpl
--         where trim(substr(itm_cd,1,4))~'344'::text --when data for  specific item are required
  group by prj_nbr, item--, strt_dt
--         order by strt_dt, prj_nbr
)


, itm_prj_smpl_meth_tstnbr as
(
  select t1.item
  , t1.prj_nbr
  , t1.smpl_id
  , t2.smpl_tst_nbr
  , t2.tst_meth
  from prj_itm_smpl as t1
  left join public.t_smpl_tst as t2
  on t1.smpl_id=t2.smpl_id
  where trim( t2.tst_meth) ='TX2QCQA14'::text or trim(t2.tst_meth)='TX2QCQA04'::text--doesn't work without trim
)


, prj_dist_zone as

(
  select t1.control_sect_job as prj_nbr--project_number may not work, may have to use control_sect_job
  , t1.to_distance_from_origin as offset_to
  , t1.from_distance_from_origin as offset_from
  , t2.dist_nm as district
  , t3.zone
  from public.dcis_proj_info_vw as t1
  left join public.texas as t2
  on t1.district_number=t2.dist_nbr
  left join public.czone as t3
        on t1.county_number=t3.cnty
  where t3.zone = 1::integer --and t3.zone is Not Null
)
```

Figure 2.2. Example SQL query linking different tables of the PUBLIC schema (SMGR) of the in-house database.

2.3 SUMMARY

In this task, an internal working data repository comprising data from the SMGR, DCIS, and PA databases was developed. This data repository contains materials information, construction parameters, and performance measures of hot mix asphalt pavements collected by TxDOT. Data related to materials include the as-produced hot mix asphalt mixture properties, collected as part of QC/QA, such as laboratory molded density, in-place air void, aggregate gradation, mixture type, binder grade and content, recycled materials, and additives. Materials quality information evaluated through the tensile strength test, overlay test, and Hamburg tracking wheel test as well as mixture design parameters and materials sources are also extracted. In addition, this data repository includes project related information such as project location, project length, county, district, climatic zone, letting and completion date, as well as bidding information such as quantity and unit price of the specification items involved in a project. Included in the data repository are also historical performance measures, such as condition scores, distress scores, ride scores, international roughness index, and surface distresses and data collection section information such as traffic, load, and vehicle speed for the state maintained highway system. Finally, common primary keys connecting different tables are identified, and a framework for an integrated data repository has been developed to enable analyses in subsequent tasks.

CHAPTER 3. DATA ANALYSIS

3.1 INTRODUCTION

Pavement performance, for a given service life, is affected by a number of factors, such as materials properties, construction and QC/QA practices, number and magnitude of traffic loading, maintenance activities, and environmental exposures. This chapter summarizes relationships between construction and QC/QA records and long-term field performance of pavements by employing several data analysis techniques. The pavement performance information, as summarized in Chapter 1, obtained from the PA database is integrated with the construction and material information from the DCIS and SMGR databases to identify construction and material parameters leading to long term satisfactory pavement performance. Construction projects in four climatic regions: dry-cold, dry-warm, wet-cold, and wet-warm are included in the analyses. Various data analysis techniques of both traditional statistical method, such as, multivariate regression analysis, and new generation data analytic tools, such as artificial neural network (ANN) and decision tree based ensemble method, have been employed to determine the relationship between the material and construction parameters and pavement performance. In particular, this chapter is laid out to answer the following questions.

1. Do the mixture volumetric and material properties affect pavement performance records for different road bed type, traffic, and environment?
2. What are the most significant mixture volumetric and material parameters that influence pavement performance?
3. Do the QC/QA performance tests (e.g., Hamburg Wheel Tracking (HWT) and Indirect Tensile Strength (IDT)) correlate to the as-built performance? In other words, are the QC/QA specification tests performed during construction proven to be good representatives of the long-term pavement performance?
4. What data analysis techniques are the most effective in terms of accurately translating the construction records into the pavement performance?

3.2 DATA STRATIFICATION

The section briefly explains the data integration and stratification techniques that provide the integrated dataset for further analysis. Material information pertaining to the mixture volumetrics and components from the SMGR and project related information including locations and start dates from the DCIS database are extracted and combined. These data are then linked with the performance indices obtained from the PA database to identify materials and construction parameters for long-term pavement performance.

3.2.1 Pavement material data combination

SMGR stores QC/QA information as a separate entry under the fld_val column for a parameter specified in the fld_nbr column. Due to this format of record-keeping, each material property and their corresponding values are queried as a separate table. Thus, each table contains four columns: *smpl_id*, *tst_meth*, *smpl_tst_nbr*, and a column indicating the value of that feature. The information in the first three columns is used as the unique identifier of each test result to combine the different indicators in separate table (the fourth column). Only the material information collected by the DOT Engineer for the QC/QA purposes are gathered in this step. In addition, information related to the project, including, item, prj_nbr, dist_nbr, district, zone, and nbr_lots (total number of lots in the project), are also included.

3.2.2 Pavement material data processing

Since a project may contain multiple lots, and lots consist of at least four sublots, material parameters are averaged over sublots to obtain information for a specific lot. The lot wise material information is then averaged over a project since the exact locations of lots, necessary to link with the PA data, are not recorded in the SMGR or DCIS database. This data-processing is conducted in two steps:

- The information for each lot is determined by taking average over the columns that contain material information for the same features from four different sublots of a lot. For instance, *dot_ac* is the average of TxDOT measured asphalt content collected from a maximum of four sublots. This process is repeated to obtain average laboratory molded density (*dot_pdl*), average field density (*dot_pdf*), average percent absorption (*dot_pal*), average volume in mineral aggregates (*dot_vma*), and average percent passing each sieve (*dot_pp*01, *dot_pp*02, *dot_pp*03, ... *dot_pp*10), and so on.
- The information for each project is determined by taking average over the rows pertaining to the same project.

- For continuous variables: the rows with the same *prj_nbr* are grouped together and the new value is the average value of those rows.
- For categorical variables: the value should be the same for the rows with the same *prj_nbr*. However, some categorical variables might have different values for the same project. In this case, extra steps are required to process these variables.
  - Since the scope of this study is limited to surface distresses, material information related only to surface courses are considered, while that in corresponding to base and intermediate courses are discarded.
  - Table 3.1 is used to determine the *spec_item*, which is based on the first four digits in *item* of that row. For example, if the *item* in one row is '3224xxxx', then the *spec_item* is '0341'. This step also consolidates all special specification items that are released later than the specification years 2004 and 2014.

Table 3.1. *item* **and corresponding** *spec_item*

spec_item	341	342	344	346	347
item	341	342	344	346	347
	3224	3269	3270	3271	3239
	3268	348	3077		
	340	3226			
	3267	3127			
	3076	3000			
		3142			
		3001			

  - Similar approach is adopted to determine mix types, as various formats of *mix* data are found in the SMGR database. Example formats of *mix*s are provided in Table 3.2. The left column is the values in the original database, and the right column is the corresponding *mix_type*.
  - If *pg_sub* (substitute PG) of a row is empty, then *pg_org* (original PG) of that row is used for a new column *pg*. Otherwise, *pg_sub* is used as *pg*.
  - If *wma* field is empty, it is reasonable to assume that no WMA additive is used and this field is filled with 'No'.
  - Likewise, if *rb_md* (recycled binder content) is null, it is likely that the mix does not use any recycled binder and therefore, 0 (zero) is used.

Table 3.2. *mix* **and corresponding** *mix_type*

mix	mix_type
341-DG-B	B
344-SP-B	B
ITEM344_SP_C_Surface	C
ITEM344_SP_C_Surface	C
341-DG-B	B
344-SP-C	C
344-SP-C	C
346-SMA-D	D
SS3224_B_Fine_Base	B
ITEM341_C_Coarse_Surface	C
SS3224_B_Fine_Base	B
SS3270_SP_C_Surface	C
SS3224_D_Fine_Surface	D
SS3224_D_Fine_Surface	D
342-PFC-C	C
ITEM344_SP_D_Fine_Mixture	D
SS3268_D_Fine_Surface	D

3.2.3 Pavement performance data identification and combination

Among the various performance indices stored in the PA database, pavement Condition Score (CS) incorporates the ride quality and the distress score, where the distress score is an indicatin of the severity of pavement surface distresses, including cracking, rutting, and patching, etc. Therefore, CS is selected to be the most representative performance measures to gauge the long-term project performance. Additionally, International Roughness Index (IRI) is also considered in the analysis. These performance measures are linked with the material and construction data using csj in PA database and prj_nbr in pavement material database as the primary keys. Roadbed types and distances from the origin (DFO) with respect to the Texas Reference Markers (TRMs) are also used to link projects to specific sections and road types of pavements.

3.2.4 Pavement performance data processing

Since performance data are typically collected at every 0.5 mile interval, and the specific location of a lot in a project is not known, performance measures are averaged over the entire project length. Thus, in the combined database, each row represents a year's performance of the pavement section for the entire project length. To analyze the relation between construction parameters and pavement performance, the year the project ends and the pavement section is open to traffic needs to be identified. This information is not directly available in any of the databases that are obtained for use under this project, and is inferred based on significant changes in the CS or IRI in two subsequent years. To be more specific, year t is considered as the project completion year of a pavement section, and consequently the year the pavement section is open to traffic, using the following conditions.

1. The difference of the *iri* in year t, iri_t, from that in the previous year, iri_{t-1}: $iri_t - iri_{t-1} < -15$.
2. The difference of the condition score CS in year t, CS_t, from the that in the previous year, CS_{t-1}: $CS_t - CS_{t-1} > 10$.
3. The different of the project start year (strt_dt) recorded in the SMGR table, T, and year t: $t - T \leq 2$.

For a year t to be the project completion year, the 3rd criterion must be satisfied to ensure that a sudden jump in CS and/or IRI caused by an in-house maintenance and/or rehabilitation does not register t as the start date of a new project, which is not recorded in the SMGR database. In addition, either the 1st criterion or the 2nd criterion should be satisfied. If both criteria 1 and 2 are satisfied, then year t is considered as the project completion year without the need of manual check. Otherwise, this project is manually checked to confirm whether the change in the performance data is caused by a new construction or anomalies in the performance measurements or data recordings. With the project completion year determined, the number of years the project is in service is then calculated.

3.3 DATA ANALYSIS

3.3.1 Identification of materials and traffic data for analysis

After data related to the attributes for materials, construction, traffic, and performance are integrated, the correlations among these attributes are investigated to identify collinearity problem. Pair plots showing the distributions of the various independent variables are plotted in Figure 3.1. Significant correlations are detected between the *dot_ac* and *dot_vma* and between sum_meas_18kip and $aadt\_current$. Similar correlations are detected between *zone* and *dot_ac* and between *pg_cont* and $highway_sys$. Therefore, *dot_vma*, *aadt_current*, *zone* and *highway_sys* are discarded from the rest of the analysis. The selected independent variables and their definitions are summarized in Table 3.3. In addition, *hwt_tri*, *hwt_tri_cyc*, *idt_tri* are included as independent variables to determine if the laboratory tests performed to measure performances of fresh mixes are good representatives of long-term pavement performances.

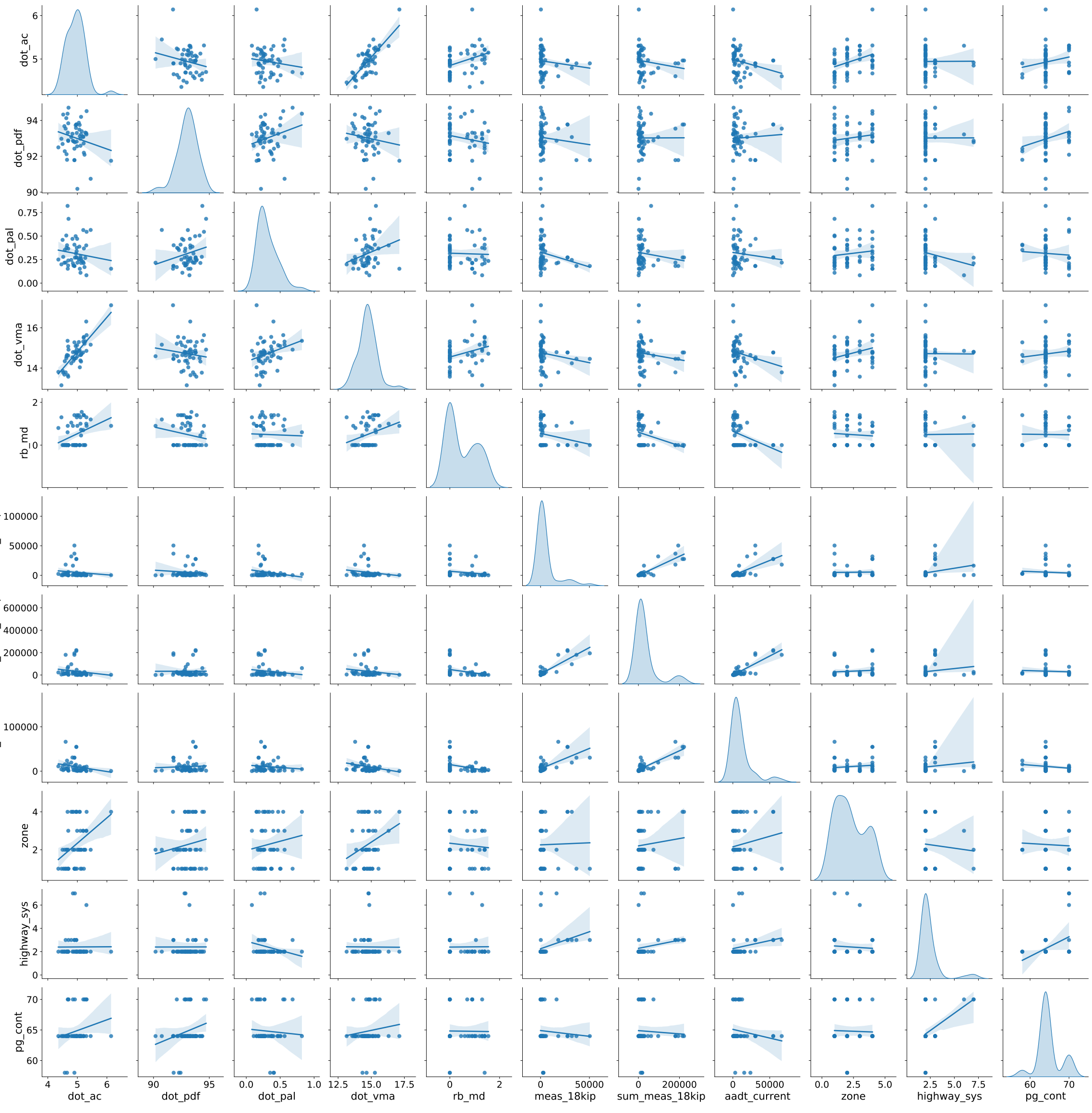


Figure 3.1. Independent variable distributions and the pairwise relationships between them for 5 year materials, construction, and traffic data for items 341 and 344.

