MoDOT Pavement Preservation Research Program
Volume III, Development of Pavement Family and Treatment Performance Models

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16. Abstract

Pavement performance models describe the deterioration behavior of pavements. They are essential in a pavement management system if the goal is to make more objective, reliable, and cost-effective decisions regarding the timing and nature of pavement maintenance activities. The general objective of Task 2 was to develop performance models for a variety of pavement families and pavement preservation treatments used by the Missouri Department of Transportation (MoDOT). Using the data collected in Task 1, linear least-squares regression techniques were used to generate deterministic models that predict the International Roughness Index (IRI), the pavement condition measure most widely used today. Family IRI-prediction models were developed for full-depth asphalt (FDA), concrete (PCC), and composite (Comp) pavements. Treatment IRI-prediction models were developed for 1-in. overlays on FDA pavements, chip seals on FDA pavements, and 3.75-in. overlays on PCC pavement. Predictor variables consistently shown to be highly significant in predicting IRI for both FDA and Comp pavements were initial IRI (IRI_o or the IRI value right after treatment) and pavement surface age (SA). The majority of the PCC pavement sections selected were so old that IRI_o could not be determined (or estimated with any confidence), therefore SA was the dominant predictor variable in the PCC pavement family model. Terminal IRI (IRI_t which was the IRI just prior to a treatment) was also a significant predictor of IRI and was directly or indirectly included in the FDA and Comp family and treatment models. Additional significant IRI predictors (depending on the model) were the climate parameters DT32 (days/year that air temperature was below freezing), FT (freeze/thaw cycles per year), and DP01 (days/year that precipitation was at least 0.1–in.), subgrade soil parameters P200 (percent passing the #200 sieve) and Pclay (percent clay-size soil), and LstTrtThk (the last treatment thickness).

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MoDOT PAVEMENT PRESERVATION RESEARCH PROGRAM
MoDOT TRyy1141

FINAL REPORT

VOLUME III
DEVELOPMENT OF PAVEMENT FAMILY AND TREATMENT PERFORMANCE MODELS

July 29, 2015

Prepared for the
Missouri Department of Transportation

by

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EXECUTIVE SUMMARY

Pavement performance models describe the deterioration behavior of pavements. They are essential in a pavement management system if the goal is to make more objective, reliable, and cost-effective decisions regarding the timing and nature of pavement maintenance activities. The general objective of Task 2 was to develop performance models for a variety of pavement families and pavement preservation treatments used by the Missouri Department of Transportation (MoDOT).

Using the data collected in Task 1, linear least-squares regression techniques were used to generate deterministic models that predict the International Roughness Index (IRI), the pavement condition measure most widely used today. Family IRI-prediction models were developed for full-depth asphalt (FDA), concrete (PCC), and composite (Comp) pavements. Treatment IRI-prediction models were developed for 1-in. overlays on FDA pavements, chip seals on FDA pavements, and 3.75-in. overlays on PCC pavement.

Predictor variables consistently shown to be highly significant in predicting IRI for both FDA and Comp pavements were initial IRI (IRI_o or the IRI value right after treatment) and pavement surface age (SA). The majority of the PCC pavement sections selected were so old that IRI_o could not be determined (or estimated with any confidence), therefore SA was the dominant predictor variable in the PCC pavement family model. Terminal IRI (IRI_t which was the IRI just prior to a treatment) was also a significant predictor of IRI and was directly or indirectly included in the FDA and Comp family and treatment models. Additional significant IRI predictors (depending on the model) were the climate parameters DT32 (days/year that air temperature was below freezing), FT (freeze/thaw cycles per year), and DP01 (days/year that precipitation was at least 0.1–in.), subgrade soil parameters P200 (percent passing the #200 sieve) and Pclay (percent clay-size soil), and LstTrtThk (the last treatment thickness).

Although the literature indicated that traffic is a significant factor affecting treatment service life, neither Annual Average Daily Traffic (AADT) nor Annual Average Daily Truck Traffic (AADTT), both measured by direction of travel (one-way), showed significance as predictors on their own. Even accumulated traffic, the product of SA and AADT (or AADTT), seldom showed significance and/or possessed the expected sign on the regression coefficient. The theory is that a compounding of inaccuracies occurs in the traffic data due to a series of assumptions by MoDOT in the assignment of traffic volume to pavement sections, and possibly subsequent decisions by the Task 1 researchers regarding traffic volume fluctuation over time. Another reason that could explain why increasing traffic did not show up significantly in the models as a cause for increasing IRI could be that some variables that reduce deterioration are associated with traffic level and actually increase along with increasing traffic: thickness, quality of materials and construction, and maintenance quality; an increase in these variables will counteract to a certain degree the deteriorating action of increasing traffic.

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1 INTRODUCTION

Pavement performance models describe the deterioration behavior of pavements. They are essential in a pavement management system (PMS) if the goal is to make more objective, reliable, and cost-effective decisions regarding the timing and nature of pavement maintenance activities.

The purpose of a performance model is to predict pavement condition, primarily as a function of time. Models for pavement families (groups of pavements with similar characteristics and conditions) and preservation treatments are relied upon as tools in pavement management decision-making. For this reason, development of reliable pavement performance models is of the utmost importance in this project.

1.1 Objectives

The primary objectives of Task 2 were to:

- Perform a literature review to determine how transportation agencies or other researchers have approached pavement performance modeling
- Collaborate with the Missouri Department of Transportation (MoDOT) to obtain information needed to understand MoDOT's experience with performance modeling and expectations for any newly developed models
- Compile data collected by the Task 1 team into a usable format and generate pavement performance models and preservation treatment models

1.2 Scope

The Pavement Preservation Research program study scope was limited to "minor" roads. It was somewhat difficult to determine exactly what the definition of "minor" roads is in terms of AADT. This is an important distinction because of the way the pavement families were determined for model-building. For this study, the cut-off of less than 3500 AADT was used.

Selection of roadway segments was conducted in close coordination with Task 2, which developed pavement family and treatment models. Originally, roads were classified as to "Design Pavement Name" because it is the best system for delineating design features: traffic levels, internal drainage, widened travelways, and type of shoulders. However, this effort was abandoned because of so many missing records in SS Pavement. Ultimately, pavement families were comprised of two-lane, undivided highways, and further defined by pavement type (full-depth asphalt, concrete, or composite) and traffic level (for the full-depth asphalt family, there were four traffic levels based on AADT: less than 400, 400-750, 750-1700, 1700-3500). "Full-depth" was defined as an asphalt pavement with no concrete in the cross-section. Very few "Full-Depth" asphalt pavements were truly full-depth, but actually had some unbound granular base beneath the asphalt.

Ten candidate full-depth asphalt routes for data collection were identified for each of the four traffic levels using ArcMap with SS Pavement data. At the recommendation of the MoDOT Research leadership, for most pavement families, all full-depth routes were selected from the Central District to serve as a model of how the rest of the state pavement system should eventually be modeled. Routes for each traffic level were selected from across the district, usually three north of the Missouri River and seven south of the Missouri River, to provide some geographic, subgrade, and climate variability.

Additionally, 13 composite segments at up to 12,000 AADT were evaluated over a larger geographic area to garner a sufficient number of segments. There were no concrete-only segments that satisfied the above requirements for a separate dataset. Ultimately, routes in 24 counties across six districts (Central, NE, NW, Kansas City, SE, and SW) were sampled to cover the three different pavement types.

After the potential routes were identified, they were screened with ARAN Viewer to delineate continuous and homogenous segments of at least 1 mile in length. Homogeneity was defined as having no change in surface type (e.g. overlays or chip seals, bridges, etc.) and no change in speed (speed limits, stop signs, etc.). This step resulted in a total of 40 full-depth asphalt segments and 13 composite pavement segments. Because each route segment was two-lane, undivided, the actual number of “traveled lane” segments for modeling purposes was 80 full-depth (20 per traffic level) and 26 composite (and, thus, concrete prior to first asphalt overlay) routes.

2 LITERATURE REVIEW

The purpose of the literature review was to determine how transportation agencies and other researchers have approached pavement performance modeling. Identification of the pavement condition parameters (the model response or dependent variable) and model main effects (the predictor or independent variables) that are commonly utilized in pavement performance modeling, and the various model forms, was a necessary first step in formulating a strategy for developing MoDOT's models based on the types of data available.

2.1 AASHTO Pavement Management Manual

The American Association of State Highway and Transportation Officials (AASHTO) published the second edition of its guide to pavement management in 2012. A 2011 draft of this document (Zimmerman et al. 2011) was the first document reviewed for guidance on Task 2 work within the MoDOT Pavement Preservation Project. Chapter 5 of the AASHTO guide describes the types of data required for modeling, different approaches to modeling such as the type of pavement condition measures to be predicted, the various model types (probabilistic, Bayesian, deterministic, or expert-based) and forms (e.g. linear, power, logarithmic, sigmoid), the various applications of performance models (e.g. pavement family models, preservation treatment models, or remaining service life), and the statistical requirements for any model that is considered.

The Bayesian and expert-based model types rely to some degree on subjective data which may be appropriate when empirical data is not readily available. That is not the case for this project task. The probabilistic approach does not predict a single pavement condition value but gives a likelihood or probability that a pavement will be in one of several condition states. This feature is advantageous in that it does account for pavement variability, but the model does not lend itself easily to implementation into pavement management software. The deterministic model is the most common model type for pavement performance modeling and is generated using regression analysis procedures.

2.2 MoDOT

Donahue (2002) performed pavement performance modeling for various pavement families based on pavement type and functional classification. The linear model form was utilized with surface age (X_1) as the only predictor variable (Eq. 1). However, several pavement condition measures were used as the response variable: IRI, condition score, ride score, present serviceability rating (PSR), and specific distress indices such as rut depth and cracking index.

$$y = a + b(x_1) \qquad \text{(Eq. 1)}$$

2.3 Other State DOTs

2.3.1 Pennsylvania DOT

Wolters and Zimmerman (2010) developed a recommended pavement performance modeling option for the Pennsylvania Department of Transportation (PennDOT). Their investigation included a 2009 survey of state agencies regarding current modeling practice, and summarized some of the key state survey results as case studies in developing PennDOT's recommended modeling option. Although the concept of individual roadway section models was discussed, the recommended modeling option was for creating an overall condition index for each pavement family in the PennDOT system, which would result in 37 models. The recommended model type was deterministic, but no specific model of any form was actually developed. The work of data collection and model building was left to PennDOT to pursue.

2.3.2 Mississippi DOT

George (2000) authored a report about pavement family prediction models used by the Mississippi DOT's pavement management system (PMS). Model types utilized were mostly deterministic but some Bayesian modeling was generated. Deterministic models were of the general power form (Eq. 2). Predictor variables of significance were age, traffic, modified structural number/slab thickness, and overlay thickness. Predicted pavement condition parameters included IRI, a composite condition index (PCR or pavement condition rating), and various distress indices such as alligator cracking in asphalt pavements and punch-outs in continuously reinforced concrete pavements.

$$y = a + b(x_1)^c (x_2)^d \qquad \text{(Eq. 2)}$$

Of interest in the George report was one of the predicted asphalt or composite pavement distresses: the 85th percentile rutting distress. A primary maintenance trigger can simply be user discomfort (quality of the ride). The driving public does not usually wait until an entire stretch of roadway is bad before complaining; just a few deep ruts or other forms of distress in a roadway can trigger phone calls to customer service. Modeling deterioration of the poorest sections of a roadway could be beneficial to maintenance planners.

2.3.3 Louisiana DOT

Khattak et al. (2000) issued a report addressing performance models used in Louisiana's PMS. Family and preservation treatment performance models were developed. Families were based on pavement type and functional classification. Preservation treatments modeled were chip seals, 2-in. overlays, and micro-surfacing. Model forms evaluated were polynomial, power, exponential, and logarithmic, with the general power form shown in Eq. 2 ultimately being utilized but the only predictor variable was surface age. Pavement condition measures to be predicted were IRI, rutting, various forms of cracking, and patching. Models were developed for the lower, middle, and upper 1/3 percentiles for select distresses, a concept also reported in the Mississippi study (George 2000).

2.3.4 Colorado DOT

Colorado (2012) models (curves) are both of the site-specific and family varieties. Models predict five types of distress and smoothness, and are a function of surface age. As shown in Fig. 2.1, a non-linear-type function is fit to distress/performance data and remaining surface life (RSL) is estimated through extrapolation. RSL is a relatively common pavement management parameter in the literature.

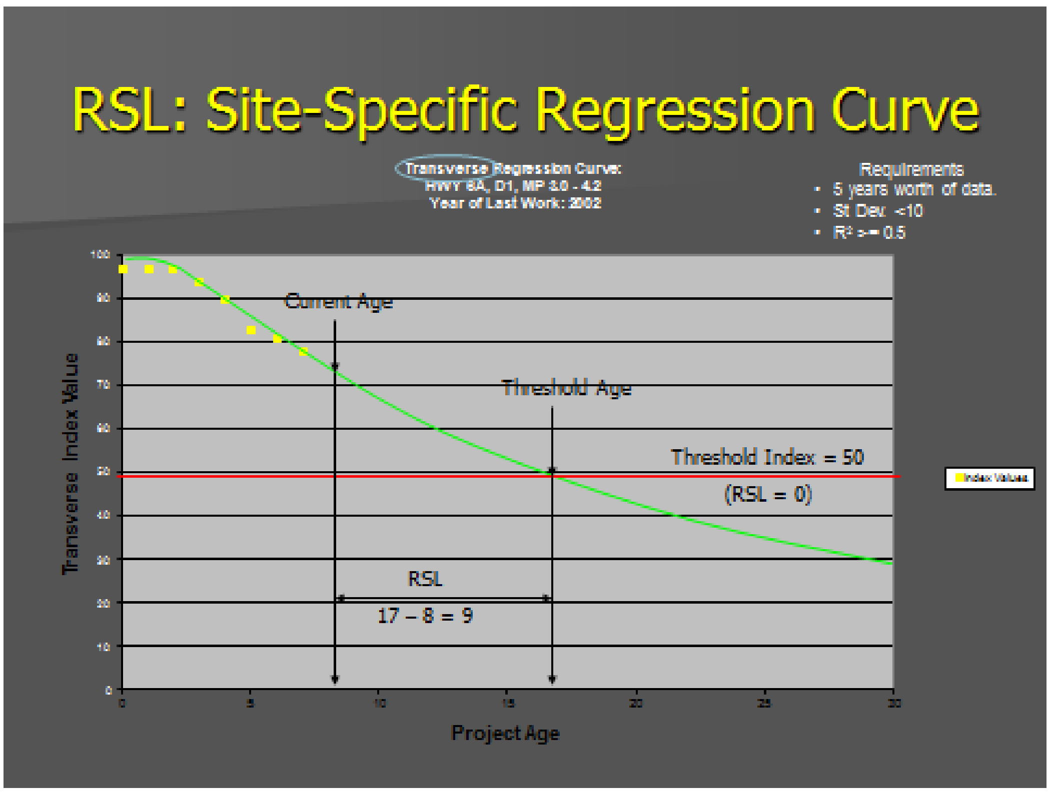

Fig. 2.1—Colorado DOT model example for determining RSL.

2.3.5 Virginia DOT

Virginia (2007) uses IRI as its pavement smoothness parameter but developed models that used load- and non-load-related distress indices (LDR and NDR, respectively) to characterize pavement condition. LDR and NDR values are assigned to several different types of distress, such as alligator cracking, and those indices become the response variable in a regression analysis where surface age is the only predictor variable and is in the "deduct point" term of the model (Eq. 3).

$$\text{index} = 0 - e^{a-b(c)^t} \qquad \text{(Eq. 3)}$$

where: 0 = Index immediately after rehabilitation (age zero)
e = Euler's number
a, b, c = regression coefficients
t = natural log of (1/Age); i.e. ln(1/Age)

2.3.6 South Dakota DOT

South Dakota (2011) developed 168 pavement performance models using the linear, power, and polynomial forms where surface age is the only predictor variable. Response variables were individual distress condition indices and a composite condition index. Models covered various pavement types.

2.4 Researchers

2.4.1 Khattak et al.

Khattak et al. (2013) developed treatment models for an asphalt overlay on: 1) an asphalt pavement and 2) a composite pavement. The natural log of IRI was the predicted response. The model form was multiple-linear; i.e. a multiple-*X* form of Eq. 1. The predictor variables were a mixture of natural-log transformed values and non-transformed values. The predictor parameters were surface age, the IRI just prior to treatment, cumulative equivalent single-axle loads (ESAL), precipitation and temperature indices, layer thicknesses (hot mix asphalt [HMA] and concrete), and functional classification.