Once the independent variables are sorted, distributions of the dependent variables, i.e. CS and IRI, with respect to the independent variables are plotted in Figures 3.2 and 3.3,

Table 3.3. Definition of the Independent Variables in the Multivariate Regression Analysis

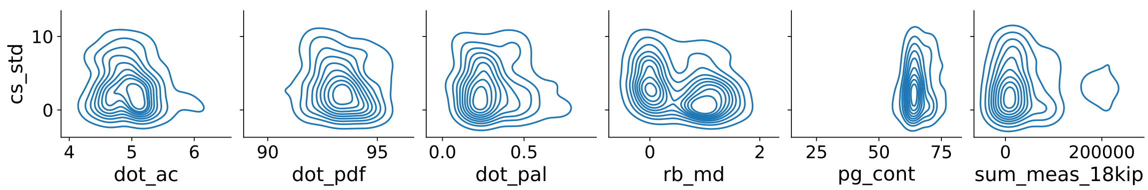
Variable	Definition
sum_meas_18kip	Total 18 kip ESALs of that pavement section.
dot_ac	Average DOT measured asphalt content
rb_md	Recycled binder content obtained from the mixture design
pg_cont or pg_continuous	The high grade value of the performance grade treated as a continuous variable eg. 76-22, 76 is used as a continuous variable
dot_pdf	Average DOT measured field density
dot_pal	Average DOT measured percent absorption
max_year	The year of that pavement since construction.
hwt_tri	Rut depth from the Hamburg wheel tracking test performed for the trial batch
hwt_tri_cyc	Number of wheel passes corresponding to the hwt_tri rut depth
idt_tri	Indirect tensile test strength obtained for the trial batch

respectively. Four different datasets are filtered and used for these plots. Since, items 341 and 344 use similar mix types, data for these items with 3 years and 5 years of service life are used and plotted in Figures 3.2a and 3.2b, respectively. Both of these datasets are filtered further to reduce variability, whereby data with CS standard deviation less than 10 are included. Figures 3.2c and 3.2d show distributions for Item 341 mix type C and D, repectively. For the later two datasets, current projects that are still in service are hand-picked based on low and high standard deviations in CS. Distributions of IRI with respect to different independent variables for the same datasets are plotted in Figure 3.3.

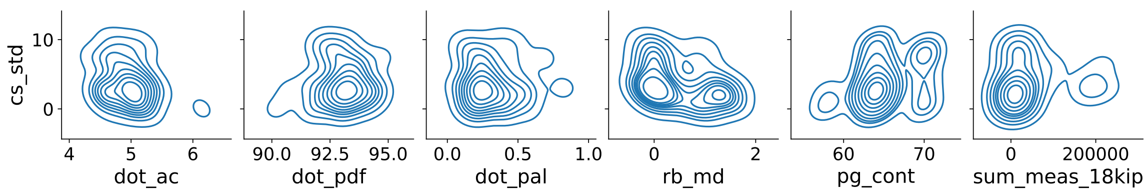
3.3.2 Multivariate regression

3.3.2.1 Analysis of data for Items 341 and 344 with 5 years of service life

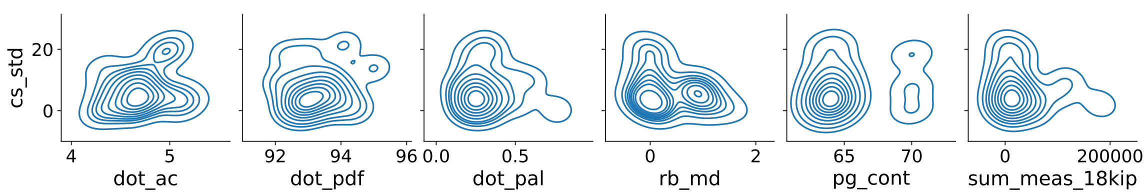
With 52 filtered datasets presented in Figure 3.2b, linear regression analyses are performed to estimate the dependence of the condition score standard deviation on the selected independent variables and plotted in Figure 3.4. ScikitLearn software is used to conduct these analyses. Five-fold cross validation has been used to determine the effect of sampling on the variability of the coefficients. In this process the entire data are divided in $k = 5$ folds or subsets. In the first iteration, the model is trained using *4* folds and tested on the remaining



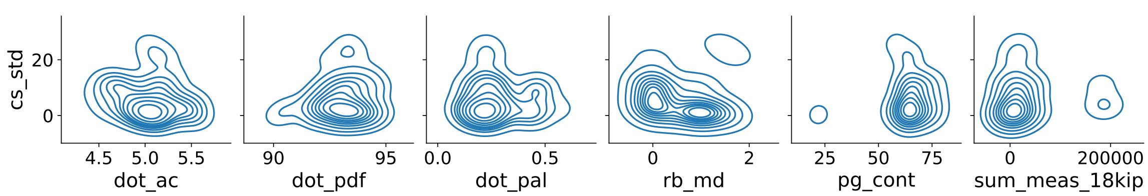
(a) Items 341 and 344 with 3 years of service



(b) Item 341 and 344 with 5 years of service

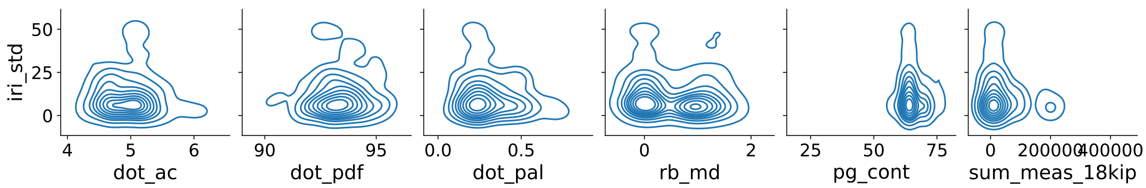


(c) Item 341 mix C

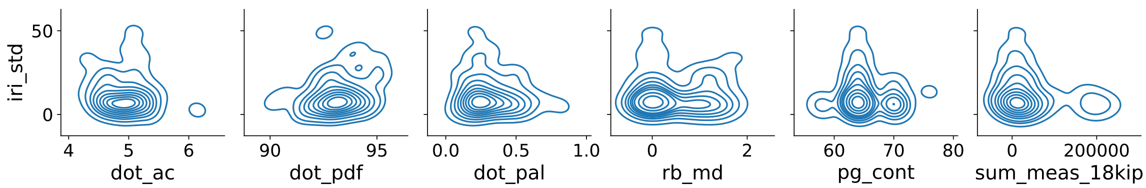


(d) Item 341 mix D

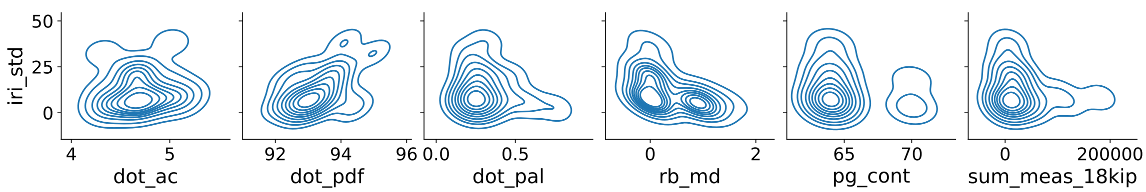
Figure 3.2. Distribution of condition score standard deviation with independent variables for different dataset s



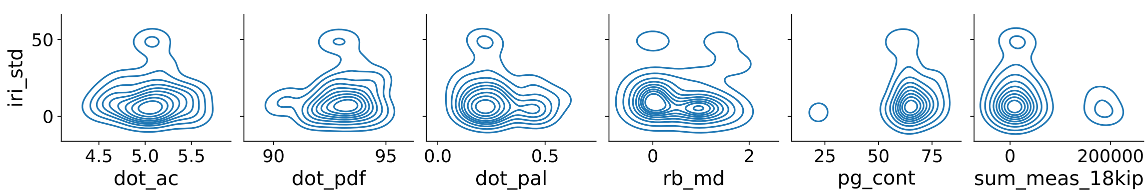
(a) Items 341 and 344 with 3 years of service



(b) Items 341 and 344 with years of service



(c) Item 341 mix C



(d) Item 341 mix D

Figure 3.3. Variation of IRI standard deviation with independent variables for different dataset s

5th fold. This process is repeated for all five combinations of training folds, where the model is tested on a different fold each time. For each iteration, the model performance is estimated in terms of the coefficient of determination on the training score,

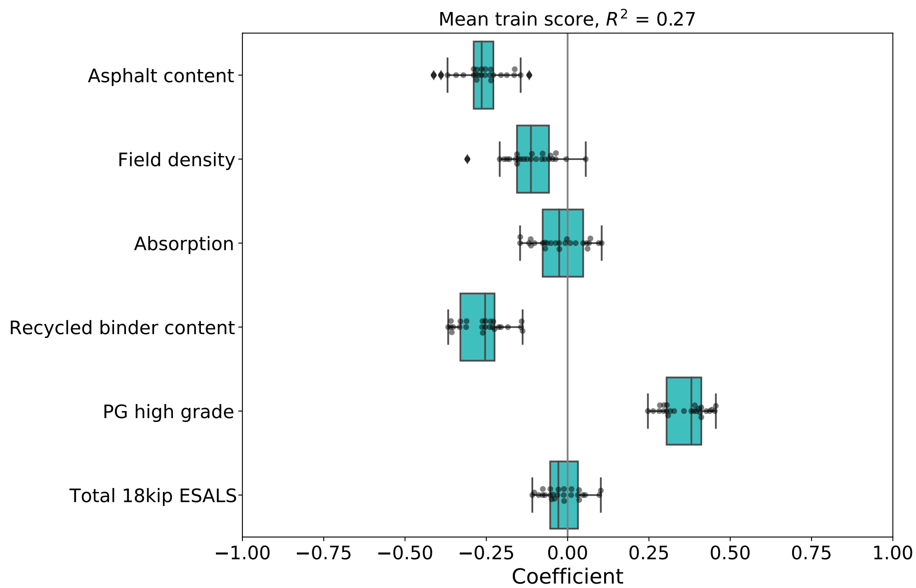
$$R^2 = 1 - \frac{\sum_{i=1}^{n}(P_i - A_i)}{\sum_{i=1}^{n}(A_i - \overline{A})}, \tag{3.1}$$

where R^2 is the coefficient of determination, P_i is the predicted value, A_i is the measured or actual value of the i^{th} instance in the testing set, and $\overline{A}$ is the mean of the measured or actual target values of the testing set. The five-fold cross validation is iterated five more times providing a total of 25 sets of coefficients for each independent variable. The mean R^2 is then calculated by taking the average of R^2 obtained from *25* different train-test combinations looping through the entire data. The mean and variability of these coefficients are shown for Ordinary Least Squares (OLS) regression in Figure 3.4a and for Ridge regression, which imposes a penalty on the size of the coefficients, in Figure 3.4b. Both models predict a decrease in the CS standard deviation with increasing asphalt content, field density, and recycled binder content, whereas the variability in CS increases with an increase in the high grade of the binder performance grade. These results somewhat translate the distribution shown in Figure 3.2b and indicate poor dependence of CS on the independent variables, probably because the available data size of 52 barely meets the minimum requirement of sample size for analysis using ScikitLearn and results in a poor training and performance of the regression models.

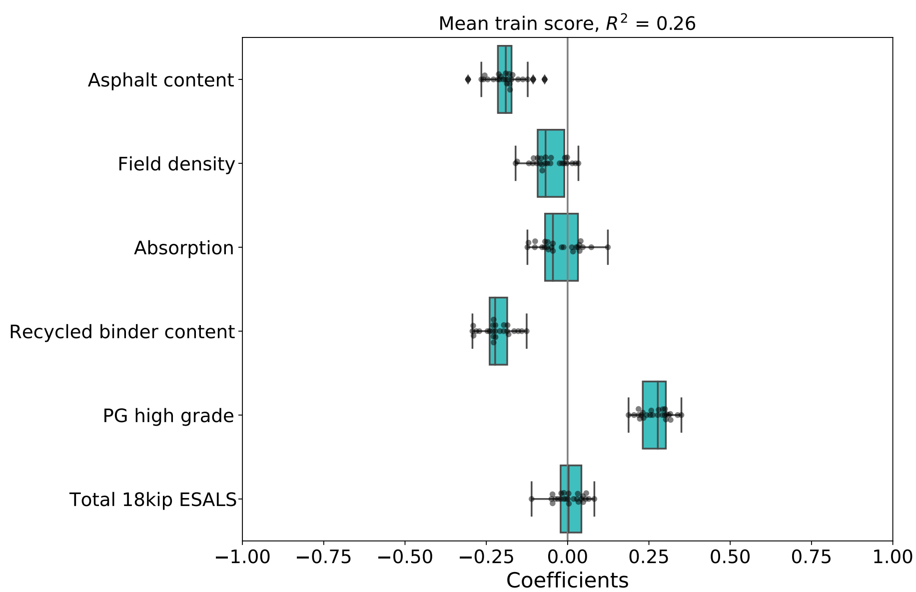
3.3.2.2 Analyses of data for Item 341 mix C

Pavement sections with item 341 and mix type *C* are selected for the analyses of this section. 34 projects from 341C are hand picked to perform the analysis. For the multivariate regression analysis, the dependent variables includes the average condition score of that pavement section (*cs_avg*), the standard deviation of condition score (cs_std), the average IRI (*iri_avg*), and the standard deviation of IRI (*iri_std*). Two sets of independent variables for this analysis: the first set contains sum_meas_18kip, *max_year*, *dot_ac*, *rb_md*, $pg\_continuous$, dot_pdf, and the second set contains $\frac{hwt\_tri}{hwt\_tri\_cyc}, idt\_tri$.