2.4.2 Liu et al.

Liu et al. (2009) evaluated chip seal data in Kansas and developed multiple-linear models that predict IRI and rut depth based on initial IRI or initial rut depth (respectively), surface age, and a coded dummy variable for roadway classification (depending on the response variable). Models were also developed to predict transverse and fatigue cracking based on the initial cracking distress measurement, surface age, the roadway classification dummy variable, and cumulative ESALS (depending on the model). The initial distress values were taken a year after the actual chip seal treatment.

2.5 Literature Review Summary

The literature review included several more studies than those discussed above. Many studies included extensive literature reviews of pavement performance/deterioration modeling; the Mississippi DOT report referenced above is an example of one such study (George, 2000), as well as a Pierce and Kebede (2015) analysis for the Washington state DOT on the best practices of chip seal performance measures. Additionally, personal communication with state DOT personnel responsible for pavement management and modeling was performed via phone and e-mail. Based on the review and personal communications, 1) deterministic model types are predominant with preference to the linear least-squares and power forms, 2) pavement families are generally based on pavement type and roadway classification system, and 3) the primary pavement condition measure is IRI although specific pavement distress parameters and condition indices are still in use.

It has been shown in the Task 1 report (Vol. II) that the longevity of pavement maintenance treatments depends upon:

- Original pavement type
- Layer thicknesses
- Base characteristics, including internal drainage
- Specific design features
- Subgrade type
- Condition prior to treatment
- Initial condition after treatment
- Quality of treatment
- Climate
- Accumulated traffic, especially truck traffic
- Interim maintenance procedures
- Surface age

However, not all of the above factors can always be used as predictor variables, usually because sufficient quantities of good quality data are not available.

3 INVESTIGATION

This chapter describes the procedure followed for generating three pavement family and three treatment performance models that predict IRI. No models are presented for MoDOT's former 20-point Condition Index, and there was not enough data collected to develop models for the new PASER (10-point) system.

3.1 Task 1 Data Reduction and Configuration

The following steps describe the method for configuring the Task 1 supplemented data files (again, still in raw or unit form; each record represented ~0.02 miles) into a form that allowed for importation into statistical software.

1. Each Task 1 pavement section file first received the following treatment:

    a. Cleaned up the file by removing Task 1 notes, plots, other annotations, unnecessary rows/columns, etc.

    b. Created and populated additional columns: e.g. Assumed Last Treatment Date, Last Treatment Thickness, Surface Age, Unit IRI, and Pdiff. The Assumed Last Treatment Date column was created in the day/month/year format and may have been, ultimately, different than the "Last Treatment Date" determined by the Task 1 team (see Steps 1c and 1d, next). Last Treatment Thickness (LstTrtThk, expressed in inches) was taken directly from documentation or estimated based on surface widths and asphalt tonnage per mile (NOTE: all chip seals were assigned a thickness of 0.375 inches). Surface Age (SA, expressed in years) is the difference between the date the ARAN data was collected (ARAN table field labeled as DATE0) and the Assumed Last Treatment Date. The Unit IRI (representing ~0.02 miles of roadway) is the average of the passenger and driver IRI (fields extracted from the ARAN Inventory tables during Task 1). Pdiff is defined as the percent difference between the passenger IRI and the driver IRI, and is explained in further detail in Step 5, below.

    c. Task 1 Last Treatment Dates were double-checked if the SA (or plots of the 20-point Condition Index as a function of DATE0) indicated that there may have been a pavement treatment missing in the Task 1 data.

    d. If the Task 1 Last Treatment Date was given as a year only (no month or day), July 31 was taken as the Assumed Last Treatment Date for that particular year (i.e. the approximate middle of the construction season). Other assumptions for dd/mm/yyyy values may have been made for logical reasons; e.g. missing ARAN Viewer years, missing surface treatments found and added, etc.

2. After Step 1 was complete, the section file was saved with another name (or in another folder) indicating its status in the data reduction strategy.

3. Removed any pre-1993 data as IRI data was not collected prior to 1993. Also, based on information from MoDOT's Transportation and Planning division, all 1997 to 2001 (inclusive) IRI data was removed due to an algorithm error during ARAN collection for those years. This data was either removed prior to sending the ARAN inventory table data to the Task 1 team or after the verified/supplemented Task 1 section files were returned to the Task 2 team.

4. For all section files, double-checked that irrational IRI (e.g. IRI=999 or identical IRI and/or CI values through entire section length) were removed during the Task 1 ARAN table querying and retrieval.

5. Removed all data for a given year/section where passenger and driver IRI were extremely different; i.e. a potential error had occurred in IRI collection for that year/section.

Generally, the passenger IRI will be higher than the driver IRI due to its measurement location next to the shoulder of two-lane, undivided roadways (debris, etc.) and potentially lower compaction (density) due to lower confinement at the edge of the mat. There were instances where the difference was so great that there was concern this large differential was due to mechanical/digital errors during data collection and would falsely affect the Unit IRI, which would ultimately adversely affect the average IRI for that section (Note: the average section IRI is the base response variable in all regression analyses, and each analysis is weighted based on the section length). Plotting the passenger, driver, and Unit IRI as a function of the year helped identify particular trends, but the question that needed to be answered was how large a differential is too large? Fig. 3.1 shows a plot generated that displays this concept. The data is associated with a section of MO 21 in Washington County. The Travelway ID (TWID; the unique sequence number for the route that each SS Pavement record resides on), is 16 for the southbound lane and 17 for the northbound lane.

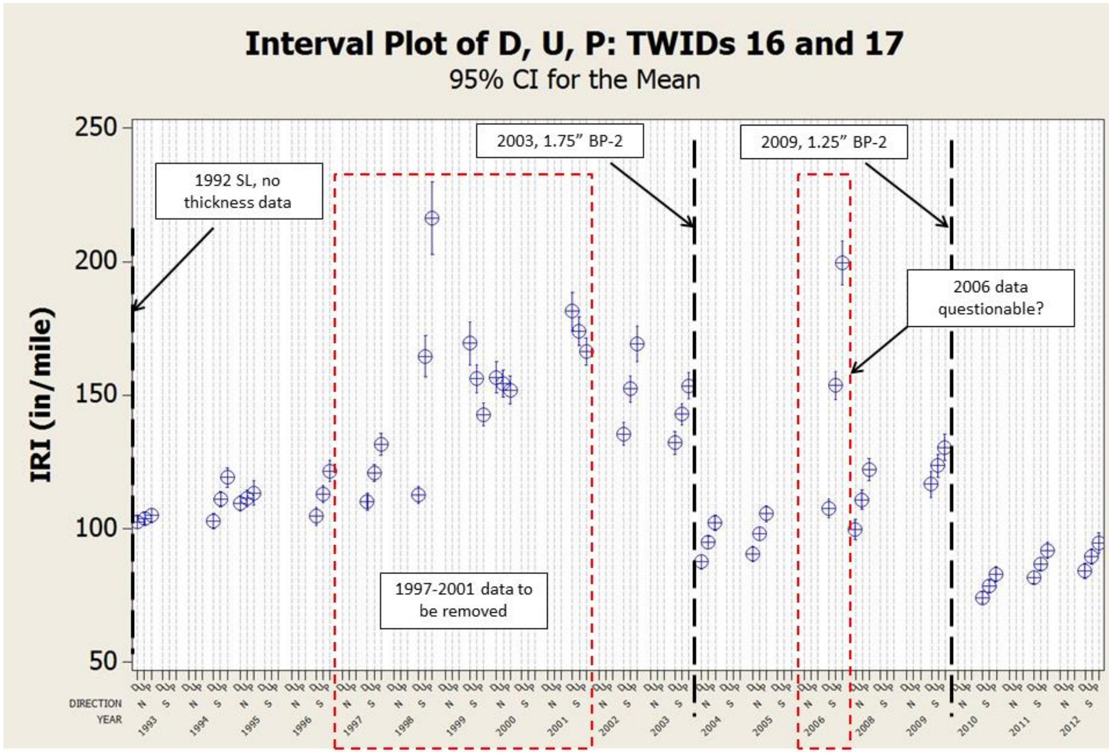

Fig. 3.1— Interval plot of driver (D), Unit (U), and passenger (P) IRI.

Fig. 3.1 shows that the passenger and driver IRI differential is significant for the 2006 data and is completely different from the other years between the 2003 and 2009 overlay (OL) treatments (e.g. SL=surface leveling plant mix; BP-2=bituminous pavement plant mix). Note that the data is plotted not only as function of year, but a function of direction (N=North, S=South, in this example); this is another source of variability that needed to be taken into account when deciding whether data was to be removed (Note: the 1997 to 2001 IRI data, inclusive, was eventually removed from all analyses; see Step 3, above). One could subjectively decide to discard the 2006 data because it is so obviously problematic (even relative to the 2009 data that was obtained traveling in the same direction), but some passenger-driver IRI differentials were not quite so dramatic. Therefore, a systematic solution for the IRI differential evaluation was applied that used the percent difference between the passenger and driver IRI as a criteria for deciding whether the differential was too large. The percent difference, Pdiff, was calculated as follows:

$$\text{Pdiff} = \frac{(\text{Passenger IRI - Driver IRI})}{\text{Unit IRI}} \times 100\% \qquad \text{(Eq. 4)}$$

The calculated Pdiff values were plotted using a run chart which is shown in Fig 3.2.

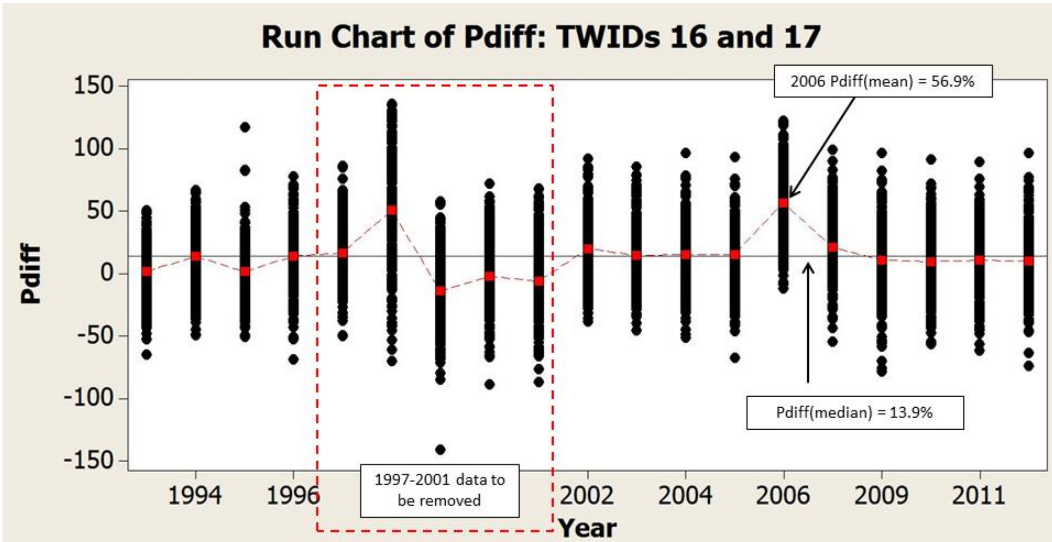

Fig. 3.2— Run chart of Pdiff for IRI differential evaluation.

The black dots in Fig. 3.2 are the individual Pdiff values associated with each data record (data row or Unit IRI), and the red square is the average Pdiff ($Pdiff_{mean}$) for that year's data (red squares are connected by the dashed lines). Also indicated in the plot is the median Pdiff reference line that is based on all years' data. The 2006 $Pdiff_{mean}$ of 56.9% is significantly different from the adjacent years' $Pdiff_{mean}$ values. After several IRI differential evaluations for other selected roadway sections, a $Pdiff_{mean}$ value of 40% was chosen as the criteria for likely removal from the dataset. However, it was not only the absolute value of $Pdiff_{mean}$ that was considered in culling data but how far $Pdiff_{mean}$ fell from the median Pdiff line, relative to the other $Pdiff_{mean}$ values. The following is a summary of data removal based on the IRI differential (IRIdiff) evaluations for all 40 full-depth asphalt (FDA) sections and the 13 composite (Comp) and concrete (PCC) pavement sections. Note that the Comp and PCC sections were actually the same and delineated only by the year the first asphalt overlay was applied to the existing PCC sections.

FDA: 1700-3500 one-way AADT:

- MO 21, Washington County, TWIDs 16 (Southbound=SB) and 17 (Northbound=NB).
  - 2006 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 56.9%. Last treatment was 1.75-in. BP-2 done in 2003.
- Rt T, Pulaski County, TWIDs 1911 (SB) and 1912 (NB).
  - 2003 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 56.2%. Last treatment was 1.25-in. BP-2 done just a couple of months before the date IRI data was collected via the ARAN van (i.e. DATE0).
- MO 124, Boone County, TWIDs 3577 (Eastbound=EB) and 3578 (Westbound=WB).
  - 2009 data shows driver IRI switching over and becoming higher than the previously available data from 2006. However, the 2009 data was NOT removed as the overall trend for the UnitIRI was reasonable. Last treatment was a 1-in. SL done in 2002.

- Rt F, Callaway County, TWIDs 7234 (EB) and 7235 (WB).
    - No data removed.
- Rt BB, Phelps County, TWIDs 1488 (EB) and 1489 (WB).
    - No data removed. However, the EB data from 2004 through 2010 is pretty erratic. 2005 $Pdiff_{mean}$ = 44.7% and 2008 $Pdiff_{mean}$ = 40.3%. Note that the last treatment was a chip seal. It should be noted that chip seals affect ride, as a function of time, in unusual ways. Therefore, chip seal IRIdiff data was NOT subjected to as stringent an analysis when determining whether it should be removed.
- MO 5, Moniteau County, TWIDs 1975 (SB) and 1976 (NB).
    - 2006 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 58.6%. Last treatment was a 1-in. SL done in 2000.
    - 2010 data removed based on the passenger IRI dropping significantly from the overall trend. $Pdiff_{mean}$ = 11.1% in 2010 whereas it was 38.6% in 2009 and 38.3% in 2011. Last treatment was a 1-in. SL done in 2000.
- MO 28, Gasconade County, TWIDs 7829 (EB) and 7830 (WB).
    - 2005 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 46.7%. Last treatment was, supposedly, a scrub seal done sometime between 1998 and 2000 (per the maintenance superintendent's memory). Scrub seal treatment date was assumed to be July 31, 1999.
    - Although the 2009 data has a somewhat odd driver side AvgIRI, the 2009 data was NOT removed.
- MO 32, Laclede County, TWIDs 1056 (EB) and 7824 (WB).
    - No data removed.
- MO 52, Morgan County, TWIDs 52 (EB) and 53 (WB).
    - 1995 data removed based on IRIdiff evaluation. $Pdiff_{mean}$ = 9.4%. Last treatment was 1.25-in. SL in 1991. This was one of the very first IRIdiff evaluations before the criteria of 40% $Pdiff_{mean}$ was established. The data was NOT restored once deleted.
    - 2003 data removed based on IRIdiff evaluation. $Pdiff_{mean}$ = -25.2%. Last treatment was 1.25-in. SL in 1991. Again, this was one of the very first IRIdiff evaluations. The data was NOT restored once deleted.
- Rt C, Cole County, TWIDs 3550 (EB) and 3551 (WB).
    - No data removed.

FDA: 750-1700 one-way AADT:

- MO 47, Washington County, TWIDs 50 (SB) and 51 (NB).
    - 1993 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 47.6%. Last treatment was 1.25-in. BP-2 OL earlier in 1993.
- MO 19, Gasconade County, TWIDs 54 (SB) and 55 (NB).
    - 1993 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 58.9%. Last treatment was 1.25-in. BP-2 OL earlier in 1993.