First, a correlation matrix of the independent variables is plotted for each of the two independent variable sets to identify the potential correlation among the independent variables. The correlation matrix of the independent variable sets 1 and 2 are shown in Figures 3.5 and 3.6 respectively.



(a) Regression



(b) Ridge

Figure 3.4. Coefficients and their variability for condition scores determined by re gression analysis

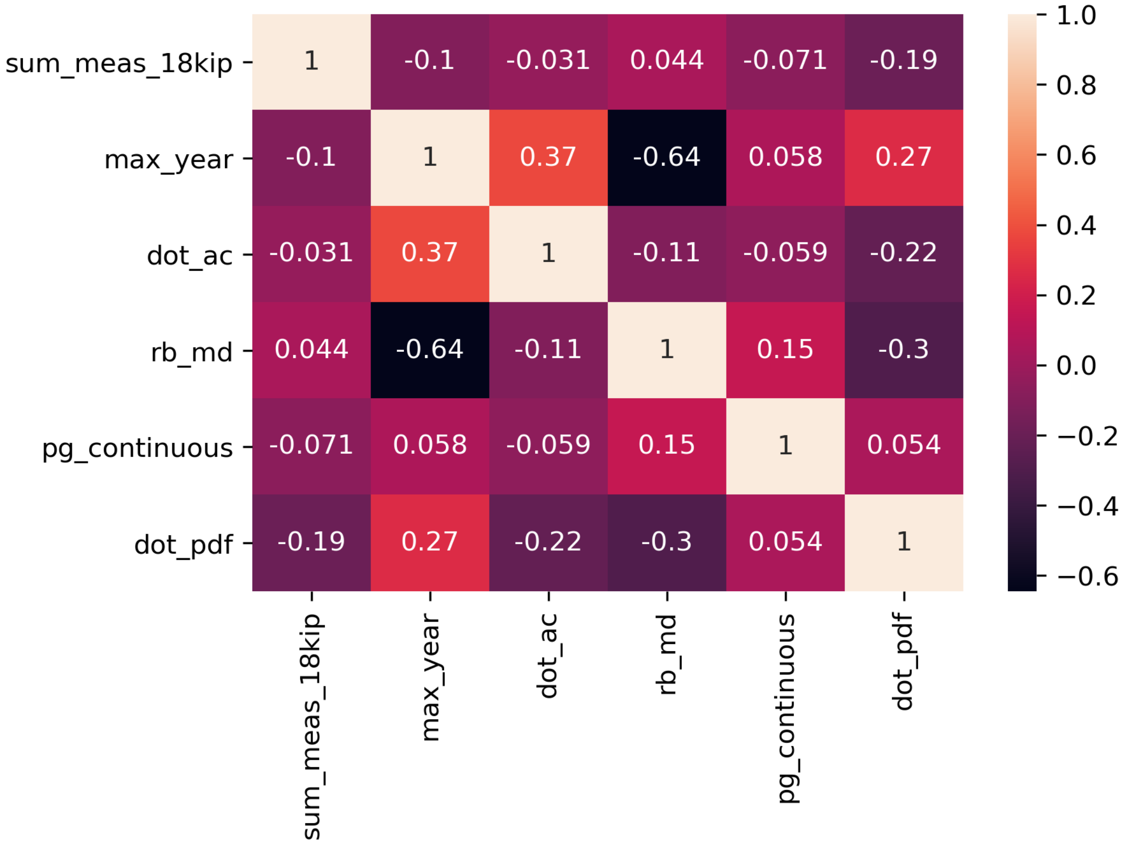


Figure 3.5. Coorelation Matrix of the Independent Variables Set 1

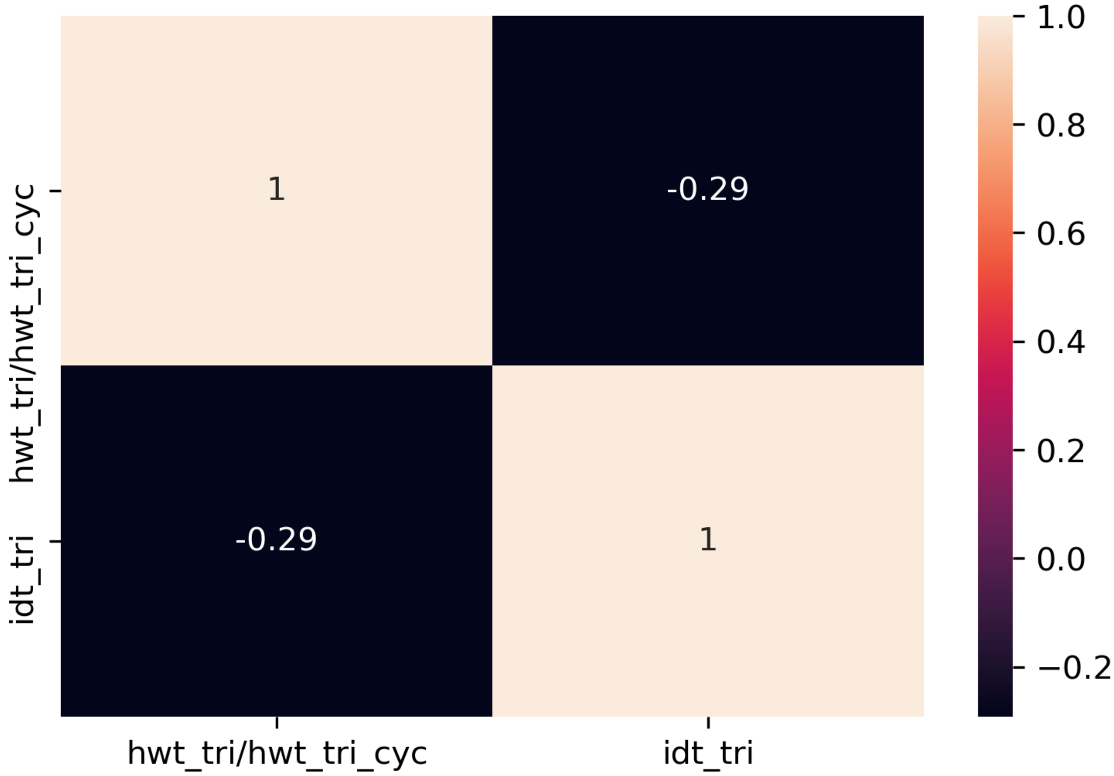


Figure 3.6. Coorelation Matrix of the Independent Variables Set 2

It can be seen from Figure 3.5 that, *max_year* have relatively high correlation with *rb_md* (-0.64) and *dot_ac* (0.37). Therefore, *max_year* is not included in the further analysis to avoid the collinearity problem. Then, with the finalized independent variables, the multivariate regression analysis is conducted for each of the dependent variables with the two independent variables sets. Due to the data availability, 28 projects for the 1st set of independent variables and 15 projects for the 2nd set of independent variables are included in the analysis.

The analysis results using the 1st set of independent variables are presented in the Tables 3.4 to 3.7.

Table 3.4. Regression Results 1

Dep. Variable:	cs_avg	**R-squared:**	0.103
Model:	OLS	**Adj. R-squared:**	-0.101
Method:	Least Squares	**F-statistic:**	0.5054
Log-Likelihood:	-92.578	**Prob (F-statistic):**	0.769
No. Observations:	28	**AIC:**	197.2
Df Residuals:	22	**BIC:**	205.1
Df Model:	5		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	165.0219	235.889	0.700	0.492	-324.182	654.226
sum_meas_18kip	-2.023e-05	3.57e-05	-0.567	0.576	-9.42e-05	5.37e-05
dot_ac	-8.2366	6.174	-1.334	0.196	-21.040	4.567
rb_md	0.5316	3.153	0.169	0.868	-6.007	7.070
pg_continuous	-0.4808	0.773	-0.622	0.541	-2.085	1.123
dot_pdf	-0.0190	2.404	-0.008	0.994	-5.004	4.966

Table 3.5. Regression Results 2

Dep. Variable:	cs_std	**R-squared:**	0.164
Model:	OLS	**Adj. R-squared:**	-0.026
Method:	Least Squares	**F-statistic:**	0.8653
Log-Likelihood:	-85.984	**Prob (F-statistic):**	0.520
No. Observations:	28	**AIC:**	184.0
Df Residuals:	22	**BIC:**	192.0
Df Model:	5		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	-85.1034	186.389	-0.457	0.652	-471.651	301.445
sum_meas_18kip	-1.231e-05	2.82e-05	-0.437	0.667	-7.07e-05	4.61e-05
dot_ac	5.2948	4.878	1.085	0.290	-4.822	15.412
rb_md	-3.1166	2.491	-1.251	0.224	-8.283	2.050
pg_continuous	0.5593	0.611	0.915	0.370	-0.708	1.827
dot_pdf	0.3429	1.899	0.181	0.858	-3.596	4.282

Table 3.6. Regression Results 3

Dep. Variable:	iri_avg	**R-squared:**	0.086
Model:	OLS	**Adj. R-squared:**	-0.122
Method:	Least Squares	**F-statistic:**	0.4133
Log-Likelihood:	-127.13	**Prob (F-statistic):**	0.834
No. Observations:	28	**AIC:**	266.3
Df Residuals:	22	**BIC:**	274.2
Df Model:	5		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	-231.8495	810.116	-0.286	0.777	-1911.928	1448.228
sum_meas_18kip	-0.0001	0.000	-0.919	0.368	-0.000	0.000
dot_ac	9.1620	21.203	0.432	0.670	-34.810	53.134
rb_md	3.0099	10.827	0.278	0.784	-19.445	25.465
pg_continuous	-2.2342	2.656	-0.841	0.409	-7.743	3.274
dot_pdf	4.6290	8.255	0.561	0.581	-12.491	21.749

Table 3.7. Regression Results 4

Dep. Variable:	iri_std	**R-squared:**	0.401
Model:	OLS	**Adj. R-squared:**	0.265
Method:	Least Squares	**F-statistic:**	2.942
Log-Likelihood:	-94.584	**Prob (F-statistic):**	0.0351
No. Observations:	28	**AIC:**	201.2
Df Residuals:	22	**BIC:**	209.2
Df Model:	5		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	-499.6704	253.411	-1.972	0.061	-1025.213	25.872
sum_meas_18kip	-2.376e-05	3.83e-05	-0.620	0.542	-0.000	5.57e-05
dot_ac	5.3834	6.632	0.812	0.426	-8.371	19.138
rb_md	-6.2208	3.387	-1.837	0.080	-13.245	0.803
pg_continuous	-0.5326	0.831	-0.641	0.528	-2.256	1.190
dot_pdf	5.6120	2.582	2.173	0.041	0.257	10.967

From the results shown in the above tables, the models do not fit the data well, only dot_pdf has a p-value less than 0.05 when *iri_std* is the dependent variable, indicating that dot_pdf is statistically significant related to *iri_std*. Since the p-values of other independent variables are greater than 0.05, no conclusive remarks could be made about the relationships of these variables with the dependent variables.

The analysis results using the 2nd set of independent variables are presented in Tables 3.8:

Table 3.8. Regression Results 5

Dep. Variable:	cs_avg	**R-squared:**	0.057
Model:	OLS	**Adj. R-squared:**	-0.100
Method:	Least Squares	**F-statistic:**	0.3633
Log-Likelihood:	-52.507	**Prob (F-statistic):**	0.703
No. Observations:	15	**AIC:**	111.0
Df Residuals:	12	**BIC:**	113.1
Df Model:	2		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	77.1911	17.587	4.389	0.001	38.872	115.510
hwt_tri/hwt_tri_cyc	1.5775	7.977	0.198	0.847	-15.803	18.958
idt_tri	0.0919	0.108	0.851	0.412	-0.143	0.327

Table 3.9. Regression Results 6

Dep. Variable:	cs_std	**R-squared:**	0.070
Model:	OLS	**Adj. R-squared:**	-0.085
Method:	Least Squares	**F-statistic:**	0.4528
Log-Likelihood:	-49.401	**Prob (F-statistic):**	0.646
No. Observations:	15	**AIC:**	104.8
Df Residuals:	12	**BIC:**	106.9
Df Model:	2		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	16.9662	14.297	1.187	0.258	-14.185	48.117
hwt_tri/hwt_tri_cyc	-5.7223	6.485	-0.882	0.395	-19.851	8.407
idt_tri	-0.0525	0.088	-0.598	0.561	-0.244	0.139

Table 3.10. Regression Results 7

Dep. Variable:	iri_avg	**R-squared:**	0.102
Model:	OLS	**Adj. R-squared:**	-0.047
Method:	Least Squares	**F-statistic:**	0.6836
Log-Likelihood:	-68.529	**Prob (F-statistic):**	0.523
No. Observations:	15	**AIC:**	143.1
Df Residuals:	12	**BIC:**	145.2
Df Model:	2		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	134.2103	51.177	2.622	0.022	22.705	245.715
hwt_tri/hwt_tri_cyc	-26.2469	23.212	-1.131	0.280	-76.821	24.328
idt_tri	-0.1931	0.314	-0.614	0.550	-0.878	0.492

Table 3.11. Regression Results 8

Dep. Variable:	iri_std	**R-squared:**	0.025
Model:	OLS	**Adj. R-squared:**	-0.137
Method:	Least Squares	**F-statistic:**	0.1539
Log-Likelihood:	-56.977	**Prob (F-statistic):**	0.859
No. Observations:	15	**AIC:**	120.0
Df Residuals:	12	**BIC:**	122.1
Df Model:	2		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	13.6492	23.693	0.576	0.575	-37.973	65.271
hwt_tri/hwt_tri_cyc	-5.5397	10.746	-0.516	0.616	-28.953	17.874
idt_tri	0.0067	0.146	0.046	0.964	-0.310	0.324

From the above results, it can be observed that none of the variables in the 2nd set of independent variables have a p-value less than 0.05, indicating that linear models do not work well with the given set of data in terms of capturing the complex relationships among the variables. Therefore, new generation data analysis tools, including the decision tree based ensemble model and the neural network model, are used to capture the non-linear relations among the independent and the dependent variables.

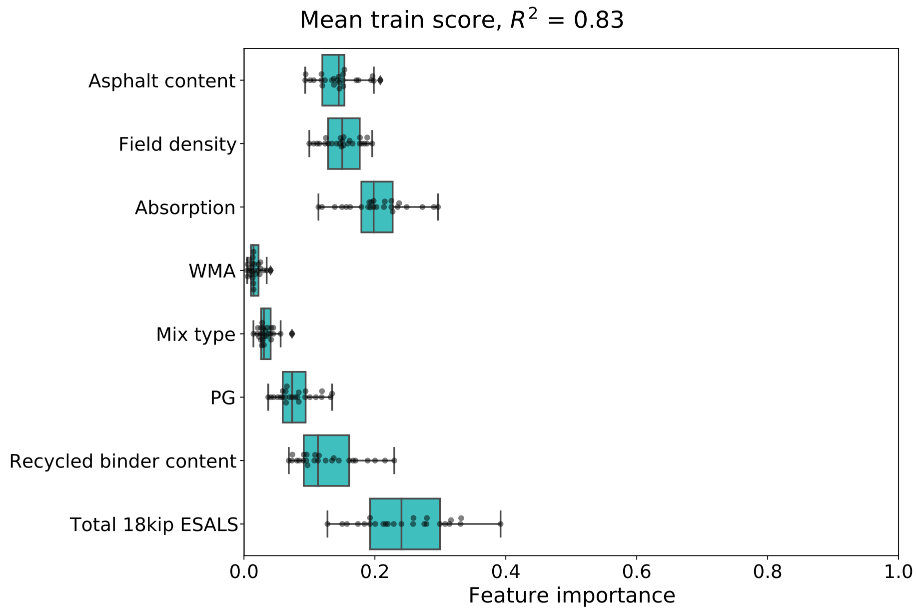
3.3.3 Random forests ensemble model

Several ensemble models are available to handle a variety of data classes and regression analysis. Ensemble methods are an aggregation of multiple decision trees that use simple decision rules to find logical splits in the data features and predict the target variables. They reduce the variance of a single decision tree by introducing randomization into its construction procedure. These methods overcome over-fitting resulted by the inefficient splitting of training/test data that are not representative of the full dataset and increase accuracy. However, this is achieved at the cost of lost simplicity and interpretability.

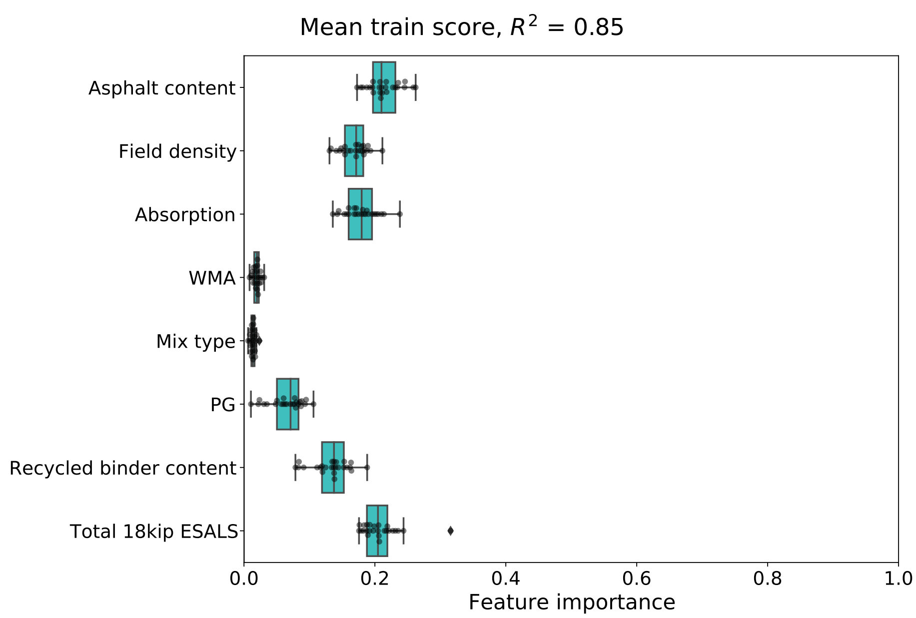
Random forests are ensemble meta-estimators that construct multiple decision trees using randomly selected subset of the original dataset and a limited number of variables for the base trees. These models produce unique trees with randomly selected variables and result in a reliable and final decision structure with low variability. As random forests use a subset of variables to construct a base tree, they are considered a weakly-supervised learning technique. In addition, these models have a feature importance attribute that assesses the contribution of a feature to the predictive ability of a model. This concept is built on the impurity function estimated as the squared error loss that defines the reduction in variance associated with a split.

3.3.3.1 Random forests model results

Random Forests ensemble algorithm of ScikitLearn is used to analyze the dependence of CS and IRI on the material properties (asphalt content, recycled binder content, PG, percent absorption, mix type, and WMA), construction parameter (percent density, dot_pdf, achieved during construction in the field), and traffic data (total 18kip ESALS). As dependent variables, standard deviations of CS and IRI are used to determine the effect of the independent variables on the variability of the selected performance measures. Since there is a minimum requirement of 50 datasets for these models, dataset containing Items 341 and 344 with 5 years of service life (shown in Figure 3.2b) are used. Figure 3.7 presents the feature importance detected by the random forests algorithm for these data points. Similar to the five-fold cross validation approach described earlier, a total of 25 sets of feature importance data are obtained for each variable, and their mean and variability are plotted.



(a) Condition score



(b) IRI

Figure 3.7. Dependence of pavement performance on materials, construction, and traffic detected by random forests ensemble method.

Relatively high R^2 values are obtained for both CS ($R^2 = 0.83$) and IRI ($R^2 = 0.85$) standard deviations, showing the high learning ability of the model even with a limited number of data. Since a limited number of data are used to train the model, it is likely that these data do not represent the entire population of various combinations possible among different variables, resulting in poor performance scores on the test data. Hence, the model's generalization ability i.e., the predictability of the model on unknown data or test data, is not reported.

According to Figure 3.7, the total 18kip ESALS is found to have the most significant impact on the CS variability, followed by percent absorption, field density, and asphalt content. Whereas, IRI standard deviations are affected by the material properties (asphalt content and percent absorption) more than the traffic load and field density. Recycled binder content is found to influence the standard deviation of both the CS and IRI.

3.3.4 Neural network model

To facilitate a large number of data points in the neural network model, the performance of the pavement section in one year is considered as a single data point. Consequently, the dependent variables used for the neural network model are CS and IRI of the pavement for a specific year.

The independent variables selected for the neural network model are similar to the independent variables of the multivariate regression model: $meas\_18kip$, $dot\_ac, dot\_pdf, rb\_md, pg\_continuous, highway\_sys, zone, spec\_item, mix\_type$.

Compared to the independent variables used in the multivariate regression model, a few categorical variables, *highway_sys* and *zone*, are included to indicate the type of highway system of the pavement section and the climatic zone the pavement section is located. All pavement sections with specification items 341 or 344 are included in this analysis, as both of these items consist of similar mix types. Since both of these items have more than one mixes that are often used in constructions, *mix_type* is also included as an independent variable to incorporate their variability in the analysis.

After removing the data points with one or more missing independent variables, a total of 505 data points remain. To test the model accuracy, these 505 data points are randomly split into a training dataset and a test dataset. 70 percent of the data points are used to train the model, and 30 percent is set aside to test the model's predictability on unknown data. A three-layer (each layer has 500 neurons) neural network is used to predict the IRI and condition score.

3.3.4.1 Neural network model results

The results are discussed by presenting the R-square of the model, and plotting the predicted value against the actual value in the test dataset.

Two models are trained separately for the two dependent variables, CS and IRI:

- For the model with CS as the dependent variable, the achieved $R^2 = 0.57$. Since the maximum value of CS is 100, the maximum value of the predicted CS is restricted to 100.

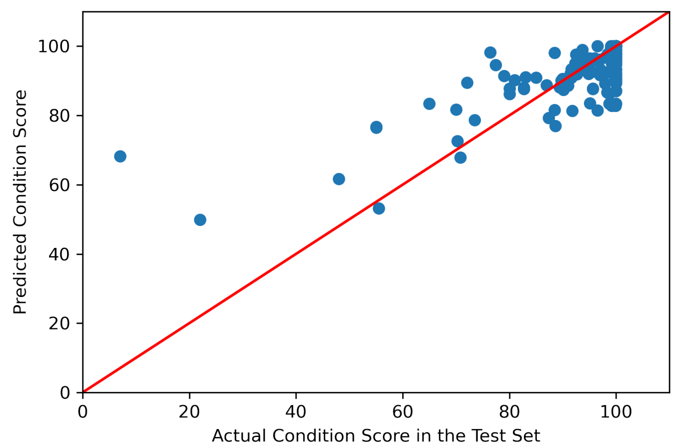


Figure 3.8. Test Results of the Neural Network Model with *CS* as the Dependent Variable

- For the model with IRI as the dependent variable, the achieved $R^2 = 0.71$.

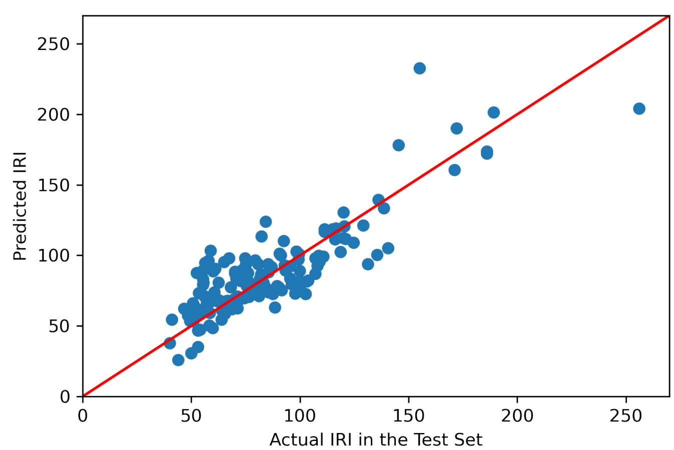


Figure 3.9. Test Results of the Neural Network Model with IRI as the Dependent Variable

From these results, it can be observed that both models can fit the data points relatively well and relate the dependent variables to the independent variables. It is obvious that neural network models perform better than the previous multivariate regression models in terms of the achieved R-squared value (R^2). With a relatively high R-squared value of 0.59, a clear relationship between the predicted IRI and the actual IRI in the test dataset can be observed, demonstrating the goodness of fit of the model.

3.4 SUMMARY

This chapter integrates pavement performance data with materials properties, construction and QC/QA practices, number and magnitude of traffic loading for a given service life to identify the influence of construction and material parameters on long-term pavement performance. The influence of material properties, including asphalt content, recycled binder content, binder grade, aggregate percent absorption, and mix type, construction parameter in terms of the field density, and traffic loading, such as 18kip ESALs and AADT, on the variability of condition score (CS) and international roughness index (IRI) is studied. Several analytical techniques, including the traditional statistical analysis techniques and the new generation data analysis tools, such as decision tree based ensemble models and artificial neural networks, are also employed for these analyses. The most important findings of this task are summarized below:

1. Material properties, including asphalt content, percent absorption, and recycled binder, field density - a construction parameter, and 18kip ESALs are predicted to influence the variability of both CS and IRI.
2. No conclusive relations have been found between the QC/QA performance tests (e.g., HWT and IDT) data and the as-built performance data. This is likely because the true pavement performance is masked by maintenance activities as discussed later.
3. The poor correlations detected by the linear regression analysis between the independent and dependent variables indicate the existence of non-linear interdependence of the variables.
4. Random forests, a decision tree based ensemble method, can better detect the impact of the materials, construction, and traffic loading on pavement performance than the linear models.
5. Artificial neural network models significantly outperform the linear regression models, signifying that there exist complex relations among the variables, which cannot be deciphered by linear models.

CHAPTER 4. VALIDATION OF ANALYZED RESULTS: SITE VISITS

4.1 INTRODUCTION

The primary objective of this task is to validate the results from analyses performed in Task 4 by visiting sites for a sample of projects and reviewing project performance including discussion with area engineers at TxDOT as needed. In Task 4, (summarized in Chapter 3), material properties, construction and QC/QA data, age, and traffic loading were analyzed to determine their influence on the long-term performance of the hot mix asphalt pavement. Condition score (CS) and international roughness index (IRI) were studied using the traditional statistical analysis and the new generation data analysis tools, such as decision tree based ensemble methods and artificial neural network. The artificial neural network and decision tree based ensemble models outperformed the linear models and implicated that complex relationship exists among the construction and material properties and pavement performance.

Based on the analysis performed in Task 4, a list of several projects from several TxDOT districts with satisfactory and unsatisfactory performance was created. In this task, performance of the projects as a function of material characteristics, age, and traffic is closely looked into to finalize a selected number of projects for validation through site visits and interviews. Local TxDOT engineers were contacted as subject matter experts who have the first-hand knowledge to corroborate the analyzed results for these projects. The project sites were also visited for the visual inspection of the current condition of these pavement sections. This chapter summarizes findings from these analysis, communications with the TxDOT personnel, and site visits.

4.2 PROJECT IDENTIFICATION

Mixture performance is a complex function of traffic, age, and materials properties. In order to better understand the effect of traffic, age, and mixture characteristics on the long-term mixture performance, the projects were analyzed in two steps. In the first step, mixture performance was analyzed against age and traffic to verify if there is a general trend among these factors. The mixture performance is then further analyzed against the mixture characteristics, including recycled binder content, binder content, and binder grade. Two mixtures, Mix (*C* and *D*), from Item 341 were analyzed separately to identify projects for site visits and interviews.

For both *341 C* and *341 D* projects, the relation between performance measurements and the material characteristics were plotted to identify potential projects that needed further attention and verification. This section presents the performance and material characteristics plots and discusses the rationale behind the projects selected to be interviewed for further investigation through interviews with local engineers at TxDOT districts.

4.2.1 Performance metrics as functions of time and traffic

This section shows cracking and rutting as a function of time. For the figures presented in this section, time is shown on the x-axis and traffic volume are represented by the size of the markers.

Figure 4.1 presents the percent fatigue cracking observed for 34 projects that used Type C mixtures (Item 341). These projects are numbered from 1 to 34 (labeled in the figure) to facilitate locating the project in the dataset. The circle size is used to represent the relative magnitude of ESALs. The dashed line shows a general trend when some of the extreme cases are ignored. Projects that showed poor performance despite having moderate or low traffic are located in the top-left area, whereas projects located in the bottom-right part away from the dashed curve demonstrated superior performance over a long period of time.