- 2006 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 58.5%. Last treatment was 1-in. SL in 2000.
- MO 17, Pulaski County, TWIDs 58 (NB) and 59 (SB).
  - 1995 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 43.7%. Last treatment was 1-in. SL in 1993.
- MO 32, Dent County, TWIDs 1056 (EB) and 7824 (WB).
  - 2005 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 43.3%. Last treatment was a limestone chip seal (verified during visit to Charlie Schroyer) just a month or so before DATE0 2005.
  - 2006 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 64.3%. Last treatment was a limestone chip seal (verified during visit to Charlie Schroyer) just a month or so before DATE0 2005.
- MO 7, Camden County, TWIDs 1966 (NB) and 1967 (SB).
  - No data removed. Although borderline, 2006 $Pdiff_{mean}$ = 36.9%, general trend for UnitIRI is reasonable.
- MO 135, Cooper County, TWIDs 2015 (SB) and 2016 (NB).
  - 2003 data removed based on identical driver and passenger IRI values.
- MO 64, Laclede County, TWIDs 2063 (EB) and 2064 (WB).
  - No data removed.
- Rt E, Boone County, TWIDs 3539 (SB) and 3540 (NB).
  - No data removed.
- MO 240, Howard County, TWIDs 5053 (EB) and 5054 (WB).
  - 1995 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 53.1%. Last treatament was 1-in. (calculated based on mat width and tonnage/mile data in asphalt summary) SL in 1985.
  - 2003 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = -40.4%. Last Trtmnt was 1-in. (assumed) SL in 1996.
- Rt C, Callaway County, TWIDs 7119 (NB) and 7120 (SB).
  - 2009 data removed based on unreasonably high driver IRI values which drove the UnitIRI higher than reasonably expected…same direction as the years before and after (2007 and 2010).

FDA: 400-750 one-way AADT:

- MO 185, Washington County, TWIDs 20 (SB) and 21 (NB).
  - No data removed.
- Rt T, Osage County, TWIDs 48 (SB) and 49 (NB).
  - No data removed.
- MO 17, Miller County, TWIDs 58 (NB) and 59 (SB).
  - 1995 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 54.7%. Last treatment was resurfacing of unknown thickness (1-in. SL, perhaps?) in 1973.
- MO 133, Pulaski County, TWIDs 60 (SB) and 61 (NB).

- No data removed.
- Rt F, Phelps County, TWIDs 1490 (EB) and 1491 (WB).
  - No data removed. However, the 2008 $Pdiff_{mean}$ was 41.3% but the median $Pdiff_{mean}$ for the 8 years of data was 31.5%. So, because the 2008 data was not considerably different than the median value, it was left in the overall data.
- Rt W, Morgan County, TWIDs 1997 (SB) and 1998 (NB).
  - No data removed.
- Rt J, Laclede County, TWIDs 2633 (EB) and 2634 (WB).
  - No data removed.
- MO 3, Howard County, TWIDs 4988 (SB) and 4989 (NB).
  - 2002 data was removed because IRI data was the same. Median Pdiff = 11.2%.
- Rt N, Boone County, TWIDs 7271 (SB) and 7272 (NB).
  - 2002 and 2003 data was removed because IRI data was the same within each year. Median PDiff = 27.7%.
- Rt B, Callaway County, TWIDs 7461 (EB) and 7462 (WB).
  - 2002 and 2003 data was removed because IRI data was the same within each year. Median PDiff = 28.6%.

FDA: <400 one-way AADT:

- MO 133, Osage County, TWIDs 60 (SB) and 61 (NB).
  - No data removed.
- Rt M, Crawford County, TWIDs 1265 (SB) and 1266 (NB).
  - No data removed.
- Rt K, Dent County, TWIDs 1781 (SB) and 1782 (NB).
  - 2007 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 44.7%. Last treatment was a chip seal a few months earlier in 2007. It should be noted that the median Pdiff = 19%, and 7 of the 8 years of data deviated very little from the median. Because the chip seal was very new in 2007, that could account for the large jump in $Pdiff_{mean}$ to 44.7% in 2007.
- Rt J, Camden County, TWIDs 2779 (SB) and 2780 (NB).
  - No data removed.
- Rt J, Cooper County, TWIDs 4862 (EB) and 4863 (WB).
  - No data removed.
- MO 87, Howard County, TWIDs 5051 (SB) and 5052 (NB).
  - No data removed.
- Rt E, Cole County, TWIDs 7077 (EB) and 7078 (WB).
  - No data removed.
- Rt HH, Boone County, TWIDs 7113 (EB) and 7114 (WB).
  - No data removed.
- Rt D, Callaway County, TWIDs 7115 (WB) and 7116 (NB).

-
  - 1994 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 45.7%. Last treatment was a SL of unknown thickness in 1977. This is another instance where the median Pdiff was quite high: 31.2%.
- Rt Y, Gasconade County, TWIDs 7285 (EB) and 7286 (WB).
  - No data removed.

Comp: Typical one-way AADT levels are given for each section:

- US 67, Butler County, TWIDs 14 (NB) and 15 (SB). AADT ≈ 2300.
  - 2010 data removed based on average section IRI being significantly low relative to 2009 and 2011 data even though data was obtained traveling southbound all 3 years.
- US 63, Phelps County (North of Rolla), TWIDs 56 (NB) and 57 (SB). AADT ≈ 2600.
  - No data removed as only 2013 data was obtained.
- US 63, Phelps County (South of Rolla), TWIDs 56 (NB) and 57 (SB). AADT ≈ 1800.
  - 2008 data removed based on extremely high average section IRI. Construction was still occurring at the time the ARAN data was collected.
  - 2013 data removed based on very low average section IRI relative to the preceding 2 years of data.
- US 63, Schuyler County, TWIDs 56 (NB) and 57 (SB). AADT ≈ 2400.
  - No data removed.
- MO 8, St. Francois County, TWIDs 1054 (EB) and 1055 (WB). AADT ≈ 5000.
  - No data removed.
- MO 32, St. Francois County, TWIDs 1056 (EB) and 7824 (WB). AADT ≈ 900.
  - No data removed.
- US 65, Grundy County, TWIDs 2009 (SB) and 2010 (NB). AADT ≈ 900.
  - 2006 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 57.8%.
- MO 174, Lawrence County, TWIDs 2289 (EB) and 2290 (WB). AADT ≈ 1300.
  - No data removed.
- US 50, Pettis County, TWIDs 3507 (EB) and 3508 (WB). AADT ≈ 3300.
  - No data removed.
- MO 6, Grundy County, TWIDs 3556 (EB) and 3557 (WB). AADT ≈ 1100.
  - No data removed.
- US 24, Monroe County, TWIDs 3562 (EB) and 3563 (WB). AADT ≈ 900.
  - No data removed.
- Rt M, Cooper County, TWIDs 4133 (SB) and 4134 (NB). AADT ≈ 200.
  - No data removed.
- MO 87, Cooper County, TWIDs 5051 (SB) and 5052 (NB). AADT ≈ 2100.
  - No data removed.

PCC: Because the sections are the same as the Comp, only those PCC sections that had data removed are listed below:

- US 63, Schuyler County, TWIDs 56 (NB) and 57 (SB). AADT ≈ 2400.

- 1995 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 56.8%.

- MO 8, St. Francois County, TWIDs 1054 (EB) and 1055 (WB). AADT ≈ 5000.
  - 2007 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 42.5%.
- MO 32, St. Francois County, TWIDs 1056 (EB) and 7824 (WB). AADT ≈ 900.
  - 2006 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 51.9%.
- MO 174, Lawrence County, TWIDs 2289 (EB) and 2290 (WB). AADT ≈ 1300.
  - 1993 data removed because average section IRI is ≈ 25% higher than all subsequent yearly data. Not able to determine whether diamond-grind or some other treatment occurred between 1993 and 1994.
- US 24, Monroe County, TWIDs 3562 (EB) and 3563 (WB). AADT ≈ 900.
  - 1995 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 40.6%.
  - 2002 data removed based on significant IRIdiff evaluation. $Pdiff_{mean}$ = 40.2%.

6. Combined all section files per pavement family (i.e. FDA, Comp, and PCC) into a single worksheet per family, and configured for proper importation into statistical software.

7. Removed all yearly FDA section data with extremely high surface ages (SAs). These are FDA pavement sections that either did not actually receive any “total-width” surface treatment, or there were likely missing treatments in the data.

Some FDA pavement sections had calculated SAs of 30+ years, which seemed unlikely. A histogram was generated to visualize the distribution of SAs for the resultant FDA pavement dataset. That histogram is given in Fig. 3.3. Frequency refers to the number of Unit IRI records and the bins represent SAs in years.

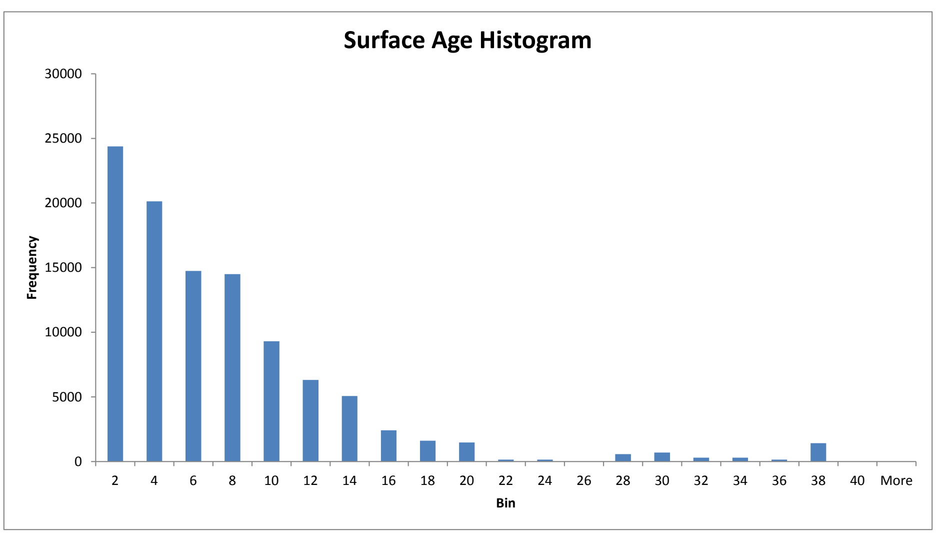

Fig. 3.3— Histogram of FDA pavement sections surface ages (SAs).

Based on the distribution shown in Fig. 3.3 , and the fact that the overwhelming majority of SA values in the 19 – 20 year SA bin were 19 (when rounded to the nearest year), all data associated with SAs older than 19 years was removed. The resulting dataset was used for beginning the next step in the FDA pavement family and treatment model development. The removal of high-SA data for the Comp sections was not necessary as none of those were older than about 7 years. There was no removal of data for the PCC sections based on high SAs, which were considerable (e.g. $SA_{max} \approx 65$ years).

All files based on Unit (raw) IRI data were now ready to be transformed into average values using statistical software. The records in SS Pavement were not usable because there was just too little confidence in their accuracy for what was needed in the study. The SS Pavement records are dynamically-segmented meaning each record varied widely in length, the average IRI associated with each record could be based on invalid Unit IRI values (e.g. 999), the homogeneity of the section is not evident per record, etc. It became evident that the highest degree of confidence in the data could only be achieved if the raw data was obtained, cleansed, compiled, and analyzed. A large part of the effort of Task 1 and Task 2 was spent preparing the data for model-building.

3.2 Generating Pavement Section Averaged Data Files for Regression Analyses

Performing regression analyses and developing models using the Unit (raw) IRI data was ruled out primarily because the initial IRI (IRI_o) for a particular pavement section had to be expressed as an average value that represented the average smoothness of the entire length of the section. It would have been possible to determine the average IRI_o for a section, add that value to every "Unit IRI" record as a potential predictor variable, and then perform regression analyses. However, early work during this study showed that the regression coefficients (parameter estimates) of a model generated using the "Unit" (~0.02 mile) data were very similar to the regression coefficients generated using "averaged" data, especially when the regressions using averaged data were weighted based on the pavement section length. The major difference when running regressions using Unit data versus averaged data was the resulting extreme difference in the goodness-of-fit statistics, specifically R^2 (and adjusted R^2 when comparing models). Unit data regressions had very low R^2 values relative to the averaged data regressions, primarily due to the extreme differences in number of observations (n) per dataset (e.g. tens of thousands when using Unit data versus hundreds using averaged data).

Another reason that averaged data was used in the regressions was that almost all of the other potential predictor variables in the datasets were single values that were applied across the entire length of the pavement section of interest, e.g. all climate and subgrade soil parameters. The only parameters that varied in a given year across the length of a pavement section were IRI (and, possibly, the condition index) and, sometimes, the two traffic parameters, AADT and AADTT.

Generating the averaged data files was a matter of importing the Unit data into a statistical software package, running a procedure that would export selected summary statistics (e.g. means or averages), and grouping the output based on a select variable or variables. An example of the described procedure is given below:

1. The 99,759 record (row) FDA dataset was reduced in size by averaging all numerical parameters into groups by County, Travelway Name (TW Name), and Year, in that order. For example, the Boone County MO 124 data was reduced from 2250 Unit records representing 11 years of data to just 11 records where all parameters for each year of the Boone County MO 124 data were averages The original 99,759 record, FDA Unit data file was reduced to 394 records of averaged data.
2. The averaged data worksheet was augmented with additional parameters: section length (SecLength, expressed in miles), IRI$_o$, terminal IRI (IRI$_t$ or the IRI just before a surface treatment), the last treatment thickness/type (if not determined during the Task 1 data configuration), the climate parameters, and the subgrade soil parameters. The IRI$_o$ and IRI$_t$ values were determined by one of two methods: 1) they were taken as the average IRI just after or just prior to treatment, respectively, if the IRI had been measured with the ARAN van within approximately a year from the assumed treatment date, or 2) they were estimated using extrapolation (forward or backward) based on at least two yearly average IRI values. Fig. 3.4 shows an image of a portion of the original FDA averaged data worksheet.

County	TW Name	SecLength	Year	TWID	IRI	IRIt	IRIo	SurfaceAge
BOONE	124	4.0	1996	3578	111.9			5.3
BOONE	124	4.0	2002	3577	82.1		82.1	0.1
BOONE	124	4.0	2003	3577	84.0		82.1	1.0
BOONE	124	4.0	2004	3578	90.6		82.1	2.5
BOONE	124	4.0	2005	3578	92.4		82.1	3.0
BOONE	124	4.0	2006	3578	98.2		82.1	4.1
BOONE	124	4.0	2007	3577	100.2		82.1	4.9
BOONE	124	4.0	2008	3577	102.0		82.1	6.0
BOONE	124	4.0	2009	3578	125.1		82.1	6.9
BOONE	124	4.0	2011	3577	118.7		82.1	9.2
BOONE	124	4.0	2012	3578	73.5	118.7	73.5	0.8
BOONE	E	10.0	1993	3539	134.3		***126.0***	4.7
BOONE	E	10.0	1995	3539	137.7		***126.0***	6.7
BOONE	E	10.0	2003	3540	130.1	***152.0***	***93.7***	5.5
BOONE	E	10.0	2004	3539	125.9	***152.0***	***93.7***	6.6
BOONE	E	10.0	2005	3540	142.5	***152.0***	***93.7***	7.4
BOONE	E	10.0	2006	3539	133.6	***152.0***	***93.7***	8.5
BOONE	E	10.0	2007	3540	149.5	***152.0***	***93.7***	9.4
BOONE	E	10.0	2008	3539	147.3	***152.0***	***93.7***	10.5
BOONE	E	10.0	2009	3539	146.3	***152.0***	***93.7***	11.3
BOONE	E	10.0	2010	3540	164.7	***152.0***	***93.7***	12.6
BOONE	E	10.0	2011	3540	175.7	***152.0***	***93.7***	13.5
BOONE	E	10.0	2012	3540	110.2	175.7	110.2	1.0

Fig. 3.4— Portion of FDA averages dataset for two Boone County routes.

Fig. 3.4 shows a portion of the original FDA averages dataset for two of the Boone County routes selected for analysis. The dotted horizontal lines indicate that a treatment occurred sometime between the records above and below the dotted line. Bolded, italicized values are estimates based primarily on extrapolation forward or backward in time. The Boone

County, Route E, data will be used to explain, for example, how the IRI_t value of 152.0 in./mi (2003 – 2011) was estimated. The Task 1 team determined that there had been treatments on Route E in 1988 (assumed to be July 31) and December 1, 1997. SAs were calculated for all years in the Route E dataset (up through 2011) based on these two treatment dates. Through linear extrapolation, the 1993 and 1995 IRI and SA values were used to estimate a 1997 IRI value of 140.8 in./mi. However, 1997 data had actually been collected and the recorded IRI for 1997 was 163.3 in./mi. Remember, though, that all 1997 – 2001, inclusive, IRI data was removed for regression analysis purposes due to reported errors in the IRI algorithm. Nevertheless, for this particular estimation, the average of 140.8 and 163.3, or 152.0 in./mi, was taken as the IRI_t value for the years 1998 through 2011. The taking of an IRI estimate slightly higher than that of a straight-line estimation seemed valid in this case because deterioration becomes non-linear with time.

Values that are underlined in Fig. 3.4 indicate that they are measured values but they come from data associated with travel in the opposite direction, i.e. the other Travelway ID (TWID). Again, the IRI value is the average of all Unit IRI for the associated SecLength. Table 3.1 shows the number of observations, "n," (records or rows) per dataset ultimately used during model development. Introduction of some variables into a given model, such as IRI_t, sometimes reduced the number of available observations.

Table 3.1— Number of Observations per Averages Dataset for Model Development

Pavement Type	FDA		Comp		PCC
Original No. of Observations (n =)	394		54		111
Inclusion of IRI_o or IRI_t	IRI_o	IRI_o & IRI_t	IRI_o	IRI_o & IRI_t	NA
Family Models					
No. of Observations (n =)	350	237	54	54	111
Treatment Models					
1-in. Overlay: (n =)	216	119			
Chip Seal: (n =)	74	65			
3¾-in. Overlay: (n =)			40	40	

Treatment model datasets were created by subdividing the FDA and Comp pavement family files into subset files with similar treatment types/thicknesses. All regression analysis input files are presented in Appendices 2A through 2F.

3.3 Regression Analysis Methodology

Two different automated model selection methods were utilized to help determine the best model for the various datasets: stepwise and minimum R^2 improvement. Stepwise is a procedure that adds and/or removes predictor variables based on a selected criteria for adding and/or keeping variables in the model. There are three basic stepwise procedures: backward elimination, forward selection, and mixed (or combined) which utilizes the backward and forward procedures. In backward elimination, all predictor variables are included in the model initially then removed one at a time based on the criteria to stay in the model and how well each deletion improves the model. The model is evaluated with all variables, the least significant variable is removed, the model is re-evaluated, and the procedure is repeated until all variables left in the model meet the criteria. Forward selection finds the best or single most significant variable, evaluates the model, adds another variable that improves the model and meets the criteria, then repeats this process until no more variables meet the criteria for entry. Mixed stepwise uses both processes, testing at each step to determine if a variable stays or is removed. For this study, the mixed stepwise procedure was utilized and the criteria selected was the significance level as measured by the p-value. The significance level to enter the model (SLE) was set such that the p-value of the variable if included in the model must be ≤ 0.15, and the significance level to stay in the model (SLS) was set such that the p-value when included in the model must be ≤ 0.10. The mixed stepwise procedure would automatically stop once no more variables could be added/removed based on the selected SLE and SLS levels.

An important concept to stress is that the statistical "significance" of a particular predictor (independent) variable is relative to the other predictors present in a model. A particular predictor may be very significant on its own in predicting (or explaining or correlating to) a particular response, but when combined with other predictors in a multivariate model may become insignificant if one or more of those additional predictors have a greater effect on the response (dependent) variable.

The minimum R^2 improvement method uses only the R^2 value as the model selection criteria. This procedure evaluates many more potential models than the mixed stepwise method. The output lists the best 1-variable, 2-variable, etc. models based solely on the R^2 value of the model. Using additional statistics given for each model, one had to evaluate the model of interest for validity and utility. Another point to keep in mind is that R^2 is a function of the number of observations in the dataset used to generate a model. Therefore, one must be careful when comparing models generated with different numbers of observations.

Major items of interest when evaluating any model were the predictor variable significance (preferably, p-values ≤ 0.05; the smaller the p-value, the more significant the predictor) and the sign on the regression coefficient (parameter estimate). The sign on the regression coefficient was important to watch because it indicates the relationship between the predictor variable and the predicted response. If the sign was positive, this means that as the predictor variable increases in magnitude, the predicted response also increases in magnitude. A negative sign on the regression coefficient indicates an inverse relationship between predictor variable and response variable. If the sign did not make sense based on known relationships, the regression was re-run and re-evaluated using different predictor variables. This concept of evaluating the signs on the regression coefficients is fairly straightforward when applied to an additive, linear model with two or more unique predictor variables, also called main effects, and no interactions. An interaction, for numerical variables, is the multiplicative product of two or more main effects. Having interactions in a model makes evaluation of that model much more complicated. An additional statistic of interest when evaluating a model is the variance inflation factor (VIF) associated with each predictor variable. The VIF is one measure of potential collinearity between one or more predictor variables. If multi-collinearity is sufficiently high, the regression coefficients could be unstable, meaning one might find that re-running the regression on the same data might generate different regression coefficients.

The general rule of thumb is that VIFs between 1 and 5 indicate moderately correlated predictor variables, and VIFs greater than 5 indicate highly correlated predictor variables. Again, VIFs are most useful when there are only main effects in the model and no interactions.

For each model selection method, different pools of potential predictor variables were evaluated. Different variable pools were utilized based on a priori knowledge of relationships between certain variables that might exhibit multi-collinearity. For example, many of the soil parameters are mathematical functions of other soil parameters also being evaluated as potential predictor variables, therefore it was logical to avoid including potentially correlated predictor variables in a particular variable pool. An example is PI and liquid limit of soil. An additional check included generating correlation matrices to look at all variables and their correlation to each other, and especially the IRI. It should be noted that, occasionally, correlations between variables were not logical based on the significance of the correlation and/or the sign on the correlation constant (Pearson's r), but when included in a multiple-linear least-squares regression, some of those non-logical relationships became logical and significant.

Another recommendation in any model-building process is validation of the model by fitting it to an independent set of data and evaluating how well the model predicts that data. There are several methods in which the independent data could be acquired:

1. Set aside data specifically for model validation during the initial data collection
2. Use all collected data for model-building and validate the model with data collected at a later time
3. Randomly select a portion of all collected data, use that portion for model-building, then use the remaining portion for model validation.

Khattak et al. (2013) used a model validation procedure slightly different than method 3 described above in that all the data was used for model-building and generation of regression coefficients, and validation of the model(s) was performed in a two-step procedure involving random extraction of portions of the original dataset. 75% of the original data used to develop each of their two final models was randomly extracted and a new regression was run on this partial dataset using the same final model predictor variables. This generated a new set of regression coefficients for those predictor variables. The modified-coefficients model was fit to the remaining 25% of the data and the quality of the prediction was evaluated. This procedure was repeated over one hundred times per final model. The distribution of the percentage error between the measured and predicted IRI for each of the many runs per model was evaluated to determine the predictive ability of the two final models.

Although the Khattak et al. method was considered as a potential model validation procedure to be used in this study, the specific procedure described above as method 3 was preferred and initially pursued. Unfortunately, those initial pursuits of the method 3 procedure were ultimately abandoned due to recent decisions to add IRI_t to the pool of predictor variables and re-evaluate all of the IRI_o-only models already generated. Thus, the models presented later in this report have not been validated. MoDOT will need to validate the various models' predictive ability based on method 2, described above; i.e. validate at the first instance additional field data is collected to be added to the model-generating databases.

4 REGRESSION ANALYSES RESULTS

Six IRI-predictive models were generated and are presented in this section. Three are family models: one for FDA, one for Comp, and one for PCC. Three are treatment models: one for a 1-in. overlay on a FDA pavement, one for a chip seal on a FDA pavement, and one for a 3.75-in. overlay on a Comp pavement. In four of the six models, the transformation of IRI to the natural log of IRI was actually the response in the regression analyses, but those particular models are presented below in a form such that IRI, and not the natural log of IRI is the predicted response. All regressions were performed using JMP® software and were weighted based on the length of the pavement section (SecLength in miles).

4.1 Full-depth Asphalt (FDA) Pavement Models

4.1.1 FDA Family Model

The FDA family model is based on 237 observations, all from the Central District. The regression output is given in Fig. 4.1.

Response lnIRI

Weight: SecLength

Summary of Fit

RSquare	0.86679
RSquare Adj	0.863315
Root Mean Square Error	0.19573
Mean of Response	4.680695
Observations (or Sum Wgts	1217.3

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	6	57.334953	9.55583	249.4320
Error	230	8.811379	0.03831	**Prob > F**
C. Tota	236	66.146332		<.0001 *

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
Intercep	3.2046599	0.145831	21.98	<.0001 *	.
IRIt	0.0009721	0.00026	3.73	0.0002 *	1.501042
IRIo	0.0082896	0.00036	23.04	<.0001 *	2.0700367
SA	0.0427144	0.00171	24.98	<.0001 *	1.2660641
FT	0.0046686	0.001398	3.34	0.0010 *	1.3386628
lnPclay	0.0446079	0.023331	1.91	0.0571	1.2226792
LstTrtTh	-0.086607	0.017192	-5.04	<.0001 *	2.5951646

Fig. 4.1— FDA family model regression output.

It should be noted that of the variables listed in section 2.5 that should be in a model, many have been successfully included: existing condition prior to treatment, condition after treatment, surface age, climate, subgrade soil, and treatment thickness. Also, original pavement type is inherent to the model. Traffic is not included explicitly, but is a major factor at work in surface age. The R^2 value of 0.86679 for the FDA family model shown in Fig. 4.1 is very respectable. Note that the $R^2_{adjusted}$ value is also a goodness-of-fit parameter but is utilized primarily for comparing models during model selection that have different numbers of predictor variables. All predictor variables, with the exception of lnPclay, are highly significant in that their p-values (i.e. Prob>|t|) are much smaller than 0.05, which is a commonly used maximum for many scenarios involving the development of predictive equations. The 0.05 "limit" is actually arbitrarily set; other studies have used limits as high as 0.10. Despite its borderline significance, the lnPclay parameter is still valuable as a predictor. The fact that it is one of the very few soil parameters that showed up in the model selection procedures with the correct sign on the regression coefficient (direction of effect) was enough to keep it in the model. Regarding the signs on the regression coefficients, a positive sign (or an absence of a negative sign) indicates that as the magnitude of the predictor increases, the predicted IRI (predicted roughness) also increases. The LstTrtThk predictor has a negative sign on the regression coefficient which indicates that as the thickness of the last treatment increases, the predicted IRI decreases; i.e. a thicker FDA surface treatment results in a smoother pavement over time, which makes sense. The VIF values indicate an acceptable (low to moderate) level of correlation between the predictor variables.

The model shown in Fig. 4.1 has been mathematically manipulated such that the response, lnIRI (natural log of IRI), is now non-transformed and is given in Eq. 5 as IRI_{pred}.

$$\mathrm{IRI_{pred}} = e^{3.205+0.001(\mathrm{IRIt})+0.008(\mathrm{IRIo})+0.043(\mathrm{SA})+0.005(\mathrm{FT})+0.045(\mathrm{lnPclay})-0.087(\mathrm{LstTrtThk})} \qquad \text{(Eq. 5)}$$

where: IRI_{pred} = Predicted IRI (in./mi)
IRI_t = Terminal IRI prior to treatment (in./mi)
IRI_o = Initial IRI after treatment (in./mi)
SA = Surface Age (years)
FT = Freeze Thaw Cycles (number/year)
lnPclay = natural log of Percent Clay (defined in Task 1 report)
LstTrtThk = Last Treatment Thickness (in.)

The intercept and regression coefficients (parameter estimates) in Eq. 5 have been truncated slightly from those in Fig. 4.1 to fit Eq. 5 on one line. Fig. 4.2 shows the actual (measured) IRI versus the predicted IRI according to Eq. 5.

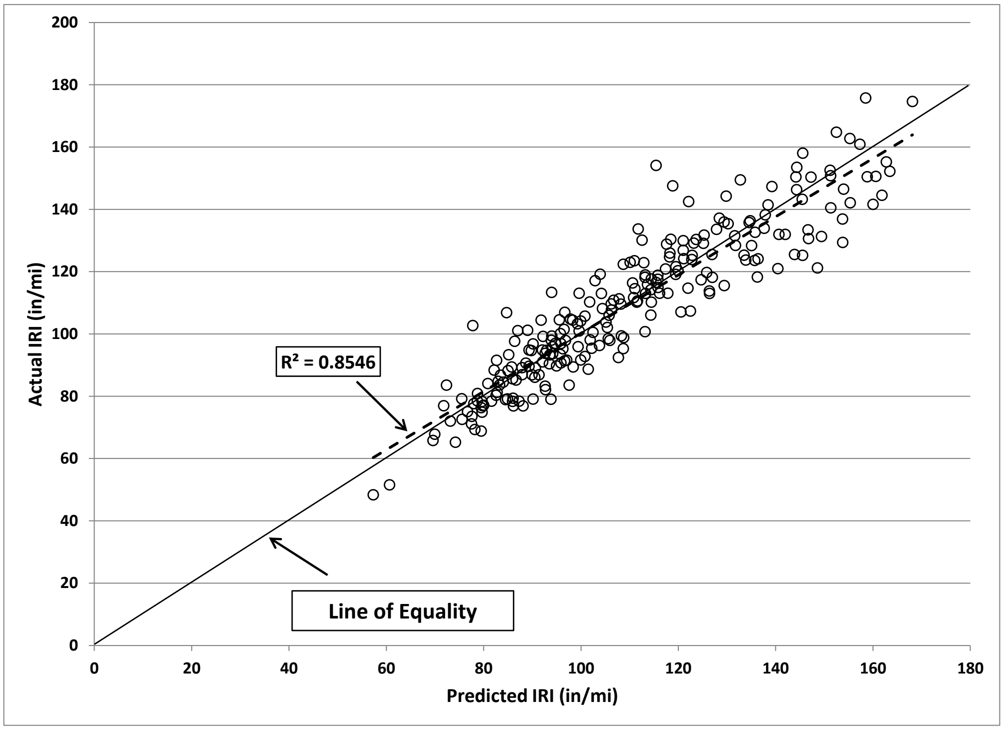

Fig. 4.2— FDA family model: actual versus predicted IRI.

The plot given in Fig. 4.2 shows a very good agreement between the actual and predicted IRI in that the linear trendline lies almost exactly on top of the line of equality with very little bias (i.e. over- or under-prediction, and/or skewness across the line of equality). The R^2 value indicates a very good fit of the linear trendline to the data. The slight difference between the R^2 value in Fig. 4.2 relative to the R^2 value shown in the regression output in Fig. 4.1 may be due to the conversion from lnIRI in Fig. 4.1 to the non-transformed IRI_{pred} in Eq. 5, and/or slightly different algorithms in Excel® versus JMP in fitting linear regression lines, and/or different precision levels in the displayed regression coefficients in Fig. 4.1 (used to generate predicted IRI in Fig. 4.2) and those actually used by JMP to calculate R^2. This discrepancy between R^2 values in Excel and JMP is present in the remaining model presentations and will, therefore, not be discussed further. The dataset used to develop the FDA family model is given in Appendix 2A.

4.1.2 FDA 1-in. Overlay Model

The FDA 1-in. overlay model is based on 119 observations, all from the Central District. The regression output is given in Fig. 4.3.

Response lnIRI

Weight: SecLength

Summary of Fit

RSquare	0.827445
RSquare Adj	0.81981
Root Mean Square Error	0.191824
Mean of Response	4.623581
Observations (or Sum Wgts	579.7

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	5	19.938660	3.98773	108.3731
Error	113	4.157985	0.03680	**Prob > F**
C. Tota	118	24.096646		<.0001 *

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
Intercep	3.2547075	0.194012	16.78	<.0001 *	.
IRIt	0.0013964	0.000391	3.57	0.0005 *	1.6689669
IRIo	0.0065029	0.000647	10.06	<.0001 *	1.6237095
SA	0.0398967	0.002379	16.77	<.0001 *	1.3066821
FT	0.0034073	0.001796	1.90	0.0603	1.1372521
lnPclay	0.0550363	0.031419	1.75	0.0825	1.159419

Fig. 4.3— FDA 1-in. overlay model regression output.

Again, a respectable R^2 value for the FDA 1-in. overlay model shown in Fig. 4.3, good VIFs, and the predictor variables possess the expected signs on the coefficients and exhibit high-to-borderline significance. The model shown in Fig. 4.3 has been mathematically manipulated such that the response, lnIRI, is now non-transformed and is given in Eq. 6 as IRI_{pred}.

$$\mathrm{IRI_{pred}} = e^{3.2547+0.0014(\mathrm{IRIt})+0.0065(\mathrm{IRIo})+0.0399(\mathrm{SA})+0.0034(\mathrm{FT})+0.055(\mathrm{lnPclay})} \quad \text{(Eq. 6)}$$

where: IRI_{pred} = Predicted IRI (in./mi)
IRI_t = Terminal IRI prior to treatment (in./mi)
IRI_o = Initial IRI after treatment (in./mi)
SA = Surface Age (years)
FT = Freeze Thaw Cycles (number/year)
lnPclay = natural log of Percent Clay (defined in Task 1 report)

Again, the intercept and regression coefficients in Eq. 6 have been truncated slightly from those in Fig. 4.3 to fit Eq. 6 on one line. Fig. 4.4 shows the actual versus the predicted IRI according to Eq. 6. Both climate and subgrade soil are included.