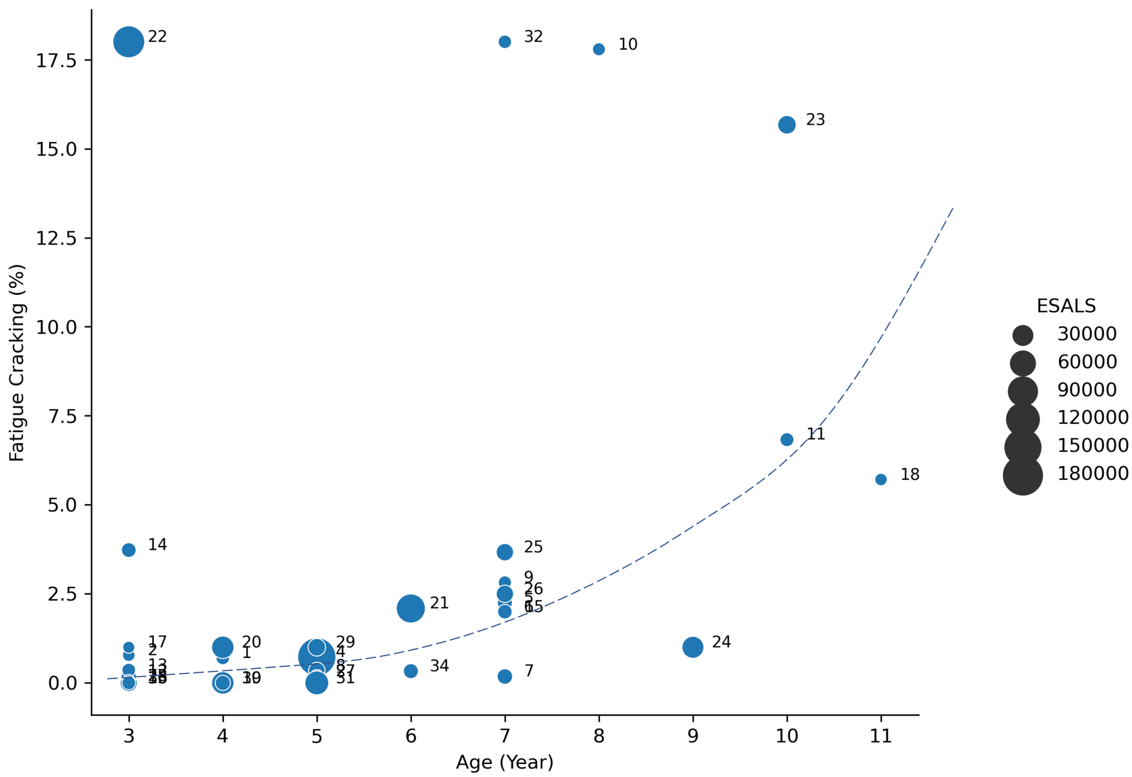


Figure 4.1. Maximum alligator cracking, age and ESALS of $341C$ **mixtures.**

Similarly, Figure 4.2 presents the percent fatigue cracking for 55 projects with Type D mixtures (Item 341). The circle size represents the relative magnitude of ESALs and the dashed line shows a general trend. Unlike Type C mixtures, all mixtures show a relatively stronger trend whereby increased cracking is observed for high ESALs over time. Likewise, Figures 4.3 and 4.4 show rut depths recorded in inches extracted from the PA database (it should be noted that the PA standard is to record rutting in inches, however, it is evident that several readings are unrealistically high to be in inches) for Type C and Type D mixtures as a function of age, with the circle size representing the relative magnitude of ESALs.

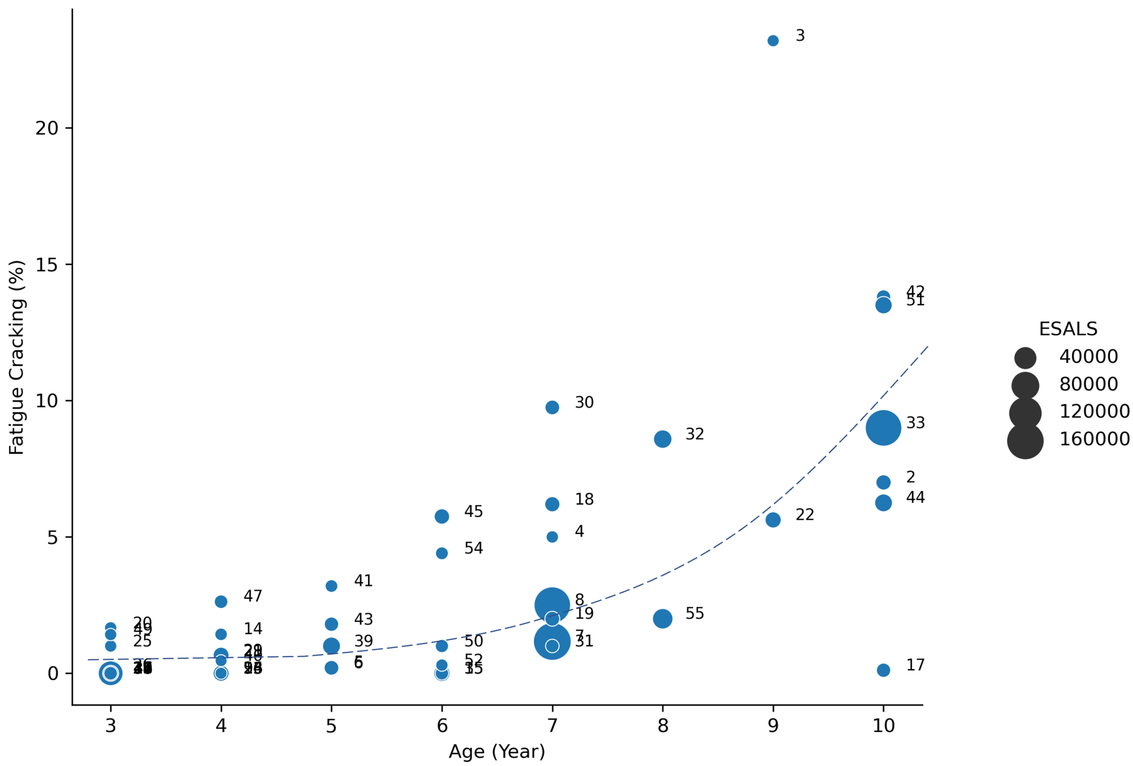


Figure 4.2. Maximum alligator cracking, age and ESALS of $341D$ mixtures.

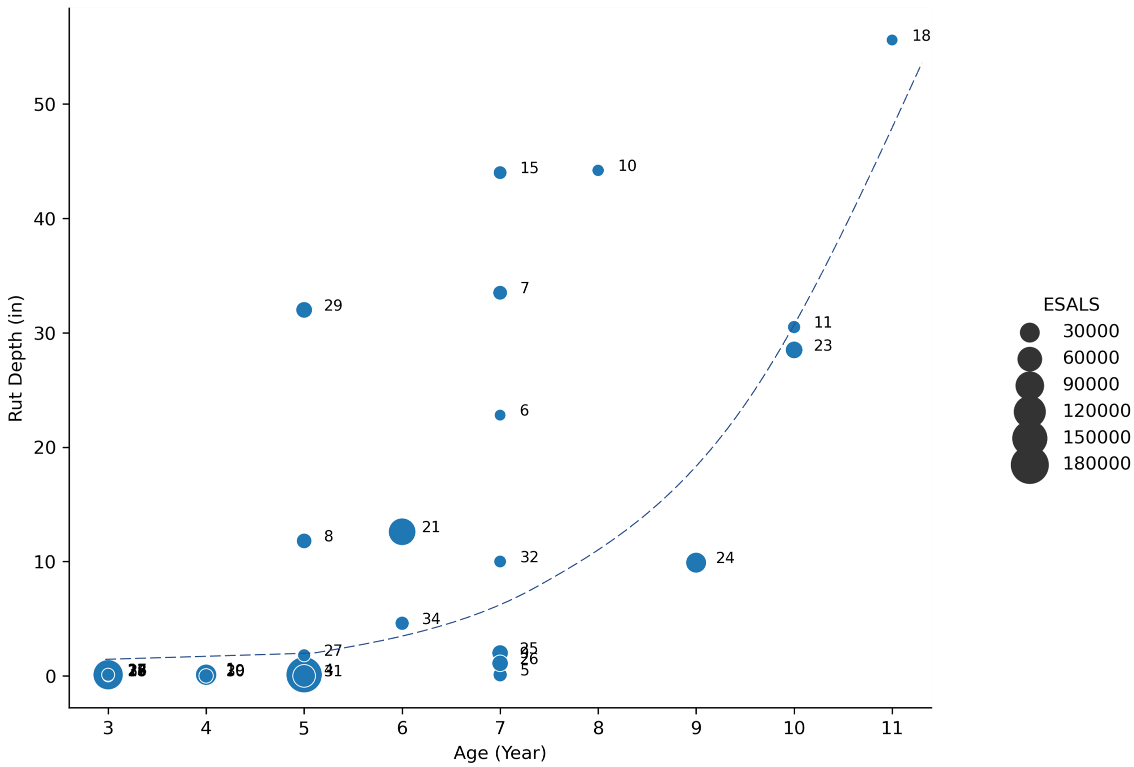


Figure 4.3. Maximum average rutting, age and ESALS of $341C$ **mixtures (note: The PA standard is to record rutting in inches, however, it is evident that several readings are not in inches).**

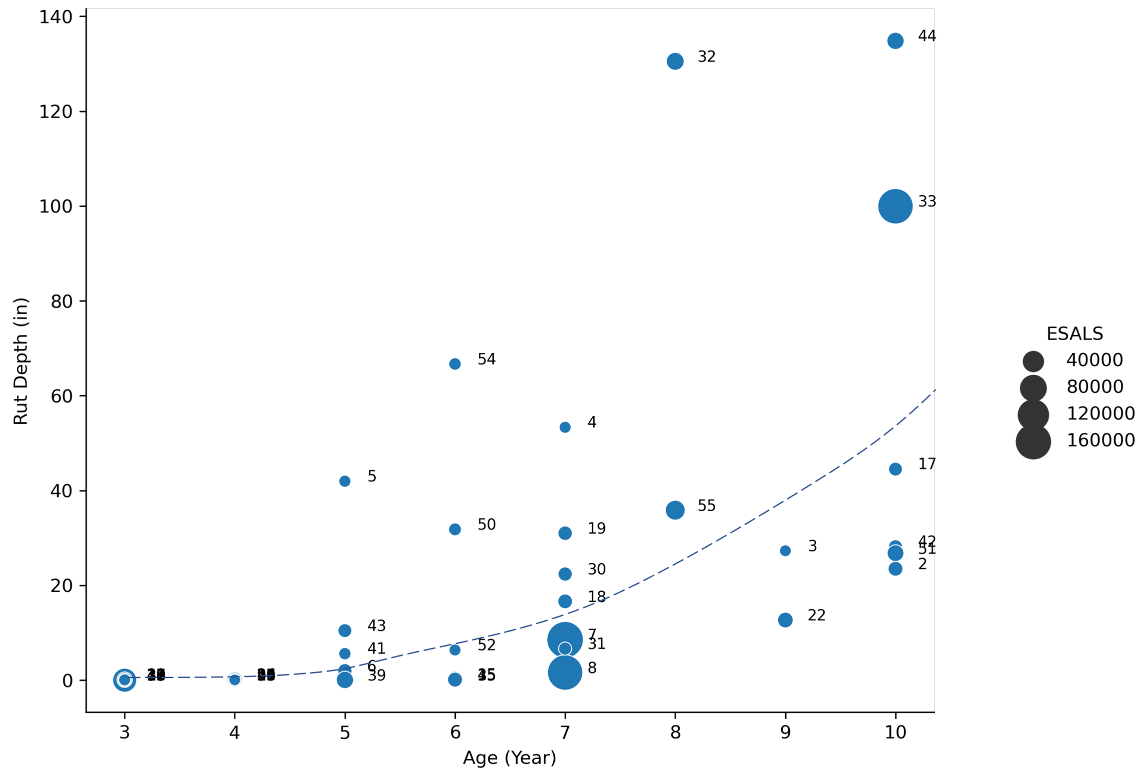


Figure 4.4. Maximum average rutting, age and ESALS of 341D mixtures (note: The PA standard is to record rutting in inches, however, it is evident that several readings are not in inches).

All the plots include mixtures that deviate from the general trend in both directions; some mixtures show sustained performance over time, whereas some exhibit premature failure, implying that other factors, such as material characteristics may influence the mixture performance. In order to capture the combined effect of age and traffic along with the mixture characteristics on the mixture performance, the predicted variables, e.g. *IRI* and fatigue cracking, were normalized by the number of years in service and the cumulative traffic volume in ESALs. For example, cracking was normalized as the percentage of the wheel path length per year per 1,000 ESALs (i.e., $cracking/year/1,000ESALs$ to reflect the effect of both age and traffic. The normalized performance metric were then analyzed with respect to the following material characteristics:

- Effective binder content, i.e. total binder content minus the absorbed binder;
- PG of the binder; and
- Recycled binder content.

While the thickness of the pavement layers are found to affect the progression of the pavement distresses, the structural information was not included in this study as information related to the structural design was not readily available from any of the databases analyzed in this study.

Also note that this study focused on alligator or fatigue cracking more than rutting or thermal cracking. The primary reasons for not including rutting were: (i) the magnitude of rutting recorded was very low for most sections, and (ii) this is an early-stage distress that becomes less likely over time and the projects that were analyzed here had 3 to 11 years of service history. The primary reason for not including transverse or thermal cracking was because very few sections were reported to have this distress, therefore making it difficult to draw any broader comparisons.

4.2.2 Normalized performance metrics as functions of material characteristics

Since statistical analysis using linear and non-linear regression did not yield any clear outcomes that relate material properties to the normalized performance because of the small amount of available data and the large variations associated with the data, a different approach was adopted. The performance metrics were normalized and the normalized metrics (alligator cracking or *IRI* changes) were analyzed against the effective binder content.

The rational for using effective binder content as the basis was as follows. As described earlier, the performance metric that was of primary focus was alligator cracking. Since mixtures were already being grouped by mix type, this ensured that the variability among mixtures in terms of aggregate gradation was consistent (at least to the extent of gradation bounds defined by Item 341). This then leaves four other material factors that could influence cracking: binder content, binder grade, aggregate absorption, and recycled asphalt binder content. Aggregate absorption was accounted for by using effective binder content thus reducing the analysis to remaining three factors.