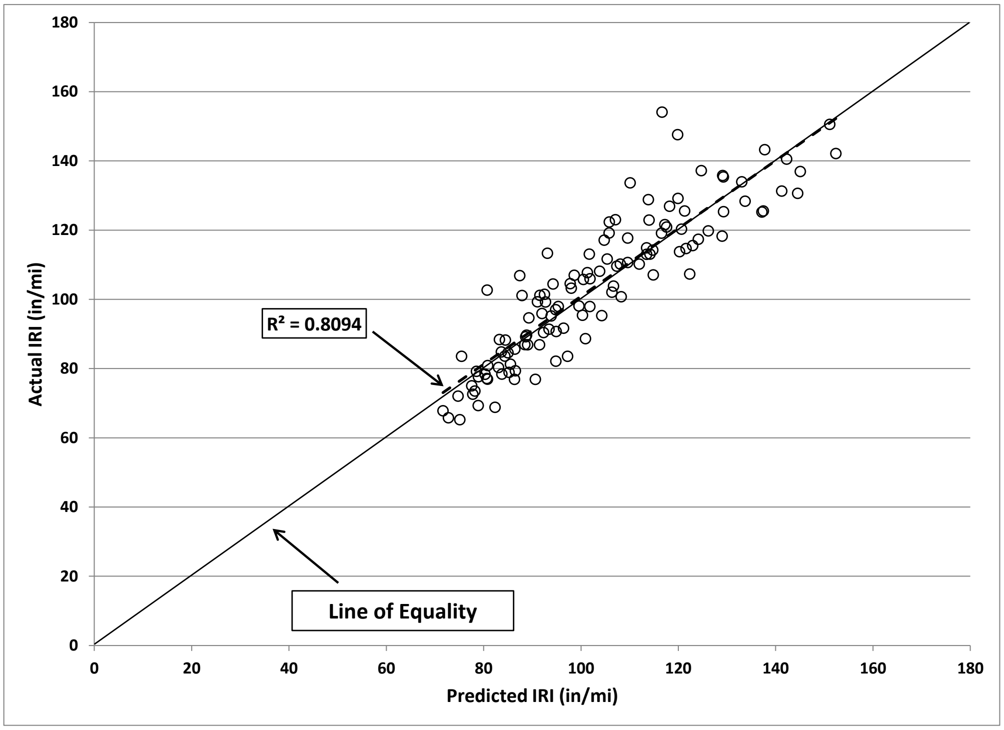

Fig. 4.4— FDA 1-in. overlay model: actual versus predicted IRI.

The plot given in Fig. 4.4 shows good agreement between the actual and predicted IRI in that the linear trendline, again, lies almost exactly on top of the line of equality with almost non-existent bias. The R^2 value indicates a good fit of the linear trendline to the data. The dataset used to develop the FDA 1-in. overlay model is given in Appendix 2B.

4.1.3 FDA Chip Seal Model

The FDA chip seal model is based on 65 observations, all from the Central District. The regression output is given in Fig. 4.5.

Response IRI

Weight: SecLength

Summary of Fit

RSquare	0.881962
RSquare Adj	0.874092
Root Mean Square Error	17.06447
Mean of Response	124.4248
Observations (or Sum Wgts	330.3

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	4	130545.97	32636.5	112.0773
Error	60	17471.77	291.2	**Prob > F**
C. Tota	64	148017.74		<.0001 *

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
Intercep	-49.09792	16.56062	-2.96	0.0043 *	.
IRIt	0.1640288	0.086816	1.89	0.0637	1.8169463
IRIo	0.8535786	0.066887	12.76	<.0001 *	2.4105515
SA	2.8641822	0.493417	5.80	<.0001 *	1.2742504
FT	0.7539027	0.262767	2.87	0.0057 *	1.2159111

Fig. 4.5— FDA chip seal model regression output.

Again, a very respectable R^2 value for the FDA chip seal model shown in Fig. 4.5, good-to-fair VIFs, and all predictor variables exhibit high-to-borderline significance with expected signs on the coefficients. The response used in the regression analysis shown in Fig. 4.5 is the non-transformed IRI, thus there was no need for mathematical conversion. The model in Fig. 4.5 is given in Eq. 7 as IRI_{pred}.

$$\mathrm{IRI_{pred}} = -49.098 + 0.164(\mathrm{IRIt}) + 0.854(\mathrm{IRIo}) + 2.864(\mathrm{SA}) + 0.754(\mathrm{FT}) \qquad \text{(Eq. 7)}$$

where: IRI_{pred} = Predicted IRI (in./mi)

IRI_t = Terminal IRI prior to treatment (in./mi)

IRI_o = Initial IRI after treatment (in./mi)

SA = Surface Age (years)

FT = Freeze Thaw Cycles (number/year)

The intercept and regression coefficients in Eq. 7 have been, again, truncated slightly from those in Fig. 4.5 to fit Eq. 7 on one line. Fig. 4.6 shows the actual versus the predicted IRI according to Eq. 7. Climate is included.

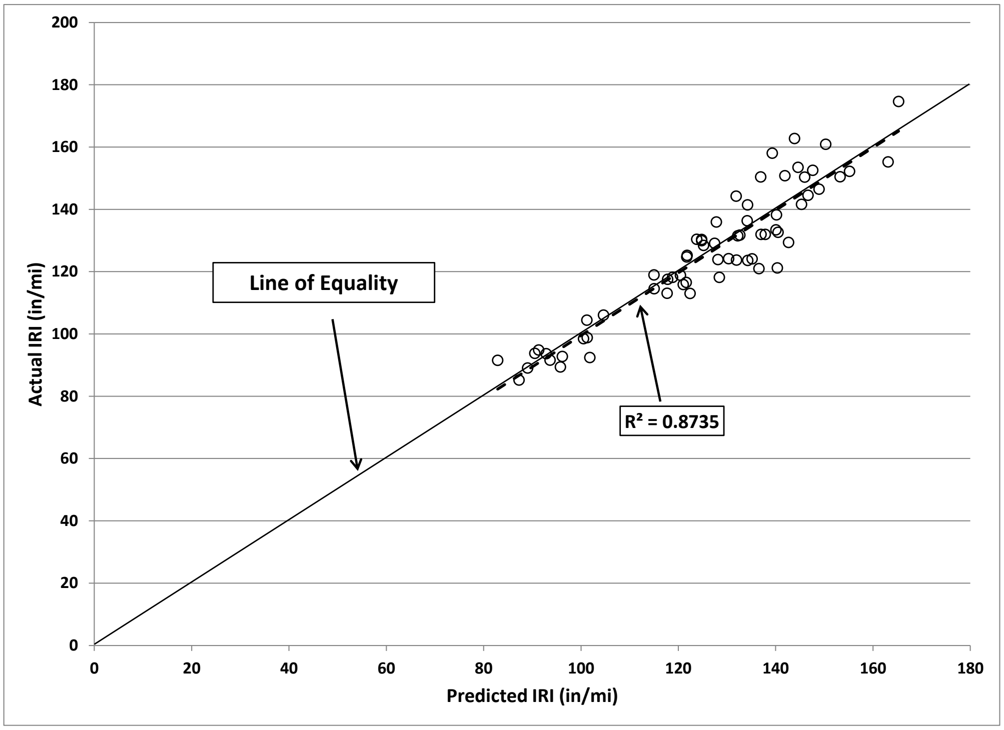

Fig. 4.6— FDA chip seal model: actual versus predicted IRI.

The plot given in Fig. 4.6 shows very good agreement between the actual and predicted IRI in that the linear trendline, again, lies almost exactly on top of the line of equality with almost non-existent bias. The R^2 value indicates a very good fit of the linear trendline to the data. The dataset used to develop the FDA chip seal model is given in Appendix 2C.

4.2 Composite (Comp) Pavement Models

4.2.1 Comp Family Model

The Comp family model is based on 54 observations from six districts. The regression output is given in Fig. 4.7.

Response LnIRI

Weight: SecLength

Summary of Fit

RSquare	0.722616
RSquare Adj	0.699972
Root Mean Square Error	0.190184
Mean of Response	4.139059
Observations (or Sum Wgts	166.6

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	4	4.6171228	1.15428	31.9125
Error	49	1.7723364	0.03617	**Prob > F**
C. Tota	53	6.3894592		<.0001 *

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
Intercep	3.6258889	0.144172	25.15	<.0001 *	.
IRIt	0.0053057	0.000688	7.71	<.0001 *	1.9525864
IRIimpro	-0.364676	0.033334	-10.94	<.0001 *	2.4760857
SA	0.0591985	0.009733	6.08	<.0001 *	1.2604702
DT32	0.0053319	0.001305	4.09	0.0002 *	1.1536983

Fig. 4.7— Comp family model regression output.

The Comp family model shown in Fig. 4.7 has a slightly less respectable R^2 value relative to the FDA models, good-to-fair VIFs, and all predictor variables exhibit very high significance with expected signs on the coefficients. The model shown in Fig. 4.7 has been mathematically manipulated such that the response, lnIRI, is now non-transformed and is given in Eq. 8 as IRI_{pred}.

$$\mathrm{IRI_{pred}} = e^{3.6259+0.0053(\mathrm{IRIt})-0.3647(\mathrm{IRIimprov})+0.0592(\mathrm{SA})+0.0053(\mathrm{DT32})} \qquad \text{(Eq. 8)}$$

where: IRI_{pred} = Predicted IRI (in./mi)
IRI_t = Terminal IRI prior to treatment (in./mi)
IRI_{improv} = IRI improvement; ratio of IRI_t to IRI_o
SA = Surface Age (years)
DT32 = Number of days/year that the air temperature was below freezing

Note that the Comp family model has a couple of predictor parameters that are different from those in the FDA models: IRI_{improv} and DT32. Considerable effort went into trying to get both IRI_o and IRI_t to work in all of the models. Sometimes IRI_o or IRI_t were insignificant, on their own, as co-parameters in the multivariate models; this was the case with the Comp models. Therefore, using the ratio of IRI_t to IRI_o seemed like a potential method for indirectly including both parameters, and it worked, best, provided it was used in conjunction with IRI_t as a coparameter (or IRI_o, as will be seen in the Comp 3.75-in. overlay model, below). DT32 is another climate parameter that showed up most often during all model selection processes as being significant with a positive effect on IRI. The intercept and regression coefficients in Eq. 8 have been truncated slightly from those in Fig. 4.7 to fit Eq. 8 on one line. Fig. 4.8 shows the actual versus the predicted IRI according to Eq. 8.

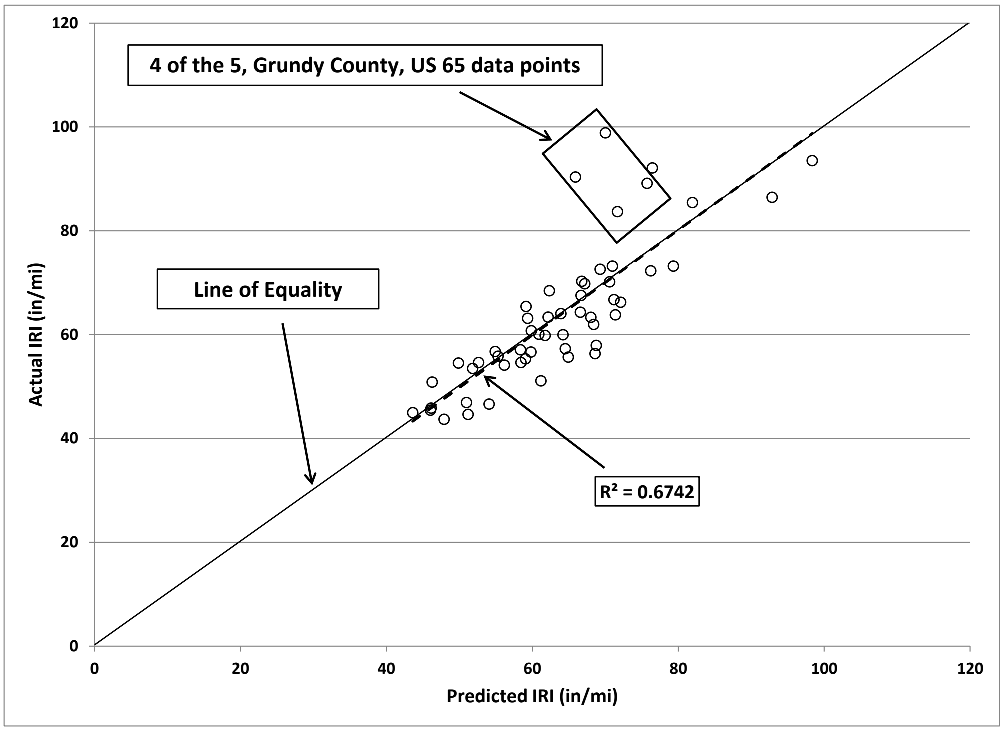

Fig. 4.8— Comp family model: actual versus predicted IRI.

The plot given in Fig. 4.8 shows very good agreement between the actual and predicted IRI in that the linear trendline lies almost exactly on top of the line of equality with almost non-existent bias. The R^2 value of the linear trendline fit on Fig. 4.8, as with the R^2 value in Fig. 4.7, is less respectable than those for the FDA models, even though there are fewer observations (data points) in the Comp models than in the FDA models. The poorer R^2 value is directly related to the few extreme data points on Fig. 4.8, some of which are delineated as a majority of the Grundy County, US 65 records. Of all the Comp pavement sections, the Grundy County, US 65 section showed the greatest rate of deterioration; i.e. the largest rate of IRI growth/year, much higher than the rest of the segments, which indicates that a structural issue was causing the accelerated deterioration. There was significant investigation into modeling with and without the five Grundy County, US 65 records. Without the Grundy County, US 65 values, the goodness-of-fit improved significantly, but some of the predictor variables that were preferred to be in the models would not work. The decision was made that it was more important to identify predictor variables that were significant in predicting IRI for Comp pavements than to produce a model with a somewhat higher R^2 value. After all, these are essentially preliminary models that will be improved in the future. The dataset used to develop the Comp family model is given in Appendix 2D.

4.2.2 Comp 3.75-in. Overlay Model

The Comp 3.75-in. overlay model is based on 40 observations from six districts. The regression output is given in Fig. 4.9.

Response LnIRI

Weight: SecLength

Summary of Fit

RSquare	0.646373
RSquare Adj	0.605959
Root Mean Square Error	0.191746
Mean of Response	4.139998
Observations (or Sum Wgts	122.8

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	4	2.3521155	0.588029	15.9936
Error	35	1.2868288	0.036767	**Prob > F**
C. Tota	39	3.6389443		<.0001 *

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
Intercept	2.4381974	0.332245	7.34	<.0001 *	.
IRIo	0.0167499	0.003653	4.58	<.0001 *	2.6004675
lnIRIimpro	-0.449377	0.174966	-2.57	0.0146 *	4.557134
SA	0.0656809	0.011359	5.78	<.0001 *	1.3616367
DT32	0.0097153	0.002282	4.26	0.0001 *	3.0010426

Fig. 4.9— Comp 3.75-in. overlay model regression output.

The Comp 3.75-in. overlay model shown in Fig. 4.9 has an even smaller R^2 value relative to the Comp family model, despite fewer observations. The VIFs are fair-to-borderline, but all predictor variables exhibit high-to-very high significance with expected signs on the coefficients. The model shown in Fig. 4.9 has been mathematically manipulated such that the response, lnIRI, is now non-transformed and is given in Eq. 9 as IRI_{pred}.

$$\mathrm{IRI_{pred}} = e^{2.438+0.0167(\mathrm{IRIo})-0.449(\mathrm{lnIRIimprov})+0.0657(\mathrm{SA})+0.0097(\mathrm{DT32})} \qquad \text{(Eq. 9)}$$

where: IRI_{pred} = Predicted IRI (in./mi)

IRI_o = Initial IRI after treatment (in./mi)

$lnIRI_{improv}$ = natural log of IRI improvement; ln(ratio of IRI_t to IRI_o)

SA = Surface Age (years)

DT32 = Number of days/year that the air temperature was below freezing

As indicated in the earlier Comp family model discussion, sometimes IRI_o worked best in conjunction with IRI_{improv} instead of IRI_t. This time, as is shown in Fig. 4.9 and Eq. 9, the natural log of IRI_{improv} showed greater significance in the model than the non-transformed IRI_{improv}. The intercept and regression coefficients in Eq. 9 have been truncated slightly from those in Fig. 4.9 to fit Eq. 9 on one line. Fig. 4.10 shows the actual versus the predicted IRI according to Eq. 9.

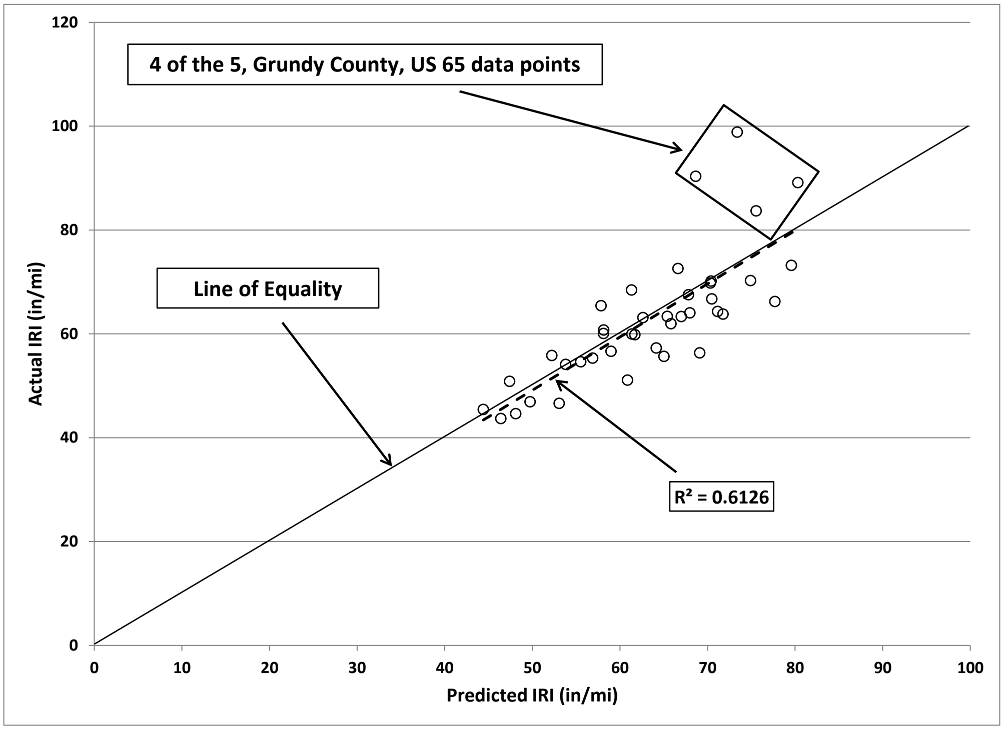

Fig. 4.10— Comp 3.75-in. overlay model: actual versus predicted IRI.

The plot given in Fig. 4.10 shows good agreement between the actual and predicted IRI in that the linear trendline lies almost on top of the line of equality with very little bias. The R^2 value of the linear trendline fit on Fig. 4.10 is smaller than those for the FDA treatment models, and smaller than the Comp family model trendline fit shown in Fig. 4.8, even though there are fewer observations in the Comp 3.75-in. overlay model than in the FDA treatment models or the Comp family model. Again, the poorer R^2 value is directly related to the few Grundy County, US 65 data points. It seemed important to keep these extreme values in the Comp 3.75" overlay model for consistency since they had been included in the Comp family model. It is notable that 40 of the 54 observations in the Comp family model dataset were 3.75-in. overlay treatment records, a large majority. The dataset used to develop the Comp 3.75-in. overlay model is given in Appendix 2E.

4.3 Concrete (PCC) Pavement Model

4.3.1 PCC Family Model

The PCC Family model is based on 111 observations from six districts. The regression output is given in Fig. 4.11.

Response IRI

Weight: SecLength

Summary of Fit

RSquare	0.765185
RSquare Adj	0.756324
Root Mean Square Error	16.74324
Mean of Response	135.3382
Observations (or Sum Wgts	335.44

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	4	96833.61	24208.4	86.3549
Error	106	29715.63	280.3	**Prob > F**
C. Tota	110	126549.25		<.0001 *

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
Intercep	-737.6002	76.14018	-9.69	<.0001 *	.
SA	1.539272	0.110901	13.88	<.0001 *	3.4664383
DP01	7.4635011	0.773384	9.65	<.0001 *	6.61385
DT32	2.3945324	0.169918	14.09	<.0001 *	4.0714332
P200	0.6465575	0.060803	10.63	<.0001 *	1.9686232

Fig. 4.11— PCC family model regression output.

The PCC family model shown in Fig. 4.11 has a respectable R^2 value, and all predictor variables exhibit very high significance with expected signs on the coefficients. The VIFs vary significantly from good to moderately severe. There seems to be some collinearity between all four predictors, especially DP01 and DT32. This is not entirely unexpected as both DP01 and DT32 are climate parameters which are geographically related. The response used in the regression analysis shown in Fig. 4.11 is the non-transformed IRI, thus there was no need for mathematical conversion. The model in Fig. 4.11 is given in Eq. 10 as IRI_{pred}.

$$\mathrm{IRI_{pred}} = -737.60 + 1.539(\mathrm{SA}) + 7.464(\mathrm{DP01}) + 2.395(\mathrm{DT32}) + 0.647(\mathrm{P200}) \quad \text{(Eq. 10)}$$

where: IRI_{pred} = Predicted IRI (in./mi)
SA = Surface Age (years)
DP01 = Number of days/year that precipitation was ≥ 0.1in.
DT32 = Number of days/year that the air temperature was below freezing

P200 = Percent passing the #200 sieve (defined in Task 1 report)

There are two more predictor variables in the PCC family model that have not been introduced earlier: DP01 and P200. It is interesting to note that during all of the model selection processes, DP01 showed significance in some of the interim models but rarely showed the proper sign on the regression coefficient. However, for this particular set of data, it exhibits both significance and expected effect on the IRI. The same is true for P200 except that it occasionally would exhibit the expected effect on the IRI but, depending on the co-predictors in the model, it would not show enough significance. The intercept and regression coefficients in Eq. 10 have been truncated slightly from those in Fig. 4.11 to fit Eq. 10 on one line. Fig. 4.12 shows the actual versus the predicted IRI according to Eq. 10.

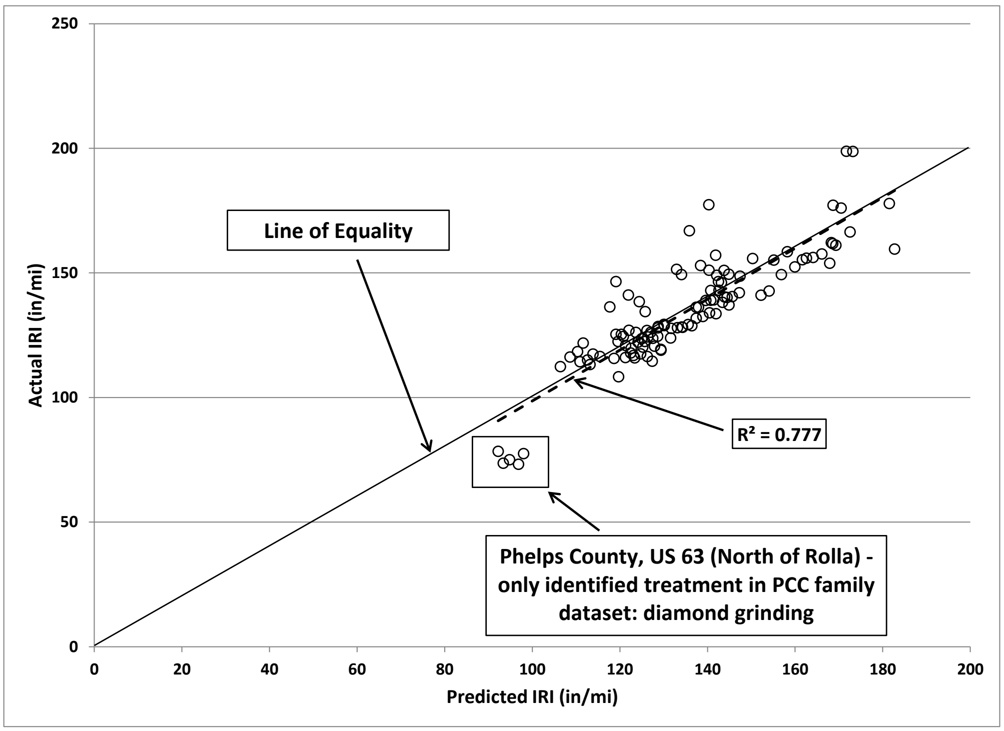

Fig. 4.12— PCC family model: actual versus predicted IRI.

The plot given in Fig. 4.12 shows good agreement between the actual and predicted IRI in that the linear trendline lies almost on top of the line of equality with very little bias. The R^2 value of the linear trendline fit on Fig. 4.12 is respectable given the fair number of observations and the influential group of data points associated with the only diamond grinding treatment identified in the PCC family dataset. The five record dataset associated with the diamond grinding treatment on US 63 north of Rolla has a maximum SA of about 3.8 years whereas the average *minimum* SA for the other sections in the PCC family model dataset is about 27 years. The diamond grinding treatment data has a heavy influence on the initial regression shown in Fig. 4.11 because the SA for this data is so extreme at the bottom end of the SA data space. Because there was only one instance of surface treatment for the selected PCC pavement sections, no

PCC treatment model development was attempted. The dataset used to develop the PCC family model is given in Appendix 2F.

4.4 Adjusted IRI vs SA Models

The Task 5 team also required simple models that predicted IRI as a function of SA in order to rearrange the equation and solve for SA at specific IRI levels for the purpose of obtaining deterioration rates. To accomplish this requirement, it was necessary that the actual IRI and SA values in each modeling dataset (evaluated by direction, or TWID, within each pavement section) be adjusted (shifted) such that 1) the youngest or first adjusted IRI value be assigned the actual average IRI_o associated with that particular modeling dataset, and 2) the first adjusted IRI value occur at one month of SA (0.08333 years). Note that the average IRI_o used for the FDA and Comp models adjusted IRIs was a calculated value, but the PCC family model adjusted IRI used 60 in/mi as the average IRI_o, a value estimated from viewing ARAN videos for several newly constructed PCC pavements and referencing the MoDOT smoothness specifications. There was no way to determine, with any confidence, the field IRI_o for each PCC pavement section because they were so old. Fig. 4.13 shows an image of a portion of the dataset used to generate the FDA family model using this adjusted IRI and SA concept.

County	TW Name	SecLength	TWID	Year	IRI	IRI Delta	IRIadj	SA	SA Delta	SAadj
BOONE	124	4.0	3577	2002	82.1	0.0	91.1	0.1	0.00000	0.08333
BOONE	124	4.0	3577	2003	84.0	1.9	93.0	1.0	0.87945	0.96278
BOONE	124	4.0	3577	2007	100.2	16.2	109.1	4.9	3.94795	4.91073
BOONE	124	4.0	3577	2008	102.0	1.8	111.0	6.0	1.11233	6.02306
BOONE	124	4.0	3577	2011	118.7	16.7	127.6	9.2	3.16986	9.19292
BOONE	124	4.0	3578	2004	90.6	0.0	91.1	2.5	0.00000	0.08333
BOONE	124	4.0	3578	2005	92.4	1.8	92.9	3.0	0.50137	0.58470
BOONE	124	4.0	3578	2006	98.2	5.8	98.6	4.1	1.06027	1.64497
BOONE	124	4.0	3578	2009	125.1	26.9	125.6	6.9	2.83836	4.48333
BOONE	124	4.0	3578	2012	73.5	0.0	91.1	0.8	0.00000	0.08333
BOONE	E	10.0	3539	1993	134.3	0.0	91.1	4.7	0.00000	0.08333
BOONE	E	10.0	3539	1995	137.7	3.4	94.5	6.7	2.00822	2.09155
BOONE	E	10.0	3539	2004	125.9	0.0	91.1	6.6	0.00000	0.08333
BOONE	E	10.0	3539	2006	133.6	7.6	98.7	8.5	1.82740	1.91073
BOONE	E	10.0	3539	2008	147.3	13.7	112.4	10.5	1.99178	3.90251
BOONE	E	10.0	3539	2009	146.3	-1.0	111.4	11.3	0.84384	4.74634
BOONE	E	10.0	3540	2003	130.1	0.0	91.1	5.5	0.00000	0.08333
BOONE	E	10.0	3540	2005	142.5	12.4	103.4	7.4	1.91233	1.99566
BOONE	E	10.0	3540	2007	149.5	7.0	110.4	9.4	1.95342	3.94908
BOONE	E	10.0	3540	2010	164.7	15.3	125.7	12.6	3.24110	7.19018
BOONE	E	10.0	3540	2011	175.7	11.0	136.7	13.5	0.90685	8.09703
BOONE	E	10.0	3540	2012	110.2	0.0	91.1	1.0	0.00000	0.08333
BOONE	HH	3.5	7113	2006	144.6	0.0	91.1	9.6	0.00000	0.08333
BOONE	HH	3.5	7113	2008	175.0	30.4	121.4	12.4	2.79452	2.87785
BOONE	HH	3.5	7114	1996	90.1	0.0	91.1	0.1	0.00000	0.08333
BOONE	HH	3.5	7114	2004	138.7	48.6	139.6	8.5	8.39178	8.47511
BOONE	HH	3.5	7114	2009	207.5	68.8	208.4	12.9	4.40000	12.87511
BOONE	HH	3.5	7113	2012	126.9	0.0	91.1	2.0	0.00000	0.08333
BOONE	HH	3.5	7114	2010	110.6	0.0	91.1	0.1	0.00000	0.08333
BOONE	HH	3.5	7114	2011	114.9	4.3	95.3	1.0	0.87123	0.95456
BOONE	N	5.4	7271	2004	112.5	0.0	91.1	0.2	0.00000	0.08333
BOONE	N	5.4	7271	2006	134.1	21.6	112.7	1.9	1.71781	1.80114
BOONE	N	5.4	7271	2007	139.1	5.0	117.6	3.0	1.11233	2.91347
BOONE	N	5.4	7271	2008	142.3	3.2	120.8	4.0	1.04384	3.95730
BOONE	N	5.4	7271	2009	143.8	1.5	122.3	4.6	0.52329	4.48059
BOONE	N	5.4	7271	2010	154.0	10.2	132.5	6.0	1.45205	5.93265
BOONE	N	5.4	7271	2011	153.6	-0.3	132.2	6.4	0.39178	6.32443
BOONE	N	5.4	7271	2012	170.9	17.3	149.4	7.8	1.41096	7.73538
BOONE	N	5.4	7272	2005	114.8	0.0	91.1	1.2	0.00000	0.08333

Fig. 4.13— Portion of FDA family dataset with adjusted IRI and SA concept.

The table shown in Fig. 4.13 is a portion of the FDA family dataset and shows four different Boone County pavement sections, all delineated by solid lines. Within each section, a dotted line (if it is present) indicates that the data above and below the dotted line is associated with different pavement surfaces on that same section; i.e. a surface treatment occurred. The data within each treatment is first sorted by TWID (direction) then by year.

All initial IRI values (IRI_o) for each roadway segment needed to be adjusted to the average IRI_o of the data set. To understand the adjustment mechanism, begin by looking at the very first row or record; Boone County, MO 124, TWID 3577 (eastbound), Year 2002. The IRI_{adj} for that row is taken as the actual average IRI_o for the FDA family dataset, which is 91.1 in/mi (based on the IRI_o-only FDA dataset; n = 350; see Table 1). The SA_{adj} for that same row is set at 0.08333 years (i.e. one month). Now look at the second row, Year 2003. The IRI_{delta} and the SA_{delta} values are the difference between the 2003 and 2002 actual IRI values (84.0 – 82.1 = 1.9), and the difference between the 2003 and 2002 actual SA values (1.0 – 0.1 = 0.87945), respectively. The 2003 IRI_{adj} and SA_{adj} values are the sum of the 2002 IRI_{adj} and SA_{adj} values and the 2003 IRI_{delta} and SA_{delta} values (91.1 + 1.9 = 93.0; 0.08333 + 0.87945 = 0.96278). Note that the IRI_{delta} and SA_{delta} values for 2002 are zero because there is no change (delta) in IRI in 2002 as it is the first year of the directional time-series. The calculations performed on the second row are repeated for all remaining years for the same TWID (direction) per treatment per section. In summary, for each directional set of data per treatment per section, the first row adjusted values are determined differently from the subsequent rows (provided there are more than one row per direction/treatment/section). Sections 4.4.1 through 4.4.6, below, give the TableCurve 2D® plots and the associated equations based on the same six pavement family and treatment modeling datasets analyzed previously, unless noted otherwise. The curve fitting in the following analyses was also weighted based on SecLength.