Figures 4.5 and 4.6 present the normalized alligator cracking with respect to the effective binder content (*total binder content â binder absorbed*) for Type C mixtures. In the first figure, PG of the binder is denoted by the color of the circle with the circle size representing the relative magnitude of the recycled binder ratio (RBR). While in Figure 4.6, the circle color denotes age.

Two general groups can be observed from these data. In the first group (referred to as Group 1 in Figure 4.5) towards the bottom of the curve highlighted in the green box, the normalized alligator cracking shows very little change with the effective binder content.

This group contains projects that used high recycled binder content as well as projects that used very low recycled binder content. The second group of data (referred to as Group 2), highlighted using the brown box, shows that a decrease in effective binder content resulted in increased normalized cracking for the same RBR. Finally, a transition group (Group 3) can also be observed that include projects that fall between these two broader trends.

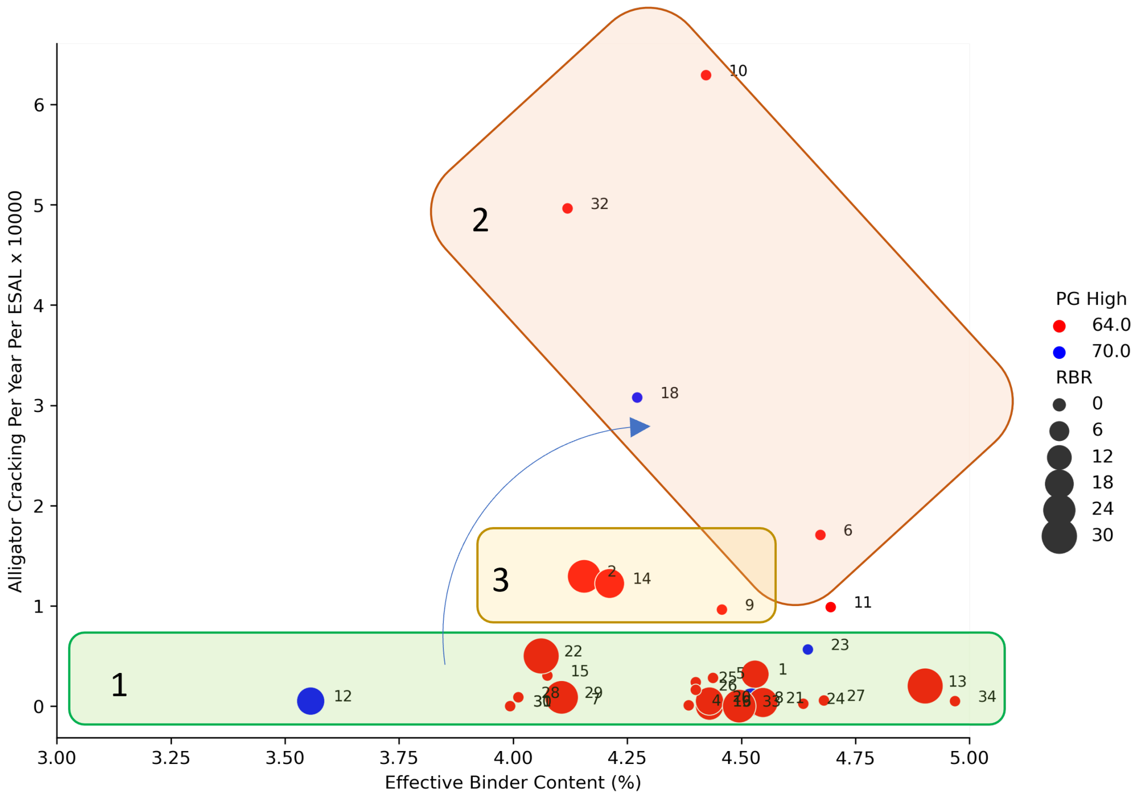


Figure 4.5. Relation between normalized alligator cracking and effective binder content of $341C$ **mixtures.**

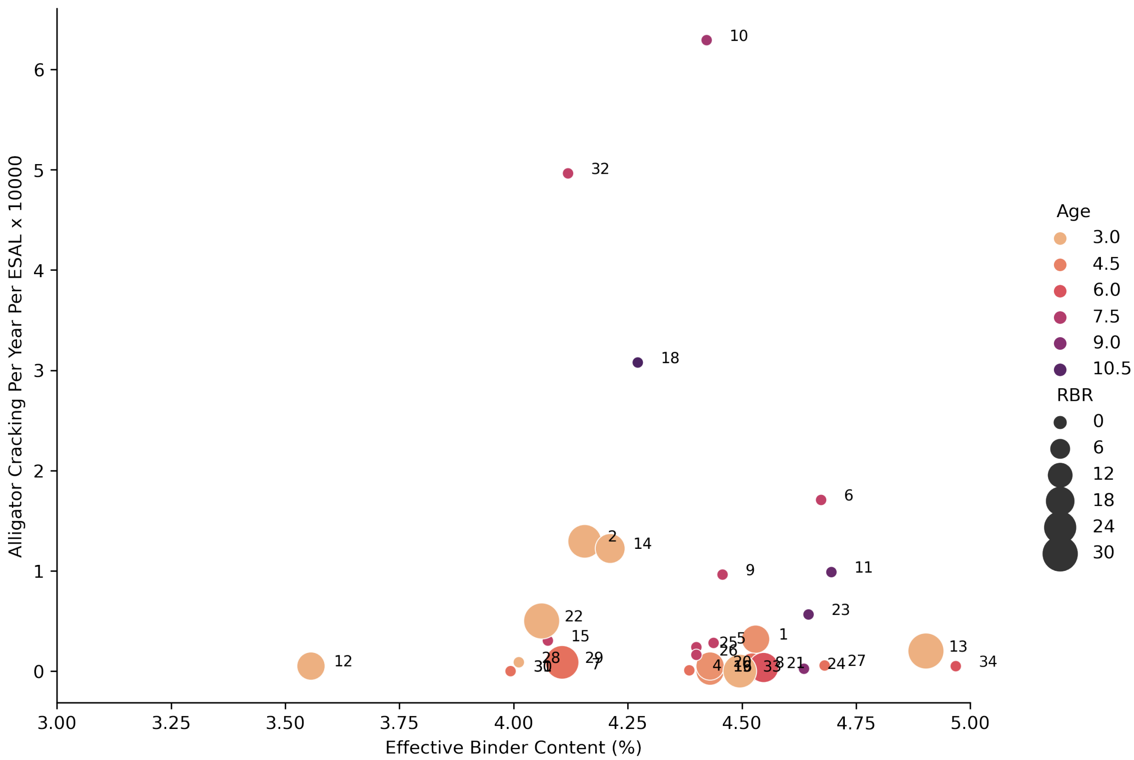


Figure 4.6. Relation between normalized alligator cracking and effective binder content of 341C **mixtures.**

Figure 4.7 shows the normalized ΔIRI with respect to the effective binder content for 341C mixtures, where ΔIRI indicates the change in IRI from the year the project was open to traffic to analysis year. The marker size was used to represent the RBR and the marker color was used to represent the PG.

There is no apparent trend between PG or RBR with respect to the normalized performance. Group 1 in Figure 4.5 contains mixtures that have high RBR, a PG 64 grade binder, and an effective binder content that is of the order of 4 to 4.25 percent. The same group also contains mixtures (e.g. Sections 10, 18, 32) that used a reasonable percentage of high PG polymer modified binder but still resulted in unusually high levels of normalized cracking. This is in contrary to the conventional norm or intuitive understanding of the impact of these factors on expected performance, where poor performance is expected with high RBR and low PG.

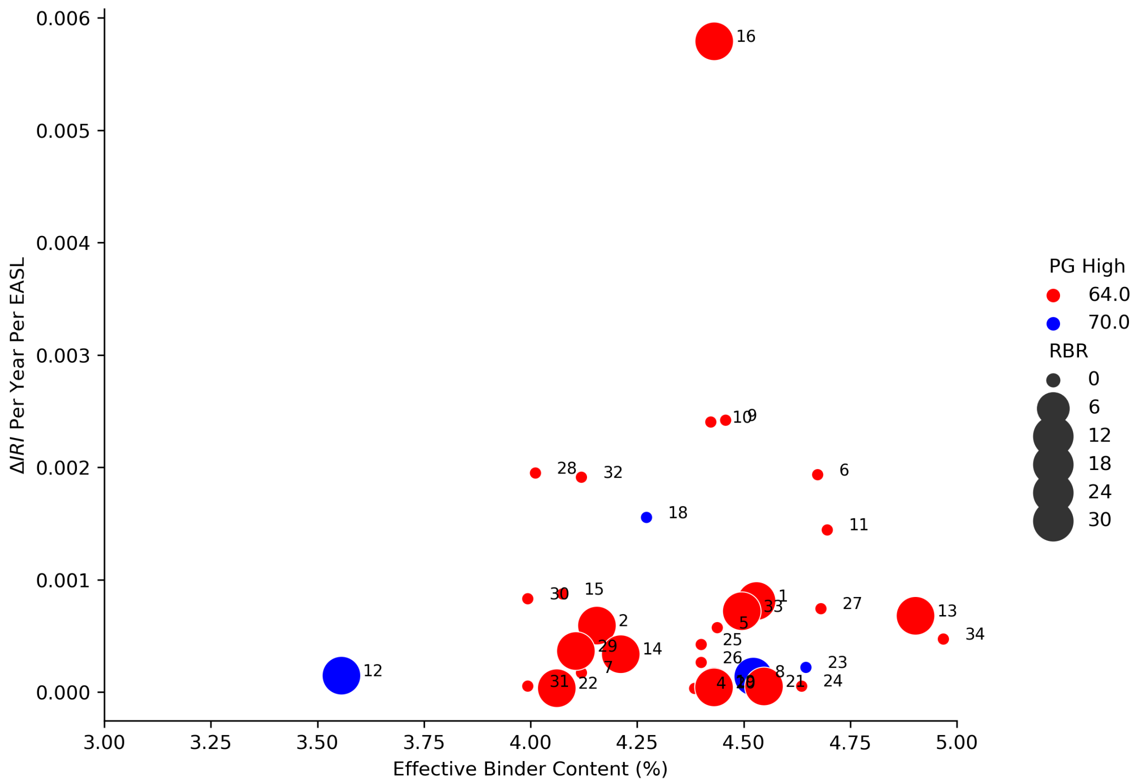


Figure 4.7. Relation between normalized *IRI* changes and effective binder content of 341*C* **mixtures.**

The main observation based on previous sections was that some sections demonstrated cracking behavior that was consistent with conventional understanding of mixture cracking susceptibility, i.e. lower effective binder content and higher RAP content presented more propensity to crack. Interestingly, there were sections that defied this norm as well, i.e. demonstrated low propensity to crack even when the binder content was low or contained high percentage of recycled binder. It is important to emphasize here that these observations are based entirely on the face value of the data extracted from PA. However, as discussed later, field inspection demonstrated that the PA data was not the most accurate or current descriptor of material performance in the field. Based on Figures 4.5 and 4.7 and the above discussion, the following projects with Type C mixtures were identified for site visits.

- Sections 12, 22, 29 for exhibiting good performance, as demonstrated by a small change in *IRI* and low fatigue cracking, despite having low effective binder content.
- Sections 2, 10, 18, 32 that had intermediate effective binder content, however showed poor performance as indicated by high fatigue cracking and a high increase in *IRI*.

Figures 4.8 and 4.9 show the normalized percent alligator cracking with respect to the effective binder content for Type D mixes. A notable observation of Figure 4.8 is that there is no PG 70 or 76 in the group marked with the brown box that showed high percentage of alligator cracking. Figure 4.10 shows the normalized *IRI* changes with respect to the effective binder content of 341*D* mixtures. Since many projects fall into the range between 0 and 0.004 unit of normalized *IRI*, Figure 4.11 is plotted to clearly differentiate different projects in this group.