4.4.1 FDA Family Model

Fig. 4.14 shows the plot for the FDA family model using the adjusted IRI and SA concept.

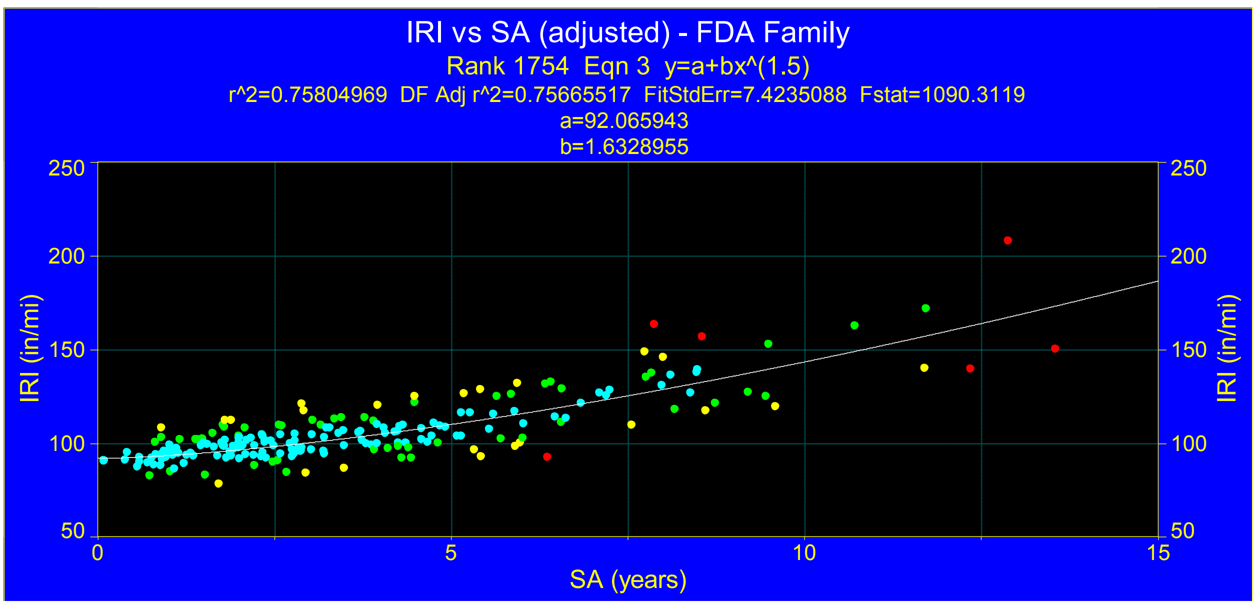

Fig. 4.14—FDA family model using IRI_{adj} and SA_{adj} concept.

TableCurve 2D is a curve fitting program with 3,665 built-in equations. The area in the top of the TableCurve 2D plot shows the plot title, the model equation (along with the equation number and associated ranking based on all equations fit to the data), the regression statistics, and the regression coefficients. All equations fit to the data can be grouped by equation form such as simple, non-linear, polynomial, rational, etc., and viewed in the plot window. For purposes in this investigation, only simple and non-linear equations were reviewed. Within these groupings, the equations can be ranked according to various statistics such as R^2. Models were selected such that they had the highest possible R^2 (and adjusted R^2) value, they were as simple as possible, and the curves were logical.

Fig. 4.14 shows the best "simple" model for the FDA family model "adjusted" data (n = 350). The blue-colored data points are within ± 1 standard deviation (SD). The green data points are outside ± 1SD but within ± 2SD. The yellow data points are outside ± 2SD but within ± 3SD. The red data points are outside ± 3SD. The equation intercept (regression coefficient "a") is 91.1, when rounded to the nearest 0.1, which is expected. Remember that the actual average IRI_o for the FDA family dataset was 91.1 in/mi. Technically, the intercept is the y-value of the equation when x = 0 but the lowest x-value in the adjusted data is really 0.08333. Note that there are 140 instances of x = 0.08333 and y = 91.1 on the plot, which really forces the curve through that particular point. The selection of 0.08333 years (one month) as the initial SA_{adj} was beneficial because many of the 3,665 equations in TableCurve 2D would probably not work if there was an x = 0 value in the dataset.

As pointed out earlier in this section, selected equations/curves should be logical; i.e. they should make physical sense. For example, as SA increases, the predicted IRI should also increase. However, there is a general physical limit to how "rough" a pavement will get even with the most severe deterioration, meaning a deterioration (IRI or roughness) curve should begin to flatten out at some point in time. A function with this particular characteristic that is widely referenced in the literature for pavement deterioration is the sigmoid function (Zimmerman et al. 2011). During preliminary curve fitting of the FDA family model "adjusted" data used to generate the curve in Fig. 4.14, one of the logically and statistically superior functions was the sigmoid. Fig. 4.15 shows that plot with the SA extended out to 30 years.

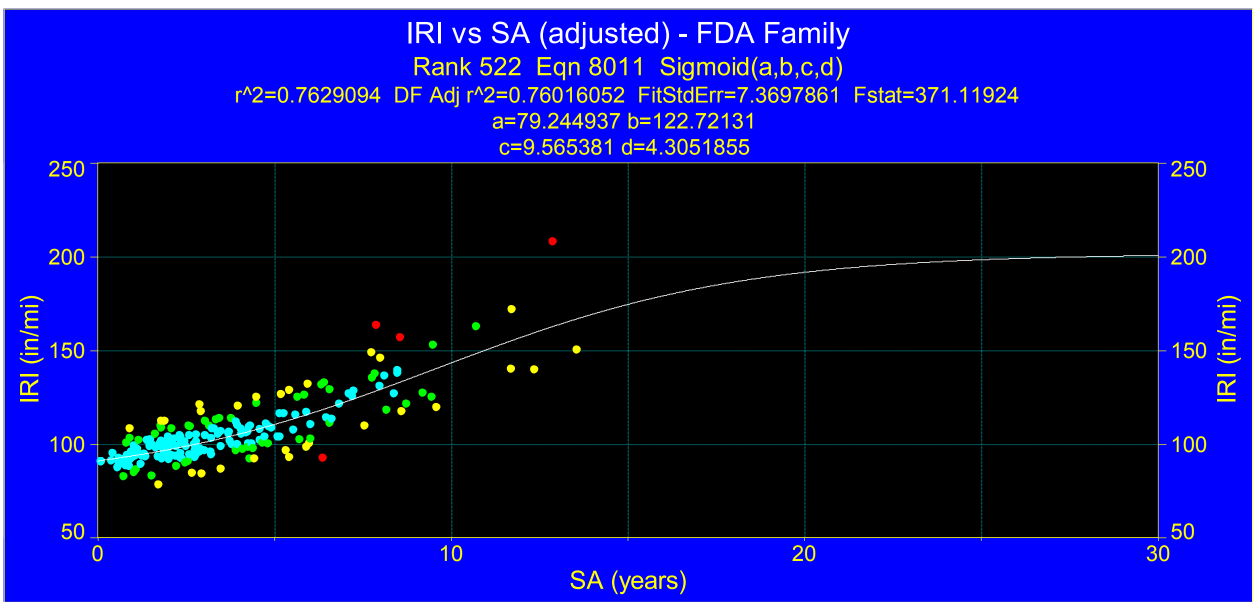

Fig. 4.15— FDA family IRI_{adj} and SA_{adj} concept model with sigmoid function.

Relative to the Fig. 4.14 model, the sigmoid model shown in Fig. 4.15 has a slightly higher R^2 (and adjusted R^2) and flattens out in time past the actual data used to generate the model. Under most scenarios, the sigmoid model would be preferred. However, the portion of the curve begins to flatten beyond the range of the data. In reality, the literature indicates that curves probably do not flatten until the pavement is in a much rougher condition, well over an

IRI of 200 in./mi. Additionally, MoDOT has adopted a threshold of 220 in./mi for certain treatment actions for low volume routes. Thus, the Task 5 team required the curve to extend further in the y-direction, to at least an IRI value of 220 in./mi. Fig. 4.16 shows the same model as that in Fig. 4.14 but with SA extended out to 30 years.

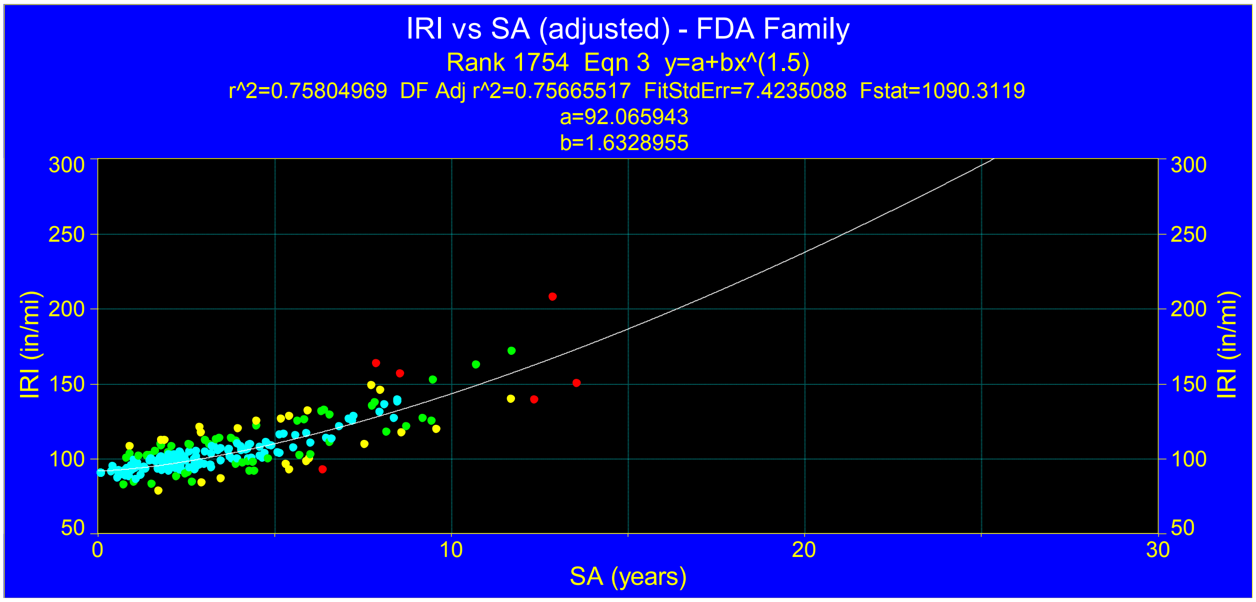

Fig. 4.16— FDA family IRI_{adj} and SA_{adj} concept model (Fig. 4.14) with extended SA axis.

As can be seen in Fig. 4.16, the "simple" model has a forever-increasing slope, which is not physically logical for pavement deterioration, but neither is flattening at 200 in./mi. Nevertheless, because the extent of necessary extrapolation was not extreme (out to ~18 years), the model shown in Fig. 4.14 (and Fig. 4.16) was chosen. It is important to remember that extrapolation outside of the range of data utilized to generate a model can be risky and should be undertaken with caution.

4.4.2 FDA 1-in. Overlay Model

Fig. 4.17 shows the plot for the FDA 1-in. overlay model using the adjusted IRI and SA concept.

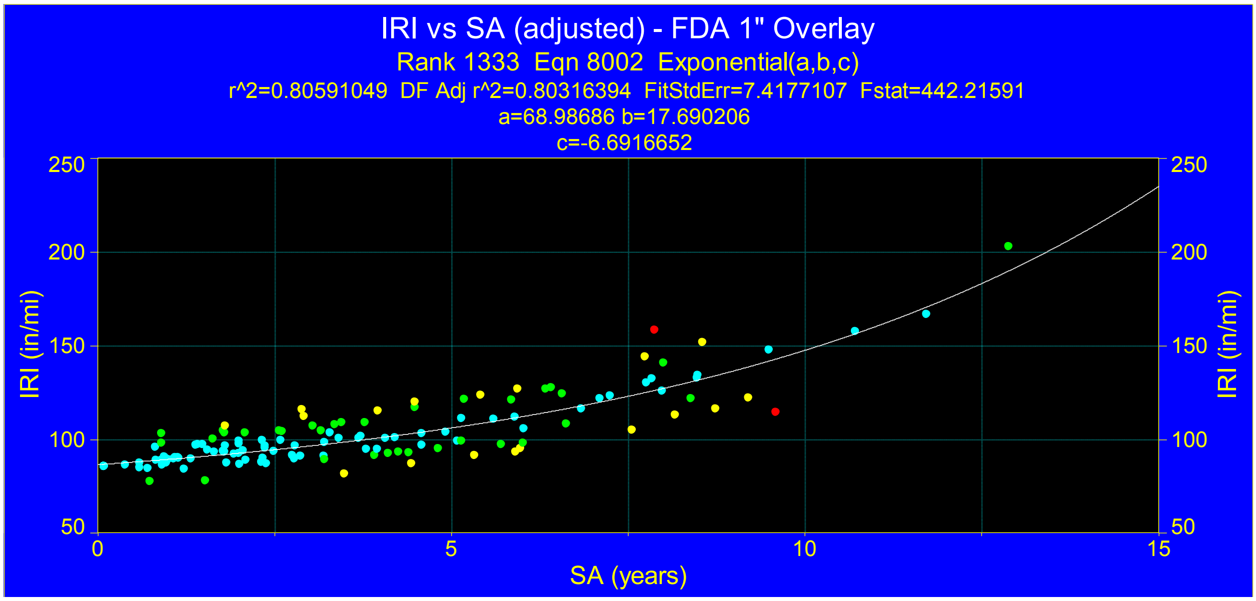

Fig. 4.17— FDA 1-in. overlay model using IRI_{adj} and SA_{adj} concept.

Fig. 4.17 shows the selected "non-linear" model for the FDA 1-in. overlay model "adjusted" data (n = 216). The form of the non-linear equation is given below in Eq. 11.

$$\mathrm{IRI_{adj}} = a + b\left(exp^{\left(\frac{-\mathrm{SA_{adj}}}{c}\right)}\right) \qquad \text{(Eq. 11)}$$

where: $\mathrm{IRI_{adj}}$ = Adjusted IRI (in/mi)
$\mathrm{SA_{adj}}$ = Adjusted SA (years)
a, b, c = regression coefficients (values shown at top of Fig. 4.16)

The non-linear function in Fig. 4.17, too, is not physically logical if extrapolation out in time is extreme. Again, however, there is very little extrapolation necessary in this case.

4.4.3 FDA Chip Seal Model

Fig. 4.18 shows the plot for the FDA chip seal model using the adjusted IRI and SA concept.

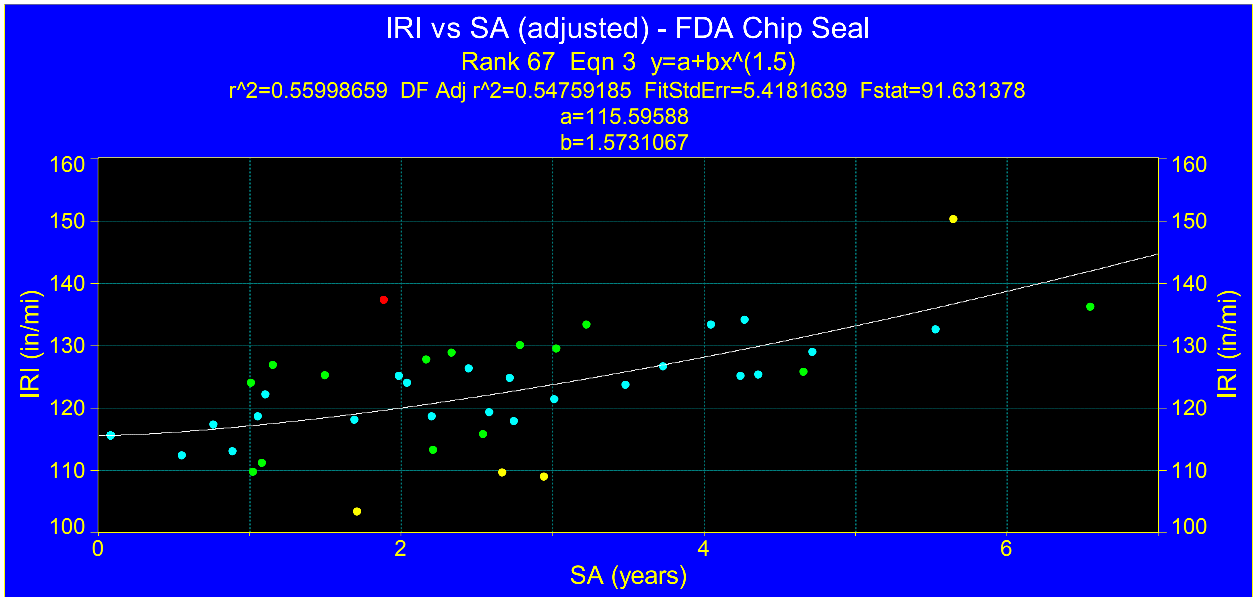

Fig. 4.18— FDA chip seal model using IRI_{adj} and SA_{adj} concept.

Fig. 4.18 shows the best "simple" model for the FDA chip seal model "adjusted" data (n = 74). It is the same form of equation as that used for the FDA family model.

4.4.4 Comp Family Model

Fig. 4.19 shows the plot for the Comp family model using the adjusted IRI and SA concept.

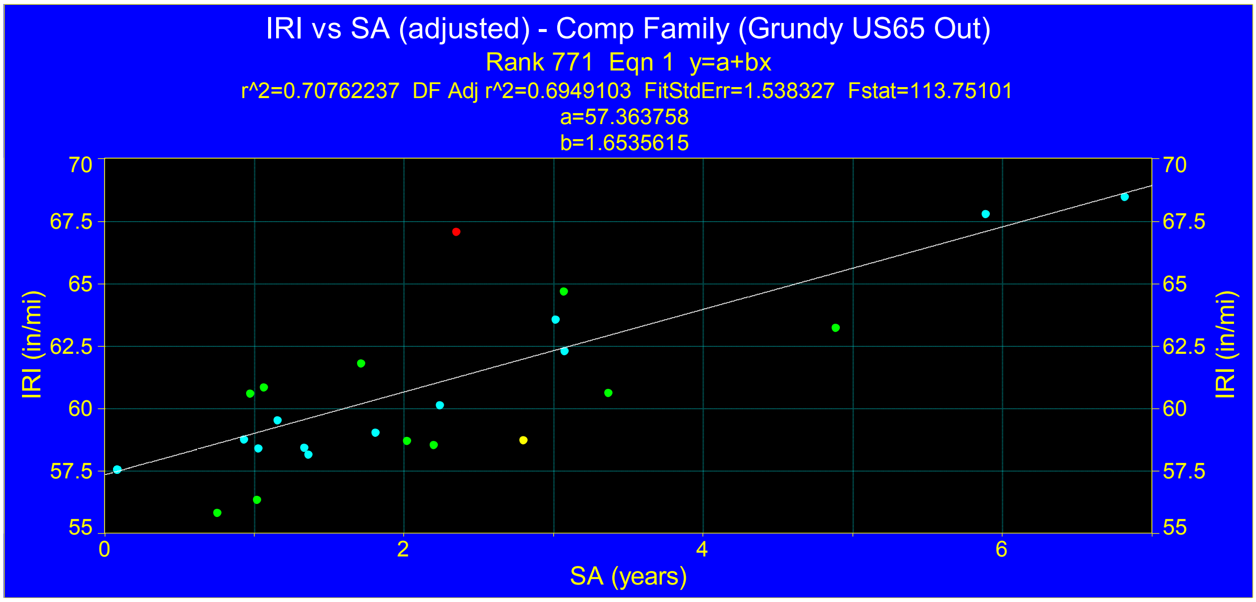

Fig. 4.19— Comp family model using IRI_{adj} and SA_{adj} concept.

Fig. 4.19 shows the selected "simple" model for the Comp family model "adjusted" data (n = 49). Of all the available equations in the equation catalog, TableCurve 2D equation #1, shown in Fig. 4.19, was the best model based on adjusted R^2, while still being logical within limits (i.e. extreme extrapolation warning due to constant, positive slope). Also, note that the five Grundy County, US 65 extreme data points included in the multivariate Comp models presented earlier, were taken out for this particular analysis.

4.4.5 Comp 3.75-in. Overlay Model

Fig. 4.20 shows the plot for the Comp 3.75-in. overlay model using the adjusted IRI and SA concept.

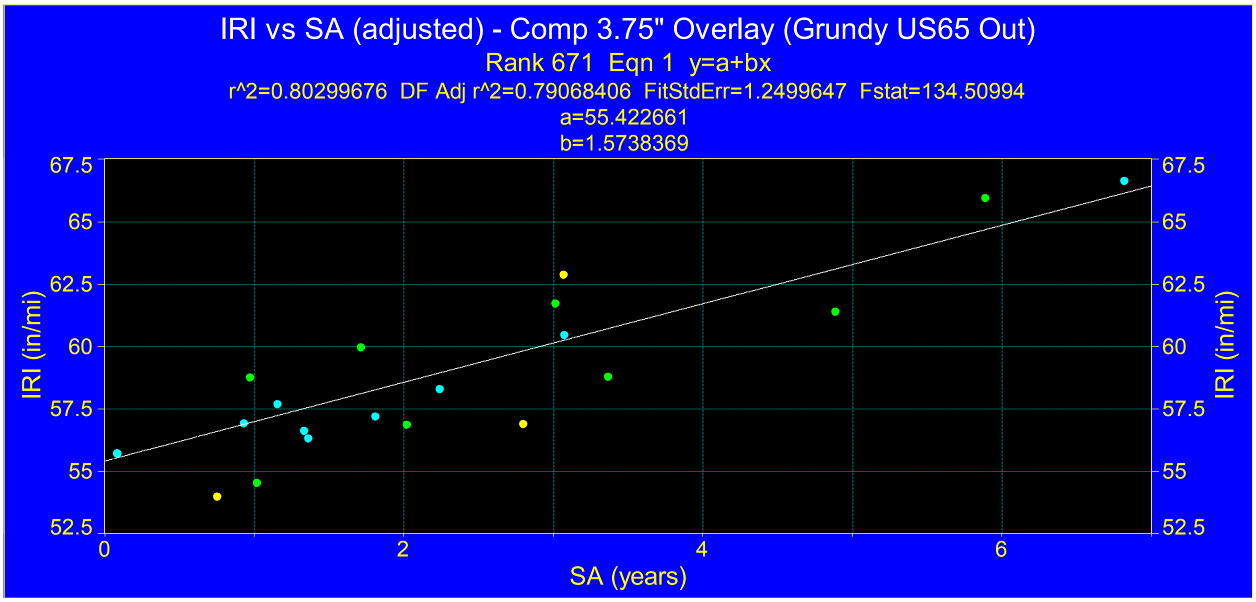

Fig. 4.20— Comp 3.75-in. overlay model using IRI_{adj} and SA_{adj} concept.

Fig. 4.20 shows the selected "simple" model for the Comp 3.75-in. overlay model "adjusted" data (n = 35). For consistency, the five Grundy County, US 65 data points were also removed for this analysis.

4.4.6 PCC Family Model

Fig. 4.21 shows the plot for the PCC family model using the adjusted IRI and SA concept.

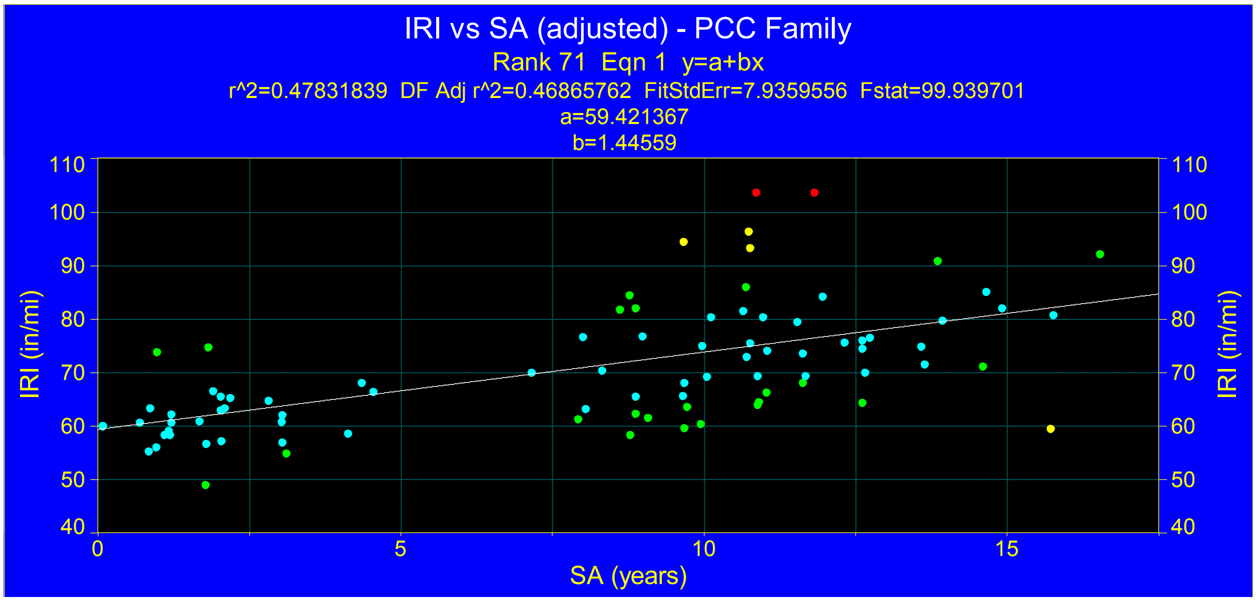

Fig. 4.21— PCC family model using IRI_{adj} and SA_{adj} concept.

Fig. 4.21 shows the selected "simple" model for the PCC family model "adjusted" data (n = 111). This family model includes the data for the one PCC surface treatment identified in the data for the selected sections in the PCC investigation: diamond grinding on US 63 in Phelps County, north of Rolla.

5 CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

All of the pavement family and treatment performance models presented in this report have moderate-to-high R^2 values with good significance statistics and expected signs on the regression coefficients. They were all based on averaged data that was applied to the entire homogenous section, the regressions were weighted based on the length of each section, and each section was a two-lane, undivided roadway. It is also important to remember that the models are most accurate when data applied to them are within the range of data used to develop them. The datasets used to generate each multivariate model presented are embedded as Excel® spreadsheets in Appendices 2A through 2F and show the maximum, minimum, average, median, and standard deviation statistics for each relevant response and predictor variables.

The predictor variables that did end up in the models track with those cited in the literature (existing condition prior to treatment, condition after treatment, surface age, climate, subgrade soil, and treatment thickness). Original pavement types were inherent to the models. However, explicit traffic volume data (such as cumulative total (or truck) traffic), a parameter that is cited in the literature as highly significant in predicting pavement deterioration, did not show up in the results of these analyses. The traffic data was analyzed in various forms (AADT (or AADTT), annual total (or truck) traffic, and cumulative total (or truck) traffic), but almost always showed up in the regressions as insignificant and/or had the wrong sign on the regression coefficient. The theory is that the traffic data itself was inaccurate due to a combination of 1) the methodologies by MoDOT in its assignment of traffic volume values to different pavement sections/routes (although MoDOT reportedly follows FHWA guidelines in this regard) and possibly 2) the Task 1 team's decision to apply the most recent traffic data to all years of data per section (and direction); i.e. not account for a possible change in traffic volume as a function of time. Another reason that could explain why increasing traffic did not show up significantly in the models as a cause for increasing IRI could be that some variables that reduce deterioration are associated with traffic level and actually increase along with increasing traffic: thickness, quality of materials and construction, and maintenance quality; an increase in these variables will counteract to a certain degree the deteriorating action of increasing traffic.

During the FDA pavement analyses, and in response to the various traffic parameters not showing up in the regressions in the expected manner, a dummy variable was created called TrafLvl which was coded in such a way to account for the four different traffic levels as defined by AADT: 1700-3500 (coded as 1), 750-1700 (coded as 2), 400-750 (coded as 3), and <400 (coded as 4). The pavement sections associated with each of these four traffic levels was assigned the appropriate dummy code. Interestingly, but not necessarily surprisingly, this dummy variable did occasionally show up during the interim FDA family model selection procedures as significant and with the expected sign on the coefficient. Ultimately, however, TrafLvl was not used due to its relative insignificance when combined with other, more impactful, predictors like IRI_o, SA, and IRI_t.

Another dummy variable was created to attempt incorporation of total pavement thickness into the FDA family model. This dummy variable was also coded based on AADT levels where those sections with AADT levels ≥ 400 were coded as 0 (zero) and those with AADT levels < 400 were coded as 1. The theory was that the very low volume routes would be significantly thinner in cross-section than higher volume routes and more vulnerable to load-induced distress. The cutoff at 400 AADT was somewhat arbitrary but was partly based on discussions with MoDOT pavement engineers. This predictor, too, showed up in some of the interim FDA family model selection procedures as significant and with the expected sign on the coefficient. It, too, however, was not used in the end because the variables ultimately included in the final models overwhelmed it in the regressions.

Regarding the parameters that did prove to be significant in predicting IRI, one should remember that the FDA data applied only to the Central District. Increasing the range of climate and subgrade soil parameter values by expanding the analyses to the entire state could not only improve the models but allow for additional parameters to play a role in predicting IRI. Although the Comp/PCC sections were selected from regions spread throughout the state, the number of homogenous sections was fairly limited which would also limit the probability of identifying additional parameters to predict IRI.

The data quality checks, reduction, and configuration in preparation for regression analyses were the most time-consuming portions of Task 2. Follow-up verification or determination of treatment type, thickness, etc., determination of a more accurate date corresponding to the opening of the pavement to traffic, and culling of invalid IRI data are activities that were tedious. Hopefully, this process will become more efficient through automation and/or the use of new methodologies by MoDOT, such as the Pavement Tool.

5.2 Recommendations

The following are recommendations for improving future performance modeling activities for MoDOT's lower volume routes:

- The first order of business is for the models presented in this report to be validated with independent data.
- Improve the accuracy of the traffic data:
    - Increase the instances of actual traffic counts on the lower volume routes.
    - Add additional criteria to, or further delineate the route categories when assigning actual traffic counts to "similar" routes per the FHWA guidelines.
    - Implement a system of traffic spectra, similar to, or the same as those defined in the AASHTOware M-E Pavement Design procedure, e.g. include impact of axle loads in addition to truck traffic (AADTT).
- More precisely document the type of the latest full-width surface treatment, whether it be in-house or contract work. The "Surface Type" field in SS Pavement is not completely reliable as it may reflect shoulder work, etc., instead of the actual traveled-lane surface type.

- More precisely document the actual date that a pavement was opened to traffic after a treatment; this will increase the accuracy of any SA calculation.
- More precisely document the actual thickness of a treatment.
- In cases of "mill and fill," be sure that the mill-depth is accurately and conspicuously documented. This will help with tracking accumulated total thickness.
- Make an effort to somehow document total thickness and composition of existing FDA pavements, perhaps by retroactively updating through work performed for some other reason such as coring, culvert trenching, or non-destructive evaluation.
- When adding sections to a dataset, be sure that they are homogenous sections. The dynamically-segmented sections in SS Pavement may not be "homogenous" as defined in the Task 1 report (i.e. similar cross-section and material type, traffic is relatively uniform across the section length and direction, and traffic moves at highway speeds with no stops/starts).
- Automate the procedure for removing invalid Unit IRI data.
- Continue to collect and compile data for the parameters used in the current models.
- Also continue to collect and compile those parameters not used in the current models but included in the datasets given in Appendices 2A through 2F; e.g. AADT, AADTT (COM_VOL_BY_DIR field in SS Pavement), AFI50 (climate parameter), and the subgrade soil parameters.
- Add potentially predictive parameters to the datasets where possible; e.g. bituminous mixture types, lift thicknesses and number of lifts per overlay.

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APPENDIX 2A – FDA Family Model Dataset

FDA Family (237
n).xlsx

APPENDIX 2B – FDA 1” Overlay Model Dataset

FDA 1 inch OL (119
n).xlsx

APPENDIX 2C – FDA Chip Seal Model Dataset

FDA ChipSeal (65
n).xlsx

APPENDIX 2D – Comp Family Model Dataset

Comp Family (54
n).xlsx

APPENDIX 2E – Comp 3.75” Overlay Model Dataset

Comp 3.75 inch (40
n).xlsx

APPENDIX 2F – PCC Family Model Dataset

PCC Family (111
n).xlsx