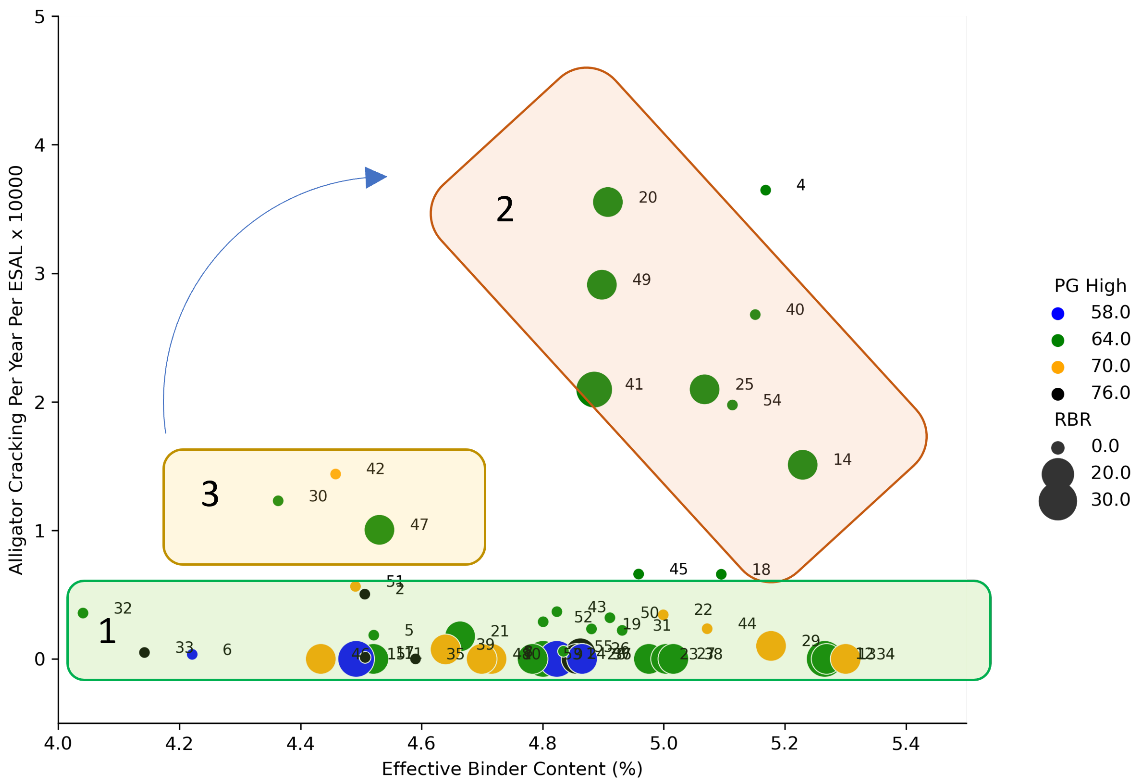


Figure 4.8. Relation between normalized alligator cracking and effective binder content of 341*D* **mixtures.**

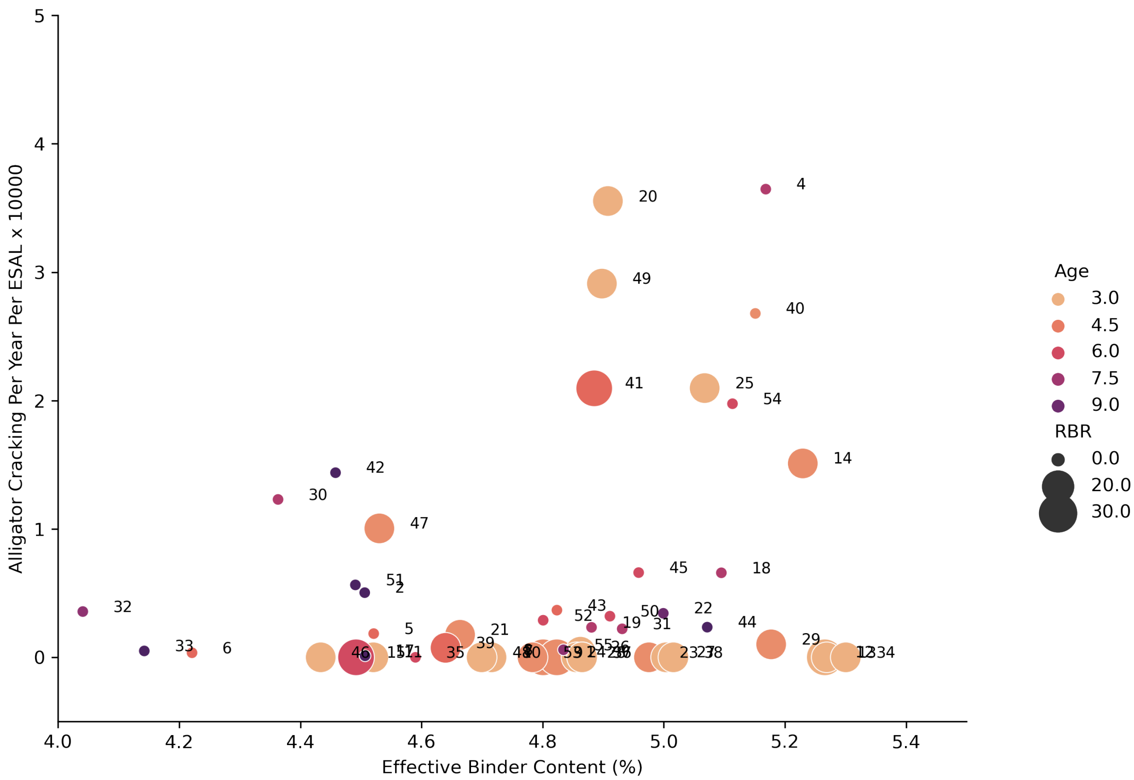


Figure 4.9. Relation between normalized alligator cracking and effective binder content of $341D$ mixtures.

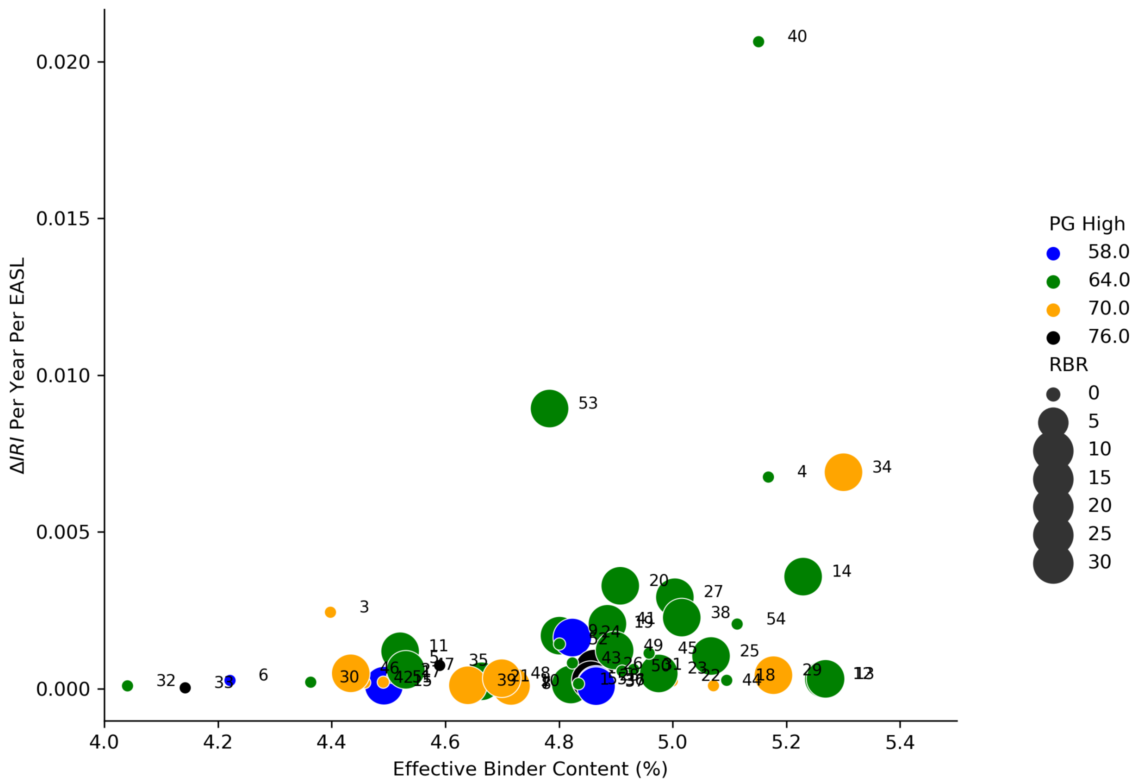


Figure 4.10. Relation between normalized *IRI* changes and effective binder content of 341*D* mixtures

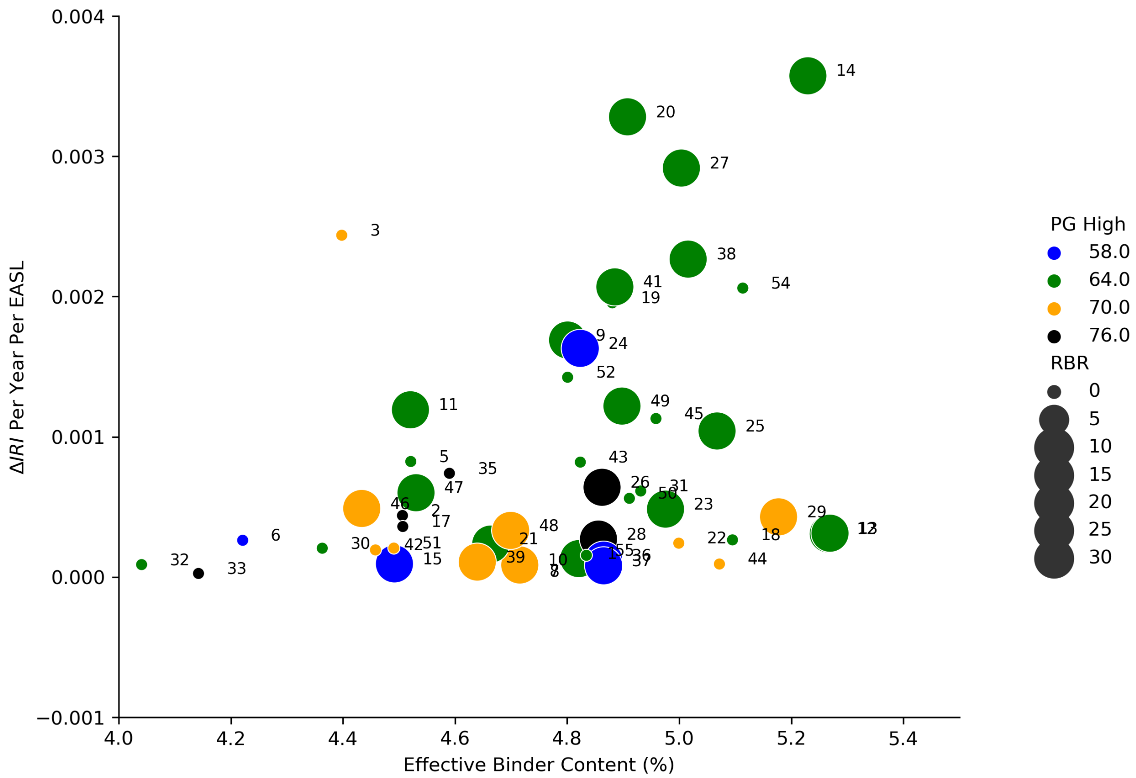


Figure 4.11. Relation between normalized *IRI* changes and effective binder content of 341*D* mixtures without outliers.

Similar to Type C mixes, Type D mixes also showed behavior that aligned well with the expected norm and vice-versa (as before also based on the face value of data extracted from PA). From Figures 4.8 to 4.11, the following projects are selected for validation through site visits:

- Section 11 contains a dry mixture of the PG 64-22 binder and RAP. This section has been performing well despite showing high *IRI*. It should be noted that high *IRI* does not necessarily indicate high percentage of cracking, however high percentage of cracking may cause the *IRI* to go up.
- Section 47 contains a dry mixture of the PG 64-22 binder and RAP. This section has also been performing will with signs of intermediate *IRI* and cracking.
- Section 20 contains a relatively less dry mixture of the PG 64-22 binder and RAP than the above sections. However, this section is not performing well in terms of cracking compared to Sections 11 or 47 as indicated by high *IRI*.
- Section 49 is similar to Section 20 in terms of mixture constituents. This section is

also performing poorly compared to Sections 11 or 47 exhibiting high percentage of cracking and intermediate *IRI*.

- Section 4 contains relatively high percentage of the PG 64-22 binder. This section does not have any RAP, but is showing severe rutting and cracks with very high *IRI*.
- Section 40 also contains high percentage of the PG 64-22 binder without any RAP. Deep rutting and longitudinal cracking along with high *IRI* have been reported for this section.

Table 4.1 summarizes the projects finalized for site visits, and the locations of the projects are shown in Figure 4.12. The most notable mixture constituent properties for these projects are listed in Table 4.2. It is important to emphasize that throughout this entire process, the location of the sections was anonymized and all comparisons were made on an aggregate basis.

Table 4.1. Selected project sites to be visited.

Section ID	Mix type	Years in Service	ESALs	Alligator Cracking (%)	ΔIRI
12	C	3	12025	0.18	5.27
22	C	3	119927	18.00	12.39
29	C	5	22797	1.00	41.62
10	C	8	3533	17.79	67.94
18	C	11	1688	5.71	28.86
32	C	7	5181	18.00	69.33
2	C	3	2002	0.78	61.00
14	C	3	10159	3.73	33.81
11	D	3	12603	0.00	45.10
47	D	4	6535	2.63	15.72
20	D	3	1563	1.67	15.39
49	D	3	1627	1.42	5.95
4	D	7	1958	5.00	92.56
40	D	4	430	0.46	35.56

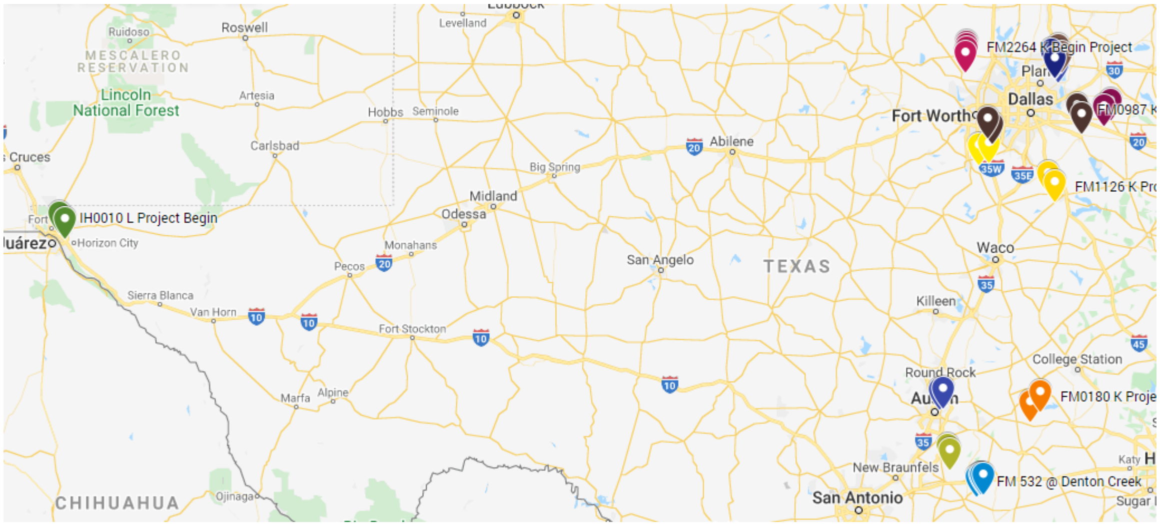


Figure 4.12. Locations of the Selected projects.

Table 4.2. Material properties of the selected projects.

Section ID	Mix type	$AC_{eff}(\%)$	PG	RBR(%)	VMA(%)
12	C	3.56	PG 70-28	20	14.55
22	C	4.06	PG 64-22	35	14.94
29	C	4.44	PG 64-22	30	13.81
10	C	4.42	PG 64-22	0	14.12
18	C	4.27	PG 64-22	0	14.65
32	C	4.12	PG 64-22	0	13.23
2	C	4.16	PG 64-22	30	13.61
14	C	4.21	PG 64-22	22	13.18
11	D	4.52	PG 64-22	20	15.34
47	D	4.53	PG 64-22	20	14.08
20	D	4.91	PG 64-22	20	15.57
49	D	4.90	PG 64-22	20	15.29
4	D	5.17	PG 64-22	0	15.65
40	D	5.15	PG 64-22	0	14.83

4.3 SITE VISITS

Local engineers from TxDOT districts for routes listed in Table 4.1 were contacted via emails and were asked to provide the following information on the selected projects:

- Maintenance activity in the past few years
- The engineers' assessment of how the section has performed over the years
- What are the primary factors that influence the performance of the project

Information on experiences related to early cracking and rutting or sections with exceptional performance was also sought from the district engineers. The information gathered from the site visits and responses from the engineers is summarized in Table 4.3. The images from these sections are presented in Figures 4.13 to 4.39. Sections 12 (Figures 4.13 to 4.16) , 10 (Figures 4.19 and 4.20), 32 (Figures 4.23 and 4.24), 2 (Figures 4.25 and 4.26), 11 (Figure 4.30), 20 (Figure 4.33), 49 (Figure 4.34), and 4 (Figures 4.35 to 4.37) showed distresses consistent with the PA data. Whereas, sections 29 (Figures 4.17 and 4.18), 14 (Figures 4.27 to 4.29), 47 (Figures 4.31 and 4.32), and 40 (Figures 4.38 and 4.39) could not be verified since these sections were treated recently with chip seals or thin overlays or ultra-thin bonded wearing courses.

Table 4.3. Site visit observations.

Section	Route	Site visit information
12	FM2264 K	The pavement surface showed a few longitudinal cracks (Figures 4.13 to 4.16). The area engineers indicated that this was in fact an experimental section placed three years ago to include high percentage of RAP and RAS with a 70-28 binder that was modified using SBR onsite during mixture production.
29	FM2514 K	Even though significant rutting was reported by the PA database, no visible rutting was seen from the site visit. A thin overlay was present, with visible cracks that might have been propagated from the layer underneath.
10	FM0987 K	Significant rutting and cracking were visible, which are also evident from the PA records (Figures 4.19 and 4.20).

Continued on next page

Table 4.3 continued

Section	Route	Site visit information
18	FM1126 K	Deep rutting reported by the PA database was not observed, rather the surface was appeared to be treated with a chip seal (Figures 4.21 and 4.22).
32	FM2965 K	Significant cracking was seen on the pavement surface (Figures 4.23 and 4.24).
2	FM0546 K	Visible distresses had been observed during the site visit (Figures 4.25 and 4.26).
14	FM1378 K	The pavement surface had been recently treated with a thin overlay mix and appeared to be in good condition (Figures 4.27 to 4.29).
11	FM0969 K	Longitudinal and transverse cracking were visible on the pavement surface (Figure 4.30).
47	FM2738 K	The pavement surface appeared to be in excellent condition. However it appeared that the surface had a new thin overlay mix or an ultra-thin bonded wearing course. Cracks, if any, were probably in the layers underneath (Figures 4.31 and 4.32).
20	FM1322 K	The pavement surface showed rutting in the wheel path (Figure 4.33).
49	FM0180 K	Similar to section 20, rutting was observed (Figure 4.34).
4	FM0532 K	The pavement surface showed signs of transverse cracking in addition to the longitudinal and alligator cracking reported by the PA database (Figures 4.35 to 4.37).
40	FM2415 K	The pavement surface had a chip seal. The chip seal appeared to be relatively new and there appeared to be no signs of distress bleeding through the chip seal but this does not preclude that there was no distress in the Type D mix (Figures 4.38 and 4.39).

4.4 SUMMARY

The results from the previous task were further analyzed yielding 14 projects for validation through interviews with local engineers at TxDOT districts and site visits. These projects were selected based on their relative performance with similar material constituent properties. Based on the credibility and consistency in the reported data, alligator cracking and *IRI* were selected to be the best indicator of the field performance; to better reflect time and traffic in the analysis, the original alligator cracking and IRI values extracted from the PA database were normalized by age and ESALs. The normalized parameters were then analyzed against RBR, effective binder content, and binder grade. Mixtures that were dry and contained RAP but were performing well as well as mixtures that were composed of high binder content without any RAP but were showing poor performance were selected for site visits. Performance of these projects recorded in the PA database was validated through visiting the project sites and contacting the district engineers. While the performance metrics for some of the projects were consistent with observations made during the site visit, others could not be verified because these sections were recently treated with chip seals or thin overlays or ultra-thin bonded wearing courses.

One of the main observations from these field visits was that of the 13 sections that were inspected, 5 had a chip seal or thin overlay already placed over the Type C or Type D mix. Some of these sections that were overlaid were only 3 to 5 years old. This information was not evident from PA or other databases that were included in this study. Further, this was only a sample of the sections that were included in the previous analysis, which suggests that it is possible for some of the well performing sections according to PA are well performing only because of an overlay that may have been placed since the time of construction.

Figure 4.13. Site Visit Picture of Type C mixture Section 12 (1).

Figure 4.14. Site Visit Picture of Type C mixture Section 12 (2).

Figure 4.15. Site Visit Picture of Type C mixture Section 12 (3).

Figure 4.16. Site Visit Picture of Type C mixture Section 12 (4).

Figure 4.17. Site Visit Picture of Type C mixture Section 29 (1) (the pavement surface being investigated appears to have an overlay/chip seal and is 5 years old).

Figure 4.18. Site Visit Picture of Type C mixture Section 29 (2) (the pavement surface being investigated appears to have an overlay/chip seal and is 5 years old).

Figure 4.19. Site Visit Picture of Type C mixture Section 10 (1)

Figure 4.20. Site Visit Picture of Type C mixture Section 10 (2)

Figure 4.21. Site Visit Picture of Type C mixture Section 18 (1) (the pavement surface being investigated appears to have an overlay/chip seal and is 11 years old).

Figure 4.22. Site Visit Picture of Type C mixture Section 18 (2) (the pavement surface being investigated appears to have an overlay/chip seal and is 11 years old).

Figure 4.23. Site Visit Picture of Type C mixture Section 32 (1).


Figure 4.24. Site Visit Picture of Type C mixture Section 32 (2).


Figure 4.25. Site Visit Picture of Type C mixture Section 2 (1).

Figure 4.26. Site Visit Picture of Type C mixture Section 2 (2).

Figure 4.27. Site Visit Picture of Type C mixture Section 14 (1) (the pavement surface being investigated appears to have an overlay/chip seal and is 3 years old).

Figure 4.28. Site Visit Picture of Type C mixture Section 14 (2) (the pavement surface being investigated appears to have an overlay/chip seal and is 3 years old).

Figure 4.29. Site Visit Picture of Type C mixture Section 14 (3) (the pavement surface being investigated appears to have an overlay/chip seal and is 3 years old).

Figure 4.30. Site Visit Picture of Type D mixture Section 11.

Figure 4.31. Site Visit Picture of Type D mixture Section 47 (1) (the pavement surface being investigated appears to have an overlay/chip seal and is 4 years old).

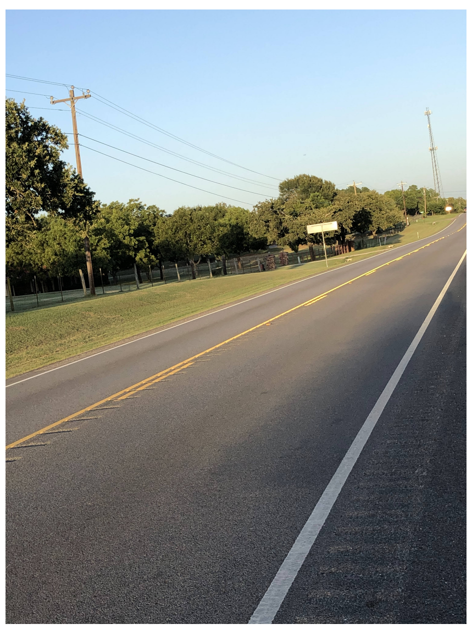


Figure 4.32. Site Visit Picture of Type D mixture Section 47 (2) (the pavement surface being investigated appears to have an overlay/chip seal and is 4 years old).

Figure 4.33. Site Visit Picture of Type D mixture Section 20.

Figure 4.34. Site Visit Picture of Type D mixture Section 49.

Figure 4.35. Site Visit Picture of Type D mixture Section 4 with transverse cracks.

Figure 4.36. Site Visit Picture of Type D mixture Section 4 with longitudinal cracks.

Figure 4.37. Site Visit Picture of Type D mixture Section 4 with fatigue cracks.

Figure 4.38. Site Visit Picture of Type D mixture Section 40 (1) (the pavement surface being investigated appears to have an overlay/chip seal and is 4 years old).

Figure 4.39. Site Visit Picture of Type D mixture Section 40 (2) (the pavement surface being investigated appears to have an overlay/chip seal and is 4 years old).

CHAPTER 5. CONCLUSIONS AND RECOMMENDATIONS

In this study we developed an internal working database integrating the materials characteristics, long-term performance, and project related information of hot mix asphalt pavement. Both traditional and new generation data analytic tools were applied to analyze the integrated data from the SMGR and PA databases. The effect of materials characteristics on the long-term pavement performance was analyzed. Based on the analyzed results, several projects were selected for site visits. The major findings from this study are summarized below.

1. To determine the effect of the material properties on the pavement performance, an internal working data repository comprising data from the SMGR, DCIS, and PA databases was developed. Data related to materials included the as-produced hot mix asphalt mixture properties, collected as part of QC/QA, such as aggregate gradation, mixture type, binder grade and content, recycled materials, aggregate absorption, and additives. The materials characteristics and information from the PA database about the traffic loading for a given service life as well as pavement performance measures in terms of cracking, rutting, distress score, condition score, and IRI were compiled together using the project location.

2. TxDOT typically records the materials information from every sublot and collects performance measures every 0.1 mile of a roadway. Since SMGR does not collect the specific location of a sublot or a lot, the performance information could not be linked to the materials characteristics for a given location. Rather the materials information and performance measures were averaged over the project length, creating artificial data sparsity and limiting the applicability of many new generation data analytic tools.

3. Several analytical techniques, including the traditional statistical analysis techniques and the new generation data analysis tools, such as decision tree based ensemble models and artificial neural networks, were employed for data analyses. No strong relations were detected by the linear regression models between the QC/QA parameters and the as-built performance data. The poor correlations found by the regression models imply that non-linear interdependence exist between the QC/QA parameters

and pavement performance.

4. Newer generation data analysis tools showed promising results- random forests, a decision tree based ensemble method, were able to detect the impact of the materi-als, construction, and traffic loading on pavement performance. Furthermore, artifi-cial neural network models significantly outperformed the linear regression models. These models were able to use parameters such as asphalt content, binder grade, recycled binder content, aggregate gradation, percent density achieved during field compaction, and total 18 Kip ESALs to predict the variability in the condition score and IRI with an R^2 of 0.83 and 0.85, respectively. Despite these encouraging results, researchers believe that two additional pieces of information can significantly improve the quality of predictions and also more confidently establish the importance of each factor on the observed performance: (i) structural information and (ii) maintenance activities carried out on each section.

5. While analyzing data in the PA database it was revealed that several records showed unrealistic values, as high as several hundreds of inches in rut depth, implying the current PA database may have a standard method for automatically detecting outliers or preventing abnormal data from being registered. If such a method is al-ready in place in PA, then additional fine-tuning might be needed.

6. Based on the materials information collected from the SMGR database and performance reported in the PA data, 13 projects from Item 341 with type C and D mixtures were selected for site inspection. While the performance metrics for some of the projects were consistent with observations made during the site visit, others could not be verified because these sections were recently treated with chip seals or thin overlays or ultra-thin bonded wearing courses. This information was not evident from PA or other databases that were included in this study. Further, this was only a sample of the sections that were included in the previous analysis, which suggests that it is possible for some of the well performing sections according to PA are well performing only because of an overlay that may have been placed since the time of construction. Some of the results from unified database were consistent with expectations (e.g. low binder content can result in durability problems when all other factors were similar), whereas for a cluster of sections this was not the case. Researchers believe that the

latter was due to false negatives or false positives that are not being captured in the current databases.

Depending on the reviewed construction and performance records, performed analyses, visited project sites, and feedback received from local subject matter experts at TxDOT, the following recommendations are provided for immediate and future implementations.

1. In order to utilize the PA and SMGR database to their full potential, it is recommended that the offset distance of a sublot with respect to the beginning of the highway should be recorded as part of QC/QA. This way, materials properties of the plant produced materials for each sublot can be linked to the performance metrics from the PA database potentially furnishing multiple data points for any project rather than one average value for the entire project length. Additionally, GPS information of field cores could be easily incorporated into the QC/QA template which can also facilitate linking materials properties to performance measures. This will address the data sparsity issue and potentially improve the performance of machine learning algorithms.

2. The PA manual specifies that the rut depth is recorded in inches. However several hundreds of inches of rut depth have been recorded in the PA database, which suggests that there might exist more than one standard to upload data in the data management system and requires human intervention. Therefore, an enhanced evaluation tool/protocol should be developed that can be used to validate the quality and consistency of the data storage, management, and processing techniques for rut depth and crack detection. In addition, even though it is understood that a strict QC/QA process is used to ensure the quality of PA data entries, further enhancements to standard formats for the data type and data unit should be incorporated to ensure the quality of the measured and recorded data.

The following two recommendations are for more immediate implementation.

3. It was evident from the site visit that several projects selected for further investigation were already treated with chip seals or overlays which were not captured by the PA database. As a result, the total dollar value spent on a highway section for maintenance activities could not be incorporated in the study. An integrated approach/ methodology incorporating all maintenance activities in addition to the construction

and performance information needs to be adopted to obtain the accurate records of the total dollar spent through the project life. Such a method could be encoded into existing SMGR templates for ease of use, training, and implementation.

4. During this research a temporary database that combined other databases was developed and used. It is of tremendous value to TxDOT that this unified system be implemented through a commercial platform that is already available to TxDOT (e.g. Tableau) for real-time use on a sustained basis. This is also critical as TxDOT transitions to newer asphalt specifications (e.g. Item 344 instead of Item 341). Information on extent of use of these specifications across the state and an ability to monitor performance at a project level would be extremely valuable to assess the impact of these changes. Such a system could also incorporate features such as maintenance activities as described in the aforementioned bullet point.

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